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YOLOv11-based Detection of Wagon Brake Cylinder Conditions

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ABSTRACT

Railway transportation stands out as a safe and efficient mode of transport for both freight and passengers. However, failures in train braking systems pose financial and safety risks. In this study, it is proposed to use the recently introduced YOLOv11 (You Only Look Once) models to monitor the mechanical brakes used in wagons. This approach aims to prevent the locking of wheels due to stuck mechanical brakes while the train is in motion, thereby avoiding continuous metal friction and mitigating risks such as flatted wheels, wheel fractures, rail damage, and fire hazards. Such failures not only cause material damage and operational disruptions but also lead to potential loss of life and costly accidents. Traditional methods of manually inspecting brake cylinders provide limited safety and are inefficient in terms of operational effectiveness. Therefore, the automatic monitoring and fault detection of brake cylinders have become crucial. To achieve this, a dataset consisting of three different classes—braked, empty, and evacuated—was used. Using this dataset, YOLOv11n, YOLOv11s, YOLOv11m, YOLOv11l, and YOLOv11x models were trained. The performance of these trained models was evaluated based on accuracy, precision, recall, and F1 scores. The results indicate that the YOLOv11X model is more suitable for cases where reducing false negatives (FN) is critical. However, when minimizing false positives (FP) is a priority, YOLOv11m or YOLOv11s models are more appropriate. For an overall balanced performance, the YOLOv11X model is preferable for the braked condition, while YOLOv11s or YOLOv11m models are more suitable for the evacuated condition. Ultimately, this study demonstrates that the detection of braking mechanisms in trains with high accuracy using YOLOv11 models can significantly contribute to reducing train accidents, thereby preventing loss of life and costly incidents.

Keywords: YoloV11, Railway Safety, Brake Cylinder Detection, Workplace Safety.

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1 Introduction

Railways are one of the fundamental pillars of modern transportation systems, offering significant economic, environmental, and logistical advantages. Evolving since the Industrial Revolution, railway transportation has remained a reliable and efficient option for both passenger and freight transport. During the Ottoman period, a total of 8,619 km of railways were constructed, of which 4,136 km remained within today's borders. In the Republican period, between 1923 and 1950, a total of 3,764 km of railways were put into operation. However, between 1951 and 2003, in parallel with the development of road networks and vehicles, there was no balanced growth in other transportation modes. As a result, the total length of railway lines constructed during the 1951-2002 period remained at 945 km. Since 2003, with the adoption of railways as a state policy, the railway network, which was 10,959 km in 2003, reached 13,919 km by the end of 2023 (Demiryolu Sektör Raporu, 2023). Figure 1 shows a steam train.

The transportation activities of passengers and cargo in Turkey for the years 2019, 2020, 2022, 2021, 2022, and 2023 are presented in Table 1 below. In 2023, passenger transportation increased by 7% compared to 2022, reaching 342.5 million passengers (including YHT, Conventional, Marmaray, Izban, Baskentray, and Gaziray). The number of passengers transported by YHT was 9.36 million in 2022, increasing to 11.86 million by the end of 2023. In freight traffic, there was a 19% decrease compared to the previous year, reaching a value of 13.1 billion ton-km in 2023. The total freight transported in 2023 amounted to 32.4 million tons. Table 1 presents the freight and passenger transportation activities (Demiryolu Sektör Raporu, 2023).

Figure 1: Steam train

Table 1: *Passenger and Freight Transportation Activities in Turkey.*

Passenger Transport	**2019**	**2020**	**2021**	**2022**	**2023**
Number of Passengers (Thousand passengers)	245.852	148.639	191.586	321.589	342.524
High Speed Train	8.274	2.833	4.376	9.364	11.865
Suburban Train	220.022	142.191	181.562	295.138	317.611
Conventional Train	17.556	3.615	5.648	17.087	13.048
Passenger Traffic (Million x km)	14.208	7.981	10.743	19.619	20.913
High Speed Train	2.678	941	1.507	3.244	4.165
Suburban Train	9.347	6.541	8.518	13.875	14.876
Conventional Train	2.183	499	718	2.500	1.872
Cargo Transport	**2019**	**2020**	**2021**	**2022**	**2023**
Freight Transportation (Thousand tons)	33.535	34.549	38.155	38.571	32.408
Load Traffic (Million x km)	14.707	15.428	15.862	16.188	13.108

There are various types of wagons used in railway transportation, including covered wagons, open wagons, flat wagons, tanker wagons, and passenger wagons, as shown in Figure 2. These wagons are designed to transport passengers or various types of cargo, depending on their structure. The transported goods may include food products, electronic devices, delicate materials, minerals, stones, coal, scrap metal, containers, heavy machinery, vehicles, liquid and gaseous substances, petroleum products, and liquefied gases.

Railway transportation is widely preferred worldwide as a safe and efficient transportation alternative. However, this mode of transport requires all components of the system to operate flawlessly (Yorgun, 1989). Braking systems, which have a significant impact on the movement and stopping of trains, play a critical role in railway safety. Even the slightest malfunction in these systems can lead to serious accidents in both passenger and freight transportation, resulting in significant economic losses (Rakshit et al., 2018). Traditionally, the maintenance and inspection processes of railway braking systems have been carried out manually by human labor (Çak & Çelebi, 2002). The methods used for repairs in the workshop not only carry the risk of human error but also fall short in terms of time and cost efficiency. Modern technologies offer new solutions to overcome these challenges. In particular, image processing techniques hold significant potential for the automatic monitoring of braking systems and the early

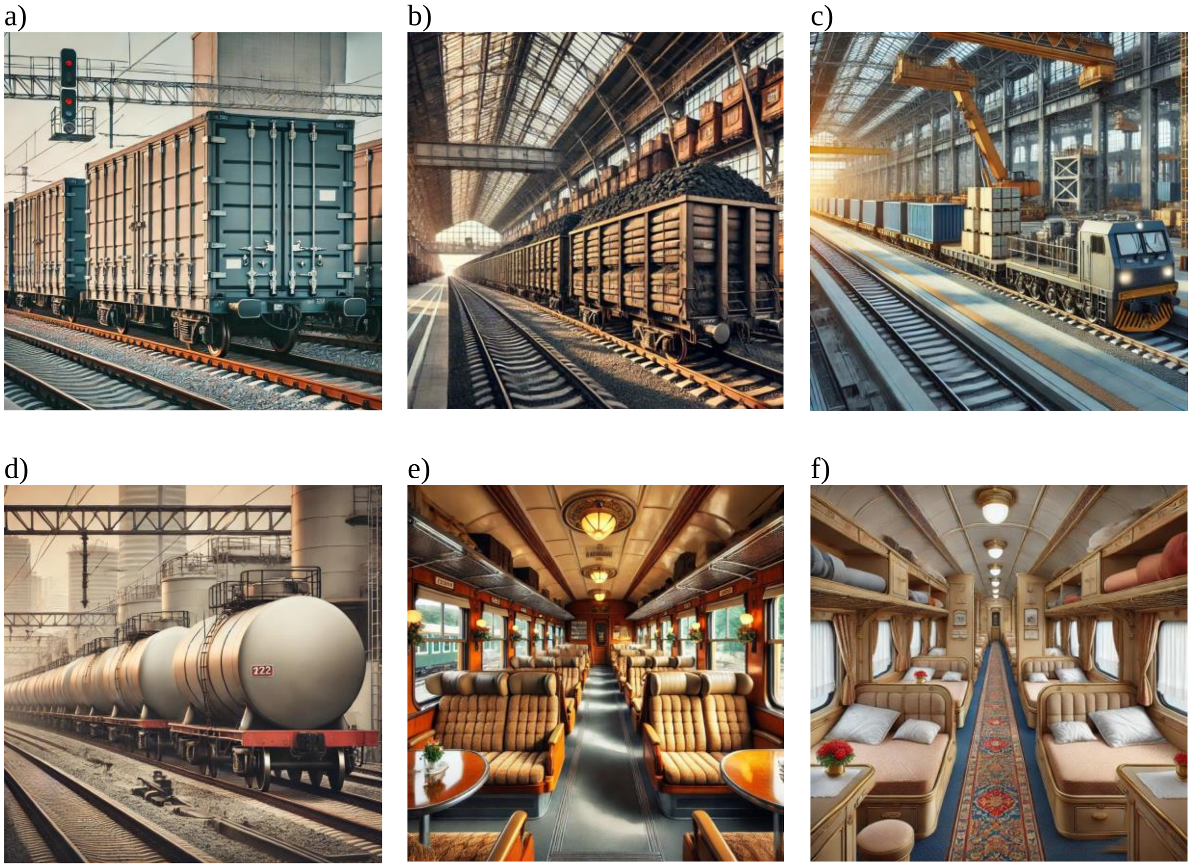


Figure 2: a) Covered wagon, b) Open wagon, c) Flat wagon, d) Tanker wagon, e) Passenger wagons, f) Sleeper wagon

detection of faults. Tasks such as image recognition and classification enable various operations to be performed efficiently (Cimen et al., 2021; M. E. , Çimen et al., 2021; M. E. Çimen, 2024; M. E. Çimen et al., 2019, 2020; Y. Liu et al., 2020; Öztürk & Eldoğan, 2024; Pala et al., 2021, 2022; Yıldırım & Cagıl, 2020). In their study, Lisanti et al. used image processing techniques to extract serial numbers and IDs from wagons, enabling their recognition and classification. Additionally, they verified the correctness of their positioning to ensure railway safety (Lisanti et al., 2018). Similarly, Saina et al. proposed a study where they used drones to capture railway images. Using their proposed deep learning-based RCNN structure, they successfully detected and segmented fishplates on railway tracks (Saini et al., 2024). Wei et al. conducted a comparative study focusing on the detection of mispositioned fasteners in railway tracks. In this study, they utilized the Dense-SIFT method and compared CNN-based models such as VGG16 and Faster R-CNN, achieving successful results (X. Wei et al., 2019). Shang et al. proposed a novel two-stage approach for rail defect detection, which focuses on both the localization and classification of target images (Shang et al., 2018). In another study, Marta Garcia Minguell and her team compared three object detection models—YOLOv5, Faster R-CNN, and EfficientDet—to identify issues on railway tracks. Their analysis, based on a dataset of 31 images featuring three track components (clip, fishplate, and rail), revealed that Faster R-CNN outperformed the other models in terms of accuracy (Minguell & Pandit, 2023). Additionally, Xiaohong Sun et al. introduced an enhanced version of the Faster R-CNN algorithm, designed to improve the detection of multi-class wheel hub faults by sharing convolution layers between Fast R-CNN and the Region Proposal Network (RPN) (Sun et al., 2019). Meanwhile, Gabriel Krummenacher and his colleagues proposed two machine learning techniques that leverage vertical force data, collected from a sensor system permanently installed on the railway track, to automatically identify wheel defects (Krummenacher et al., 2017).

A crucial aspect to consider is the implementation of undercarriage inspection systems for wagons. This method aims to ensure the safety of the lower components of the wagons. Kishore and his team developed algorithms aimed at extracting and localizing defective parts from the bogie (Kishore & Prasad, 2017). N. Sasikala and her colleagues proposed an adaptive multi-object, multi-template matching algorithm for recognizing train bogie components. This method achieved a recognition accuracy of 91%, with a false recognition rate of 15% (Sasikala et al., 2019). Meanwhile, detecting defects in pantograph-catenary systems is essential for ensuring safe and efficient railway operations. Chen and his team proposed a deep neural network-based method for detecting defects in the pantograph-catenary system (PCS) (Chen et al., 2022). Liu et al. used Generative Adversarial Networks (GANs) for pantograph-catenary arcing detection, attempting to identify arcs occurring in these areas (X. Liu et al., 2024). Yan et al. used the Inception V3 model for pantograph-catenary arc detection in trains and achieved successful results (Yan et al., 2025). Zahang et al. used the YOLO V5 model in their study for object detection on railway tracks and early warning purposes. The dangerous objects were distinguished, and the warning level was determined according to the obstacle's position and severity (Zhang et al., 2024). Brintha and Jawhar used a deep learning-based FOD-YOLO to identify fastener defects in railways, achieving successful results (Brintha & Joseph Jawhar, 2024). Chenghai et al. trained a revised YOLO V8-based model to detect defects such as chipping, cracks, and wear in railway switches, achieving successful results (Yu & Lu, 2024). Yang et al. used UAV images to detect foreign objects on railway tracks in their study. They trained a YOLO-based model on these images to identify foreign objects on railway tracks and provide early warnings, aiming to enhance safety (Y. Yang et al., 2025). Ghahremani et al. aimed to detect faults that might occur in solar panels during operation using drones. A dataset was created with images obtained by drones, and training was performed on YOLO V10 and YOLOv11 models, with successful results (A. , Ghahremani et al., 2025). Yang et al. established unmanned aerial vehicle (UAV) highway distress detection using YOLOv11 and achieved successful results (Z. Yang et al., 2025). There are many versions of YOLO used in object detection. The YOLO V11 model, produced in 2024, pushes the boundaries further by addressing the challenges associated with real-time object detection, which is critical for applications requiring rapid and accurate responses. In recent years, it has been applied in various fields such as ship fire detection (Akhmedov et al., 2024), agriculture (Alif & Hussain, 2024; R. , Sapkota et al., 2024), gaming (Savran & Bulut, 2024; Tian et al., 202 C.E.), energy (A. Ghahremani et al., 2025; Khanam et al., 2025), farming (Guarnido-Lopez et al., 2024; R. Sapkota & Karkee, 2025), biology (Mehta et al., 2025; W. Wei et al., 2025), and many more.

This study focuses on detecting the operational status of the brake cylinders of railway wagons. In the project, the condition of the braking systems was analyzed using image processing techniques and artificial intelligence algorithms. When the brakes are not functioning correctly, the locomotive pulls the train from the front, but the train's wheels remain locked. Since the conductor cannot check every wagon, the train continues to move with locked wheels. During this time, as the train moves for hundreds of kilometers, the wheels will not rotate, causing excessive heating due to the continuous metal-on-metal friction on the tracks, as shown in Figure 3. As a result of this heating, the lifespan of the wheels decreases and may cause instability in the wagon. Additionally, the heated wheels can cause the wagon made of metal parts to heat up and potentially lead to a fire. On the other hand, wagons carrying dangerous chemicals, oil, or aviation fuel can be at risk of explosions due to radiation from locked wheels. The method aims to increase safety while also reducing maintenance costs.

Figure 3: Broken malfunctioning brake

The main purpose of the study is to effectively monitor the status of brake cylinders in railway transportation using Yolov11 and to detect faults in advance. In this context, a dataset was created by collecting images of brakes collected from wagons and this dataset was classified. Then, the data collected on Yolo V11 models developed in recent years was trained and successful results were obtained. This study demonstrates that the detection of braking mechanisms in trains with high accuracy using YOLOv11 models can significantly contribute to reducing train accidents, thereby preventing loss of life and costly incidents.

2 Materials and Methods

In this study, the working principle of the mechanism that provides braking of the wagons used in railways will be explained. Then, YOLO will be explained for the classification of the image.

2.1 Brake Systems

Brake systems in trains are important components that ensure the safe stopping of wagons (Yorgun, 1989). The general structure of the system is given in Figure 4. Air brake systems are generally used in wagons. This system consists of brake cylinders and brake blocks that work with air pressure produced by compressors. Driver brake valve provides fast and effective braking through air brake systems and keeps the movement of wagons under control. In addition, there are mechanical brake systems used in emergency situations.

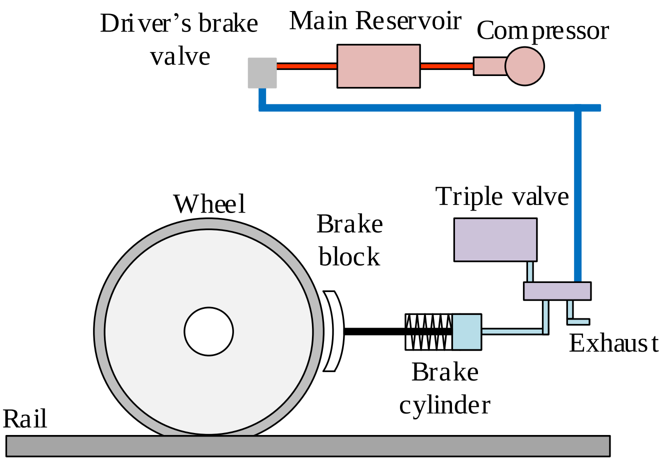


Figure 4: Brake Cylinders and Blocks

The triple valve is a critical component of the railway freight wagon braking system. This valve is used in air brake systems and ensures the automatic engagement and release of the brakes. The triple valve performs three main functions: braking, exhaust, and charging. During braking, compressed air from the air reservoirs is directed to the brake cylinders through the valve. In the exhaust process, the air pressure in the brake cylinders is released, and the brake pads are separated from the wheels. The charging process fills the air reservoirs and ensures the continuous operation of the brake system (Yorgun, 1989). In this case, when the driver activates the valve, the triple valve opens to allow the braking of the cylinder, and the piston moves forward, causing the brake block to rub against the wheel. This results in braking.

2.2 YOLOV11

YOLO is an important artificial intelligence algorithm in the field of object detection. Operating as a single-stage convolutional neural network-based model, YOLO is used to identify and classify objects in images. This model provides fast and efficient solutions for real-time applications. The YOLO algorithm is a preferred method in various applications that require real-time object detection, particularly in image processing and artificial intelligence fields. Used effectively in areas such as autonomous vehicles, security systems, and video analysis, YOLO plays a crucial role in quickly and accurately detecting and classifying objects. The algorithm's high speed, accuracy, and multi-object classification capabilities have made it widely applicable in both industry and research.

YOLO algorithm, first introduced by Joseph Redmon and his team in 2015, has been successfully used in many object detection applications over time. The YOLOv7 object detection algorithm proposed by Wang and his colleagues has proven to outperform other object detection algorithms in the literature, achieving a success rate of 51.2%. The YOLO algorithm has garnered significant attention due to its ability to solve object detection problems quickly, making it a preferred method in many studies. Despite the existence of over ten versions of YOLO, YOLOv5 (M. E. Çimen, 2024; Y. Liu et al., 2020; Olorunshola et al., 2023; Öztürk et al., 2024), YOLOv8 (M. E. Çimen, 2024), and YOLOv10 (Ding et al., 2025) have emerged as the most prominent choices for edge deployment applications. These three variants are particularly notable for their excellent balance of speed, accuracy, and efficiency, making them ideal for environments with limited resources.

YOLOv11 was introduced in 2024 and brought significant innovations in the field of object detection. YOLOv11 represents the newest advancement in the YOLO series, bringing notable enhancements in speed, accuracy, and feature extraction. As depicted in Figure 5 (Rasheed & Zarkoosh, 2024), its architecture is composed of three primary elements: the backbone, the neck, and the head.

Backbone: The backbone is the primary component of YOLOv11, designed to extract crucial features from the input image across multiple scales. It consists of several convolutional (Conv) blocks, each made up of three subcomponents: Conv2D, BatchNorm2D, and the SiLU activation function, as shown in Figure 5. In addition to these Conv blocks, YOLOv11 incorporates several C3K2 blocks, which replace the previous C2f blocks used in YOLOv8 (A. Ghosh, 2024). The C3K2 blocks enable a more efficient implementation of Cross-Stage Partial (CSP) (C.-Y.Wang et al., 2021), as illustrated in Figure 13. The last two layers of the backbone include Spatial Pyramid Pooling Fast (SPPF) and Cross-Stage Partial with Spatial Attention (C2PSA) (K. He et al., 2015). The SPPF block uses multiple max-pooling layers to capture features at various scales effectively, while the C2PSA block applies an attention mechanism to improve the model's performance.

Neck: The neck is the second crucial part of YOLOv11, as shown in Figure 5. It consists of several convolutional layers, C3K2 blocks, concatenation operations, and upsampling layers, while also benefiting from the C2PSA mechanism. The primary role of the neck is to merge multi-scale features and pass them efficiently to the head blocks (A. Ghosh, 2024).

Head: The final component of YOLOv11 is the head, which is crucial for generating predictions. This module is responsible for classifying objects, calculating the objectness score, and accurately determining the bounding boxes around detected objects (N. Jegham et al., 2024).

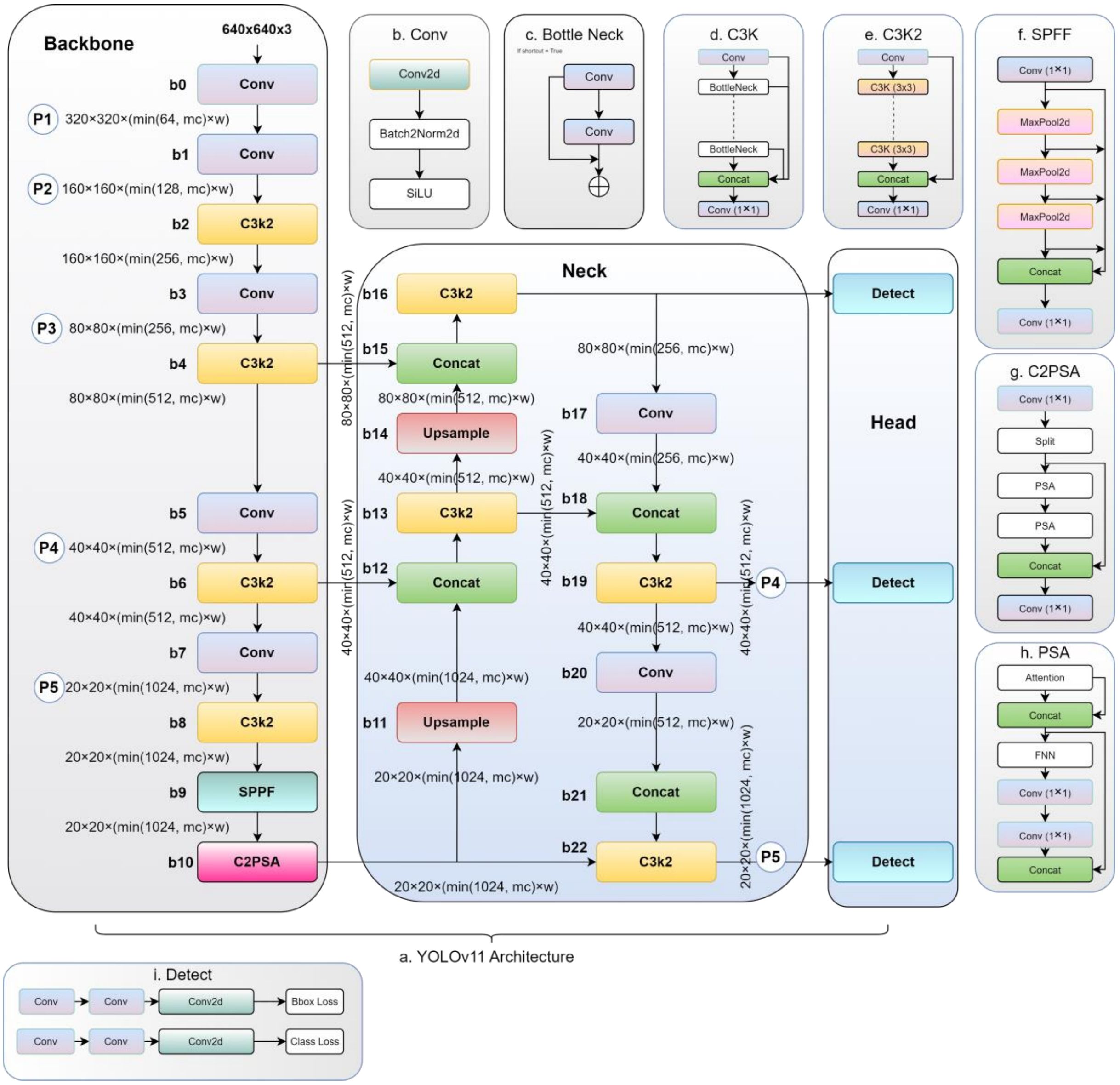


Figure 5: YOLOV11 Architecture(Rasheed & Zarkoosh, 2024)

YOLOv11 improves the detection of both small and large objects by utilizing multi-scale detection and global feature maps, while integrating contextual information from the entire image into the model's decision-making process. YOLOv11 has been extensively tested on standard benchmarks such as COCO, demonstrating superior performance and efficiency, as illustrated in Figure 6. The model achieves state-of-the-art results in different variants, showing significant improvements in latency and accuracy compared to previous versions and other contemporary detectors (*Ultralytics YOLO Dokümanlar*, 2025).

In terms of real-time performance, YOLOv11 provides a significant advantage with its high image processing capacity, particularly in applications such as autonomous vehicles, surveillance systems, and live video analysis. Its modular architecture enables easy integration with various hardware and software platforms, allowing developers and engineers to efficiently use YOLOv11 in diverse applications (*Ultralytics YOLO Dokümanlar*, 2025). YOLOv11 ushers in a new era in object detection technology, offering significant improvements in accuracy, speed, and efficiency, making it an ideal object detection model for use in autonomous vehicles, surveillance systems, robotics, healthcare, and many other fields.

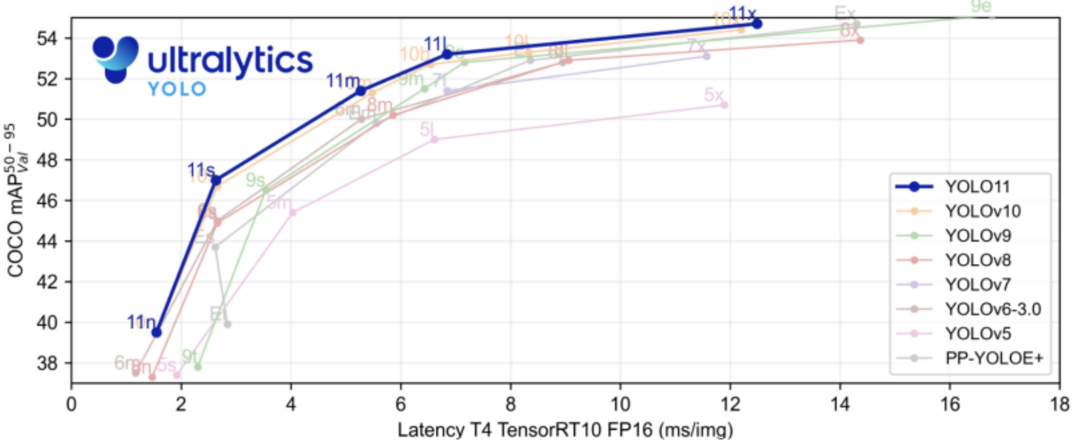


Figure 6: Performance of YOLOV11 Models (*Ultralytics YOLO Dokümanlar*, 2025)

3 Proposed Approach for Status Detection of Wagon Brake Cylinders

The scope of this study is focused on detecting the status of brake systems in railway wagons. In this context, as shown in Figure 7, images of the brake cylinders are captured by a camera when a wagon passes a specific point. These images are then evaluated using YOLOv11 to detect the status of the brake cylinders.

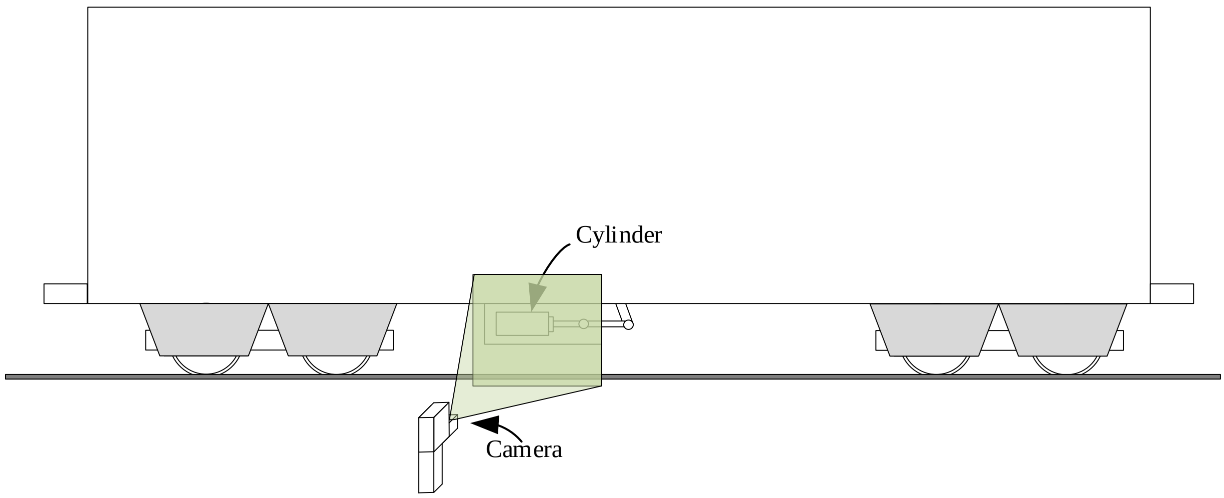


Figure 7: Detection of Brake Cylinder in Wagons Sample Image

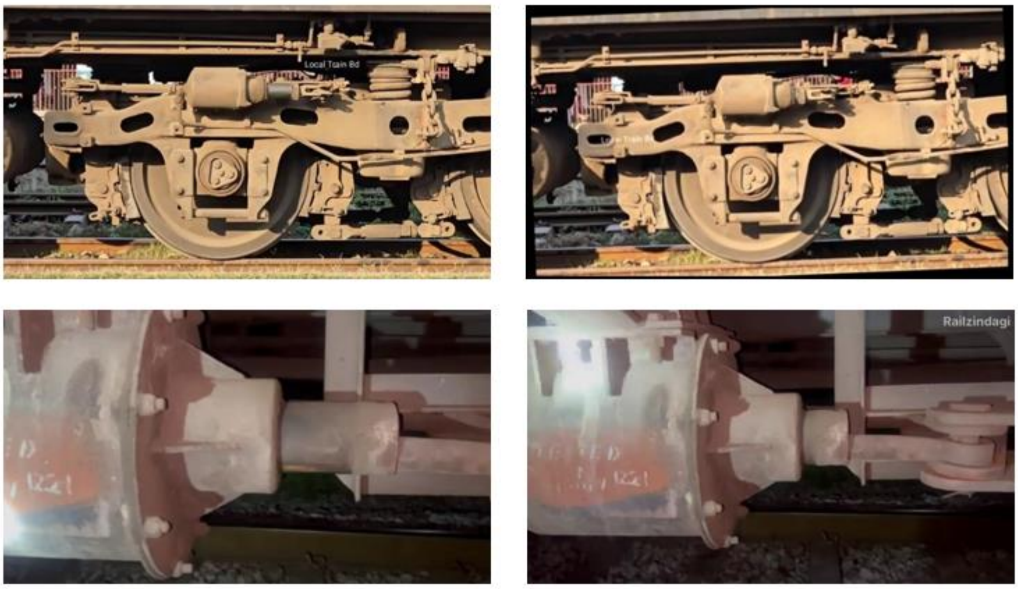
In the discussion section, the conclusions of the current study are compared with the conclusions of similar studies in the literature while interpreting the possible reasons for the conclusions.

3.1 Dataset

The study focuses on the status detection of wagon brake cylinders, and a dataset has been created for this purpose. This dataset was primarily collected from wagons in the Sakarya region, on the internet, and through image capture. A total of 1,132 images were obtained. The numerical data regarding the images are provided in Table 2. Sample images are shown in Figure 8. After the dataset was collected, it was classified into three categories: Braked, Evacuated, and Empty. If the image contains a braked cylinder, it is classified as "Braked." If the cylinder in the image is not braked, it is classified as "Evacuated." If no cylinder is present in the image, it is classified as "Empty." The images were then randomly split into 20% for testing and 80% for training data.

Table 2: *Dataset details.*

Classes	Test (Sample, %Rate)	Training (Sample, %Rate)	Total (Sample)
Braked	340, %20	1360, %20	1700
Evacuated	777, %20	3108, %20	3885
Empty	3, %20	12, %80	15
Total	1120	1120	5600



a) Braked b) Evacuated

Figure 8: Sample images from the dataset: a) Braked images, b) Evacuated images.

After the data is trained on the models, it is necessary to test the accuracy of the model. In this context, the accuracy matrix of the tested model is provided in Table 3.

Table 3. *Confusion Matrix.*

<table>
<tr><td colspan="2" rowspan="2"></td><th colspan="2">Actual</th></tr>
<tr><th>Positive</th><th>Negative</th></tr>
<tr><th rowspan="2">Predicted</th><th>Positive</th><td>True Positive (TP)</td><td>False Negative (FN)</td></tr>
<tr><th>Negative</th><td>False Negative (FN)</td><td>True Negative (TN)</td></tr>
</table>

Accuracy: It indicates how accurately the model classifies in general. High correct classifications suggest that the model performs well. The formula for calculating accuracy is given in Equation 1.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision: These results demonstrate the accuracy and reliability of the developed system for detecting the status of brake cylinders. High values of precision and recall metrics indicate that the model can correctly identify positive classes and has a low error rate. The formula for calculating precision is given in Equation 2.

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

Recall: This recall-confidence curve is used to evaluate how well the model performs at different confidence levels. High recall values indicate that the model is generally successful in identifying positive examples. However, it should be noted that recall values may slightly decrease as the confidence level increases. This is important for determining the confidence level at which the model performs best. The formula for calculating recall is given in Equation 3.

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

F1 Score: It is the harmonic mean of precision and recall. It indicates that the model demonstrates a balanced performance overall. These results show the general performance of the developed system for detecting the status of brake cylinders. High F_1 values prove that the model is balanced and successful in both precision and recall metrics. This suggests that the system can be reliably and effectively used in industrial applications. The formula for calculating the F_1 Score is given in Equation 4.

$$F_1 = \frac{2 \times Precision \times Recall}{Precision \times Recall} \quad (4)$$

4 Simulation Studies

Google Colab is used to train YOLOv11 models for detecting the Status Detection of Wagon Brake Cylinders. Transfer learning is applied by utilizing the pre-trained weights of YOLOv11 versions. The models used, the number of parameters of the models, and the size of the weight files are provided in Table 4. The training parameters of YoloV11 models are presented in Table 5.

Table 4. *Yolo V11 Models details for detect the Status Detection of Wagon Brake Cylinder.*

	YOLOv11n	YOLOv11s	YOLOv11m	YOLOv11I	YOLOv11X
Parameter (Million)	1.6	5.5	10.4	12.9	28.4
Memory	3.1MB	10.7MB	20.39MB	25.339MB	55.7MB

Table 5. *Training parameters for Yolo V11 versions.*

Parameters	Value
Image size	640x640
Batch size	8
Epoch	5

5 Results and Discussion

To evaluate the performance of YOLOv11 models in detecting the status detection of wagon brake cylinder, the models are trained on a dataset. Then, the trained models were compared in terms of metrics such as TN, FN, FP, TP, accuracy, precision, and F_1 score. First, the training time of the trained model and the loss values obtained during the training process are provided in Table 6. Then, performance was measured in terms of classification using test data. For classification, confusion matrices for each model are given between Figure 9 and Figure 13. Subsequently, for each model, TP, FP, FN, TN, accuracy, precision, recall, and F_1 scores for the braked and evacuated classes are provided in Table 7 and Table 8.

When the loss values of the models are examined in Table 6, it can be seen that the lowest value is produced by the YOLOv11n model. On the other hand, the lowest performance is observed with the YOLOv11X model. This is due to the YOLOv11X model having a large number of parameters and the relatively low number of iterations chosen. Additionally, when the training durations of the models are examined, it is found that the YOLOv11n model can be trained in the shortest time, while the model that takes the longest time to train is the YOLOv11X model.

The confusion matrix produced by the YOLOv11n model, which was trained according to the dataset and later tested, is shown in Figure 9. Using the data from Figure 9, the TF, TP, FP, FN values obtained from the classification results for the YOLOv11n model were calculated in Table 7 and Table 8. Subsequently, accuracy, recall, and F_1 values were calculated using these values.

Table 6. *Yolo V10 training results.*

	YOLOv11n	**YOLOv11s**	**YOLOv11m**	**YOLOv11I**	**YOLOv11X**
Loss value	0.20173	0.20584	0.24551	0.24429	0.30835
Training Duration (sec)	1447.21	3786.04	9249.28	13384.3	25644.4

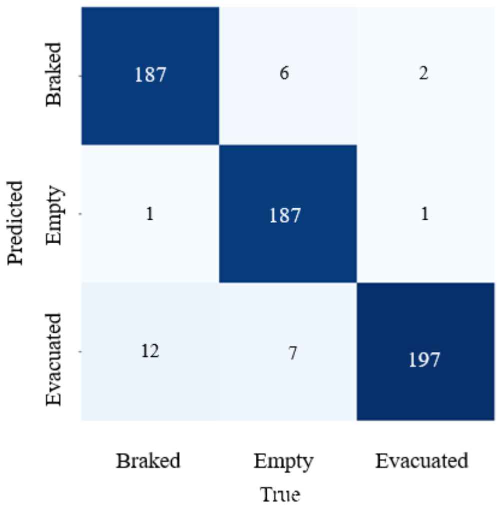


Figure 9: Confusion Matrix for YOLOv11n

The confusion matrix produced by the YOLOv11s model, which was trained according to the dataset and later tested, is shown in Figure 10. Using the data from Figure 10, TF, TP, FP, FN values obtained from the classification results for the YOLOv11s model were calculated in Table 7 and Table 8. Subsequently, accuracy, recall, and F_1 values were calculated using these values.

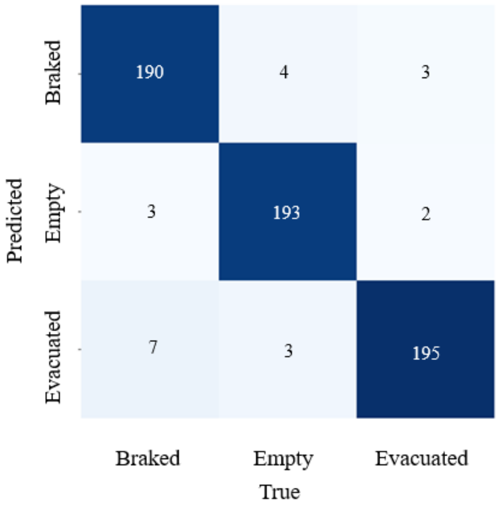


Figure 10: Confusion Matrix for YOLOv11 s

The confusion matrix generated by testing the YOLOv11m model, which was trained on the dataset, is presented in Figure 11. Using the data from Figure 11, TF, TP, FP, and FN values obtained from the classification results of the YOLOv11m model were calculated in Table 7 and Table 8. Subsequently, these values were used to compute the accuracy, recall, and F_1 scores.

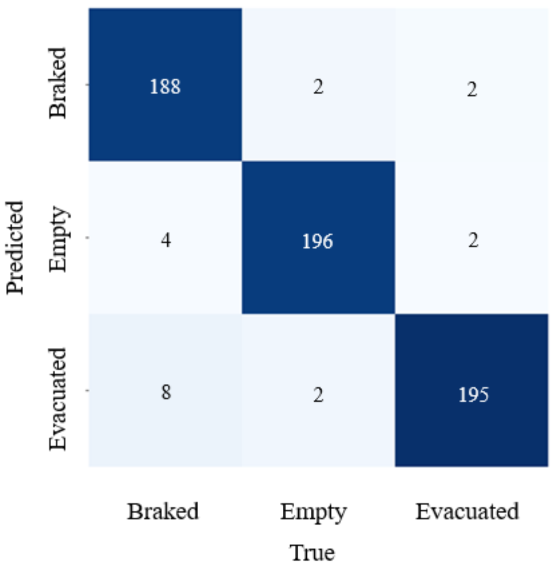


Figure 11: Confusion Matrix for YOLOv11 m

The confusion matrix generated by testing the YOLOv11l model, which was trained on the dataset, is presented in Figure 12. Using the data from Figure 12, TF, TP, FP, and FN values obtained from the classification results of the YOLOv11l model were calculated in Table 7 and Table 8. Subsequently, these values were used to compute the accuracy, recall, and F_1 scores.

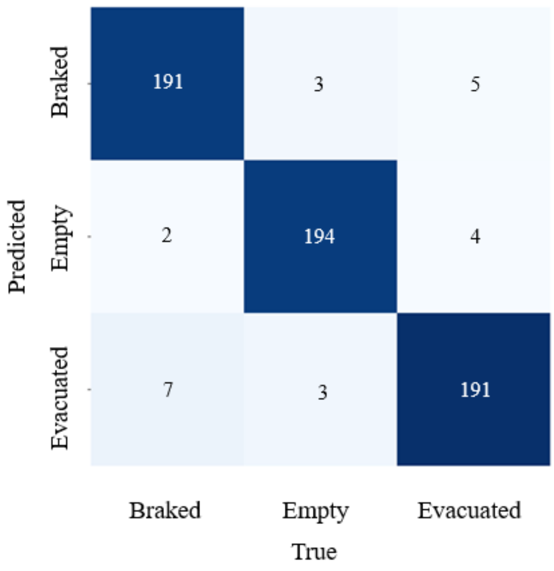


Figure 12: Confusion Matrix for YOLOv11l

The confusion matrix produced by the YOLOv11x model, which was trained according to the dataset and later tested, is shown in Figure 13. Using the data from Figure 13, TF, TP, FP, FN values obtained from the classification results for the YOLOv11x model were calculated in Table 7 and Table 8. Subsequently, accuracy, recall, and F_1 values were calculated using these values.

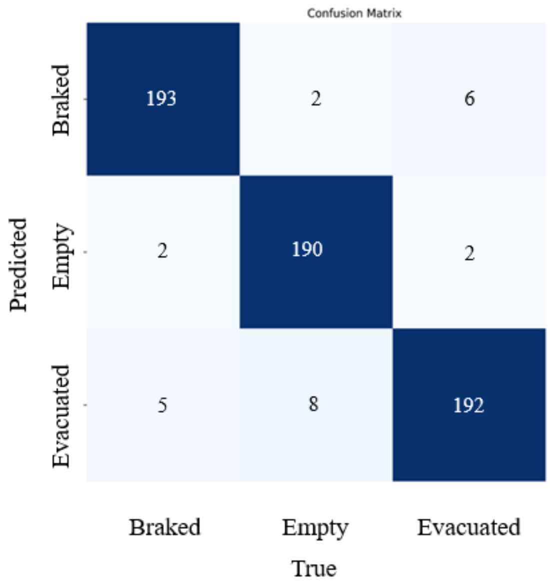


Figure 13: Confusion Matrix for YOLOv11x

The metrics for the Braked and Evaluated classes of all models have been calculated, and the results are presented in Table 7 and Table 8. The best results are marked in bold. For the TP result, when the Braked class is examined, it represents the number of instances where the actual data and the results produced by the model both correspond to Braked. The model with the highest value indicates the best performance. In this regard, it can be observed in Table 7 that the YOLOv11x model produced the best result for the Braked data. In Table 8, for the Evaluated class, the YOLOv11n model produced the best result. FN metric corresponds to cases where the actual data is Braked, but the model outputs Evaluated or Empty. A lower value for this metric is preferred. When examining Table 7 for the Braked class, it is observed that the YOLOv11x model produced the best result. For the Evaluated class in Table 8, the YOLOv11n model produced the best result. FP metric refers to the number of times the model classifies an instance as Braked when the actual class is either Empty or Evaluated. A lower FP value ensures the model generates accurate results. In this context, Table 7 shows that the YOLOv11m model produced the best result for the Braked class. When examining Table 8 for the Evacuated class, it can be seen that many models produced similar results. On the other hand, the TN metric has been evaluated for the models. The TN metric represents the number of instances where a non-Braked data point is correctly classified as Empty or Evacuated. In this regard, Table 7 shows that the YOLOv11m model produced the best result for the Braked class. For the Evacuated class in Table 8, many models produced similar results. Based on the data provided in Table 7 and Table 8, the performance of different YOLOv11 models in brake cylinder detection has been compared. The results were evaluated based on accuracy, precision, recall, and F_1-score. For the Braked (closed brake cylinder) condition, the YOLOv11x model achieved the highest accuracy (0.975) and F_1-score (0.9699), showing the best overall performance. However, the highest precision value of 0.9741 belongs to the YOLOv11m model. A high precision indicates that the model minimizes FP. The YOLOv11s model demonstrated a balanced performance with a recall value of 0.95 and a precision of 0.9645. Therefore, while the YOLOv11X model can be considered the best in terms of overall performance, the YOLOv11m model could be preferred for minimizing FP. For the Evacuated (open brake cylinder) condition, the YOLOv11s and YOLOv11m models achieved the highest accuracy (0.975), precision (0.9512), and recall (0.975), providing the most balanced results. YOLOv11X model, with a recall value of 0.96, minimized FN, while its precision was calculated to be 0.9366. The YOLOv11n model was identified as the model producing the most FP, with the lowest precision (0.9120).

Table 7. *Performance Metrics for Braked of Yolov11 for Brake Cylinder Detection*.

Model	TP	FN	FP	TN	Accuracy	Precision	Recall	F_1
YOLOv11n	187	13	8	392	0.965	0.958974	0.935	0.949763
YOLOv11s	190	10	7	393	**0.971667**	0.964467	0.95	0.960711
YOLOv11m	188	12	**5**	**395**	**0.971667**	**0.974093**	0.94	0.955571
YOLOv11I	191	9	8	392	**0.971667**	0.959799	0.955	0.963261
YOLOv11x	**193**	**7**	8	392	0.975	0.960199	**0.965**	**0.969974**

Table 8: *Performance Metrics for Evacuated of Yolov11 for Brake Cylinder Detection*

Model	TP	FN	FP	TN	Accuracy	Precision	Recall	F_1
YOLOv11n	**197**	**3**	19	381	0.963333	0.912037	**0.985**	0.974046
YOLOv11s	195	5	**10**	**390**	**0.975**	**0.95122**	0.975	**0.975**
YOLOv11m	195	5	**10**	**390**	**0.975**	**0.95122**	0.975	**0.975**
YOLOv11I	191	9	**10**	**390**	0.968333	0.950249	0.955	0.96162
YOLOv11x	192	8	13	387	0.965	0.936585	0.96	0.962494

As a result, the YOLOv11x model is recommended for situations where minimizing FN is critical. However, when FP need to be minimized, the YOLOv11m or YOLOv11s models may be more suitable. In terms of overall balance, YOLOv11x is recommended for the Braked condition, while YOLOv11s or YOLOv11m models are recommended for the Evacuated condition.

The findings obtained in this study have confirmed the effectiveness of algorithms for automatic detection and functionality analysis of brake cylinders. Image processing techniques and data obtained from sensors have enabled the system to achieve high accuracy rates in performance evaluation.

The following key findings were obtained during the research process:

1. Brake Cylinder Detection: The developed image processing algorithms detected brake cylinders with an accuracy rate of over 95%.
2. Performance Evaluation: YOLOv11 models can analyze the overall functionality of the brake systems, identifying potential performance losses in wagons or locomotives. Additionally, these analyses can serve as an important guide in planning the maintenance and repair processes for trains.

The findings have shown that the methods used in the study were successful. The technologies developed for effectively monitoring and analyzing the condition of brake systems have demonstrated the potential to enhance railway safety and reduce costs.

6 Conclusions

In this study, the use of YOLOv11 models to detect the status of brake cylinders in railway wagons has been examined. The primary objective of the study is to effectively monitor the brake cylinder status using YOLOv11 and to detect potential failures in advance. In this context, a dataset consisting of brake images collected from wagons was created and classified. Then, this dataset was trained on the YOLOv11 models developed in recent years, and successful results were obtained. The findings confirmed that image processing techniques and data obtained from sensors are effective for the automatic detection and functionality analysis of brake cylinders. The developed image processing algorithms detected brake cylinders with an accuracy rate of over 95%. YOLOv11 models are capable of analyzing the overall functionality of brake systems by identifying potential performance losses in wagons or locomotives. These analyses can serve as an important guide for planning the maintenance and repair processes of trains. As a result of performance evaluation, it was found that different YOLOv11 models are suitable for different priorities. The YOLOv11x model is recommended for situations where minimizing FN is critical. However, YOLOv11m or YOLOv11s models may be more suitable when minimizing FP is necessary. For a generally balanced performance, the YOLOv11x model is recommended for the "Braked" state, and YOLOv11s or YOLOv11m models are suggested for the "Evacuated" state. In conclusion, this study demonstrates that the high-accuracy detection of braking mechanisms in trains using YOLOv11 models can significantly reduce train accidents, thus preventing fatalities and costly incidents. The developed technologies have the potential to enhance railway safety and reduce maintenance costs.

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