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# Evaluation of Deterioration in Brick Materials in Monumental Buildings Using CNN Models

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## Highlights

- CNN-based deep learning was utilized to enhance brick deterioration detection in historic buildings.
- Identified prevalent physical, chemical, and biological deteriorations in historic brick materials.
- We believe the five-class dataset will significantly enhance future research by extending existing datasets
- Results confirm the system's superior performance and reduced standardization differences.

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**Abstract**

The materials of historical structures undergo deterioration and deformation over time due to physical, chemical, and biological factors. Regular inspections by experts are essential for the preservation of these structures. However, the detection of such deteriorations involves significant labor, time, and cost, and incorrect diagnoses may lead to irreversible damage and structural issues. This study aims to minimize human-induced errors in identifying types of deterioration in structures by utilizing deep learning-based convolutional neural network (CNN) models, a subfield of artificial intelligence. With this study, deteriorations in historical brick buildings, which have an important place among historical buildings, will be detected with non-destructive methods, thus contributing to the preservation of historical buildings and the literature. Within the scope of the study, a total of 1709 data consisting of physical deterioration (cracks and fractures, joint discharge, abrasion and piece loss), chemical deterioration and biological deterioration types that are frequently encountered in brick materials in historical buildings were discussed. The classification process was carried out with the inputs given to the ResNet-18, ResNet-50, ResNet-101, VGG16 and VGG19 networks. Model performances were evaluated with precision, recall and F1 score metrics. The best performance values were obtained with ResNet101 (88% Precision, 88% Recall, 87% F1 Score, 88% Accuracy). Then, using Grad-CAM, the points on which the model focused while making predictions were determined. This study, which will include planning the basic principles of interventions to be applied to cultural property, will prevent the problems encountered in deterioration and deformation, and objective solutions will be produced.

## 1. INTRODUCTION

Historical buildings, which constitute an important part of the cultural heritage, have an effective value in formation and protection of a sustainable built environment. Many factors such as atmospheric, social, biological and human cause the destruction and deterioration of historical cultural heritage structures throughout the historical process. During this process, building materials are exposed to the most damage. The deterioration and destruction of materials such as stone, adobe, brick and wood, which constitute the main building material of historical buildings, over time can irreversibly damage the structural integrity and originality of cultural heritage values [1-3]. Visual examination of cultural heritage values throughout the process is necessary to better preserve the structures and pass them on to future generations. In this context, restoration works have an important place in order to preserve historical cultural heritage structures and pass them on to future generations. Faulty practices that arise as a result of incorrect detection of the

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types of deterioration in building materials in repair and restoration practices aimed at protecting cultural heritage works lead to errors that will damage the structural integrity of historical works. For this reason, accurate recognition and classification of historical building material deterioration is important to preserve the cultural heritage and pass it on to future generations. Although inspections made as a result of on-site observations in historical buildings and traditional inspection practices are frequently preferred to identify the types of deterioration that occur as a result of weather conditions, they require more time, cost and human resources [4-8]. In addition, due to factors such as location, size and limited physical access of historical buildings, the increase in margin of error determining the weathering types of building stones causes negative effects in terms of time loss and cost [9]. Nowadays, the use of vision-based techniques such as laser scanning and photogrammetry of historical artifacts is becoming widespread [10-17]. In addition to reducing field difficulties and investigation times, these techniques can increase the possibility of errors due to long data processing times, high costs, and complex data analysis requiring expert knowledge [18]. In order to prevent such problems, artificial intelligence-based applications have recently been replaced by human-based applications. Deep Learning-based algorithms are artificial intelligence applications that try to imitate human brain and have ability to extract automatic features (Cheng et al., 2019) [19]. Artificial intelligence algorithms, which basically try to imitate human skills, are a method inspired by the process that a person sees and processes in his brain. With this method, highly accurate and precise algorithms can be created to detect (Long et al., 2015) [20], segment (Yibo Sun et al., 2024) [21] and classify (Bai and Urtasun, 2017) [22] each object in an image.

The main contributions of the article are as follows:

1. It is thought that the introduction of a new five-class data set will expand the scope of existing data sets and make significant contributions to new research in this field.
2. Physical (cracks and fractures, joint ejaculation, wear and loss of parts), which are frequently encountered brick materials in historical buildings, deterioration, chemical deterioration and biological deterioration types of images based on ResNet-18, Resnet-50, Resnet-101, VGG16 and VGG19 architectures were used. In addition, the grad-gamor explanation method was included in study and accuracy of the detected regions were examined.
3. Experimental results show that proposed system exhibits superior discrimination ability compared to other studies and reduces standardization differences.

## 2. BACKGROUND

Recently, artificial intelligence applications, which are frequently used in fields such as medicine and engineering, have started to be used in the field of architecture as well. Many studies have been carried out in literature to detect distortions in cultural structures using deep learning algorithms. Machine learning and Building Information Models (BIM) based methods have been developed to identify architectural elements in historical structures and to detect and classify defects and damages especially in stone materials [9, 23, 24]. Nazarian et al. (2018) [25] developed a machine learning based platform for the condition assessment of historical structures and determined the extent and rates of damage in a six-story building with timber frame and masonry walls. Studies have been conducted using R-CNN and Mask R-CNN algorithms, which are among the CNN based algorithms, to determine and classify the types of stone deterioration frequently seen in historical stone monuments, archaeological sites and rock monuments and to map the building stone by performing petrographic detection [26-30]. A two-stage model based on Faster R–CNN and Mask R–CNN has been developed to detect damage in historical glazed tiles [31]. In their study, Mansuri et al. (2021) [32] developed a model to detect three different types of deterioration of historical tombstones in India using the artificial intelligence-based automatic defect detection system R-CNN.

As a result of the literature analysis, it was determined that there were intensive studies on types of deterioration at stone materials in historical cultural heritage works and there were not enough studies on brick materials. In this context, historical brick materials found in interior and outdoor space of the historical monumental structures were selected. In literature, the types of deterioration observed in the brick material were detected and materials are classified in 5 categories: physical (cracks and fractures, joint discharge, wear and loss of parts) deterioration, chemical deterioration and biological deterioration. After the

classification process, it is aimed to determine the deterioration with an artificial intelligence -based deep decision mechanism.

### 2.1. General Properties and Deterioration of Brick Materials

Historically, brick has been used as a building material in architecture by many civilizations for hundreds of years. The material formed by combining clay and sand in certain proportions is fired and turned into bricks. The cooking temperature is normally between 800-1200 and water and carbon dioxide are removed from the mixture by cooking [33]. The deteriorations observed extensively in the brick material through the literature study are divided into 5 categories and expressed below.

Spalling: The swelling observed on the brick surfaces is caused by salt crystallization as a result of moisture penetrating the brick or direct exposure to water, causing flaking, chipping and deterioration on the brick surfaces [34].

Chemical degradation (Blooming): The salt deposit that accumulates in powder form on the brick structure is called efflorescence. Although its color is usually white, it can also be brown, yellow and green. As a result of rising humidity and direct contact of water with the brick, soluble salts are transported to the brick. The more water there is in the brick and remains there, the more likely it is that the salts will dissolve and rise to the surface as the brick dries. In this context, efflorescence is an indicator of water penetration into the brick and the possibility of brick deterioration [34].

Joint failures: Deteriorations in structural element joints may occur as a result of physical, chemical or biological effects. Physical causes include water problems, as seen in other deteriorations. It may occur due to physical reasons such as freezing thawing and crystallization of salts dissolved in water [35, 36].

Biological deterioration: Examples of deterioration such as ivy, algal lichen, fungi and plant roots can be seen in the brick material, and these effects cause crumbling and deterioration in the terracotta material. There may be many reasons for the pattern of biodegradation. For example, it occurs in constantly humid places, under the influence of moisture and salts [37]. While plant roots growing on the wall penetrate into the wall and cause deterioration, substances such as moss cause more water retention on the wall surface [38]. Physical deterioration (cracks, fractures, etc.): Physical deteriorations occur in different ways on brick walls. [34]. Another deterioration manifests itself in the form of crack formation. Although there are different reasons for the cracks seen in the building walls and mortar, they may indicate structural problems. Cracking can occur with structural problems such as freezing, water ingress, corrosion of metals, salts, and foundation and wall movements [34, 38].

## 3. BACKGROUND

### 3.1. Material

In the study, which aims to analyze the types of brick deterioration in historical buildings with an artificial intelligence-based decision mechanism, it is necessary to obtain sufficient quantity and quality of images for the developed algorithms to be successful. For this purpose, field work was carried out on different days and times and photographs were taken at various distances, shadows and shooting angles. During the process, attention was paid to obtain brick images from near and far distances when the light was at different levels during the day. In order to ensure data richness, the images were obtained from the interior and exterior facades of historical buildings in Tokat and Elâzığ provinces, where historical and cultural heritage buildings are densely located. Images were produced using 13 megapixel (MP) and 12 MP CANON EOS 650D professional cameras. During the field study, 1709 images with a total size of 4128 x 2322 and a resolution of 72 dpi were collected. The data set is divided into five main categories: chemical degradation, biological degradation, cracks and fractures, wear and joint degradation. Images were obtained and categorized by taking into account distortion types. To ensure the size standard, the images were resized and 80% of the images were used in training and the other 20% were used in the verification and testing stages. Scaled sample images of the data set are given in Figure 1.

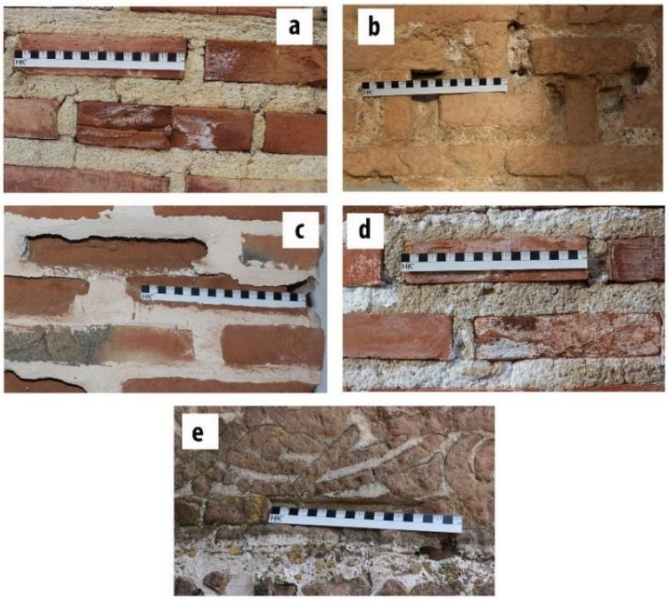



***Figure 1.*** *Common types of weathering in historical buildings are: (a) cracks and fractures, (b) joint discharge, (c) Wear and Fragment Loss, (d) Chemical deterioration, (e) Biological deterioration*

### 3.2. Method

The aim of study is developing an explainable artificial intelligence-based deep decision mechanism for detecting brick deterioration types on various surfaces in historical buildings. In first step, surface distortions in historical buildings were obtained with mobile devices and professional cameras and an image dataset was created. The images to be given to the deep networks were made ready for training by going through data pre-processing steps such as resizing to ensure standardization, isie color normalization to eliminate lighting differences, and noise removal. A versatile approach was adopted by training various CNN models with different depth and features. The performances obtained because of the study were evaluated mutually using recall, precision, F1-score and accuracy metrics. In the last step, heat maps were produced using GradCAM [39], one of the explainable artificial intelligence methods, to understand which regions model made predictions by looking and whether it focused on the correct region. The heat maps produced were examined by an expert architect in the field and model accuracy was supported by expert opinion. The method diagram of the conducted study is given in Figure 2.

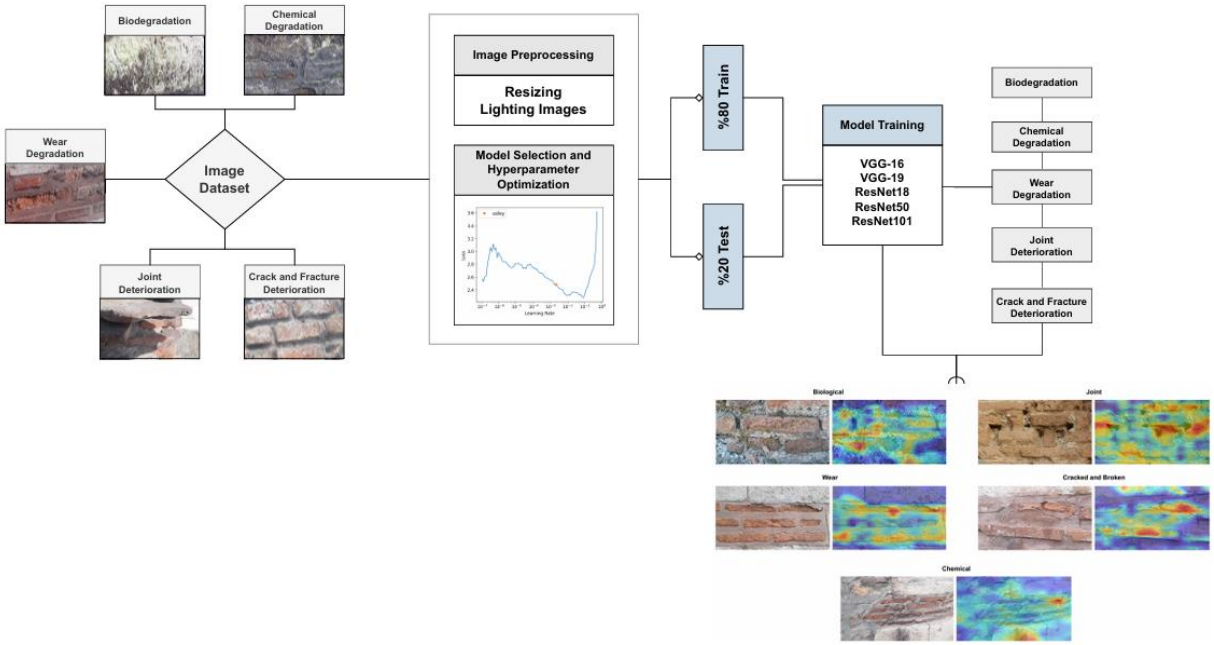



***Figure 2.*** *Recommended method flow chart*

In the first step of the method scheme given in Figure 2, images collected from various sources were brought together, categorized according to distortion types, and a data set was created. Various pre-processing steps were applied to created data set in order to prevent problems that may arise from physical factors such as shooting from different angles and different light environments and making data ready for training. In the first step, unpreprocessed data was included in training process in its raw form. Afterwards, training was carried out by applying pre-processing steps on data. It has been observed that data preprocessing increases accuracy in training process, accordance with its purpose. In this regard, firstly, the images were resized and standardized in order to increase computational efficiency and ensure size consistency between images collected from different sources. In another step of pre-processing, lighting conditions were adjusted using color normalization, contrast adjustment and noise reduction methods to improve image quality so that model could focus on important features during the training process. Comparative sample images of data obtained before and after data preprocessing step are given in Figure 3.

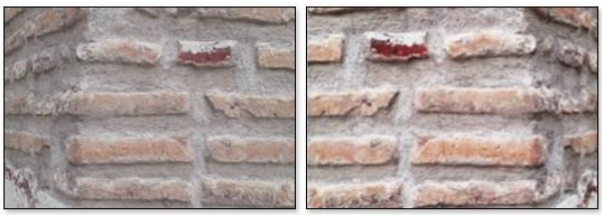


***Figure 3.*** *Example of preprocessed data*

After data pre-processing step was completed, model selection was carried out by taking into account study requirements and data set features. In model selection step, pre-trained models that are widely used in image classification studies and have high performance capacity were preferred. In this context, firstly VGG-16, VGG-19, which have simpler structures compared to others, and ResNet18, ResNet50 and ResNet101 models, which have evolved into deeper and more complex structures, were evaluated. Each architecture was examined in terms of various parameters, including various layer depths, activation properties, and connectivity properties.

Developed by Karen Simonyan and Andrew Zisserman in 2014, the VGG architecture has demonstrated high performance in various image recognition tasks since its first year of development. The VGG model is capable of learning deep structures using small filters of size 3x3. This architecture, which has a sequential CNN structure, has demonstrated high performance in various image recognition studies when

trained with large-scale data sets, with its structure containing many weight layers [40]. The layered structure of the VGG architecture is given in Figure 4.

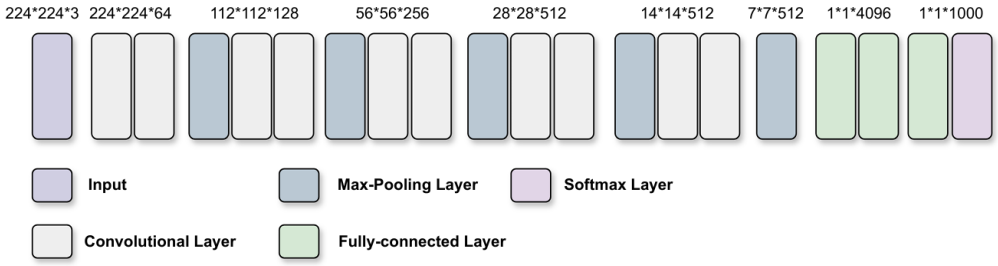



***Figure 4.*** *VGG architecture*

ResNet models use "skip connections" to make more comprehensive structures of model trainable. This method enables network to solve problem of gradient disappearance encountered during learning process. It contains architectures with various depths such as ResNet18, ResNet34, ResNet50, ResNet101 and ResNet152, and thanks to these deep architectures, it provides faster convergence and higher accuracy during training [41]. The working mechanism of the ResNet architecture is given in Figure 5.

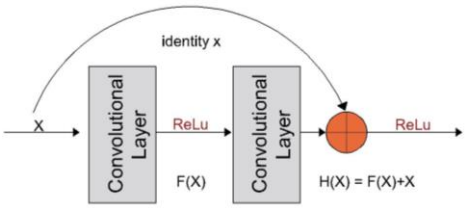



***Figure 5****. Residual Network [42]*

In Figure 5, the layers where the input expression x is processed are represented by the F(x) function. By directly adding input to the processed data, the function H(x) is obtained, which is expressed as H(x) = F(x) + x. This structure preserves gradients during backpropagation while model training takes place, and thus deeper networks are trained.

One of the most important factors affecting the performance of deep models is hyperparameter adjustments, as it directly affects both the training process and the generalization ability of the model. While performing hyperparameter adjustments in the study, various evaluations were carried out by considering the performance evaluation metrics. In the evaluations, the batch size was considered as 8, 16 and 32, and the most appropriate value was determined as 16 considering the performance metrics and training time. Similarly, in the evaluations against overfitting, since it was seen that the model performance stabilized after 50 epochs, the training time was limited to 50 epochs. Learning rates were determined separately for each model using the learn_find function of FastAI library and were included in the training process. The values of the optimized parameters are given in Table 1.

***Table 1.*** *Hyperparameters of deep networks*

| Model | VGG16 | VGG19 | ResNet18 | ResNet50 | ResNet101 |
|---|---|---|---|---|---|
| **Learning Rate** | 2.5e-2 | 2.6e-3 | 2.5e-3 | 2.5e-3 | 2.25e-3 |
| **Image size** | 224x224 | 224x224 | 224x224 | 224x224 | 224x224 |

After hyperparameter adjustments were made, training was performed for each model. After model training was completed, decision-making process was visualized using Grad-CAM, one of the explainable artificial intelligence methods. This method shows which areas of model focuses on when making predictions and which visual features affect classification selection the most [39, 43]. In the last step, model performances were comprehensively evaluated through accuracy, precision, recall and F1 score metrics. The accuracy metric expresses what percentage of the model's predictions are correct. Precision indicates the probability that the detection made when the model detects a type of distortion actually belongs to the same type of

distortion. Recall shows how accurately the model can detect existing distortions, while the F1 score shows the harmonic average of precision and recall values.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

In addition to automatically and accurately determining the types of deterioration using brick deterioration data in historical buildings, the study was carried out with the approach of investigating which areas are focused on when making predictions with explainability methods. After the first step, the data preprocessing step was performed, the data was given as input to the ResNet-18, ResNet-50, ResNet-101, VGG16 and VGG19 networks and the classification process was carried out. After evaluating the model performances with precision, recall and F1 score metrics, the points that the model focuses on while making predictions were investigated using Grad-CAM. The performance metrics obtained after the classification process are given in Table 2.

***Table 2.*** *Performance metrics after classification process*

| Avarage (%) | VGG-16 | VGG-19 | ResNet18 | ResNet50 | ResNet101 |
|---|---|---|---|---|---|
| **Precision** | 70 | 79 | 88 | 86 | **88** |
| **Recall** | 70 | 78 | 87 | 85 | **88** |
| **F1 Score** | 69 | 78 | 87 | 85 | **87** |
| **Accuracy** | 70 | 79 | 87 | 85 | **88** |

When the performances of ResNet-based models (ResNet18, ResNet50 and ResNet101) are compared with various deep learning architectures as shown in Table 2, it is seen that they show similar high performance. ResNet-based models exhibited very close performances between 85% and 88% in terms of performance metrics. While ResNet101 model achieved high success with 88% accuracy, 88% precision, 88% recall and 87% F1 score, ResNet18 model also provided similarly effective results with 88% precision and 87% accuracy, recall and F1 score. This shows that ResNet architectures generally exhibit strong performance for classification tasks. However, it is seen that VGG-16 and VGG-19 models exhibit lower performance than ResNet models with 70% and 79% accuracy rates. This shows that VGG models, despite their simpler structures, can exhibit high performance in some cases, but are disadvantaged against ResNet architectures for the study performed. The performance difference between the two architectures shows that the depth and redundant connections of ResNet architectures can enable the model to learn more complex features and, as a result, perform better. The confusion matrices from which the metrics in Table 2 are obtained are given in Figure 6.

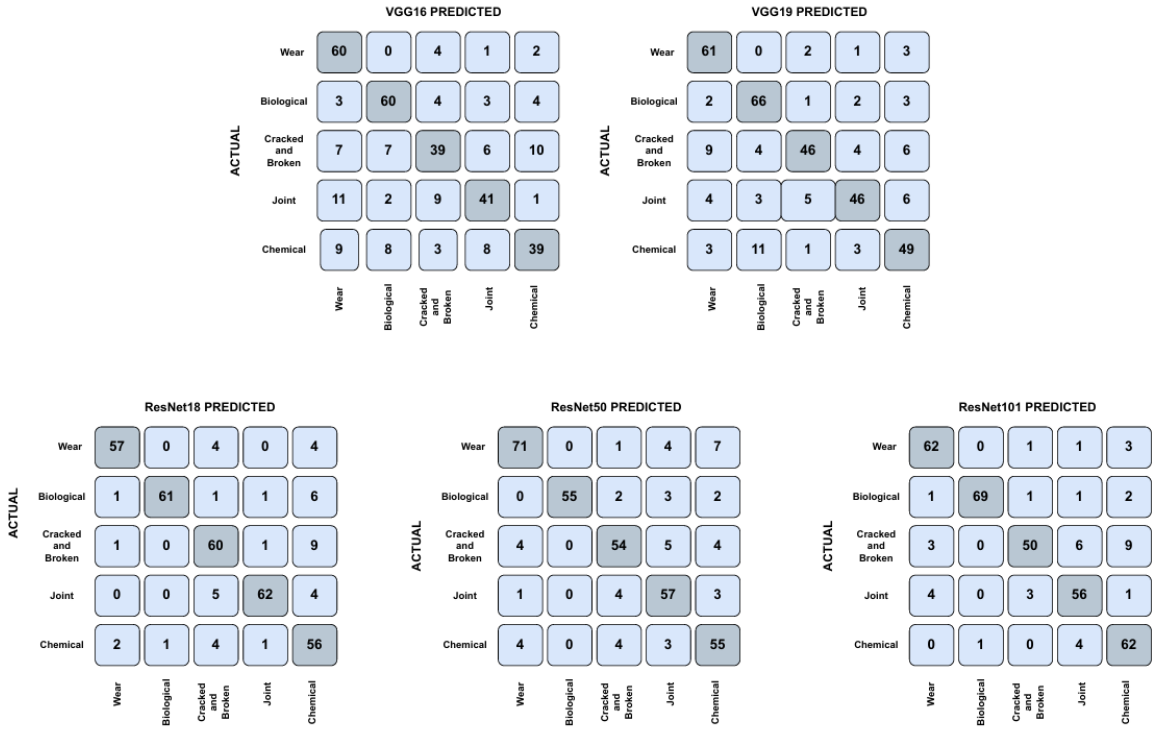



***Figure 6.*** *Classification result confusion matrices*

According to the confusion matrices in Figure 6, ResNet models showed better performance in classifying distortion types compared to VGG-16 and VGG-19 models. ResNet101 showed highest true positive rate among all classes, as well as lowest number of false positives. However, VGG models predicted more false negatives and false positives. This shows that these models have difficulty distinguishing certain classes. In study, in addition to confusion matrix, loss graphs showing the error rates of incorrectly predicted validation data were also examined to evaluate performance of the model. These graphs visualize how many errors each model makes and how these errors change over time. Loss graphs of conducted study are given in Figure 7.

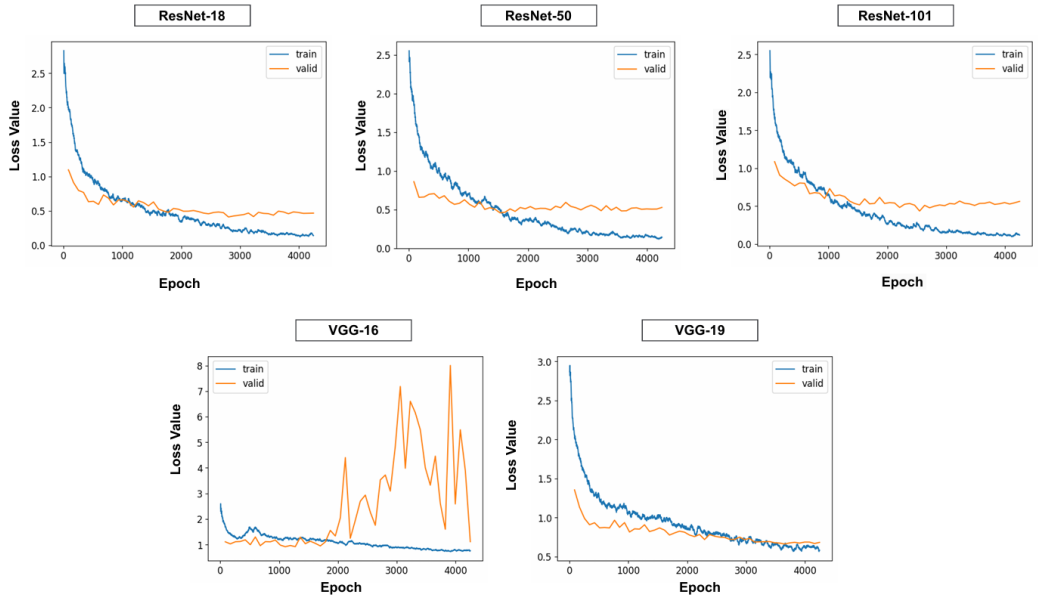



***Figure 7.*** *Loss graphs for validation data after classification*

After a rapid decrease in the loss graph of the ResNet18 model, it is seen that both the training and validation losses continue to decrease steadily. This shows that the model does not only memorize the training data but also learns the general patterns underlying the data. The fact that the validation loss decreases in parallel with the training loss and stabilizes at a low level after a certain point shows that the model can make effective predictions on data samples it has not seen before and does not show a tendency for overfitting. Loss plots for the ResNet50 and ResNet101 models show that validation loss stabilizes at a low value and training loss drops quickly. The fact that performance of the model on the validation set is as good as training set shows that possibility of overfitting is low. When the loss graph of the VGG-16 model is examined, it is seen that training loss clearly decreases and stabilizes at a low level.

However, verification loss fluctuates throughout the process. These fluctuations indicate that model made errors in some samples in validation data. The loss graph for VGG-19 model shows that validation loss and training loss decrease steadily. However, the fact that validation loss is fixed at a slightly higher level than training loss shows that model has a little more difficulty in validation set than in training set. Grad-CAM was used to explain which regions highest performing ResNet101 model focuses on when making predictions. The heat map showing which regions of model performs classification process for five class using Grad-CAM is given in Figure 8.

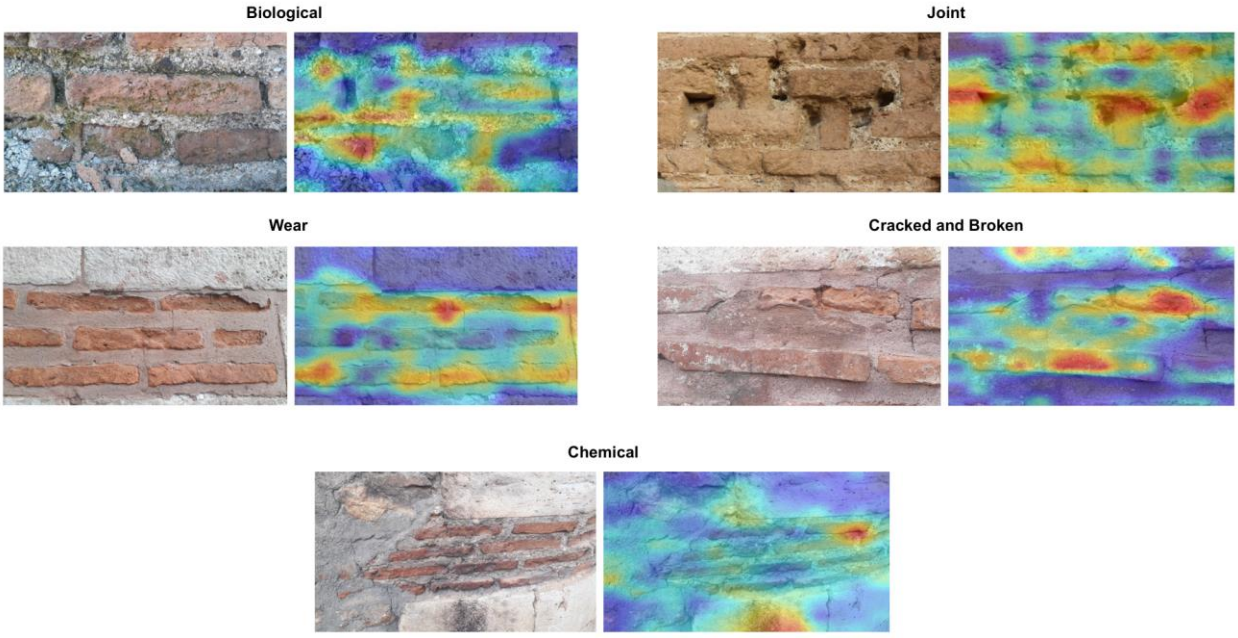



***Figure 8.*** *Heat maps for deterioration types in brick materials*

The proposed application demonstrates how complex and often difficult to understand decision-making processes of deep learning models can be improved with explainable artificial intelligence. Explainable artificial intelligence techniques have made transparent points on which models make decisions and how these decisions are made. It is estimated that the proposed study will play an important role in the conservation and restoration processes of historical buildings by supporting end users and experts with explainability mechanism it provides in decision-making process. The study has limitations such as number of data and images obtained from different angles obtained from multiple structures. It is thought that in future studies, the study results can be improved by determining the type of deterioration on a single special historical building and increasing the number of data.

## 5. CONCLUSION

In this study, a CNN -based decision support mechanism was developed to reduce time, cost, and human errors in the identification of deterioration types commonly encountered in brick materials used in historical buildings. It was observed that the developed CNN-based model has the ability to determine deterioration types with high accuracy by utilizing computer-based algorithms. The findings of the study indicate that

the proposed model can support conservation and restoration efforts by detecting and identifying brick deteriorations in historical structures. The model can directly assist the restoration process by detecting. Restoration experts can make more effective and accurate interventions based on the types of deterioration identified by the model. In this way, historical buildings can be preserved in a more durable and healthy manner. Similar technologies may also be applied in the future to different construction materials and types of deterioration. This study is expected to open new horizons in the conservation and restoration of historical buildings and to guide further research in this field.

## CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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