**Computer Vision-based CNN Model Automated Defect Detection in Concrete Through Cellphone Camera**

Afaq Ahmed1[0000-0001-9427-4296], Mati ullah 2,Muhammad Salman3, Muhammad Noman4

1 Civil engineering department, Oslo Metropolitan University, Norway

Afaq.ahmad@oslomet.no

2 Civil Engineering Department, Qatar University, Qatar

3 Civil Engineering Department, UET Taxila, Pakistan

4 Civil and Coastal Engineering Department, University of Florida, Gainesville, USA

**Abstract****:** Over time, buildings are increasingly challenged by various defects, such as cracks, mold growth, paint deterioration, and dampness. Addressing these defects is crucial to prevent excessive maintenance costs and potential disasters, but effective treatment relies on accurately identifying and detecting these issues. Traditionally, engineers have relied on building surveys to locate and assess these defects. However, manual inspections are labor-intensive, time-consuming, and often require skilled labor, increasing costs. Moreover, the accuracy of results from manual methods may be inconsistent and accessing defects in hard-to-reach or hazardous areas poses significant challenges and risks, sometimes making detection infeasible. To overcome these limitations, this study proposes an application of image processing and a Convolutional Neural Network (CNN) approach for defect detection using images captured by regular, portable cell phone cameras. The method utilizes pre-trained CNN models, including Inception, MobileNet, ResNet-18, and ResNet-50, to detect building defects. The technique employs the four famous pre-trained CNN models to detect building defects in five levels: (a) Clean state-no maintenance required with 6000 images, (b) Uncracked state-maintenance required with 2000 images, (c) Mold-maintenance required with 1000 images, (d) Light Crack-maintenance required with 1000 images, and (e) Highly cracked-maintenance required with 2000 images. The comparative study revealed that the Inception model yielded the best results among the models used. After the CNN training, Hugging Face uses to create a mobile App for this purpose.

**Key Words:** Crack, CNN models, Inspections, Mobile App

# Introduction

Cracks in concrete structures often signify structural deterioration, with their type, size, and frequency serving as key indicators of defects in reinforced concrete systems [1–3]. The durability and safety of buildings are directly influenced by the quality of these structures, underscoring the need for regular expert inspections to assess their condition and generate reliable reports [4–7]. Early recognition of cracks and issues during such inspections is essential for mitigating potential structural damage and protecting the occupants. Established approaches, which rely heavily on manual visual inspections, are often inefficient, subjective, labor-intensive, and costly [8–10]. To address these limitations, the implementation of automated and advanced evaluation methods has become necessary.

Recent advancements in Artificial Intelligence (AI) and unmanned computerized vehicles (UAVs), particularly in computer vision, have demonstrated remarkable success in crack detection and structural health monitoring (SHM), and monitoring outperforms traditional techniques. Numerous studies have proposed groundbreaking methods for effectively identifying and classifying cracks in building structures, leveraging these technologies to enhance accuracy and efficiency [11–15]. Convolutional Neural Networks (CNNs) have transformed multiple disciplines, including structural engineering, by advancing image analysis and pattern recognition techniques [11–15]. In structural engineering, the precise detection, classification, and assessment of defects are critical, and CNNs have become instrumental in automating these tasks. Their graded architecture effectively extracts spatial features from visual data and utilizes them for applications such as crack identification, structural damage evaluation, and infrastructure health monitoring [16–20]. The adaptability and learning capabilities of CNNs allow them to outperform traditional methods, providing more accurate and efficient solutions for maintaining structural integrity.

Ehtisham et al. [21] assessed several pre-trained CNN models, including ResNet and MobileNetV2, to detect and classify concrete cracks. Their inspection aimed to examine the performance of these models in real-world applications, where the precision of detecting cracks at different orientations is matched. Such research further advances the notion that pre-trained CNN models can be adjusted for SHM purposes, allowing quicker implementation in the field. Chollet [22,23] proposed Xception and Inspections models, a deep learning model built around depth-wise separable convolutions. The model's efficient design allows CNNs to handle more complex chores with fewer parameters and lower computational constraints, making them well-suited for functions such as crack detection in large datasets from infrastructure inspections [24,25].

This study aims to apply image processing and a CNN for defect detection using images captured by regular cell phone cameras. The method utilizes pre-trained CNN models, including Inception, MobileNet, ResNet-18, and ResNet-50, to detect and predict building defects. The technique employs the four famous pre-trained CNN models to detect building defects in five levels: (a) Clean state-no maintenance required with 6000 images, (b) Uncracked state-maintenance required with 2000 images, (c) Mold-maintenance required with 1000 images, (d) Light Crack-maintenance required with 1000 images, and (e) Highly cracked-maintenance required with 2000 images. The model was trained, validated, and tested on a dataset comprising 1,000 images collected from various buildings. The dataset was categorized into cracks, non-cracks, and miscellaneous defects. After the CNN training, Hugging Face uses to create a mobile App for this purpose. The comparative study revealed that the Inception model yielded the best results among the models used.

# Methodology

Building defects encompass various types, including stains, mold, minor cracks, and significant cracks [26,27]. The methodology adopted in this work primarily focused on differentiating maintenance levels based on image classifications. Therefore, the images, collected from open-source databases and various sites, are categorized into five main categories, as described in Table 1. The database was collected through an online database and by using a camera from a portable cellphone. CNN requires extensive data for training and validation purposes to show good performance results. Therefore, the number of images in our database increased through image augmentation [28–30]. Images of each group were rotated, translated, and flipped horizontally and vertically. After the augmentation processes, pictures in each class were made equal. The number of images in each is given in Table 1. The database comprised pictures of building regions with building defects in five levels, as illustrated in the Figure 2.

Table : Classifications of Images

|  |  |  |  |
| --- | --- | --- | --- |
| **Level** | **Descriptions** | **Required Actions** | **Number of Images** |
| 1 | Clean State | No Maintenance Required | 6000 |
| 2 | Uncrack-Surface Issues | Light Maintenance Required | 2000 |
| 3 | Mold | Light Maintenance Required | 1000 |
| 4 | Light Cracks | Medium Maintenance Required & Not Dangerous | 1000 |
| 5 | Major Cracks | Significant Maintenance Required & Dangerous | 2000 |

A close-up of different types of pavement with Willis Tower in the background

AI-generated content may be incorrect.

Figure : Randomly selected Images from five Levels

# Convolutional Neural Network

## CNN pre-trained models

Deep Learning (DL) is a powerful machine learning approach for feature extraction, transformation, and pattern analysis, applicable in supervised and unsupervised contexts. It involves multiple layers of nonlinear information processing [16–20]. Convolutional Neural Networks (CNNs), a type of Deep Learning (DL) model designed explicitly for visual data analysis, have been particularly successful in tasks such as image recognition and classification. Thus, CNNs are well-suited for capturing and learning complex image features, identifying patterns and anomalies, and detecting and analyzing various defects [16–20]. However, CNN-based approaches have recently gained widespread recognition and acceptance as the preferred method for tasks such as image classification, object detection, and image segmentation. The typical architecture of a CNN is shown in Figure 2.

This study employs four pre-trained CNN models, Inception, MobileNet, ResNet-18, and ResNet-50, as defined in Table 2, which are used in this study. Each model is trained, validated, and tested on the same datasets to evaluate their performance based on processing time and classification accuracy. A comparative analysis is conducted using the confusion matrix for each model, and independent tests are performed to confirm the effectiveness of these models. Notably, this work leverages pre-trained CNN models that have been further trained on a unique dataset of images, specifically designed for accurate classification across different classes.

A diagram of a computer network

AI-generated content may be incorrect.

Figure : Typical features of CNN models

Table : Pre-trained CNN models Characteristics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Sr.No** | **Model** | **Input Size** | **Depth (Layers)** | **Parameters (Millions)** | **Key Feature** |
| 1 | **Inception-v3** | 299×299×3 | 48 | ~23 | Factorized convs |
| 2 | **MobileNet-v1** | 224×224×3 | 28 | ~4.2 | Depthwise separable |
| 3 | **ResNet-18** | 224×224×3 | 18 | ~11.7 | Residual connections |
| 4 | **ResNet-50** | 224×224×3 | 50 | ~25.6 | Bottleneck blocks |

## Training of models

Figure 3- Figure 6 illustrate the confusion matrices of these four models. Figure 3, the confusion matrix evaluates the performance of an Inception-based classifier in predicting five structural condition categories, demonstrating excellent overall performance with an accuracy of 97.6%. The model yields powerful results for critical safety-related classifications, with Level 5 (Highly Cracked - Dangerous) achieving a 97.6% recall and Level 2 (Uncracked - Maintenance Required) reaching a 99.0% recall, indicating a reliable detection of maintenance-required states. Most classes perform exceptionally well, with Level 1 (Clean State) achieving a 97.2% recall rate and Level 3 (Mold) achieving a 97.7% recall rate. The primary area of minor confusion occurs with Level 4 (Light Cracked), which shows a 3.3% error rate, mostly misclassified as Level 5 (Dangerous) or Level 3 (Mold), suggesting that these intermediate damage states share some visual similarities. Precision metrics remain strong across all classes, ranging from 96.2% to 99.5%, with Level 1 (Clean State) achieving a near-perfect 99.5% precision, minimizing false positive maintenance alerts.

A chart with numbers and a number of levels

AI-generated content may be incorrect.

Figure : Confusion Matrix for Inception Model

Notably, the model achieves balanced performance across both recall and precision metrics, with no single class exhibiting a significant weakness. For likely enhancements, the focus could be directed toward better distinguishing between Level 4 (Light Cracked) and adjacent categories through the development of feature extraction or additional training examples of borderline cases.

Figure 4 illustrates a confusion matrix that estimates the performance of a MobileNetV2-based classifier in calculating five distinct structural surface situations, ranging from a clean state requiring no maintenance to a highly cracked and dangerous state. The model exhibits a strong overall accuracy of 97.0%, with strong classification performance across all classes. Level 5 (Highly Cracked - Dangerous) is identified with excellent accuracy, achieving 98.1% recall and 100% precision, which is essential for ensuring safety in critical infrastructure measurements. Level 1 (Clean State) also shows high performance, with 98.5% recall and 94.3% precision, indicating that the model effectively distinguishes well-maintained and poorly maintained surfaces.

A chart with a number of numbers and a number of text

AI-generated content may be incorrect.

Figure : Confusion Matrix for MobileNet Model

The classifier performs well on Levels 2 (Uncracked - Maintenance Required) and 3 (Mold - Maintenance Required), accomplishing recall rates of 96.7% and 97.1%, respectively. A minor confusion occurs between these two categories and Level 4, possibly due to the overlapping visual textures typical of early degradation stages. Level 4 (Light Cracked - Not Dangerous) has the lowest recall with the classes, at 94.5%, with some misclassifications into lower and higher severity levels.

Figure 5 illustrates a confusion matrix that estimates the performance of a ResNet-18-based classifier in predicting five distinct structural surface conditions, ranging from a clean state requiring no maintenance to a highly cracked and hazardous state. The model establishes a strong overall accuracy of 98.1%, with consistently high precision and recall across all classes. Level 5 (Highly Cracked - Dangerous) is ideally classified, achieving 100% recall and 99.0% precision, which is crucial for safety-critical applications. Level 3 (Mold - Maintenance Required) also shows outstanding performance with 99.0% recall and 96.7% precision, while Level 4 (Light Cracked - Not Dangerous) follows closely with 96.3% recall and 99.0% precision, indicating minimal misclassification.

A chart with numbers and a number of classes

AI-generated content may be incorrect.

Figure : Confusion Matrix for Resnet18 Model

The classifier performs well on Level 1 (Clean State), achieving 97.2% recall, although a modest fraction (2.8%) is misclassified as requiring maintenance (Level 2). Similarly, Level 2 (Uncracked - Maintenance Required) achieves a 98.1% recall, with minor confusion with Level 1 and negligible misclassification into Level 5. These results suggest the model is highly effective at distinguishing between varying degrees of surface degradation. Minor misclassifications, particularly between adjacent maintenance categories, may be attributed to visual similarity in the early stages of deterioration. Refining feature representation and expanding training data for borderline cases could further enhance performance, particularly for near-threshold conditions.

A chart with numbers and a number of text

AI-generated content may be incorrect.

Figure 6: Confusion Matrix for Resnet50 Model

Figure 6 confusion matrix demonstrates the performance of a ResNet50-based classifier in predicting five structural conditions, achieving an overall accuracy of 98.8%. The model performs exceptionally well across most classes, with Level 1 (Clean State) and Level 3 (Mold - Maintenance Required) achieving a perfect 100% recall, while Level 2 (Uncracked - Maintenance Required) and Level 5 (Highly Cracked - Dangerous) follow closely with 99% recall. Level 4 (Light Cracked - Not Dangerous) exhibits minor confusion, with 95.9% recall and 4.1% of cases misclassified, primarily as Level 3 or Level 5, likely due to overlapping visual features. The high accuracy in detecting critical states, such as Level 5, underscores the model's reliability for safety-critical applications. While performance is already robust, further refinement for Level 4, such as enhanced feature extraction or additional training data, could address its slight misclassifications. Overall, the classifier exhibits strong predictive capabilities, making it a dependable tool for structural condition assessment. This presentation establishes the Inception-based classifier as highly consistent for structural condition assessment, combining robust accuracy with particularly strong performance on safety-critical classifications. The model's balanced operation across all categories makes it notably suitable for real-world deployment, where both safeguarding optimization and safety assurance are priorities.

# GUI application

After comparing the four pre-trained models, the Inception model was selected (with a mean accuracy of 0.98, 0.98 accuracy, and 0.99 F1 and 0.98 recall values) for developing the Hugging Face app. Figure 7- Figure 11 describe the outcome of the maintenance app. This figure displays a user interface from an application developed using Hugging Face for maintenance-level prediction of wall images. The application enables users to upload a picture of a wall, automatically classifying its condition into one of five predefined maintenance levels. In the displayed example, a photo of a clean wall has been uploaded.

The application predicted “Level 1 - Clean State (no Maintenance Required)” with a confidence score of 93.03%, as illustrated in Figure 7. The right-hand panel titled "Prediction and Explanation" provides a detailed insight into the result. It explains that the wall is clean and stable, exhibiting no visible cracks or mold, thus requiring no maintenance at this stage. The interface is cleanly designed, with clear options to Clear or Submit the image, and icons below the uploaded image for additional actions, such as preview or removal. This tool is convenient for facility managers, engineers, or inspectors aiming to streamline wall maintenance assessments using AI-powered image classification.

A screenshot of a computer

AI-generated content may be incorrect.

Figure : Maintenance Level Prediction for Level 1

Figure 8 showcases a web application built on Hugging Face titled "Maintenance Level Prediction for Wall Images." The interface is designed to allow users to upload an image of a wall, enabling them to classify its condition into one of five predefined maintenance levels. The left side of the interface displays the uploaded wall image within a preview box, along with control buttons to clear or submit the photo. Once the image is submitted, the right section labeled "Prediction and Explanation" presents the model's output. In this example, the model predicts the wall condition as "Level-2 – Uncracked (Maintenance Required)" with a confidence score of 72.11%. Below this, a detailed explanation is provided: the wall does not exhibit visible cracks but may have minor issues, such as discoloration or surface wear. Regular maintenance is recommended to prevent future deterioration. The overall layout is clean and functional, effectively communicating both the predicted result and its rationale to the user. This implementation demonstrates the practical use of machine learning for structural monitoring and preventive maintenance assessment.

A screenshot of a computer

AI-generated content may be incorrect.

Figure : Maintenance Level Prediction for Level 2

Figure 9 presents another instance of the web application you developed on Hugging Face, titled "Maintenance Level Prediction for Wall Images." In this case, the model predicts the condition as "Level-3 – Mold (Maintenance Required)" with a confidence score of 44.90%. The accompanying explanation states that the wall exhibits mold signs, which establishes a risk by weakening its structural integrity and potentially affecting health. The system recommends immediate maintenance to exclude the mold and stop further damage. This intuitive and informative interface reflects a thoughtful application of AI for infrastructure monitoring and public safety, providing real-time insights that guide proactive decision-making.

A screenshot of a computer

AI-generated content may be incorrect.

Figure : Maintenance Level Prediction for Level 3

Figure 10 is a detailed screenshot of the Hugging Face web application you've developed, titled "Maintenance Level Prediction for Wall Images." The calculation here is "Level-4 – Light Cracked (Not Dangerous)" with a confidence score of 69.63%. The description provided indicates that the cracks on the wall are minor and not immediately hazardous; however, they should still be monitored. Protection is recommended to stop the cracks from expanding.

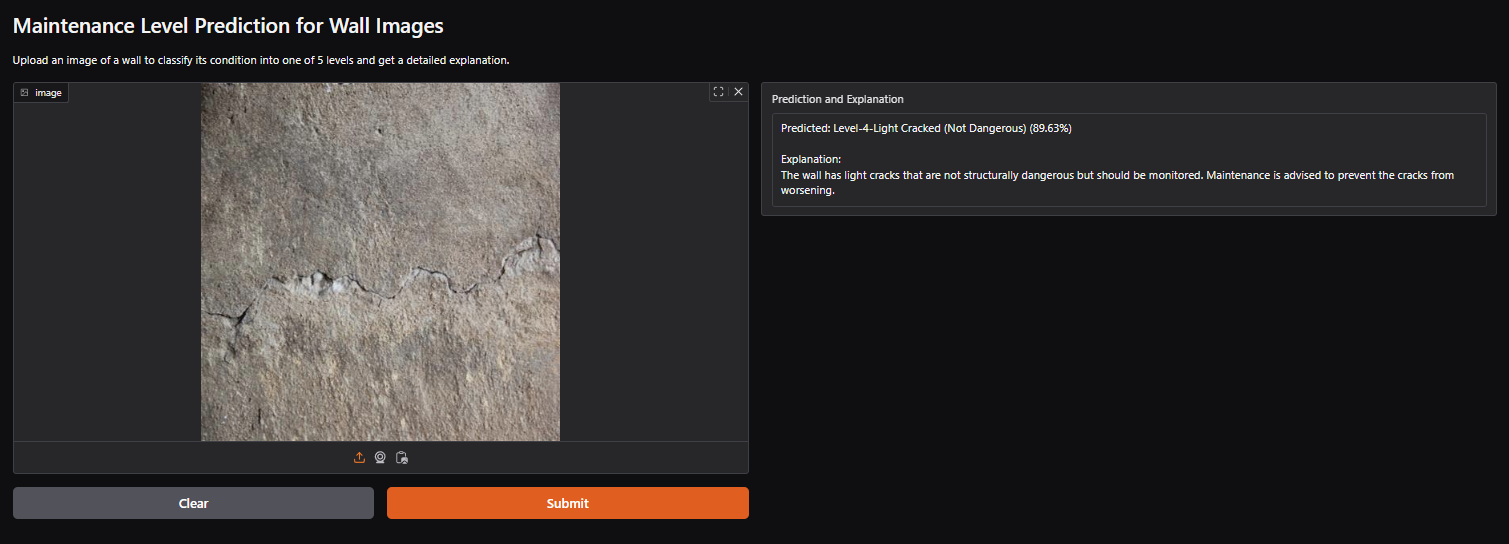


Figure : Maintenance Level Prediction for Level 4

Figure 11 is a detailed screenshot of the Hugging Face web application you've developed, titled "Maintenance Level Prediction for Wall Images." The purpose of the app is to assess the structural condition of walls by analyzing uploaded images and categorizing them into one of five maintenance levels. In this instance, the interface shows a user-uploaded image of a wall with visible surface cracks. The picture is previewed on the left side with options to clear or submit it using the prominent buttons below. Upon submission, the right-hand side under "Prediction and Explanation" displays the model's output. The prediction here is "Level-5 – Highly Cracked (Dangerous)" with a confidence score of 99,18%. The explanation provided indicates that the cracks on the wall are significant and very hazardous, but should still be monitored. Preventive maintenance is recommended to stop further collapse from expanding. The clean UI, informative predictions, and actionable insights reflect a well-designed tool that effectively uses machine learning for real-world infrastructure assessment and maintenance planning.

A screenshot of a computer

AI-generated content may be incorrect.

Figure : Maintenance Level Prediction for Level-5

# Conclusion

This work proposes an application of image processing and a Convolutional Neural Network (CNN) approach for defect detection using images captured by regular, portable cell phone cameras. This study proposes an application of image processing and a Convolutional Neural Network (CNN) approach for defect detection using images captured by regular, portable cell phone cameras. The method utilizes pre-trained CNN models, including Inception, MobileNet, ResNet-18, and ResNet-50, to detect building defects. The technique employs the four famous pre-trained CNN models to detect building defects in five levels: (a) Clean state-no maintenance required with 6000 images, (b) Uncracked state-maintenance required with 2000 images, (c) Mold-maintenance required with 1000 images, (d) Light Crack-maintenance required with 1000 images, and (e) Highly cracked-maintenance required with 2000 images. The comparative study revealed that the Inception model yielded the best results among the models used. After the CNN training, Hugging Face is used to create a mobile App for this purpose. After comparing the four pre-trained models, the Inception model was selected (with a mean accuracy of 0.98, 0.98 accuracy, and 0.99 F1 and 0.98 recall values) for developing the Hugging Face app. The prediction from the Hugging Face app yielded acceptable results, which can be used for building inspection purposes.

# References

[1] Wang X, Mazumder RK, Salarieh B, Salman AM, Shafieezadeh A, Li Y. Machine Learning for Risk and Resilience Assessment in Structural Engineering: Progress and Future Trends. J Struct Eng 2022;148. https://doi.org/10.1061/(asce)st.1943-541x.0003392.

[2] Park JK, Kwon BK, Park JH, Kang DJ. Machine learning-based imaging system for surface defect inspection. Int J Precis Eng Manuf - Green Technol 2016;3:303–10. https://doi.org/10.1007/s40684-016-0039-x.

[3] Zafar AAA, Mir J, Plevris V. Machine Vision Based Crack Detection for Structural Health Monitoring Using Haralick Features 2020. https://csce.cust.edu.pk/archive/20-206.pdf.

[4] Avci O, Abdeljaber O, Kiranyaz S. Structural Damage Detection in Civil Engineering with Machine Learning. Curr. State Art Sens. Instrum. AircraftAerospace Energy Harvest. Amp Dyn. Environ. Test., 2022. https://doi.org/10.1007/978-3-030-75988-9\_17.

[5] Aiello MA, Micelli F, Valente L. Structural Upgrading of Masonry Columns by Using Composite Reinforcements. J Compos Constr 2007;11:650–8. https://doi.org/10.1061/(asce)1090-0268(2007)11:6(650).

[6] Maniat M, Camp CV, Kashani AR. Deep learning-based visual crack detection using Google Street View images. Neural Comput Appl 2021;33:14565–82. https://doi.org/10.1007/s00521-021-06098-0.

[7] Beskopylny AN, others. Discovery and Classification of Defects on Facing Brick Specimens Using a Convolutional Neural Network. Appl Sci 2023;13. https://doi.org/10.3390/app13095413.

[8] Jing Y, others. A comprehensive survey of intestine histopathological image analysis using machine vision approaches. Comput Biol Med 2023;165:107388. https://doi.org/10.1016/j.compbiomed.2023.107388.

[9] Sony S, Dunphy K, Sadhu A, Capretz M. A systematic review of convolutional neural network-based structural condition assessment techniques. Eng Struct 2020;226. https://doi.org/10.1016/j.engstruct.2020.111347.

[10] Waris MI, Plevris V, Mir J, Chairman N, Ahmad A. An alternative approach for measuring the mechanical properties of hybrid concrete through image processing and machine learning. Constr Build Mater 2022;328:126899. https://doi.org/10.1016/j.conbuildmat.2022.126899.

[11] Mascarenhas S, Agarwal M. A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification. 2021 Int. Conf. Disruptive Technol. Multi-Discip. Res. Appl. CENTCON 2021 Pp 9699, 2021. https://doi.org/10.1109/CENTCON52345.2021.9687944.

[12] Lagaros ND, Plevris V. Artificial Intelligence (AI) Applied in Civil Engineering. Appl Sci 2022;12. https://doi.org/10.3390/app12157595.

[13] Ali M, others. Assessment of local earthen bricks in perspective of physical and mechanical properties using Geographical Information System in Peshawar, Pakistan. Structures 2020;28:2549. https://doi.org/10.1016/j.istruc.2020.10.075.

[14] Feng C-Q, Li B-L, Liu Y-F, Zhang F, Yue Y, Fan J-S. Crack assessment using multi-sensor fusion simultaneous localization and mapping (SLAM) and image super-resolution for bridge inspection. Autom Constr 2023;155:105047. https://doi.org/10.1016/j.autcon.2023.105047.

[15] Linkon AHM, Labib MM, Hasan T, Hossain M, Jannat ME. Deep learning in prostate cancer diagnosis and Gleason grading in histopathology images: An extensive study. Inform Med Unlocked 2021;24:100582. https://doi.org/10.1016/j.imu.2021.100582.

[16] Ehtisham R, Qayyum W, Plevris V, Mir J, Ahmad A. Classification and computing the defected area of knots in wooden structures using image processing and CNN, 2023, p. 1–3.

[17] Rana Ehtisham1 WQ Vagelis Plevris3, Junaid Mir1 and Afaq Ahmad1. CLASSIFICATION AND COMPUTING THE DEFECTED AREA OF KNOTS IN WOODEN STRUCTURES USING IMAGE PROCESSING AND CNN. vol. 15, 2023.

[18] Waqas Qayyum1 RE Vagelis Plevris2, Junaid Mir1 and Afaq Ahmad1. CLASSIFICATION OF WALL DEFECTS FOR MAINTENANCE PURPOSES USING IMAGE PROCESSING. vol. 9, 9th ECCOMAS Thematic Conference on Computational Methods in Structural …; 2023.

[19] Qayyum W, Ehtisham R, Plevris V, Mir J, Ahmad A. Classification of wall defects for maintenance purposes using image processing, 2023, p. 2529–39.

[20] Ahmad CF, Cheema A, Qayyum W, Ehtisham R, Yousaf MH, Mir J, et al. Classification of potholes based on surface area using pre-trained models of convolutional neural network. ArXiv Prepr ArXiv230917426 2023.

[21] Rana Ehtisham WQ Charles V Camp, Vagelis Plevris, Junaid Mir, Qaiser-uz Zaman Khan, Afaq Ahmad. Classification of defects in wooden structures using pre-trained models of convolutional neural network. Case Stud Constr Mater 2023;19.

[22] Pan Y, others. Fundus image classification using Inception V3 and ResNet-50 for the early diagnostics of fundus diseases. Front Physiol 2023;14:1. https://doi.org/10.3389/fphys.2023.1126780.

[23] L?ngkvist M, Karlsson L, Loutfi A. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. Pattern Recognit Lett 2017;42:11–24. https://doi.org/10.1609/aaai.v31i1.11231.

[24] Zhang H, Yang G, Li H, Du W, Wang J. Pixel-wise detection algorithm for crack structural reconstruction based on rock CT images. Autom Constr 2023;152:104895.

[25] Seo H, Raut AD, Chen C, Zhang C. Multi-Label Classification and Automatic Damage Detection of Masonry Heritage Building through CNN Analysis of Infrared Thermal Imaging. Remote Sens 2023;15. https://doi.org/10.3390/rs15102517.

[26] Ahmad A, Qayyam W, Mir J, Khan Q-Z. Finding Width, Angle, Endpoint Length, and Actual Path Length of Cracks in Concrete Structures Using CNN and Image Processing. Adv. Optim. Appl. Eng., IGI Global; 2024, p. 22–42.

[27] Ahmad A, ul Hassan RE, Mir J, Khan Q-Z. Predicting the Characteristics of Defects in Wood Structures Using Image Processing and CNN. Adv. Optim. Appl. Eng., IGI Global; 2024, p. 172–96.

[28] Rana Ehtisham WQ Charles V Camp, Mir J, Ahmad A. Predicting the defects in wooden structures by using pre-trained models of Convolutional Neural Network and Image Processing, 2022.

[29] Waqas Qayyum JM Nida Chairman, Afaq Ahmad. Evaluation of GoogLenet, Mobilenetv2, and Inceptionv3, pre-trained convolutional neural networks for detection and classification of concrete crack images, 2022.

[30] Waqas Qayyum RE Charles V Camp, Junaid Mir, Afaq Ahmad. Detecting cracks with Convolution Neural Network (CNN) with Variable image dataset, 2022.