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CLASSIFICATION OF WALL DEFECTS FOR MAINTENANCE PURPOSES USING IMAGE PROCESSING

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Abstract

Stakeholders are increasingly interested in finding efficient methods for regularly surveying and reporting on the state of their building assets, focusing on accuracy, consistency, and ease of use. High-rise buildings can exhibit wall surface defects and flaws such as cracks and spalls, which can significantly affect the structures' safety and appearance. Such problems need to be taken care of in a timely manner, before they become too hazardous or costly to fix. In this research work, images of several types of wall damage are classified into three main categories: (i) Undamaged; (ii) Cracked; and (iii) Miscellaneous. In total, 6000 images were used in the dataset, equally subdivided into the three categories. In machine learning, convolutional neural networks (CNNs) stand out as a form of neural network that excels at image classification. A transfer learning approach was implemented to classify wall surface defect images using three pre-trained CNN models, namely ResNet-50, ResNet-101, and Inception V3. 70% of the data set was used for training purposes, and the remaining 30% was used for validation. Several metrics including accuracy, precision, recall, and F1-score were computed for each model, in an attempt to find the best model for the damage classification task at hand. According to the results, Inception V3 demonstrated superior performance compared to the ResNet-50 and ResNet-101 models, achieving an overall accuracy of 87.1%. In contrast, ResNet-101 and ResNet-50 obtained overall accuracies of 85.3% and 78.3%, respectively. The suggested methodology offers several benefits and a clear potential for broader adoption in the future as it can significantly reduce the time and effort required for manual inspection and classification of defects, allowing for more efficient maintenance and repair processes.

Keywords: CNN, Transfer learning, Wall defects, Classification.

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1 INTRODUCTION

High-rise building construction and maintenance must achieve a high level of surface quality for both esthetic and safety purposes. Architectural structure conditions can deteriorate over time due to the combined effects of aging, climate, and human activities [1]. If left without proper care, flaws like cracks and spalls can pose problems to the building's occupants, reduce the structure's strength, and significantly lower the asset's worth. Hence, one of the main goals of routine building surveys is to identify defective areas that develop on the surface of a structure. With the increasing demand for safe and well-maintained buildings, stakeholders are interested in finding efficient methods for regularly surveying and reporting on the current state of their building assets. Therefore, wall surface defect classification is crucial to building maintenance, as defects such as cracks and spalls can seriously affect a building's safety and appearance.

Artificial intelligence (AI) methods have various applications in civil and structural engineering [2, 3], in several areas such as: Structural health monitoring [4], structural damage identification [5, 6], structural design optimization [7], structural modelling [8-10], predictive maintenance [11, 12], construction planning and management [13], risk assessment [14, 15], predicting strength and other structural characteristics [16-18], and energy efficiency [19], among others. AI methods have also been recently used in wall surface defect classification [20]. These methods usually involve the use of machine learning techniques, particularly Convolutional Neural Networks (CNNs), to analyze images of wall surfaces to identify and classify different types of defects. The benefits of using AI in wall surface defect classification include increased accuracy, speed, and efficiency. It can help to reduce errors caused by human judgment, as well as minimize the time and resources required for manual inspection and classification.

This research work proposes a machine learning-based approach for classifying wall damage in high-rise structures. We use pre-trained CNN models, namely the well-known Inception-V3 [21], ResNet-50 [22], and ResNet-101 [23] models, to classify images of wall damage into three main categories: (i) undamaged; (ii) cracked; and (iii) miscellaneous. The study relies on a carefully curated dataset consisting of 6000 high-quality images, equally divided into the three previously mentioned categories. To ensure optimal performance, we allocated 70% of the data for training purposes and 30% for validation. We evaluate the accuracy, precision, recall, and F1-score for each model, to determine the best model for damage classification of the wall conditions. The proposed approach can provide an efficient and cost-effective solution for building maintenance, enabling regular surveillance of facilities to easily identify defects before they become too hazardous or costly to fix.

2 LITERATURE REVIEW

Hoang et al. [24] developed a technique for regularly analyzing the state of wall constructions using image processing. Digital pictures were extracted using steerable filters and projection integrals based on image processing methods. Utilizing least squares support vector machine and support vector machine, the newly developed model extended the sorting boundaries that classify wall conditions into five categories: (i) longitudinal crack; (ii) oblique crack; (iii) diagonal crack; (iv) spall damage; and (v) unbroken wall. As training data for training and assessing the machine learning-based classifiers, 500 image samples were collected. Qayyum et al. [25] examined seven pre-trained neural networks, GoogLeNet, ResNet-50, ShuffleNet, ResNet-18, MobileNet V2, ResNet-101, and Inception V3, for crack recognition and sorting. Images were categorized as uncracked (UC); horizontal crack (HC); diagonal crack (DC); or vertical crack (VC). With DC, HC, UC, and VC classification accuracies reaching 96%, 94%, 92%, and 96%, respectively, the performance of Inception-V3 surpassed all other models.

Dung and Anh [26] employed three pre-trained CNN models, namely ResNet, InceptionV3, and VGG16. Classifying the images into crack and uncracked categories required the analysis of 40,000 photos. At the same time, 500 photos were employed for image segmentation. When compared to InceptionV3 and ResNet, the VGG16 model performed better. Wang et al. [27] deployed three AlexNet models to identify concrete fractures, compared them to ChaNet, and found ChaNet to be more accurate, with an accuracy of 87.91%. Chaiyasarn et al. [28] combined CNN and Support Vector Machine (SVM) to extract fracture characteristics from RGB digital images. They employed the SVM as a substitute for the SoftMax layer to improve sorting abilities and achieved an approximate 86% accuracy rate. The performance of pre-trained CNN models for classification depends on the number of images used to train the models [29].

Using deep learning models such as GoogLeNet, Inception-V3, and MobileNet-V2, Qayyum et al. [30] categorized photos of uncracked and cracked concrete and determined the orientation of the cracks (diagonal, horizontal, or vertical). Inception-V3 beat the other two models, attaining 97.2% accuracy for discriminating between cracked and uncracked images and accuracies of 92.0%, 95.0%, and 96.0% for recognizing diagonal, horizontal, and vertical cracks, respectively. Ahmed et al. [31] used the ResNet-50 model to identify pavement cracks with an accuracy and precision of 99.8% and 100%, respectively. Machine learning was utilized by Mangalathu et al. [32] to identify earthquake-related building damage. They used data from the magnitude 6.0 South Napa earthquake that struck near the city of Napa, California, in the USA in 2014, together with four machine-learning techniques to categorize damages in buildings based on the ATC-20 identifier. The models used various building-specific parameters as predictor variables and achieved a 66% prediction accuracy using the Random Forest (RF) method.

Efflorescence is a white or grayish, powdery deposit that appears on the surface of masonry, concrete, or other building materials when they are exposed to moisture. It is caused by the migration of salt-bearing water to the surface of the material, where it evaporates, leaving behind the salt crystals. On the other hand, spalling refers to the process of the surface of a structure, such as brick or concrete, breaking off into small pieces or flakes. This occurs when water gets into the pores of the material and freezes, causing the material to expand and crack. Wang et al. [33] developed an automated damage detection method for identifying efflorescence and spalling in medieval masonry constructions using a Faster R-CNN model based on the ResNet101 framework. The method was validated on 33 examples, achieving a mean average precision (AP) of 0.950, and was further tested on simple masonry structures. An Internet Protocol (IP) camera damage recognition system and a smartphone-based system were also employed for real-time detection purposes. The proposed method was reliable and efficient for managing and conserving historic buildings.

3 OVERVIEW OF THE METHODOLOGY

The first step of the process was to collect images of different wall damage scenarios. These images were captured from real buildings in the Taxila region of Pakistan. The second step involves manually dividing the dataset into three categories: (i) undamaged; (ii) cracked; and (iii) miscellaneous. The miscellaneous category includes all other damage cases besides the undamaged and cracked states i.e., efflorescence, spalling, and scaling of the surfaces. The third step involves further training the three pre-trained CNN models. Finally, the performance of the trained models is validated and matched in the last step. Figure 1 shows a flowchart of the steps of the adopted methodology.

Figure 1. The steps of the research methodology.

The image dataset consisted of 6000 images in total, which were manually and equally divided into the three categories (classes), by inspection. Each of the three categories had 2000 images. Each class dataset was further divided into 70% used for model training and the rest (30%) was used for validation. Figure 2 shows one image from each category, for illustration purposes.

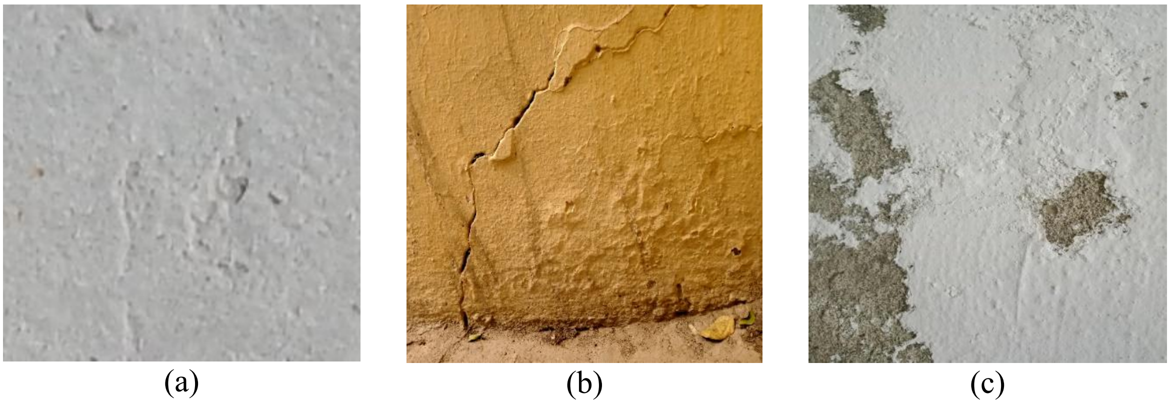


Figure 2. Sample images belonging to each category: (a) Undamaged, (b) Cracked, (c) Miscellaneous.

3.1 Pre-trained Models

Three models were used to classify images, namely ResNet-50 [22], ResNet-101 [23], and Inception-V3 [21]. **ResNet-50** is a deep CNN architecture used for image recognition and classification tasks. It is a variant of the Residual Network (ResNet) architecture, which was introduced in 2015 and won the ImageNet challenge that year. The ResNet-50 architecture consists of 50 layers, including convolutional layers, pooling layers, and fully connected layers. It utilizes residual connections, which allow information to bypass a few layers of the network and be passed directly to later layers. This helps to address the problem of vanishing gradients, where the gradients used to update the weights of earlier layers become very small, making it difficult to train deep networks. The residual connections in ResNet-50 also enable the network to learn more complex features and patterns by allowing the flow of information to be more efficient and reducing the likelihood of overfitting. Figure 3 shows the architecture of ResNet-50.

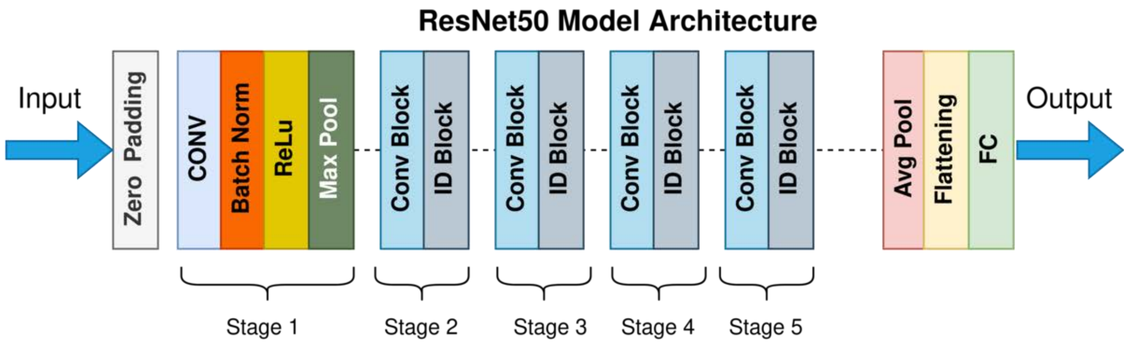


Figure 3. The architecture of ResNet-50 [22].

ResNet-101 is another variant of the ResNet architecture, which can be considered as an extension of ResNet-50 and has 101 layers, making it a deeper and more complex network. Like ResNet-50, it consists of convolutional layers, pooling layers, and fully connected layers. However, it includes more layers, and each residual block in it includes three convolutional layers, compared to two in ResNet-50. The additional layers in ResNet-101 allow it to learn more complex and abstract features in images, leading to improved accuracy and performance compared to ResNet-50. However, being a deeper network makes it more challenging to train, and additional computational resources are required. Like ResNet-50, ResNet-101 is pretrained on the ImageNet dataset, which allows for faster and more accurate training on new tasks. The pretrained model can be fine-tuned on other datasets with similar image characteristics to improve its performance on specific tasks. The architecture of ResNet-101is illustrated in Figure 4.

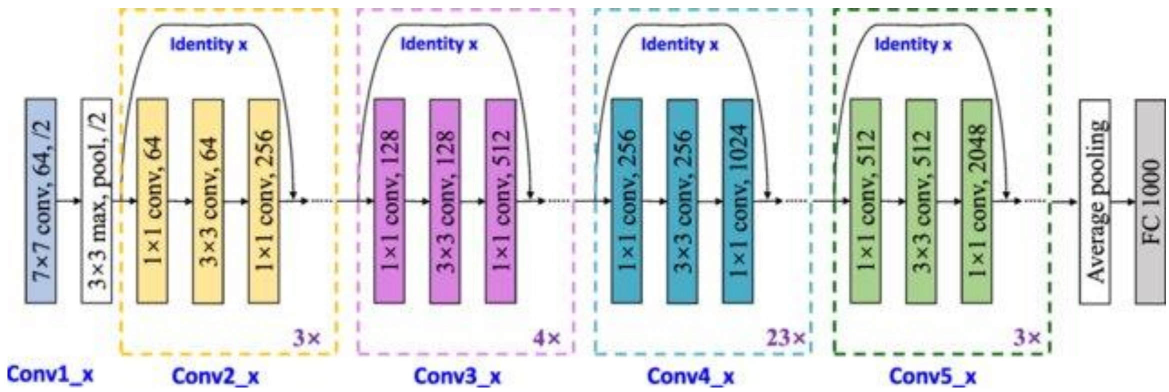


Figure 4. The architecture of ResNet-101 [34].

Inception-V3 is a CNN architecture used for image classification and recognition tasks. It was introduced in 2015 as an improvement over the original Inception network, also known as GoogLeNet. Inception-V3 consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. One of its key features is the use of Inception modules, which are designed to capture features at multiple scales and dimensions. InceptionV3 incorporates several advanced features, including factorized convolution, batch normalization, and improved auxiliary classifiers. It has achieved state-of-the-art performance on several image recognition tasks and benchmark datasets, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). It is widely used in computer vision applications, including object detection, face recognition, and image segmentation. It has also been used in the development of image-based medical diagnosis and disease classification systems. Figure 5 presents an illustration of the architecture of the Inception-V3 CNN.

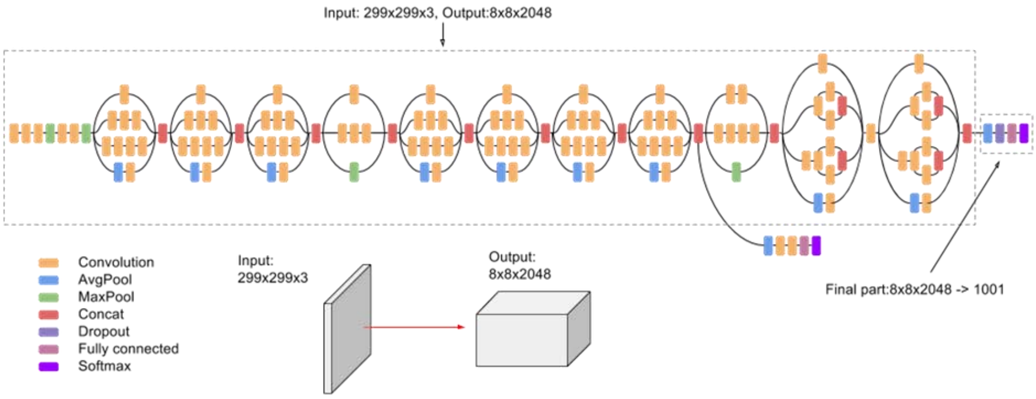


Figure 5. The architecture of Inception-V3 [21].

4 RESULTS AND DISCUSSION

70% of the image dataset was used for training, while 30% was reserved for validating the trained models. Confusion matrices were generated for each model to evaluate their performance. The performances of the ResNet-50, ResNet-101, and Inception V3 models are summarized in Table 1, Table 2 and Table 3, respectively.

Class	Undamaged	Cracked	Miscellaneous
Accuracy	84.11%	79.50%	92.94%
Precision	0.77	0.71	0.85
Recall	0.74	0.66	0.95
F1 Score	0.76	0.68	0.9

Table 1: Accuracy, precision, recall, and F1 score for the ResNet-50 model.

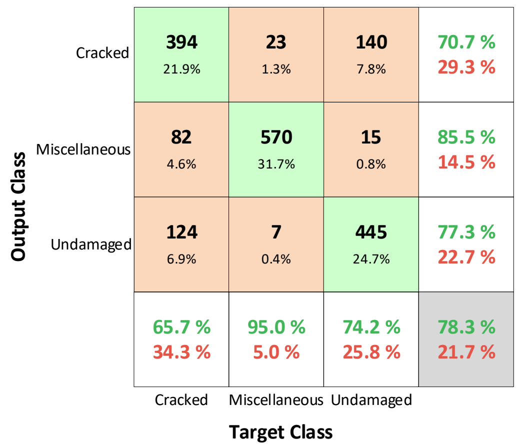
Class	Undamaged	Cracked	Miscellaneous
Accuracy	86.00%	85.78%	98.78%
Precision	0.75	0.85	0.96
Recall	0.86	0.7	1
F1 Score	0.8	0.77	0.98

Table 2: Accuracy, precision, recall, and F1 score for the ResNet-101 model.

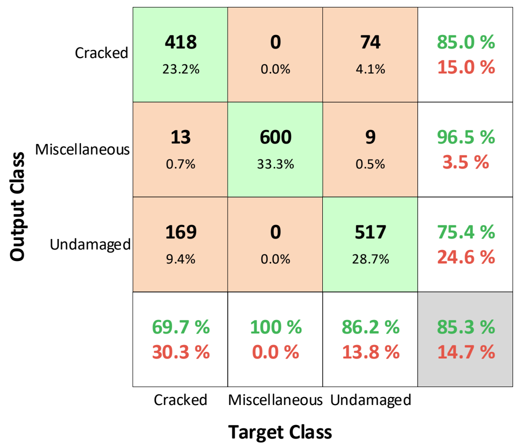
Class	Undamaged	Cracked	Miscellaneous
Accuracy	87.17%	87.11%	99.94%
Precision	0.76	0.88	1
Recall	0.9	0.71	1
F1 Score	0.82	0.79	1

Table 3: Accuracy, precision, recall, and F1 score for the Inception V3 model.

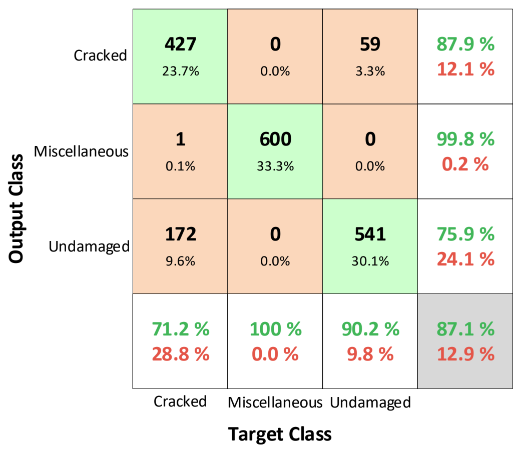
In particular, the tables show the accuracy, precision, recall, and F1-score values for each model. F1-score is a measure of a classification model's accuracy that takes into account both precision and recall. Figure 6 depicts the confusion matrices for each of the three models.



(a) ResNet-50



(b) ResNet-101



(c) Inception V3

Figure 6. Confusion matrices for each model: (a) ResNet-50, (b) ResNet-101, (c) Inception V3.

The results shown in the tables indicate that the Inception V3 model outperforms ResNet-50 and ResNet-101 in the image classification task. Specifically, the overall accuracy of ResNet-50, ResNet-101, and Inception V3 in classifying images into undamaged, cracked, and miscellaneous categories are 78.3%, 85.3%, and 87.1%, respectively.

5 CONCLUSIONS AND FURTHER WORK

Machine learning can be used in wall surface defect classification to automate the process of identifying and categorizing defects in wall surfaces. By using algorithms to analyze images of wall surfaces, machine learning models can identify patterns and classify defects based on their characteristics. This research work has demonstrated the effectiveness of using such techniques and particularly CNNs for wall surface defect classification in high-rise structures. The transfer learning approach was implemented using three well-known pre-trained CNN models, namely ResNet-50, ResNet-101, and Inception-V3. The training database consisted of 6000 labeled digital images belonging to one of the three categories: undamaged, cracked or miscellaneous. The performance of each model was evaluated using well known metrics such as accuracy, precision, recall, F1-score, and training time. Based on the results achieved for each model, it can be concluded that the Inception V3 model outperformed the ResNet-50 and ResNet-101 models, achieving an overall accuracy of 87.1%, which suggests that it was the best model for the task of damage classification of the wall.

The suggested methodology for wall surface defect classification has practical implications for building maintenance, with several benefits. It can significantly reduce the time and effort required for manual inspection and classification of defects, allowing for more efficient maintenance and repair processes. It also helps to improve accuracy and consistency in defect classification, reducing the risk of errors or oversights. Overall, the use of this machine learning technique can help to improve the safety, durability, and appearance of wall surfaces in high-rise buildings and other structures.

LIST OF ABBREVIATIONS

The following table describes the meaning of various abbreviations and acronyms used throughout the paper.

Abbreviation	**Definition**
AI	Artificial Intelligence
AP	Average Precision
ATC	Applied Technology Council
CNN	Convolutional Neural Network
DC	Diagonal Crack
HC	Horizontal Crack
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
IP	Internet Protocol
ResNet	Residual Network
RF	Random Forest
RGB	Red, Green, Blue
SVM	Support Vector Machine
UC	Uncracked
VC	Vertical Crack

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