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# Kamusal Alanlarda Transfer Öğrenme Tabanlı Hasar Tespiti

Tuğçe KELEŞ[1]*, Suha TEMUR[2], Furkan KILINÇ[3], Mehmet Veysel GÜN[4], Şengül DOĞAN [5], Türker TUNCER [6]

[1,2,3,4,5,6]Adli Bilişim Mühendisliği Bölümü, Teknoloji Fakültesi, Fırat Üniversitesi, Elazığ, Türkiye.
[1]tkeles@firat.edu.tr, [2]shatmr2304@gmail.com, [3]fkilinc732@gmail.com, [4]mvgun@firat.edu.tr, [5]sdogan@firat.edu.tr, [6]turkertuncer@firat.edu.tr

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**Öz**

Kentlerde hızla artan nüfus ve yoğun kentleşme süreci, kamusal alanların etkin yönetimini ve bu alanlardaki altyapının sürdürülebilirliğini önemli hale getirmiştir. Bu süreç, kent yönetimlerini kamusal alanlardaki hasarların hızlı ve doğru bir şekilde tespiti için yenilikçi çözümler aramaya itmiştir. Geleneksel hasar tespit yöntemleri yavaş ve maliyetli olup, büyük kentlerin dinamik yapısı karşısında yetersiz kalmaktadır. Bu durum kentsel güvenliği ve yaşam kalitesini olumsuz etkilemektedir. Bu noktada, derin öğrenme ve yapay zeka teknolojilerinin hasar tespit süreçlerini otomatik hale getirerek bu soruna bir çözüm sunduğu görülmektedir. Bu çalışmada, kentlerdeki kamusal alanlardaki hasarların otomatik olarak tespiti için yapay zeka tabanlı bir sistem geliştirilmiştir. Düşük kaynak gereksinimi ve elde ettiği yüksek başarı oranı ile MobileNetv2 modeli kullanılmıştır. Veri kümesinin sınırlı olması nedeniyle meydana gelebilecek aşırı uyum sorununu önlemek için veri artırma yöntemleri uygulanmıştır. Model, doğruluk, hassasiyet, geri çağırma ve F1 skoru açısından sırasıyla %83,33, %84,20, %83,30 ve %83,70 başarı elde etmiştir. Bu sonuçlar sayesinde modelin farklı hasar tiplerini iyi bir oranda tespit ettiği görülmektedir. Bu çalışmanın sonuçları, günümüzün hızla kentleşen dünyasında yenilikçi bir çözüm sunmaktadır. Bu çözüm altyapı unsurlarında meydana gelen hasarları hızlı ve etkili bir şekilde tespit ederek şehir yönetimlerine etkili bir yol haritası sunacaktır. Bu durum, hızlı kentleşmenin getirdiği sorunların çözülmesine olanak tanır. Bu kapsamda gerçekleştirilen çalışma hem teorik hem de pratik açıdan önemli bir değer taşımaktadır.

**Anahtar kelimeler:** Yapay zeka, Kamusal alanlar, Hasar tespiti

*Yazışılan Yazar

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Şikayet: fujece@firat.edu.tr

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# Transfer Learning Based Damage Detection in Public Areas

Tugce KELES[1]*, Suha TEMUR[2], Furkan KILINC[3], Mehmet Veysel GUN[4], Sengul DOGAN [5], Turker TUNCER [6]

[1,2,3,4,5,6]Department of Digital Forensic Engineering, Faculty of Technology, Firat University, Elazig, Türkiye.
[1]tkeles@firat.edu.tr, [2]shatmr2304@gmail.com, [3]fkilinc732@gmail.com, [4]mvgun@firat.edu.tr, [5]sdogan@firat.edu.tr, [6]turkertuncer@firat.edu.tr

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**Abstract**

The rapidly increasing population and dense urbanization process in cities have made the effective management of public spaces and the sustainability of the infrastructure in these areas important. This process has led city administrations to seek innovative solutions for rapid and accurate detection of damage in public spaces. Traditional damage detection methods are slow and costly, and are insufficient in the face of the dynamic structure of large cities. This situation negatively affects urban security and quality of life. At this point, it is seen that deep learning and artificial intelligence technologies offer a solution to this problem by automating damage detection processes. In this study, an artificial intelligence-based system has been developed for automatic detection of damage in urban public spaces. The MobileNetv2 model was used with its low resource requirement and high success rate. Data augmentation methods were applied to prevent the overfitting problem that may occur due to the limited dataset. The model achieved 83.33%, 84.20%, 83.30% and 83.70% success in terms of accuracy, precision, recall and F1 score, respectively. These findings demonstrate that, the model detects different damage types at a good rate. The results of this study provide an innovative solution in today's rapidly urbanizing world. This solution will provide an effective roadmap to city administrations by quickly and effectively detecting damage to infrastructure elements. This facilitates addressing challenges caused by rapid urbanization. The study carried out in this context has significant value both theoretically and practically.

**Keywords:** Artificial intelligence, Public areas, Damage detection

*Corresponding author

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Complaints: fujece@firat.edu.tr

## 1. Introduction

Today, urban growth and urban population density are rapidly increasing. This poses a threat to the infrastructure of cities. As a result, problems such as sustainability and the effective management of infrastructure have become increasingly important. Public areas, which are at the center of society, have an important place in social life. Damage, wear and tear of infrastructure components such as roads, benches, sidewalks, street lights and parking areas cause problems [1]. These problems can create visual, functional or security problems [2]. For example, damage to roads causes traffic accidents, while damage to other infrastructure elements directly affects people's quality of life. Failure to intervene quickly in problems in infrastructure elements increases the cost of repair. Delayed repairs also cause further deterioration of infrastructure elements. As a result, larger problems occur and economic losses occur. This also reveals the need for city administrations to use resources primarily in infrastructure repair. Today, the detection of these damages is based on intensive manpower labor. Manual inspections and controls in large cities are very time-consuming and costly. However, these inspections can be prone to error. Such reasons can make it difficult to detect damages accurately and quickly. Traditional methods may be inadequate due to the dynamically changing structure of large and developing cities [3]. In light of these limitations, AI-based methods have emerged as promising alternatives. Today, with the continuous development of technology, advances are also being made in the field of artificial intelligence and image processing. As a result of these developments, studies can be conducted in different disciplines. This study also offers an important opportunity for the damage detection process in public areas [4]. Deep learning methods can reach high accuracy rates in image analysis using convolutional neural networks (CNN) [5]. In this way, processes become faster and more reliable, and high costs can be reduced [6]. City administrations can prioritize necessary repairs by taking this process into account. This can provide an effective roadmap for more effective and efficient use of resources.

The motivation of this study is to address infrastructure problems in public areas and to offer an innovative approach to traditional solutions. The aim of the study is to develop a system that can automatically detect damages in infrastructure in social settlement areas. The developed system aims to accelerate the detection of damages and achieve high accuracy by using deep learning models. In addition, a large and constantly changing dataset will be created by encouraging citizen participation. In this way, not only dataset diversity but also individuals are active in solving problems. This will be the first step in creating livable cities and sustainability. The performance of deep learning models will be evaluated at regular intervals using the dataset, which will be constantly updated with the participation of citizens. Another aim of this project is to increase city security, improve the quality of life of individuals and make resource management more efficient. The study also aims to eliminate the deficiencies in the literature. When the studies in the literature are examined, most damage detection studies usually focus on a single category. However, most datasets are static and inadequate to reflect different regions and conditions. Unlike previous studies, this study was conducted on more than one class. In addition, the fact that the dataset will be updated regularly is one of the unique aspects of the project. This system, which aims to ensure the security and order of public spaces in cities, has the potential to offer significant innovations both theoretically and practically.

### 1.1. Literature review

In the literature, studies on detecting various types of damage in public spaces in cities are limited, with most existing research primarily focusing on crack detection. Studies on crack detection employ advanced image processing and artificial intelligence techniques to identify specific types of damage and to facilitate the classification of these types. However, these studies typically concentrate on a single class of damage, neglecting a broader spectrum of damage categories. Some of the studies conducted in the literature are reviewed as follows.

Shim et al. [7] sought to detect road damage by using super-resolution and semi-supervised learning techniques with generative adversarial network (GAN). The researchers aimed to improve the quality of road damage images and increase damage detection performance in cases where there is a limited number of labeled images. To improve image quality, super-resolution generative adversarial network (SRGAN) is applied and combined with semi-supervised learning method. As a result of the proposed method, an F1 score of 79.22% was obtained. Bibi et al. [8] developed a system that identifies road defects using Edge AI. The study aimed to help vehicles recognize road hazards and defects, such as potholes, bumps and cracks. The dataset, created using images collected from various online sources and open datasets, was trained on ResNet-18 and VGG-11 models. While ResNet-18 provided 100% accuracy for bumps and cracks, VGG-11 achieved accuracy rates of over 99% for cracks and potholes. The study focused on only four damage types. Kyslytsyna et al. [9] proposed a method called ICGA to detect road surface cracks. This model, which was developed to eliminate the difficulties that cGANs experience in shape detection despite their high accuracy, consists of two stages. This model, which removes non-road elements as noise in the first stage and only detects cracks in the second stage, reached an accuracy rate of 88.03% in the Llamas dataset containing 100,000 labeled photographs. Ye et al. [10] proposed a detection network architecture that uses deep learning-based dilated convolution for detecting concrete cracks. They also employed a watershed algorithm to segment the detected cracks. In the proposed STCNet I architecture, the number of parameters is lower and the computation speed is higher compared to traditional networks. While the VGG16 architecture achieved an accuracy of 99.29% and the ResNet50 architecture reached 96.67% accuracy, the STCNet I architecture obtained an accuracy rate of 99.33%. Zou et al. [11] proposed a fully automated method called CrackTree for detecting cracks from road images. To test this method, they collected 206 pavement images containing different types of cracks. Initially, they devised a geodesic shadow removal algorithm to eliminate road shadows while retaining the cracks. Subsequently, they generated a crack probability map through tensor voting, enhancing the connectivity of crack segments by ensuring proximity and curve continuity. Lastly, by selecting crack seed samples from the probability map and representing these seeds with a graph model, they extracted minimum spanning trees from the graph and conducted iterative pruning of tree edges to accurately identify the targeted cracks. The proposed CrackTree method achieved an average F-measure of 85%. Fan et al. [12] designed a new network called U-HDN for crack detection. This network is designed to add multi-scale features to a U-net based encoder-decoder architecture. Using the multiple expansion modulus (MDM), crack information was obtained through expanded convolutions with different expansion rates. Additionally, a hierarchical feature learning module is developed to extract multi-scale features. U-HDN outperformed other methods with an F1 score of 92.4%. Mandal et al. [13] proposed an automatic sidewalk problem analysis system using YOLO v2 deep learning. In their study, a dataset was created containing road images of 9,053 different types of cracks, obtained from a smartphone mounted on a vehicle. During the training phase, 7,240 images captured by mobile cameras were used, and 1,813 road images were employed in the testing phase. The model attained an F1 score of 87,80% for detection without predicting the crack class and 73.94% for classification including the crack class. Zhang et al. [14] introduced a deep learning method for crack detection. In their study, a dataset of 500 images with a resolution of 3264 by 2448 pixels, collected using a smartphone, was utilized. A supervised deep convolutional neural network was utilized to classify each image patch within the collected dataset. The proposed ConvNet-based method achieved an F1 score of 89.65%.

## 1.2. Literature gap

When the studies conducted in the literature are examined, it is seen that the number of studies on damage detection in public areas is limited. However, the studies conducted have focused on a single or small number of damage types. These studies generally examine cracks on the road surface. Damage detection studies focusing on different infrastructure elements in public areas are insufficient. This shows that the existing studies focus on narrow-scope problems. Comprehensive studies addressing different types of damage in public area infrastructures are quite limited. This is seen as an important gap in the literature. Methods that allow for detailed examination of various damage types are needed. In addition, when the existing studies are analyzed, it is seen that the datasets used contain a limited number of classes. This is one of the reasons that restricts the studies conducted in this field. The datasets used in this field have a static structure. For this reason, the studies conducted are not sustainable. In this study, a dynamic dataset was created in order to eliminate the deficiency in this field. The created dataset will be continuously updated depending on time and region. In this way, it is possible for different damage types to emerge and the number of classes to increase. When the studies are examined, it is seen that a comprehensive and dynamic approach is needed to identify different types of damage in public spaces and to help the decision-making mechanisms of city administrations. The aim of this study is to eliminate these deficiencies and offer an innovative solution by presenting a flexible and applicable method in different regions.

### 1.3. Novelities

- When the studies conducted in the literature are examined, it is seen that the studies conducted in the field of damage detection generally have a small number of classes. In contrast to prior research, this study expands the number of damage classes. A comprehensive dataset including 12 different damage types has been created to be used in the study. The created dataset is more comprehensive than the existing datasets in terms of the number of classes. In this respect, it is aimed to make a significant contribution to the literature.
- It is aimed to continuously update the created dataset. In this way, the dataset will be renewed and expanded depending on different regions and different times.
- In the study, unlike the studies with a small number of classes in the literature, a multi-class damage detection process has been carried out. In this way, different damage types have been separated from each other and detailed examination has been carried out.
- The developed method has a flexible architecture. It is possible to add different classes and different damage types to the dataset. This increases the applicability of the system in different cities and regions.
- The developed system has an architecture suitable for working on mobile devices. In this way, it can be used in real-time applications with future studies.

### 1.4. Contributions

- In this study, unlike the limited datasets in the literature, the most comprehensive dataset has been created to our knowledge. The created dataset has 12 classes. With this diversity, it is possible for the proposed model to detect different damage types.
- The dataset will continue to be updated continuously. In this way, different damage types from different regions will be added.
- The proposed system performs the damage detection process quickly and accurately. In this way, resources can be used more efficiently. This will allow for increased public safety.
- Unlike single-class studies in the literature, an innovative solution has been presented with multi-class examination.
- The proposed system is compatible with mobile devices. This provides a significant advantage for real-time applications in future studies.

## 2. Material and Method

### 2.1. Material

The first step of this study is the data collection phase. In this phase, images of specific objects from different cities and regions were collected. Then, these images were labeled as damaged and intact. As a result of the data collection process, a comprehensive dataset was created. The data collection process is shown in Figure 1.

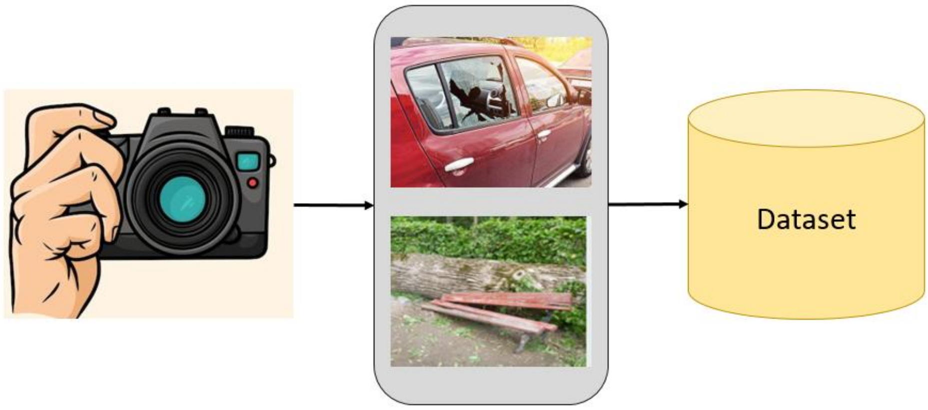


**Figure 1.** Data collection phase

First, the objects focused on in the study were determined. These objects include roads, benches, trash cans, pavement stones, street lamps and windows. Then, damaged and intact labels were defined for each infrastructure element based on certain standards. Images collected from different regions with different mobile phones were classified as damaged and intact. Sample images of each class in the obtained dataset are shown in Figure 2.


**Figure 2.** Classes and sample images in the dataset.

Data augmentation was performed to prevent negative situations such as overfitting that may occur due to the limited number of images in the obtained dataset. Data augmentation is a method used in machine learning and deep learning models to increase the number of data. The purpose of this method is to increase the dataset with various methods and thus increase the performance of the model [15]. In the data augmentation process applied in this study, images were rotated by 90, 180 and 270 degrees. For each image in the original dataset, three different variations were created that allowed the model to be trained with variations obtained from different angles. As a result, it was aimed to reduce the overfitting tendency of the model and to achieve high performance.

The resulting dataset consists of 12 classes, 6 damaged/broken classes and 6 healthy classes. Each class contains a minimum of 701 and a maximum of 3,436 images, and the total dataset consists of 23,508 images, as presented in Table 1.

**Table 1**. Dataset Details

| No | Name | Quantity | |
|---|---|---|---|
| | | **Without augmentation** | **With augmentation** |
| **1** | Damaged Sidewalk | 442 | 1768 |
| **2** | Damaged Road | 859 | 3436 |
| **3** | Damaged Lamp | 254 | 1019 |
| **4** | Broken Bench | 309 | 1236 |
| **5** | Broken Window | 680 | 2720 |
| **6** | Broken Trash Bin | 175 | 701 |
| **7** | Intact Sidewalk | 703 | 2812 |
| **8** | Intact Road | 554 | 2216 |
| **9** | Intact Lamp | 816 | 3264 |
| **10** | Intact Bench | 265 | 1060 |
| **11** | Intact Window | 222 | 888 |
| **12** | Intact Trash Bin | 597 | 2388 |

## 2.2. Method

The method used in the study consists of data preparation, comparison of traditional CNN architectures, feature selection and classification steps. This process is shown step by step in Figure 3;

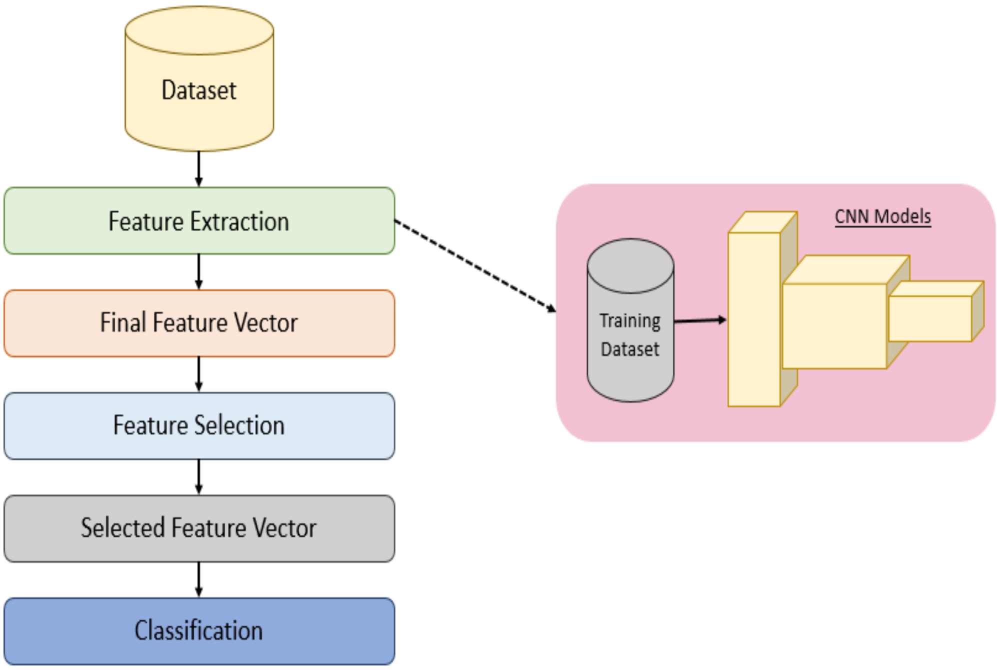


**Figure 3.** Steps of the method used in the study

In the development process of machine learning models, CNN architectures have been actively used. In this process, the first step included organizing the dataset into test and training folders. Then, CNN architectures widely used in the literature such as ResNet50 [16], MobileNetV2 [17], GoogleNet [18], AlexNet [19], InceptionResNetV2 [20], DenseNet201 [21], InceptionV3 [22], DarkNet-53 [23] were examined and the accuracy rates of each architecture were compared. The accuracy rates obtained by the compared CNN architectures [24] are shown in Figure 4. The obtained results revealed that MobileNetV2 performed well with an accuracy rate of 83.3%

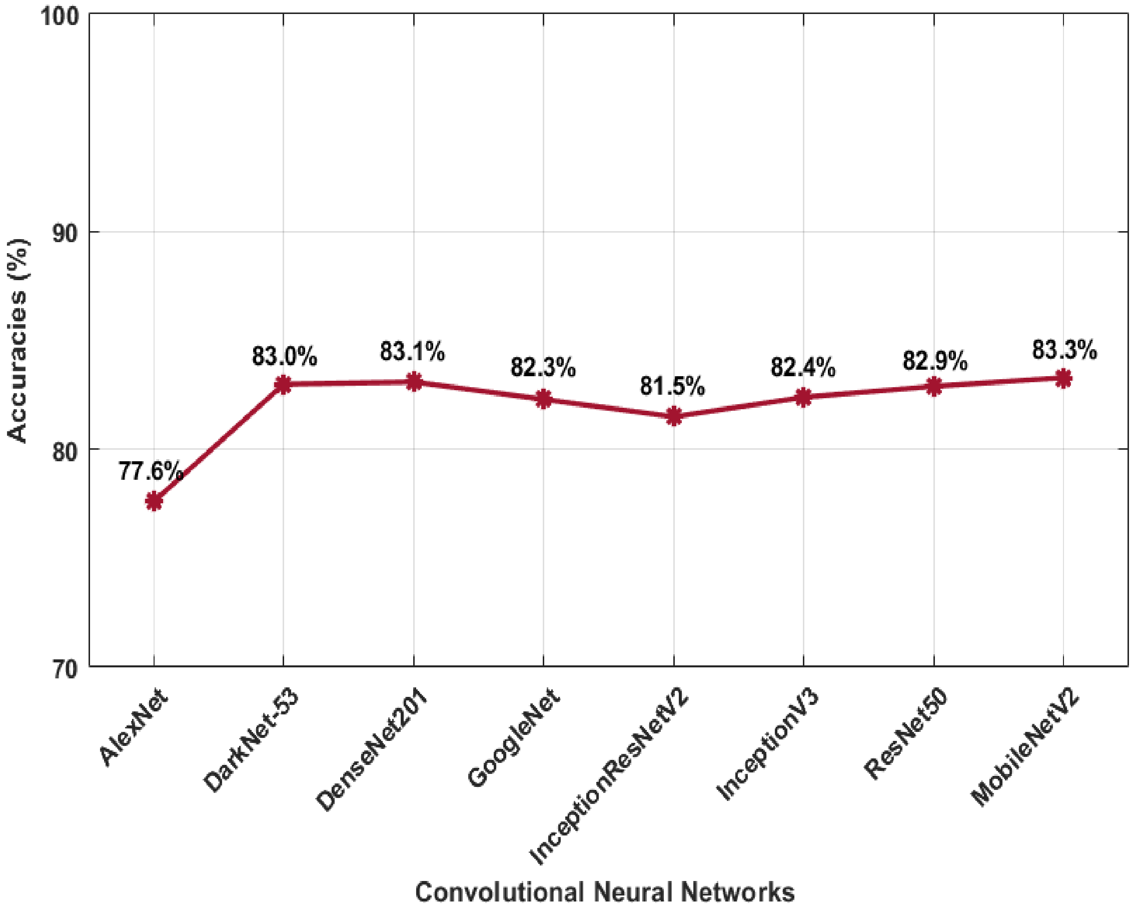


**Figure 4.** Comparison of accuracy rates of different neural networks

In addition, MobileNetV2 [17], uses depth-discrete convolutions and invert residual blocks. This design reduces model parameters and computational cost without sacrificing accuracy. It prevents gradient loss with residual connections and enables complex feature recognition.

MobileNetV2 [17] a lightweight deep learning model, is designed for mobile devices and embedded systems. The model, which performs object detection and segmentation tasks, has less computational and memory usage in image classification. It was introduced by Google as an improved version of MobileNetV1. It has 3.4 million parameters and 154 layers. Its performance has been increased with improved layer structures such as inverse residual blocks and linear bottleneck layers. The architecture of the model is shown in Figure 5.

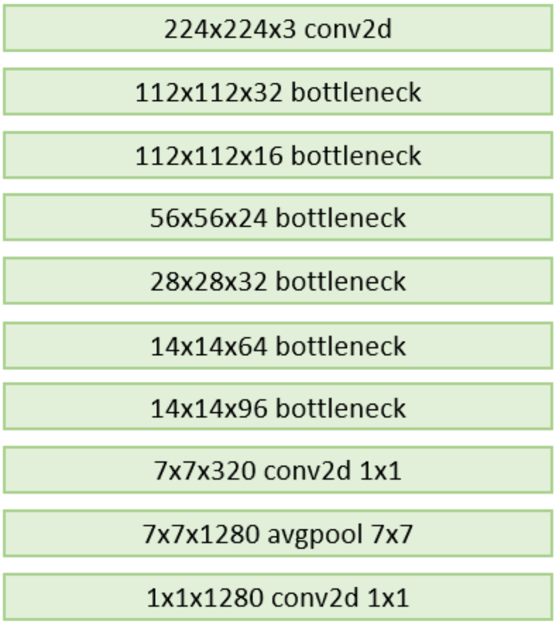


**Figure 5.** MobileNetV2 architecture

MobileNetV2 provides efficient switching between bottleneck layers without information loss through inverse residual connections. It also avoids the distortion caused by nonlinear processing of low-dimensional features by using linear bottleneck layers. This also increases computational efficiency. As in MobileNetV2, it uses depth-based separable convolutions, which increases computational efficiency and helps reduce computational cost. In the convolution process of the model, the initial step is depth-directed convolution, followed by 1x1 point convolution. The MobileNetV2 architectural structure is shown in Figure 6.

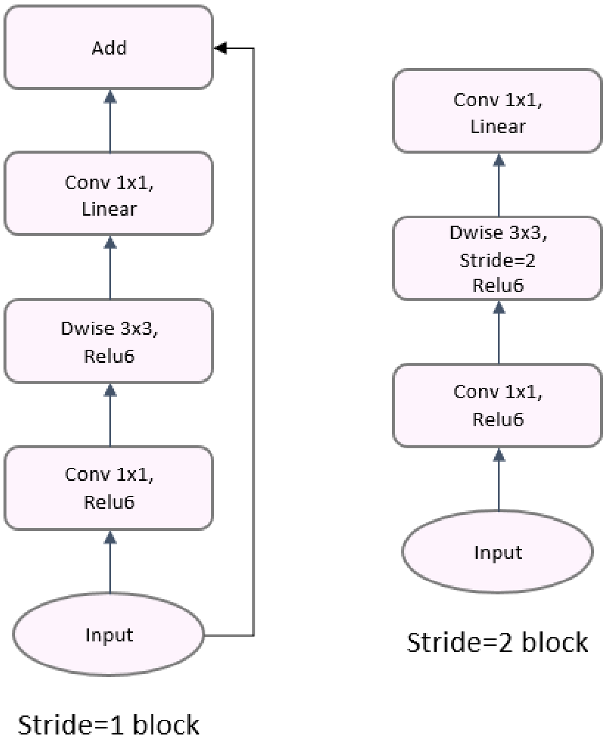


**Figure 6.** MobileNetV2 architecture 2

This structure of the architecture increases efficiency and reduces computational cost. Thanks to the expansion layer, the number of channels is increased and it processes more data. In this way, the input channels of the model are expanded and it processes more information and produces more output channels. This increases the computational power and performance of the model. Although this number of parameters is quite low compared to other CNN models, the model offers high accuracy. The 4.24 million parameters used in MobileNetV1 have been reduced to 3.47 million in MobileNetV2, further improving accuracy. Compared to MobileNetV1, MobileNetV2 has a more efficient architecture and innovations such as inverse residual connections and linear bottlenecks. It also provides efficiency in memory usage. It provides high accuracy in applications such as image classification and object detection on mobile devices.

After developing the model, feature selection step was applied to improve the result of the obtained features. Neighborhood component analysis (NCA) [25] and Chi2 algorithms [26] were used to select the best features.

While NCA performed dimensionality reduction to improve classification accuracy, Chi2 testing measured the contribution of each feature to classification and identified the most important ones. This two-stage feature selection process improved the overall performance of the model and resulted in more accurate classification results [27]. Following the feature selection phase, classification was performed with the selected features. Support Vector Machines (SVM) were preferred at this stage. SVM is an effective classification method for distinguishing between classes in high-dimensional datasets [28]. In this study, the SVM model successfully classified damaged road and pavement images. As a result of the classification, the data was divided into categories such as "Damaged Pavement," "Damaged Road" and "Intact Trash Can" and damage detection was divided into groups based on these categories.

## 3. Results

In this study, it is aimed to perform damage detection of infrastructure elements in public areas. For this purpose, the performances of different convolutional Neural Networks architectures are examined and compared. The examined models include AlexNet, Darknet53, DenseNet201, GoogLeNet, InceptionResNetV2, InceptionV3, MobileNetV2 and ResNet50 architectures. As seen in Table 2, the accuracy rates obtained from the examined models are listed below.

**Table 2.** Comparison of results from different neural networks

| **CNN Models** | **Accuracies (%)** |
|---|---|
| AlexNet | 77.6% |
| Darknet53 | 83.0% |
| DenseNet201 | 83.1% |
| GoogLeNet | 82.3% |
| InceptionResNetV2 | 81.5% |
| InceptionV3 | 82.4% |
| MobileNetV2 | 83.3% |
| ResNet50 | 82.9% |

Within the scope of the project, various classification models were tested and their accuracy rates were calculated. Table 3 presents the accuracy rates of the tested classifiers.

**Table 3.** Comparison of Accuracy Rates of Different Models

| Classifiers Names | Accuracy (%) |
|---|---|
| Fine Tree | 57.0 |
| Boosted Trees | 64.0 |
| Bagged Trees | 72.8 |
| Linear Discriminant | 76.6 |
| SVM Kernel | 81.5 |
| Medium Gaussian SVM | 80.0 |
| Quadratic SVM | 82.5 |
| Cubic SVM | 83.3 |

MobileNetV2 model was used together with Cubic SVM, reaching the highest accuracy rate of 83.33% and demonstrating high performance.

A confusion matrix was also created to further evaluate the success of the classification model. This matrix, shown in Figure 7, reveals how accurately the model predicts each class and the cases of misclassification.

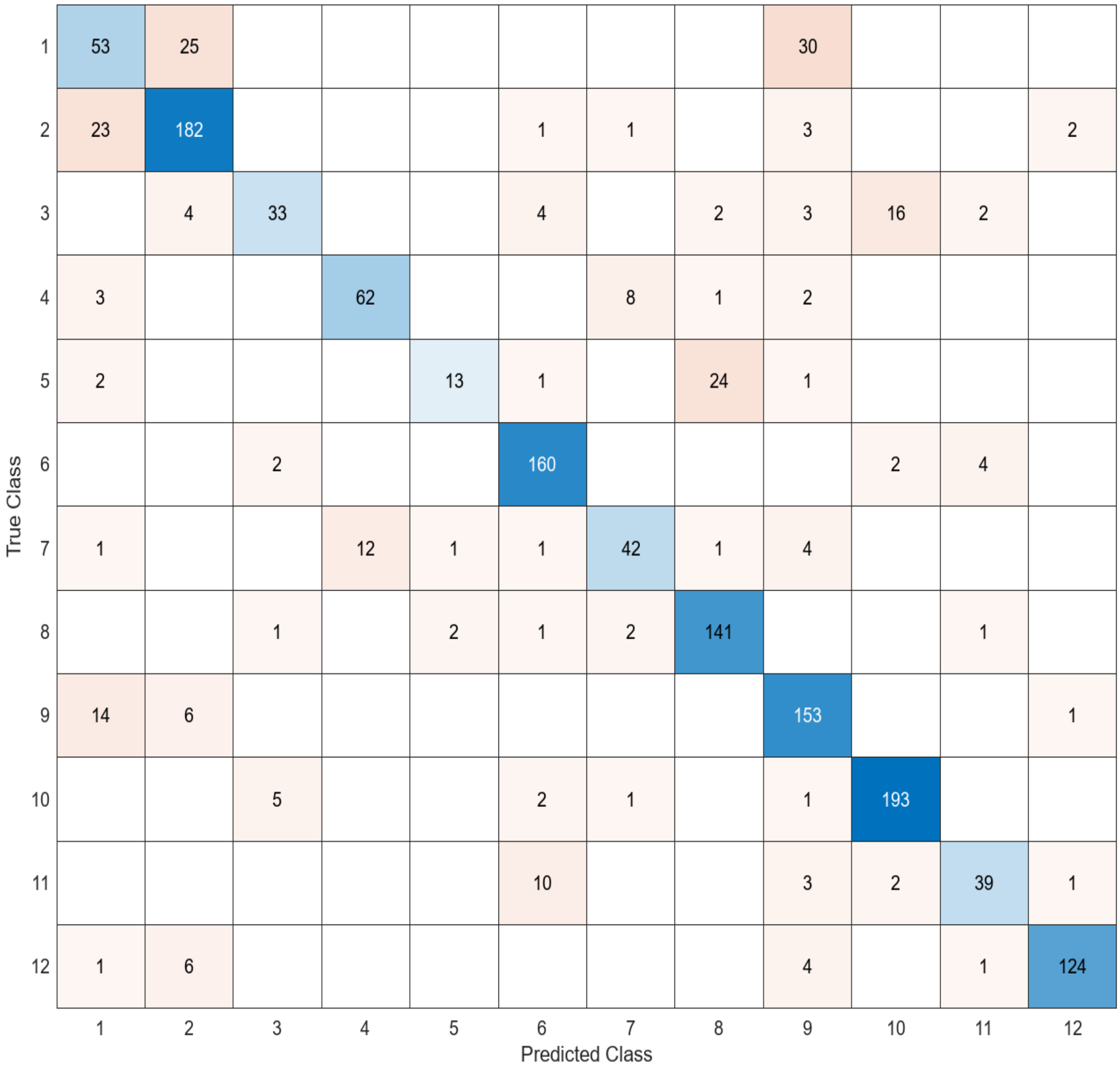


**Figure 7.** Confusion Matrix

For an overall evaluation of this performance, the average accuracy, precision, recall and F1 score for all classes were calculated and the results are presented in Table 4 [29]:

Accuracy: Accuracy is the ratio of all correct predictions to the total predictions and is calculated as in Equation 1:

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

Precision: Precision shows how many of the classes the model positively predicts are correct. It is calculated as in Equation 2:

$$\frac{TP}{TP+FP} \tag{2}$$

Recall: Recall indicates how accurately the model detects classes that are actually positive. It is calculated as in Equation 3:

$$\frac{TP}{TP+FN} \tag{3}$$

F1 Score: F1 Score is the harmonic average of Precision and Recall and provides a balanced evaluation. It is calculated as in Equation 4:

$$2*\frac{Pre*Rec}{Pre+Rec} \tag{4}$$

**Table 4.** Overall Evaluation of the Proposed Model

| Metric | Value (%) |
|---|---|
| Accuracy | 83.33 |
| Precision | 84.20 |
| Recall | 83.30 |
| F1 Score | 83.70 |

This MobileNetV2 based method applied in the study achieved 83.33%, 84.20%, 83.30% and 83.70% accuracy rates in accuracy, precision, recall and F1 score, respectively. High accuracy rate was achieved in the detection of damage types with the classification step performed after feature selection. The proposed method is not dependent on the dataset used in this study and can be applied in different scenarios. Another advantage of the method is that it can obtain effective results even with limited resources such as mobile devices. The obtained results provide an important resource for the automatic detection of damaged infrastructure objects in public areas.

## 4. Discussion

The dataset used in this study covers more classes compared to the datasets found in the literature. The created dataset includes 12 different classes that include both damaged and intact states of objects such as benches, street lamps, trash cans, sidewalks and roads in public areas. Unlike most literature studies, a multi-class classification task was performed rather than a single class. MobileNetV2 architecture was preferred to process this classification structure, and in the discussion section, the performance of this architecture on multiple classes, the accuracy of the model, its comparison with other studies in the literature, its advantages and limitations will be examined.

In Figure 8, the accuracy rates of the models obtained using various classification algorithms are presented comparatively. This analysis details the performance of classifiers such as Fine Tree, Boosted Trees, Bagged Trees, Linear Discriminant, SVM Kernel, Medium Gaussian SVM, Quadratic SVM and Cubic SVM. The results reveal that the models differ significantly in terms of accuracy. While the Fine Tree algorithm achieved the lowest accuracy rate with 57%, the highest accuracy rate was provided by Cubic SVM with 83.3%. These results reveal which model performs best under the given conditions, allowing for a comparison of the effectiveness of different classifiers on the dataset.

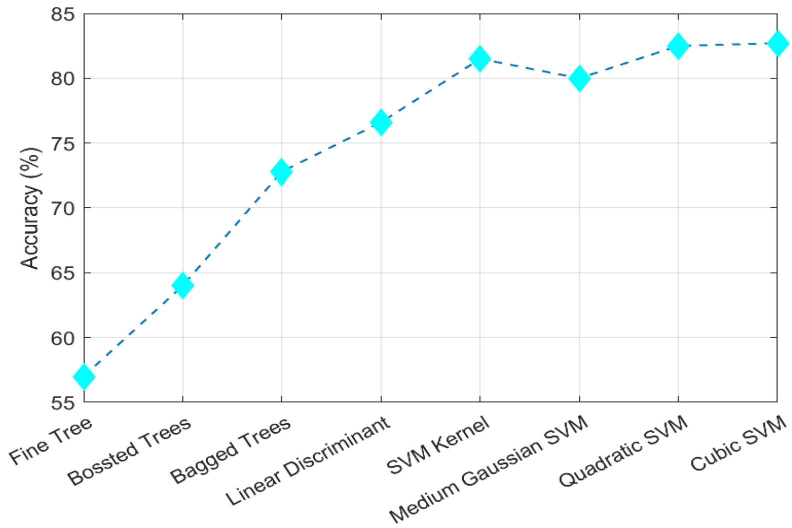


**Figure 8.** Comparison of Accuracy Rates of Different Models

The findings of other studies in the literature are summarized to help better understand the current knowledge in the literature. A comparative analysis was made with the results of this study. The findings obtained are shown in Table 5.

**Table 5.** Literature rewiev

| Study | Method | Dataset | Results (%) |
|---|---|---|---|
| Xu et al. [30] | Transformer-based deep neural network | Stone331, CrackLS315, CrackTree260, CrackWH100 | Avr. precision: 93.04%, Recall: 92.85% |
| Hu et al. [31] | YOLOv5l | 3001 images | Accuracy: 88.1% |
| Huyan et al. [32] | CrackU-net | 3000 images | Accuracy: 99.01% |
| Chen et al. [33] | Customized-CNN | 2000 images | Accuracy: 90% |
| Liu et al. [34] | YOLOv3 and U-Net | 27,966 images | Precision: 91.95%, Recall: 89.31%, F1 score: 90.58% |
| Djenouri et al. [35] | IGCNN-RCD | CrackTree, CrackForest ALE | Precision: Over 70% |
| Ahmedi et al. [36] | Machine Learning Model | 400 images | %93,86 |
| Haciefendioglu et al. [37] | Faster R-CNN | 323 images | Sunny day and a cloudy day: 100% Foggy day: 50% |
| Nguyen et al. [38] | Customized-CNN | 2StagesCrack | F1 score: 90.00% |
| Our study | MobileNetV2 | Our dataset | Accuracy: 83.33% |

Beyond technical accuracy, the model's practical utility is enhanced by enabling citizen participation. The accuracy rate achieved by the model can be beneficial not only in theory but also in real-world applications. Damage detection in public areas is carried out by municipal teams. This process is time-consuming and costly. In addition, the scope of the study can be expanded with the participation of citizens. Thanks to the participation of citizens, the infrastructure of cities can be continuously monitored and city administrations will be faster and more effective. Citizens can report infrastructure problems through mobile phones or mobile applications. In this way, city administrations can carry out repairs faster, which prevents greater economic losses. For example, citizens can report broken roads or broken banks to the municipality through mobile applications. The image uploaded to the application is classified by the developed system and can accelerate the repair process by directing municipal teams to this area. In addition, critical infrastructure problems such as roads and bridges after natural disasters can be reported and rescue and repair processes can be accelerated. By encouraging the participation of citizens, data diversity will increase thanks to the data obtained from different regions and conditions. In addition, citizens will become more sensitive and will directly contribute to infrastructure improvement. As a result of all this, the decision-making mechanism of city administrations will be assisted and resources will be used more effectively.

### 4.1. Advantages

1. Designed for mobile devices, MobileNetv2 has significant advantages for limited capacity applications.
2. In this study, data augmentation was applied to increase the performance of the model.
3. This study was carried out on 12 different classes.
4. Thanks to the optimization of the model, it allows it to be used in real-time applications in future studies.
5. The dataset created with the contribution and feedback of citizens can be improved up-to-date.

### 4.2. Limitations

1. The images in the dataset used in the study are concentrated in certain regions. And have a small number of damage types. This can make it difficult to apply the model to different regions and different damage types.
2. The images in the dataset consist of images taken by citizens from their mobile phones. This introduces variability in image quality and angle, which may affect model performance.
3. MobilNetv2, which is optimized for mobile devices, may experience difficulties in applications as the dataset grows.

## 5. Conclusion

In this study, MobileNetV2 model was used to detect different types of damages in infrastructure objects located in public areas in cities. The dataset used in the study is limited. Therefore, a data augmentation technique was applied by rotating the images at different angles in order to achieve better model accuracy. In this way, a high success rate was achieved in the damage detection task. The model achieved 83.33%, 84.20%, 83.30% and 83.70% accuracy rates in accuracy, precision, recall, and F1 score, respectively. The results obtained from the study show that the model detects different types of damage with good accuracy and is adaptable to different scenarios. Another advantage of the proposed method is its strong performance on resource-constrained platforms such as mobile devices. Thus, it increases the possibility of deployment in practical urban applications. One of the important factors in increasing the performance of the model is the application of the feature selection stage together with data augmentation. Overfitting was prevented with these techniques. This study aims to automate the maintenance of social centers in cities by increasing the performance of the model. As a result of the findings, it is demonstrated that different types of damage can be detected quickly and reliably. This enables city administrations to use resources efficiently and follow an efficient path in repair interventions. In addition, it helps improve the quality of life of the society and contribute to sustainability by encouraging the participation of citizens.

## 6. Future Directions

The findings of this method based on the Mobilenetv2 model have been explained in detail in the previous sections. However, suggestions for the diversity and development of future studies are as follows:

- The dataset used in the study is currently limited. In future studies, the dataset can be expanded by adding different damage types from different regions to increase the applicability of the model to different scenarios.
- Higher resolution images can be added so that the model can detect smaller and more complex damage types.
- To be proposed as a practical tool for municipal decision-making, the model's performance should be tested in current real-time applications.
- In future studies, applications can be implemented with different deep learning architectures and a comparison can be made with the performance of the MobileNetV2 model.
- The diversity of the dataset can be increased with different techniques such as cropping and brightness adjustments during the data augmentation process.
- Studies can be conducted on integrating the model into infrastructure repair processes to provide auxiliary support to decision-making mechanisms in cities.
- Mobile applications can be developed to encourage citizens to use it. By adding a feedback mechanism to these applications, the system's performance can be continuously improved through model updates.

## 7. Author Contribution Statement

Author 1 contributed to Conceptualization, Methodology, Software, Investigation, Resources, Data Collection, Writing - Original Draft, Writing - Review & Editing. Author 2 was responsible for Investigation, Dataset Collection. Author 3 participated in Investigation, Dataset Collection. Author 4 contributed to Software, Methodology, Visualization. Author 5 was responsible for Validation, Formal Analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision, Project Administration. Author 6 contributed to Validation, Formal Analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Supervision, Project Administration.

## 8. 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.

## 9. Ethical Statement Regarding the Use of Artificial Intelligence

No artificial intelligence-based tools or applications were used in the preparation of this study. The entire content of the study was produced by the authors in accordance with scientific research methods and academic ethical principles.

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