Turkish Journal of Science & Technology
18(2), 291-299, 2023.

Research Paper
https://doi.org/10.55525/tjst.1291814

Deep Learning for Physical Damage Detection in Buildings: A Comparison of Transfer Learning Methods

Saltuk Taha USTAOĞLU[1], Betül BEKTAŞ EKİCİ[2*]
[1] Master Student, Department of Architecture, Fırat University, Elazig, Türkiye
[2] Department of Architecture, Faculty of Architecture, Fırat University, Elazig, Türkiye
[1] saltukustaoglu@gmail.com, [*2] bbektas@firat.edu.tr

(Geliş/Received: 04/05/2023; Kabul/Accepted: 23/05/2025)

Abstract: The detection of physical damage in buildings is a critical task in ensuring the safety and integrity of structures. In this study, the effectiveness of deep learning methods for detecting physical damage in buildings, specifically focusing on cracks, defects, moisture, and undamaged classes was investigated. Transfer learning methods, including VGG16, GoogLeNet, and ResNet50, were used to classify a dataset of 7200 images. The dataset was split into training, validation, and testing sets, and the performance of the models was evaluated by using metrics such as accuracy, precision, recall, and F1-score. Results show that all three models achieved high accuracy on the test set, with VGG16 and ResNet50 outperforming GoogLeNet. Additionally, precision, recall, and F1-score metrics indicate strong performance across all classes, with VGG16 and ResNet50 achieving particularly high scores. It is demonstrated the effectiveness of deep learning methods for physical damage detection in buildings and provides insights into the comparative performance of transfer learning methods.

Key words: Structural damage classification, deep learning, convolutional neural networks, transfer learning.

Binalarda Fiziksel Hasar Tespiti için Derin Öğrenme: Transfer Öğrenme Yöntemlerinin Karşılaştırılması

Öz: Binalardaki fiziksel hasarın tespiti, yapıların güvenliğini ve bütünlüğünü sağlamada kritik bir görevdir. Bu çalışmada, özellikle çatlaklar, kusurlar, nem ve hasarsız sınıflara odaklanarak binalardaki fiziksel hasarı tespit etmek için derin öğrenme yöntemlerinin etkinliği araştırılmıştır. VGG16, GoogLeNet ve ResNet50 dahil olmak üzere transfer öğrenme yöntemleri, 7200 görüntüden oluşan bir veri kümesini sınıflandırmak için kullanılmıştır. Veri kümesi eğitim, doğrulama ve test kümelerine ayrılmış ve modellerin performansı doğruluk, kesinlik, geri çağırma ve F1-skoru gibi ölçütler kullanılarak değerlendirilmiştir. Sonuçlar, üç modelin de test setinde yüksek doğruluk elde ettiğini, VGG16 ve ResNet50'nin GoogLeNet'ten daha iyi performans gösterdiğini ortaya koymuştur. Ayrıca, hassasiyet, geri çağırma ve F1-skoru ölçümleri tüm sınıflarda güçlü performans gösterirken, VGG16 ve ResNet50 özellikle yüksek puanlar elde etmiştir. Binalarda fiziksel hasar tespiti için derin öğrenme yöntemlerinin etkinliği gösterilmiş ve transfer öğrenme yöntemlerinin karşılaştırmalı performansına ilişkin içgörüler sağlanmıştır.

Anahtar kelimeler: Yapısal hasar sınıflandırması, derin öğrenme, evrişimli sinir ağları, transfer öğrenme.

1. Introduction

The detection of physical damage in buildings is a critical task for ensuring their safety and longevity. Physical damage can take various forms, including cracks, deformation, and moisture, and can be caused by factors such as natural disasters, structural weaknesses, or aging. Detecting and assessing physical damage is typically performed by human inspectors, who visually inspect buildings for signs of damage. However, this process can be time-consuming, costly, and subject to human error [1].

Recent advances in machine learning, particularly deep learning, have opened up new possibilities for automated physical damage detection in buildings. Deep learning is a subset of machine learning that uses neural networks to learn patterns and features from large datasets and has been successfully applied to various image classification tasks, including medical diagnosis, object recognition, and natural language processing [2].

This study investigates the effectiveness of deep learning methods for detecting physical damage in buildings. Four classes of physical damage: crack, defect, moisture, and undamaged are taken into consideration. We use a dataset of 7200 images, with 1800 images in each class, and employ transfer learning methods to classify the images. Transfer learning is a popular approach in deep learning that leverages pre-trained models on large datasets to improve the performance of smaller, task-specific datasets [3], [4].

* Corresponding author: bbektas@firat.edu.tr. ORCID Number of authors: [1] 0000-0001-7378-3374, [2] 0000-0003-0142-0587.

Specifically, we compare the performance of three transfer learning methods: VGG16, GoogLeNet, and ResNet50. VGG16Net is a deep convolutional neural network architecture used for image recognition and classification. It was developed by the Visual Geometry Group (VGG) at the University of Oxford in 2014 and consists of 16 layers of convolutional and fully connected neural network layers. VGG16Net achieved state-of-the-art performance in several image recognition and classification tasks and has been widely used as a pre-trained model in transfer learning for various computer vision applications [5]. GoogLeNet, also known as Inception V1, is another CNN that won the ImageNet competition in 2014 and is known for its efficient use of computational resources [6]. ResNet50 is a more recent CNN architecture that uses residual connections to improve the training of deep neural networks [7].

We split our dataset into training, validation, and testing sets, and evaluate the performance of the models using metrics such as accuracy, precision, recall, and F1-score. Our study contributes to the growing body of literature on using deep learning for physical damage detection in buildings and provides insights into the comparative performance of transfer learning methods. The results of our study have important implications for the development of automated systems for building inspection and maintenance, which can improve the safety and longevity of buildings while reducing costs and human error.

2. Literature Review

Deep learning-based approaches have shown remarkable results in the field of computer vision, particularly in object detection and classification tasks. In recent years, these methods have also been applied to building damage detection tasks, with promising results. The detection of physical damage in buildings is a critical task for ensuring their safety and structural integrity. Traditional methods for damage detection require expert knowledge and are often time-consuming and expensive. The use of machine learning methods for physical damage detection in buildings has gained significant attention in recent years. Deep learning, in particular, has shown promise for automated building inspection and maintenance, which can improve safety, reduce costs, and increase efficiency.

Several studies have investigated the application of deep learning methods for building damage detection. For example, Kung et al. [8] proposed a method that combined UAV with a deep learning model to detect external wall tile deterioration of buildings, using images taken by the UAV. The authors made modifications to improve the efficiency of their method and tested the model's accuracy for efflorescence (Accuracy 91%, Recall 80%), spalling (Accuracy 76%, Recall 100%), cracking (Accuracy 86%, Recall 86%), and defacement (Accuracy 98%, Recall 78%). The model achieved high accuracy and recall rates for efflorescence, cracking, and defacement, but slightly lower rates for spalling. Similarly, Flah [9] has introduced an automated inspection model that employs image processing and deep learning techniques to identify defects in concrete structures that are not easily accessible. This model has demonstrated a remarkable classification accuracy of 97.63%, 96.5%, and 96.17% for the training, validation, and testing datasets, respectively. Additionally, it has achieved low quantification error in determining crack length, width, and angle of orientation.

In another study, Wang et al. [10] Wang et al. [10] have presented a two-tier approach for detecting and segmenting objects using Faster R-CNN and Mask R-CNN, respectively. This approach is specifically designed to identify and quantify the damage on historic glazed tiles. The method achieved an average precision of 0.910 and 0.890 for roll roofing and pan tiles, respectively, and an average precision of 0.975 for damage segmentation. A hierarchical CNN and gated recurrent unit framework were suggested by Yang et al. [11] for detecting structural damage, incorporating both spatial and temporal relationships. This framework was assessed using two datasets: the IASC-ASCE structural health monitoring benchmark and a scale model of a three-span continuous rigid frame bridge structure. The results of the evaluation showed that the proposed method outperformed other existing approaches with a detection rate of 84.3%. A new approach for rapid investigation and damage detection of the Great Wall was presented by Wang et al. [12], which combined mobile crowd sensing with deep learning techniques. The proposed Great Watcher system demonstrated an accuracy of 78.2% in classifying damage to the Great Wall. Furthermore, a surface damage identification and location technique based on Faster R-CNN was introduced, which quickly identified and located damage to masonry structures on the Great Wall. Nex et al. [13] proposed a CNN model for visible structural damage detection using heterogeneous and large datasets covering different locations, spatial resolutions, and platforms. The results showed that quality metrics are influenced by the composition of training samples used in the network and pre-trained networks optimized for different spatial resolutions.

In another study, Jiang et al. [14] proposed a method based on deep learning called DDSNet, combines optimized YOLOv4 and deeplabv3+ models for two-stage pavement crack detection and segmentation. They stated that the accuracy is improved by 2.23% and 7.47%, respectively, and the inference speed is increased by

35.3% and 50.3%, respectively. Lin et al. [15] proposed a structural damage detection approach using deep convolutional neural networks that can automatically extract features from low-level waveform signals. Their results show that the CNN approach achieves high accuracy, even with noisy data, and can identify multiple damages while also providing insights into the learned hierarchical features.

Transfer learning has also been widely used in deep learning-based building damage detection. For example, Dais et al. [16] used deep learning technique, including transfer learning, for crack detection on images of masonry walls, achieving 95.3% accuracy at patch level and 79.6% F1-score on pixel level. Similarly, Perez et al. [17] developed a deep learning-based method using fine-tuning transfer learning to classify images of building defects caused by dampness into four categories and achieved an overall accuracy of 87.50% on a separate evaluation set of 732 images with high precision in defect localization using the class activation mapping technique. In their study, Teng et al. [18] put forward a structural damage detection approach that relies on digital twin (DT) and transfer learning. DT technology was utilized to obtain a vast number of damage samples of numerical models, which were then used to train a convolutional neural network (CNN) as a pre-trained network. The pre-trained CNN was subsequently transferred to experimentally tested structures and a real bridge structure using transfer learning technology. The proposed method achieved a remarkable detection accuracy of up to 97.3% for the real bridge structure. Elghaish et al. [19] tested four pre-trained CNN models and developed a new CNN model to detect and classify types of highway cracks. The accuracies of the pre-trained models were above average, with GoogleNet achieving the highest accuracy of 89.08%. The newly developed CNN model outperformed all pre-trained models with an accuracy of 97.62% using Adam's optimization algorithm at a learning rate of 0.001. Feng et al. [20] processed the image data collected by high-resolution cameras from the hydro-junction infrastructure and used it for damage detection. They emphasized that the network they created by changing the structure of Inception-v3 has an accuracy value of 96.8% in damage detection. Gulgec et al. [21] used the CNN method to classify damaged and undamaged samples modeled by finite element simulations to detect deficiencies that affect the performance of the building. Based on the findings, they stated that their application has high accuracy, robustness and computational efficiency.

In addition to deep learning, other machine learning methods have been used for building damage detection. For instance, Eltouny et al. [22] presented a density-based unsupervised learning technique for detecting and localizing structural damage, which employs cumulative intensity measures for feature extraction and a statistical model construction process based on kernel density maximum entropy and Bayesian optimization. The efficacy of this framework was tested using three case studies, and the outcomes indicated an average accuracy of 92% in detecting and localizing damage in both numerical and experimental structures.

Although there have been several studies on the detection of building defects using deep learning techniques, most of them have focused on a specific type of defect or have used a relatively small dataset. In this study, we aim to develop a deep learning model that can detect and classify four types of building defects, including crack, deformation, moisture, and undamaged areas, using a larger dataset of 7200 images. We evaluate the performance of three popular deep learning models, VGG16, GoogLeNet, and ResNet50, on this dataset and compare their results. The findings of this study could potentially aid in the efficient and accurate detection of building defects, thereby reducing the costs and time associated with manual inspection and maintenance.

3. Materials and Methods

The visual data in the dataset include images of building elements made of building materials such as brick, stone, reinforced concrete, plaster and wood. In addition to these, deterioration and building damage on walls and decorations are also included. Most of the images were obtained from the authors' own archives and not used by other researchers in any previous study. A dataset of 7200 images was collected for this study, which included four categories of physical damage in buildings: crack, deformation, moisture, and undamaged [23]. The dataset was divided into four equal parts, with each category containing 1800 images. The dimensions of the images were 227x227x3. Three popular transfer learning models, VGG16, GoogLeNet, and ResNet50, were used for this study. The structure of transfer learning applied in this study is depicted in Figure 1. The collected data were preprocessed before training the models. The images were resized to fit the input size of the models. The data were also normalized to have a mean of 0 and a standard deviation of 1. The randomly selected images from each class, including cracked walls, deformed structures, moisture damage, and undamaged buildings can be seen in Figure 2.

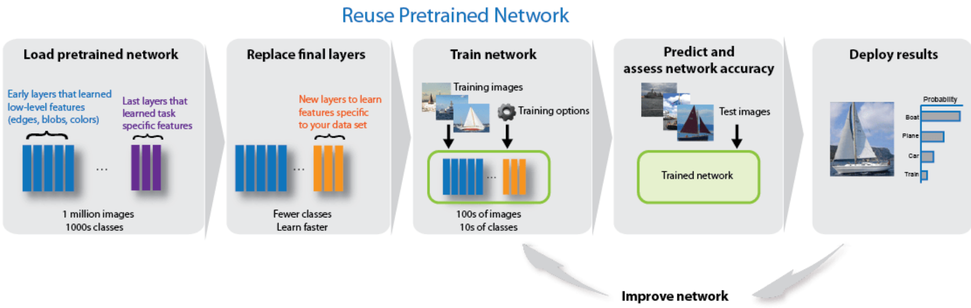

Figure 1. Structure of pre-trained neural network [24].

Figure 2. Randomly selected images from each class.

In the fine-tuning process, the pre-trained models were first loaded with their pre-trained weights, and the output layers were removed. A new output layer was added with the appropriate number of units for the 4-class classification task. The output layer was then trained with the dataset while keeping the weights of the pre-trained layers frozen. Finally, the weights of all layers were fine-tuned with the dataset. The models were trained using both MATLAB Deep Learning Designer and Python software. The training process was performed with a mini-batch size of 20 in MATLAB and 32 in Python. The number of epochs for training was 150 in MATLAB and 50 in Python, with a learning rate of 0.00001 in MATLAB and 0.0001 in Python. The validation dataset, which consisted of 20% of the training dataset, was used to optimize the hyperparameters. To visually represent the training and validation accuracy and loss over epochs, line plots were created for each of the models. Confusion matrices were also generated to visualize the number of correct and incorrect predictions for each class.

The models' performance was evaluated using several metrics, including accuracy, precision, recall, and F1-score. The accuracy of the models was calculated as the percentage of correctly classified images in the test dataset. The precision, recall, and F1-score were calculated for each class based on their scores.

The models were trained on a computer equipped with an Nvidia GeForce RTX 2070 Super graphics card. MATLAB Deep Learning Designer and Python 3.10.11 with TensorFlow 2.10.0, CUDA 11.2, and cuDNN 8.1 were used for implementing the transfer learning methods. The training parameters used in the MATLAB deep learning models are shown in Figure 3.

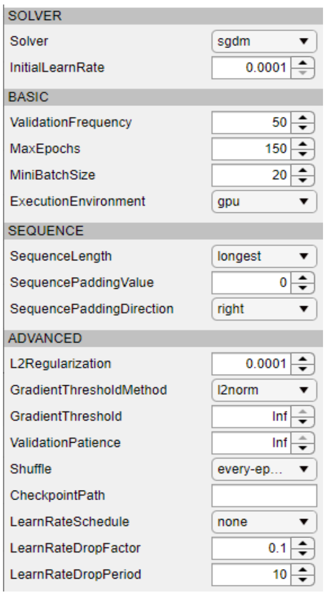

Figure 3. Training parameters for Matlab deep learning designer.

The model was trained using a solver of SGDM, a mini-batch size of 20, a max epoch of 150, an initial learning rate of 0.00001, and a learning rate drop factor of 0.1 (see Figure 2).

4. Results and Analysis

Three different deep learning models, VGG16, GoogLeNet, and ResNet50, were trained and tested on a dataset of 7200 images that were divided into four classes: crack, defect, moisture, and undamaged. The models were evaluated based on their accuracy, loss, and confusion matrices. The precision, recall, and F1-score metrics were also calculated for each class.

The accuracy and loss graphs obtained from Python experiments for the three models are shown in Figure 4-6 respectively. As can be seen from the graphs, all three models show a similar trend, with a gradual increase in accuracy and a decrease in loss over the epochs.

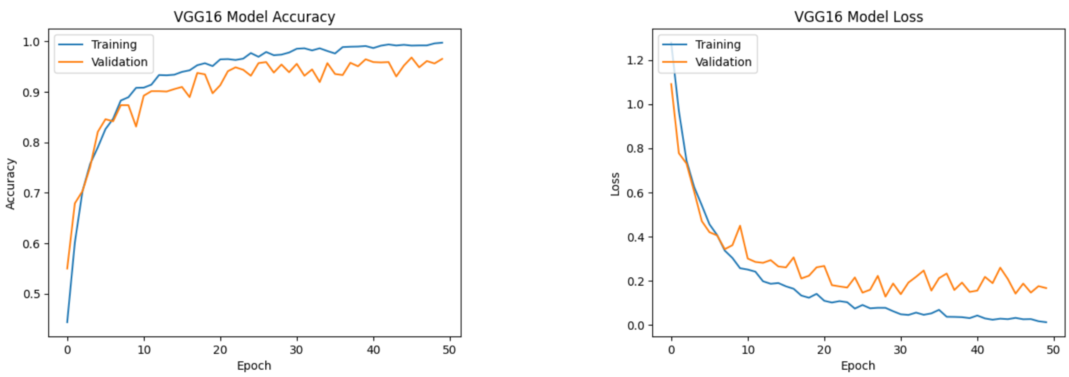

Figure 4. Accuracy and loss for VGG16 model.

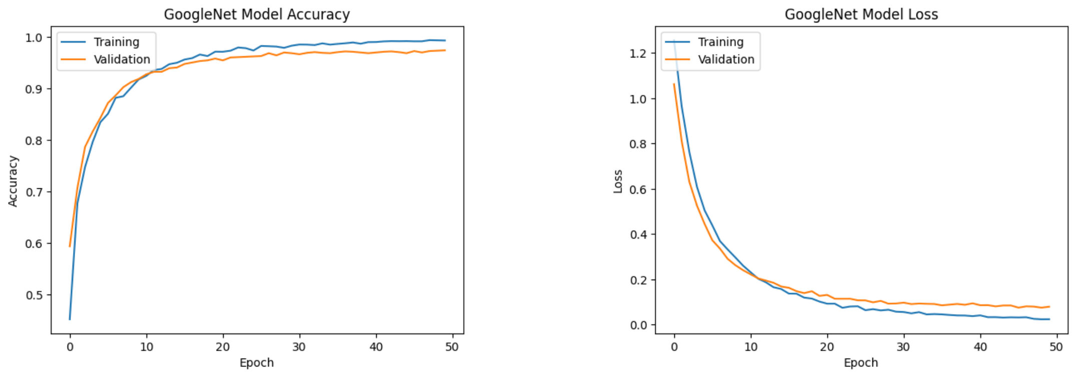

Figure 5. Accuracy and loss for GoogleNet model.

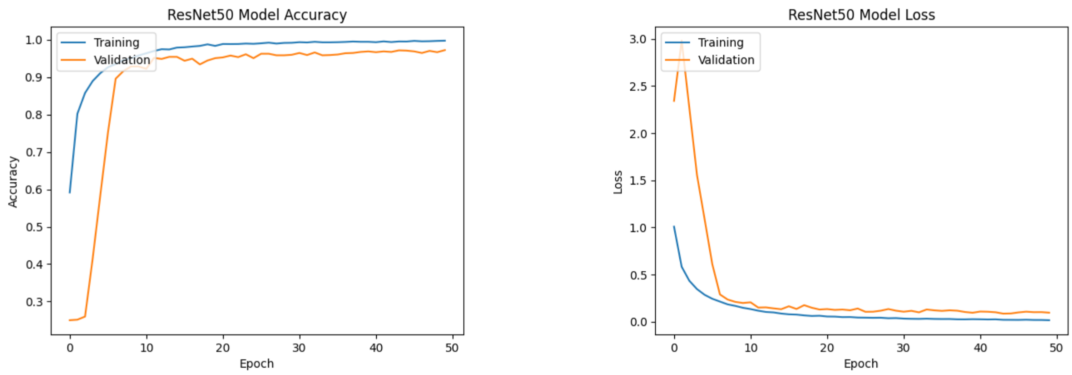

Figure 6. Accuracy and loss for ResNet50 model.

The confusion matrices for the three models are shown in Figure 7-9 respectively. As can be seen from the matrices, all three models perform well in detecting the different types of physical damage in buildings, with high accuracy rates for each class. However, the VGG16 and ResNet50 models outperform the GoogLeNet model in terms of overall accuracy. ResNet50 model has the best model according to confusion matrix results.

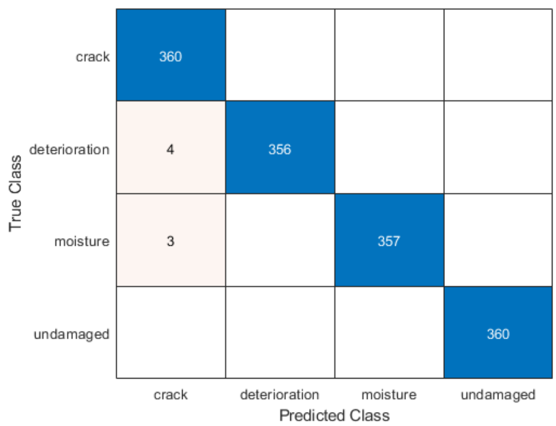

Figure 7. Confusion matrix for VGG16 model.

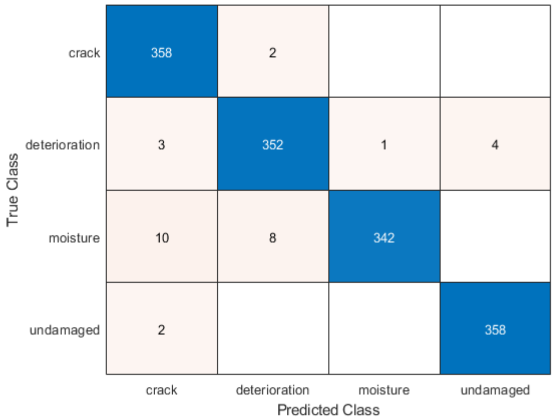

Figure 8. Confusion matrix for GoogleNet model.

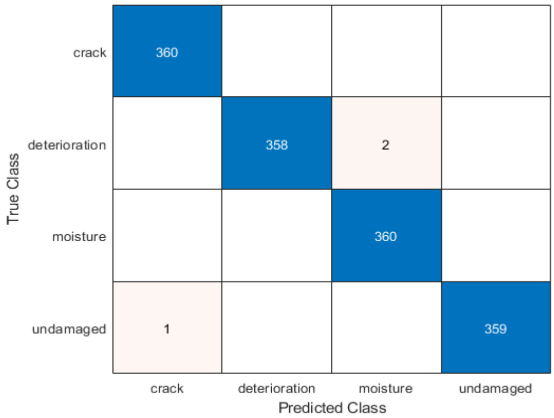

Figure 9. Confusion matrix for ResNet50 model.

The validation and testing accuracy values for the three models are shown in Table 1. The results indicate that all three models perform well, with high accuracy rates for both validation and testing datasets. The VGG16 and ResNet50 models show the highest accuracy rates, with both models achieving over 99% accuracy in the validation dataset.

Table 1. Validation and testing accuracy for three models

Model	Matlab Validation Accuracy (%)	Matlab Testing Accuracy (%)	Python Testing Accuracy (%)
VGG16	99.83	99.51	96.53
GoogLeNet	99.22	97.92	97.71
ResNet50	99.83	99.79	97.22

The precision, recall, and F1-score metrics for the three models are shown in Table 2. The results indicate that all three models perform well in detecting physical damage in buildings, with high precision, recall, and F1-score values for each class. However, the VGG16 and ResNet50 models show higher values than the GoogLeNet model for most of the classes.

Table 2. Precision, recall, and f1-score metrics for three models

Model	Class	Precision (%)	Recall (%)	F1-score (%)
VGG16	Crack	98.09	100.00	99.04
	Deformation	100.00	98.89	99.44
	Moisture	100.00	99.17	99.58
	Undamaged	100.00	100.00	100.00
GoogLeNet	Crack	95.98	99.44	97.68
	Deformation	97.24	97.78	97.51
	Moisture	99.71	95.00	97.30
	Undamaged	98.90	99.44	99.17
ResNet50	Crack	99.72	100.00	99.86
	Deformation	100.00	99.44	99.72
	Moisture	99.45	100.00	99.72
	Undamaged	100.00	99.72	99.86

Overall, the results of this study suggest that deep learning models can be effective in detecting physical damage in buildings using image data. The VGG16 and ResNet50 models show higher accuracy rates and better performance metrics than the GoogLeNet model.

5. Discussion

The results of this study demonstrate that deep learning models can be successfully applied to detect physical damage in buildings using image analysis techniques. The use of transfer learning with VGG16, GoogLeNet, and ResNet50 allowed for the accurate classification of images into four different classes of crack, deformation, moisture, and undamaged, with overall test accuracy scores ranging from 96.53% to 99.79%. The high accuracy and precision of the models suggest that deep learning could be a useful tool for identifying building damage in a variety of real-world scenarios.

In terms of model performance, VGG16 and ResNet50 achieved the highest accuracy scores in the experiments. This could be due to the deeper architecture of these models, which allowed for more complex features to be learned and extracted from the input images. GoogLeNet, although achieving high accuracy scores, was slightly less accurate than the other two models. This could be attributed to the use of "inception modules" in its architecture. GoogLeNet stacks multiple inception modules together to form a deep neural network. The main idea of the Inception module is that of running multiple operations (pooling, convolution). So, this may not have been as effective at capturing the features relevant to building damage in this particular dataset.

The results also indicate that the model performance was not significantly impacted by the choice of software or hardware used for training. Both Matlab and Python experiments using GPU achieved high accuracy scores, and the differences in accuracy scores between the two software were relatively small.

Finally, it should be noted that this study has several limitations. The dataset used in this study was limited to only four classes of building damage and did not include other types of damage such as fire or structural damage. Additionally, the dataset was generated artificially and may not fully represent the complexities and variations in real-world building damage scenarios. Nevertheless, this study provides a foundation for future research in the use of deep learning for building damage detection.

6. Conclusion

In conclusion, this study demonstrates the potential of deep learning models for detecting physical damage in buildings using image analysis techniques. The use of transfer learning with VGG16, GoogLeNet, and ResNet50 resulted in the accurate classification of images into four different classes of crack, deformation, moisture, and undamaged. The high accuracy and precision of the models suggest that deep learning could be a useful tool for identifying building damage in a variety of real-world scenarios.

Future research could expand on this study by incorporating more diverse and complex datasets and exploring other deep-learning architectures. Additionally, this study provides a foundation for the development of automated building damage detection systems that could help prevent further damage and ensure the safety of occupants in affected buildings.

Acknowledgement

The data set used in this study was obtained from the master's thesis prepared by S.T.U, entitled "Detection of Building Physics Problems with Convolutional Neural Networks". B.B.E., the idea owner and thesis advisor, played an active role in the implementation of the applications and the writing of the article. S.T.U., prepared the data set, took part in the literature review and implementation of the applications.

References

[1] Ekici BB. Detecting damaged buildings from satellite imagery. J. Appl. Remote Sens 2021; 15(3): 032004.
[2] Sharma N, Sharma R, Jindal N. Machine learning and deep learning applications-a vision. Glob. Transitions Proc 2021; 2(1): 24–28.
[3] Iman M, Arabnia HR, Rasheed K. A review of deep transfer learning and recent advancements. Technol 2023; 11(2): 40.
[4] Zhuang F, Qi Z, Duan K, Xi D, Zhu Y, Zhu H, Xiong H, He Q. A comprehensive survey on transfer learning. Proc. IEEE 2021; 109(1): 43–76.
[5] "Visual Geometry Group - University of Oxford." https://www.robots.ox.ac.uk/~vgg/ (accessed May 02, 2023).
[6] "ILSVRC2014 Results." https://image-net.org/challenges/LSVRC/2014/results (accessed May 02, 2023).
[7] "Deep Residual Networks (ResNet, ResNet50) 2023 Guide - viso.ai." https://viso.ai/deep-learning/resnet-residual-neural-network/ (accessed May 02, 2023).
[8] Kung RY, Pan NH,Wang CCN, Lee PC. Application of deep learning and unmanned aerial vehicle on building maintenance. Adv. Civ. Eng 2021; 2021: 5598690.
[9] Flah M, Suleiman AR, Nehdi ML. Classification and quantification of cracks in concrete structures using deep learning image-based techniques. Cem Concr Compos 2020; 114: 103781.
[10] Wang N, Zhao X, Zou Z, Zhao P, Qi F. Autonomous damage segmentation and measurement of glazed tiles in historic buildings via deep learning. Comput Civ Infrastruct Eng 2020; 35(3): 277–291.
[11] Yang J, Zhang L, Chan C, Li Y, Li R, Wang G, Jiang S, Zeng Z. A hierarchical deep convolutional neural network and gated recurrent unit framework for structural damage detection. Inf Sci 2020; 540: 117–130.
[12] Wang N, Zhao X, Wang L, Zou Z. Novel system for rapid investigation and damage detection in cultural heritage conservation based on deep learning. J Infrastruct Syst 2019; 25(3):04019020.
[13] Nex F, Duarte D, Tonolo FG, Kerle N. Structural building damage detection with deep learning: assessment of a state-of-the-art cnn in operational conditions: Remote Sens 2019; 11(23): 2765.
[14] Jiang Y, Pang D, Li C, Yu Y, Cao Y. Two-step deep learning approach for pavement crack damage detection and segmentation. Int. J. Pavement Eng 2022:1-14. doi: 10.1080/10298436.2022.2065488.
[15] Lin YZ, Nie ZH, Ma HW. Structural damage detection with automatic feature-extraction through deep learning. Comput Civ Infrastruct Eng 2017; 32(12): 1025–1046.
[16] Dais D, Bal İE, Smyrou E, Sarhosis V. Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning. Autom Constr; 125: 103606.
[17] Perez H, Tah JHM, Mosavi A. Deep learning for detecting building defects using convolutional neural networks. Sensors 2019; 19 (16): 3556.
[18] Teng S, Chen X, Chen G, Cheng L. Structural damage detection based on transfer learning strategy using digital twins of bridges. Mech Syst Signal Process 2023; 191:110160.
[19] Elghaish F, Talebi S, Abdellatef E, Matarneh ST, Reza Hosseini M, Wu S, Mayouf M, Hajirasouli A, Nguyen TQ. Developing a new deep learning cnn model to detect and classify highway cracks. J Eng Des Technol 2022; 20 (4): 993–1014.
[20] Feng C, Zhang H, Wang S, Li Y, Haoran W, Yan F. Structural Damage Detection using deep convolutional neural network and transfer Learning. KSCE J Civ Eng 2019: 23(1); 1-10.
[21] Gulgec, NS, Takáč M, Pakzad, SN. Structural Damage Detection Using Convolutional Neural Networks. In: 35th IMAC, A conference and exposition on structural dynamics; Ja 30-Feb 2 2016; CA, USA: Cham, Germany: Springer. pp. 331-337.
[22] Eltouny KA, Liang X. Bayesian-optimized unsupervised learning approach for structural damage detection. Comput Civ Infrastruct Eng 2021; 36 (10): 1249–1269.
[23] S. T. Ustaoğlu, "Detection of Building Physics Problems With Convolutional Neural Networks. MSc, Fırat University, Elazığ, Türkiye, 2023.
[24] "Transfer Learning Using Pretrained Network - MATLAB & Simulink." https://www.mathworks.com/help /deeplearning/ug/transfer-learning-using-pretrained-network.html (accessed May 02, 2023).