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AI and IoT-based concrete column base cover localization and degradation detection algorithm using deep learning techniques

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ABSTRACT

Internet of Things (IoT) and Artificial Intelligence (AI) technologies are currently replacing the traditional methods of handling buildings, infrastructure, and facilities design, control, and maintenance due to their precision and ease of use. This paper proposes a novel automated algorithm for the health monitoring of concrete column base cover degradation based on IoT and the state-of-the-art deep learning framework, Convolutional Neural Network (CNN). This technique is developed for instance detection and localization of the major types of column defects. Three deep machine learning training models; namely, Resnet-50, Googlenet, and Visual Geometry Group (VGG19), with 7 different network configurations and inputs were studied and compared for their classification performance and certainty. Despite that, a few articles consider the certainty of the CNN classification results, this work investigates the certainty and employs the classification error score as a new performance measure. The results of this study demonstrated the effectiveness of the proposed defect detection and localization algorithm as it managed to read all barcodes, localize defective columns, and binary classify the condition of the concrete covers against their surrounding objects. They also showed that the VGG19 network outperformed the other addressed network models and configurations. The VGG19 network yielded a health condition classification accuracy of 100% with an RMSE of 0.33% and a maximum classification error score of 0.87 %.

1. Introduction

Many facility management organizations are currently investigating technologies to efficiently and timely inspect the health condition of civil structures at reduced labor costs. Visual inspection of concrete structures is costly as it requires intensive and continuous monitoring [1]. Due to the deterioration of concrete and the criticality of the inspection task, smart automated health condition monitoring systems are highly required defects [2 3 4 5]. The following factors summarize the potential causes and the factors that influence concrete deterioration: corrosion of embedded metals is the most common cause of concrete deterioration, freeze–thaw deterioration, chemical attacks due to acids, salts, alkalis, and sulfate found in soil or dissolved in groundwater, abrasion/erosion, exposure to fire/heat, expansion of the aggregates, restraint to volume changes due to the fluctuations in moisture content and temperature, overloads, and impacts [6 7]. Concrete spalling and rebar exposure are among the major concrete column defects and widely exist in buildings and concrete structures (see Fig. 1 [6]). Those defects have the capacity to cause serious risks such as loss of property and public injury. Moreover, they can lead to serious damage to the whole structure such as damage to reinforcing bars (rebar) [8].

A timely remedy is usually a professional decision whenever concrete column spalling takes place. The repair cost and risks significantly increase with time as they depend on the concrete deterioration condition at the repair time [8]. Image processing and artificial intelligence are utilized to automatically recognize concrete spall and concrete cover defects [9].

Non-invasive techniques for the health condition monitoring of concrete structures have gained increasing importance in smart facility management and have been proposed and researched in the literature. Various research articles proposed condition health monitoring systems for concrete structures wherein AI-based methods using wireless acoustic emission sensors, embedded magnetic shape memory alloy components, capacitive sensors, and embedded PZT sensors were used for health monitoring and detecting defects [2 3 4 5]. Building concrete defects were also segmented and detected using digital cameras, image

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processing, and deep learning models, such as the Convolutional Neural Network (CNN) models that are widely used in similar applications [10 11].

Deep learning techniques are data-driven and non-rule-based algorithms. The performance of deep learning training models has been extensively researched in the literature. Artificial intelligence is applied to different engineering fields and demonstrated good performance [12 13]. Zhao and Zhou [14] developed and tested a CNN network to detect various cracks, spalling, and holes in concrete covers. Despite that the proposed network yielded good results, the detectability against the surrounding objects was not reported. Perez et al. [15] proposed a deep learning network to detect building mold (a fungus that grows in the presence of moisture), stain, and paint deterioration where they transferred learning to the Visual Geometry Group 16 (VGG16) pre-trained model. Also, VGG19 networks proved a good performance when used to classify structural cracks [16]. VGG16 and VGG19 are both deep learning networks, however, the former network consists of 16 layers, while the latter consists of 19 layers. Bhavani et al. [16] introduced a customized CNN network with 81 % accuracy to detect building damages and predict the robustness of the repaired mortar. The network is based on the widely known Resnet-50 pre-trained network. Additionally, Alexnet and Googlenet models are among the best performing pre-trained models as they proved image classification effectiveness. These networks were used to detect cracks in highways and locations of illegal buildings in [17] and [18].

In summary, spalling and rebar exposure are the most common column concrete base cover defects and may lead to serious safety hazards. Googlenet, Alexnet, Resnet-50, VGG19, and other pre-trained models have been used to develop efficient buildings and concrete defect detection algorithms. However, none of the research articles proposed an integrated, functional, and tested hybrid algorithm for both localization and binary health condition classification for concrete column base covers. Concrete columns are usually surrounded by aggregates and soil with colors similar to the columns, and sometimes with a texture close to concrete spalling and discoloration textures, which makes the classification process against surrounding objects more challenging than the rest of the concrete elements. No specific algorithm or input option can give a guaranteed precision and thus this particular classification problem requires investigation of the most performing technique and input option. Also, this work introduces a new evaluation technique based on the classification error score (certainty) to improve the reliability of the classification.

Hence, this work proposes a new functional and tested smart health condition monitoring system for concrete column base covers including IoT and image classification technologies. This new algorithm has the potential to improve facility management systems by providing accurate and timely health information about concrete column covers with higher precision and at a significantly reduced cost.

The paper includes 7 sections; Section 1 includes the literature review and the objective of the work, Section 2 explains the methodology, Section 3 lists and explains the well-proven AI-based image classification models that are used in similar algorithms, Section 4 discusses the image capturing and the training process for the addressed deep learning paradigms, Section 5 displays the classification results of the different AI models, Section 6 discusses the results shown in Section 5 and identifies the best-performing model, while Section 7 concludes the conducted study and lists the final results.

2. Methodology

The proposed automated algorithm takes a high-resolution digital image of columns from digital cameras or drones as input and outputs column barcodes, locations, and the health condition of each concrete column base cover. The algorithm provides the maintenance team with a list of defective column locations along with a digital image of each deflected column base. However, the defect identification algorithm does not consider the severity of spalling as maintenance will be immediately required in all severity cases. Additionally, the images of the defective column base covers will allow the maintenance team to decide the maintenance priority and act accordingly.

Fig. 2 depicts the defect detection process. The process starts by taking a digital image from a camera or a video camera, then reading and identifying the barcode label position in the image. The barcode label informs the column number, image scale, and column location. The image scale is calculated by identifying and dividing the width/height of the barcode label in pixels by the actual width/height of the barcode label (140 mm). An error message (error message I) will be sent to the maintenance team if the algorithm failed to identify the column number. It will also send the camera number/IP address to allow the team to identify the location of the faulty barcode label. Based on the image scale information, the algorithm will crop the image that includes the column base cover, resize it to the image size for the pre-trained network ($224 \times 224 \times 3$), and then pass it to the pre-trained CNN image classification algorithm for decision-making. If the CNN network failed to classify the image, an error message (error message II) will be sent to the maintenance team informing them about the location of the column and

(a) Corrosion of reinforcing steel

(b) Concrete posts suffered from a sulfate attack

Fig. 1. Causes of concrete spalling.

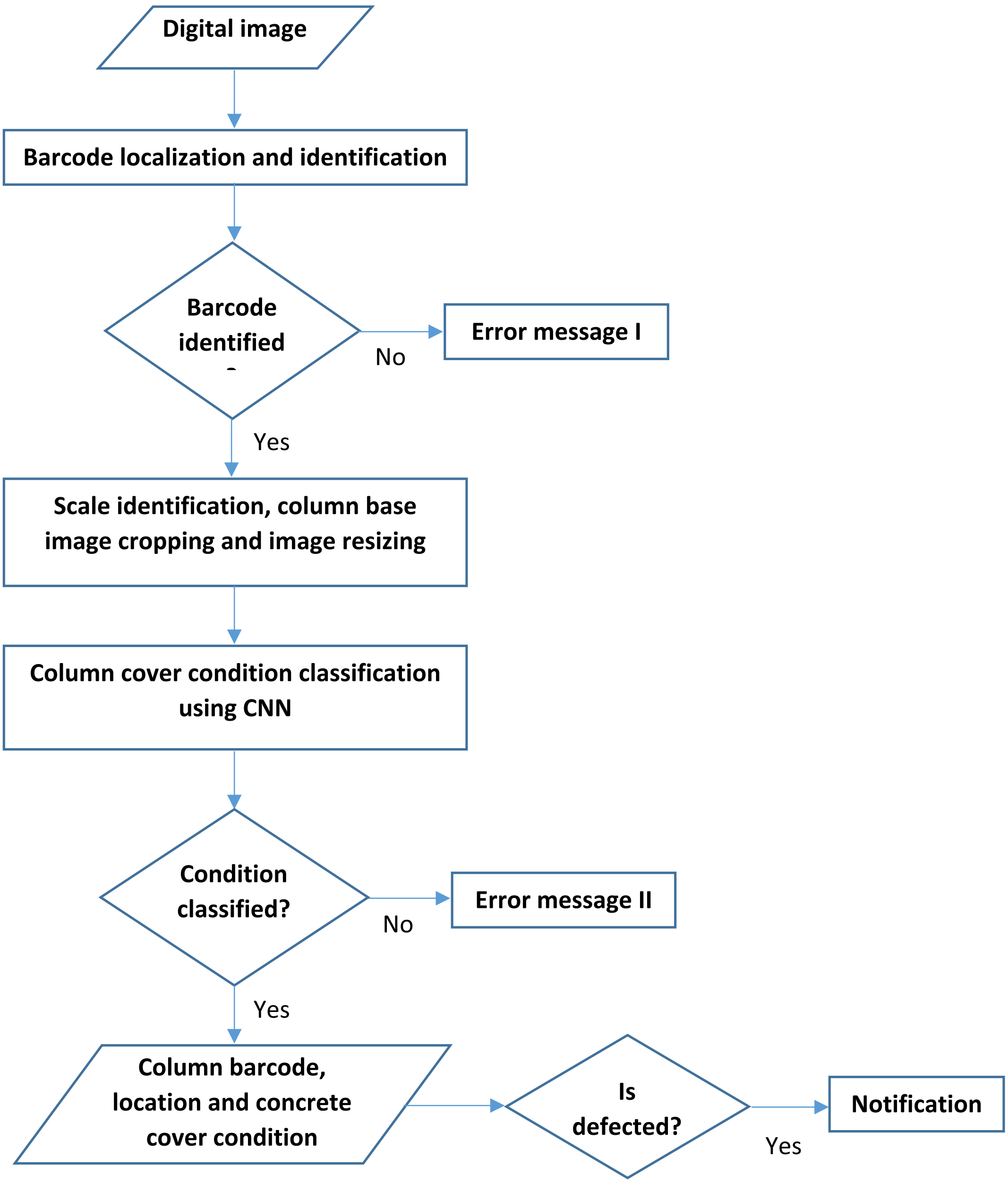

Fig. 2. Automatic AI-based defect detection algorithm for concrete column base covers.

the classification fault. If the algorithm managed to classify the image successfully with good accuracy, the algorithm will send the column barcode, location, and concrete cover health condition to the maintenance team. In order to identify the best-performing AI-based classification model, Sections 3 and 4 list, explain, and compare the performance of the well-proven deep learning AI models. This algorithm will run on a cloud server as shown in Fig. 3.

The Internet of Things became a key system in all modern automated condition monitoring systems as it facilitates remote computing and data transfer without human-to-human or human-to-computer interaction. The proposed concrete column covers health monitoring and employs an IoT system to transfer, store and analyze the data received from all wireless cameras (IoT sensors). Fig. 3 illustrates the interrelated object, computing device, digital camera, client devices, and maintenance team. The process starts by capturing digital images using Wifi cameras and transferring the digital data to the cloud server over a wireless (or Wifi) network. The cloud server receives the data, stores them, and then applies the proposed concrete column cover defect detection algorithm to all images. As shown in Fig. 3, the cloud server runs a data-driven deep learning algorithm to make decisions related to the health condition of concrete column base covers. Then, the images, barcodes, location information, and decisions made by the algorithm are sent to various IoT client devices over a wireless network to be made available to the maintenance team.

3. Column identification and image cropping algorithm

The input images to the algorithm have been taken using Nikon D610 digital camera (24 Megapixels, 6016 × 4016 resolution). The image cropping and column identification algorithm are based on the recognition and localization of barcode labels with known dimensions. The label is placed 80 cm above the ground level. The algorithm starts with the identification of the barcode and image scale using the “readbarcode” MATLAB function, which returns the barcode and the location of the barcode label in pixels. A lookup table is then used to localize the column based on the extracted barcode. The image scale can be

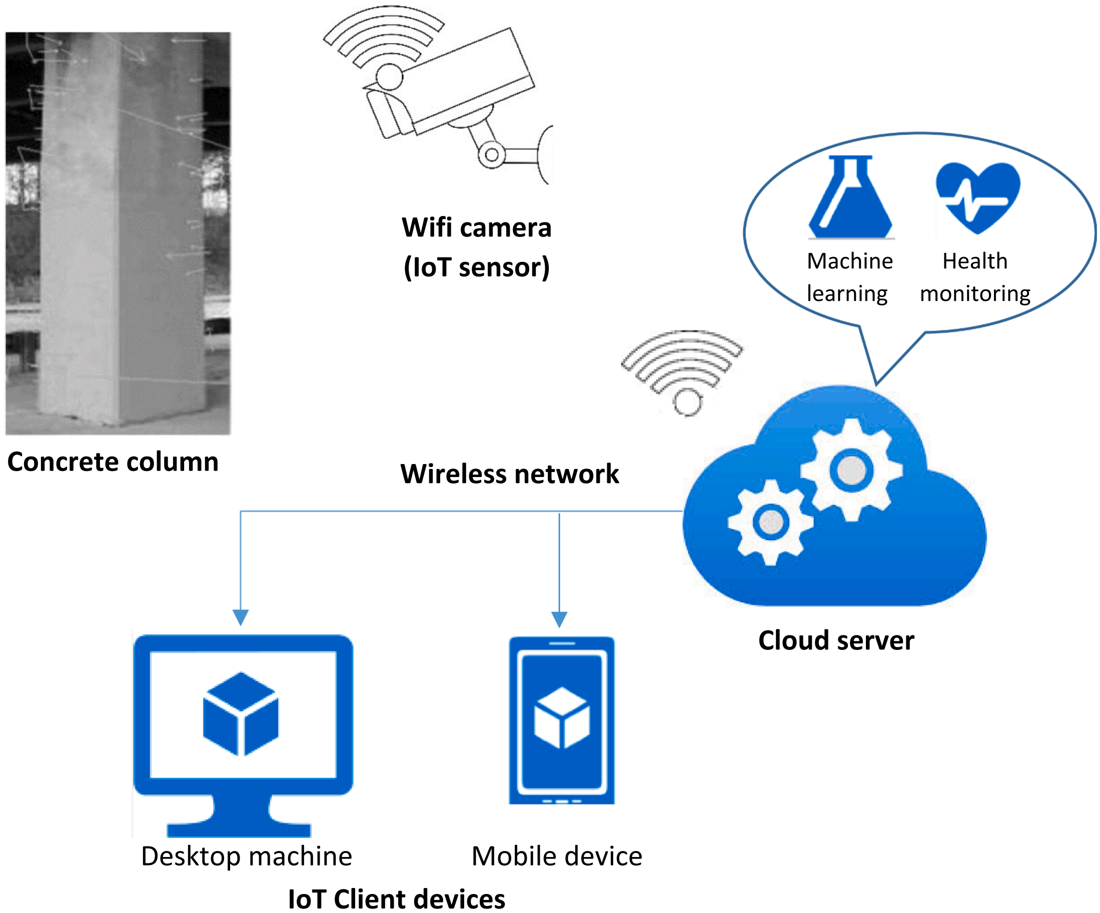

Fig. 3. Framework of the proposed IoT system.

calculated by dividing the width in pixels in the captured image by the actual width of the barcode label in mm (140 mm). The actual dimensions of the column base image in the cropped image are designed to be 900 mm in height and 800 mm in width (see Fig. 4). The cropping dimensions of the image are calculated and then converted to width and height pixels based on the identified image scale. At this stage, the column is identified and localized, and the column base is contoured and cropped. The cropped image is then passed to the CNN algorithm for classification. Further classifications can take place in the future if required.

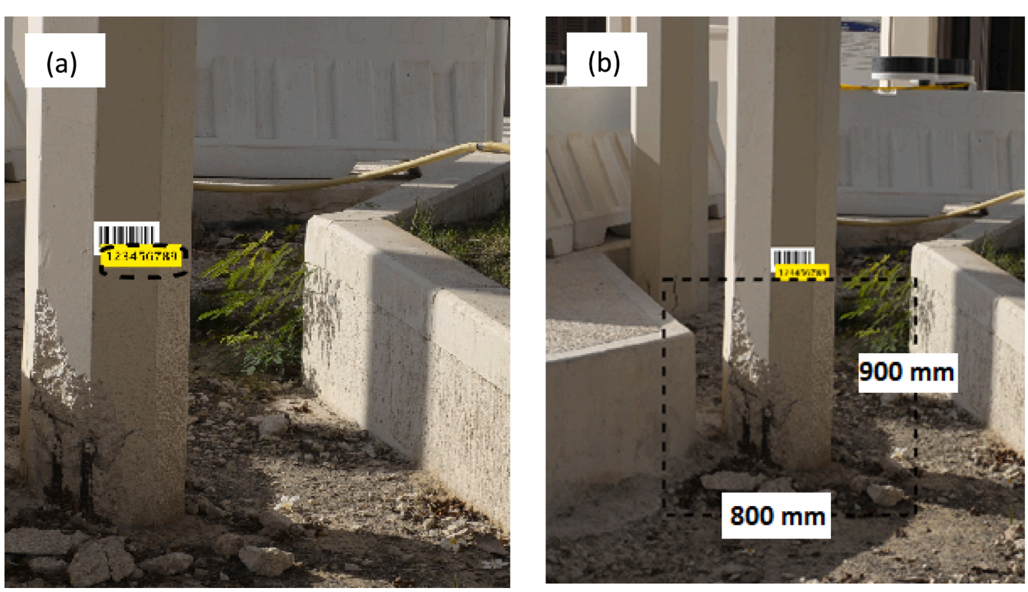

Fig. 4. Column barcode identification and localization process in (a) and column base image cropping in (b) using image processing (using Matlab).

4. Training CNN network for concrete column base cover defect detection

The image dataset includes 96 digital images; 48 images of column base covers are in good health condition and 48 images of deflected concrete covers. Only 70 % of those images were used for training while 30 % were used for validation and testing (15 % for validation and 15 % for testing). The image classification performance, and thus, defect detection accuracy is significantly affected by the pre-trained convolutional neural network model type. Several efficient pre-trained networks are considered in this paper to identify and improve the classification accuracy of the best-performing pre-trained deep learning model.

4.1. Case study object

Rebar exposure and spalling are among the major concrete column base cover defects (see Fig. 5). Hence, this paper employs a binary classification deep learning algorithm to differentiate between two classes; covers in good health condition and defected concrete covers. The defected class includes spalling and rebar exposure, given that both defects must be maintained. The maintenance team will be also provided with an image of the defect to allow them to prioritize the maintenance based on the severity of the defect. However, in this paper, all cover defects are considered severe and need immediate maintenance.

4.2. Deep and transfer learning

Deep Learning is a branch of machine learning where Artificial Neural Networks (ANNs) are employed to solve computer vision tasks such as object detection and image classification. Deep refers to the utilization of multiple layers (depth) in the neural network architecture. Thus, numerous configurations of ANNs are used to automatically extract features from several data formats such as images and text. Researchers observed that the performance has been improved with the increase in the number of ANN layers. However, very deep networks with too many layers will not be only computationally costly but also may suffer from overfitting that causes gradient and performance issues.

Convolutional neural networks (CNNs), deep neural networks(DNN), and recurrent neural networks(RNN) are examples of ANNs but with different configurations. CNNs are widely used in similar defect detection applications, particularly Googlenet, Resnet-40, and VGG19 networks. Fig. 6 illustrated how CNN networks process input images [19]. As the data go through CNNs, the depth of the input image (n) increases through convolution layers, and the width and height decrease through polling layers. This takes place to improve the processing speed as well as the precision of the results. The depth of the data increases proportionally with the number of filters. A padding layer exists in all CNN networks just before the output layer to equalize the height, width, and depth of the data to the number of the output channels of the CNN network (number of output classes). The last layer is the softmax layer and the output of this function is a score vector all up to 1, as it represents the probability of a certain class.

Googlenet, Resnet-40, and VGG19 networks demonstrated efficiency when they have been used in similar algorithms. Googlenet network is a deep convolutional network that consists of 27 deep layers; 22 deep convolution layers and 5 pool layers. The 22 layers include 9 inception modules and 2 convolution layers. The MATLAB pre-trained model, which was trained on the MATLAB ImageNet dataset, is utilized in this paper. Transfer learning was implemented by applying and adapting the knowledge gained by the pre-trained network to our image dataset. The network has an image input size of 224-by-224 pixels. Resnet-50 consists of 50 deep layers; 48 convolution layers and 2 pool layers. The network has an image input size of 227-by-227 pixels. Visual Geometry Group 19 (VGG19) network consists of 19 deep layers; 16 convolution layers with stride and padding and 3 fully connected layers. The network has an image input size of 224-by-224 pixels [20].

Transfer learning is the process of training a pre-trained network to learn new patterns in new data. This is useful to take advantage of the knowledge provided by a pre-trained network and to avoid defining a network architecture and training it from scratch. Since fine-tuning the parameters of a pre-trained image classification network using transfer learning is usually much easier and faster, it is preferred over the construction, training, and testing of a network from scratch. This will help develop adjusted networks for different applications without the need of having thousands of images or powerful computing machines. Fig. 7 details the steps required to reuse a pre-trained network the trainingOptions and trainNetwork functions in MATLAB.

4.3. Training methods and performance evaluation

Various CNN network types and configurations; namely Resnet-50, Googlenet, and VGG19, were investigated in this paper to identify the network with the best binary classification performance (either good or defective concrete cover condition). The proposed algorithm was tested using 7 different pre-trained deep learning networks, network configurations, and image types; namely, Resnet-50 using different weight learn

a. Rebar exposure b. spalling

Fig. 5. Example of original training images: (a) rebar exposure and (b) spalling.

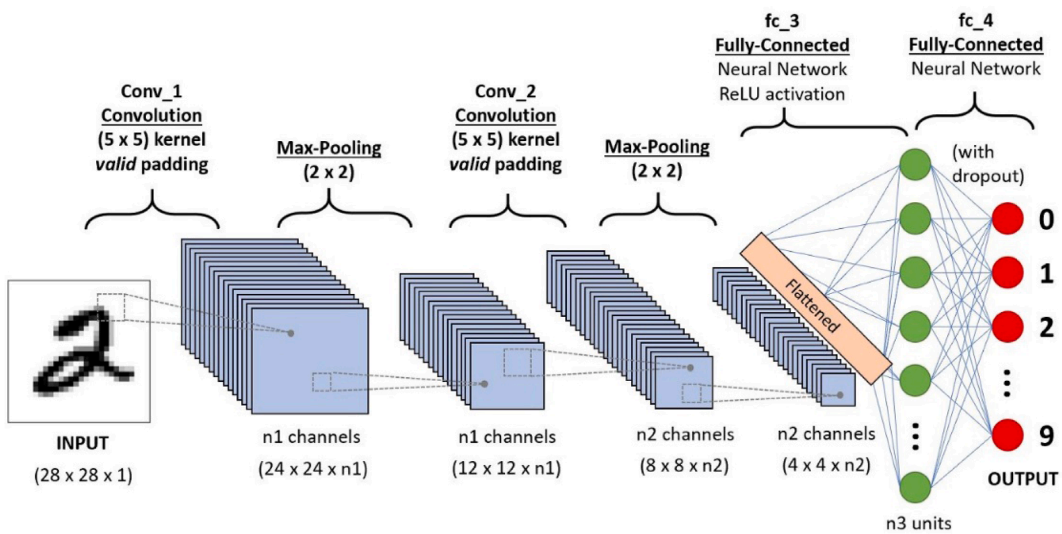

Fig. 6. An example of the CNN classification sequence.

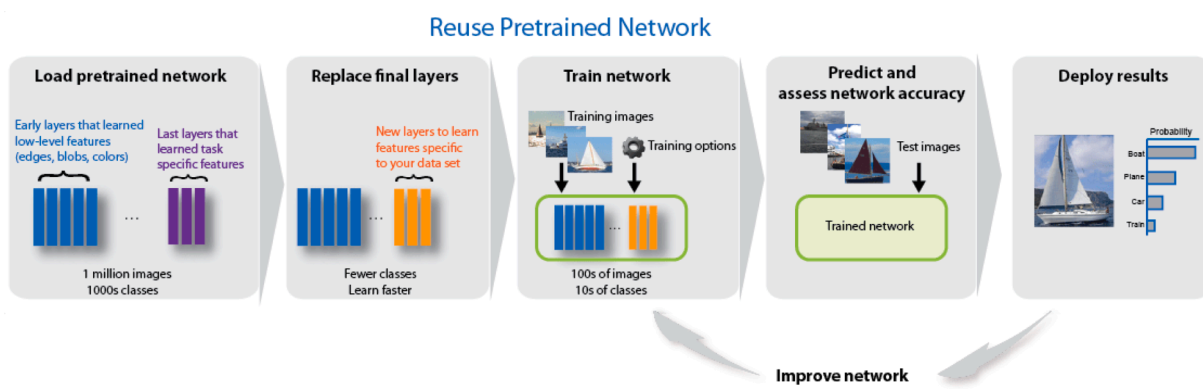

Fig. 7. Transfer learning process in MATLAB [20].

rate factors, Googlenet, VGG19, RGB images, and grayscale images. The main purpose of this investigation is to maximize the classification certainty, and thus, reduce the potential of wrong classifications (false detection). In the beginning, the Resnet-50 pre-trained deep learning network configuration was used to binary classify the cropped concrete base cover images. This network yielded a correct image classification accuracy of 92.5 % (see Fig. 8 and Table 1). The certainty level was assessed using the maximum and RMSE scores given to the wrong class (wrong condition), given that all classification scores are given in Table 1 and Table 2. Knowing that a 100 % certainty could be achieved only if a ZERO score is given to the wrong class.

Fig. 9 shows the training progress of the best-performing pre-trained CNN network. RGB and grayscale images were used as inputs to the CNN network. Despite that, the classification rate remained unchanged at 100 %, the conversion of RGB images to gray images improved the classification certainty as it reduced the maximum error score from 12.77 % to 0.87 % and the RMSE from 4.81 % to 0.29 %.

5. Results

The pre-trained networks yielded different classification performances and score certainty percentages. The last layer in any CNN network is the softmax layer and the output of this layer is a score vector all up to 1. The addressed networks were evaluated based on the classification score produced by the softmax layer, as this layer returns a score that represents the probability for each classification class (out of 1) with a total summed score value of 1 for all classes. For example, the algorithm may classify the cover as good with a score of 0.6 and as defected with a score of 0.4, given that the softmax vector includes two elements as we have two classification classes only (good or defected cover). The larger the difference between the classification score of each class, the better classification certainty. Table 1 summarizes the classification scores yielded by the Resnet-50 architecture using RGB images, grayscale images, and different learn rate factors of 10 and 20. All network configurations using different input image types yielded a performance of 100 % except the Resnet-50 network when trained using grayscale images. It yielded a classification performance of 92.5 % only (see line 11 in Table 1).

Table 2 summarizes the classification scores yielded by the Googlenet and VGG19 architectures using RGB images and grayscale images. All network configurations using different input image types yielded a classification performance of 100 %. However, the certainty of image classification is different. The VGG19 demonstrated the highest certainty with an RMSE and max error values of less than 1 %.

6. Discussion

The proposed concrete column-base cover defect detection algorithm successfully detected and localized all barcodes with an accuracy of 100 percent. To find a good-performing network configuration and input image type, the performance was investigated by training and testing the algorithm using 7 different pre-trained deep learning networks,

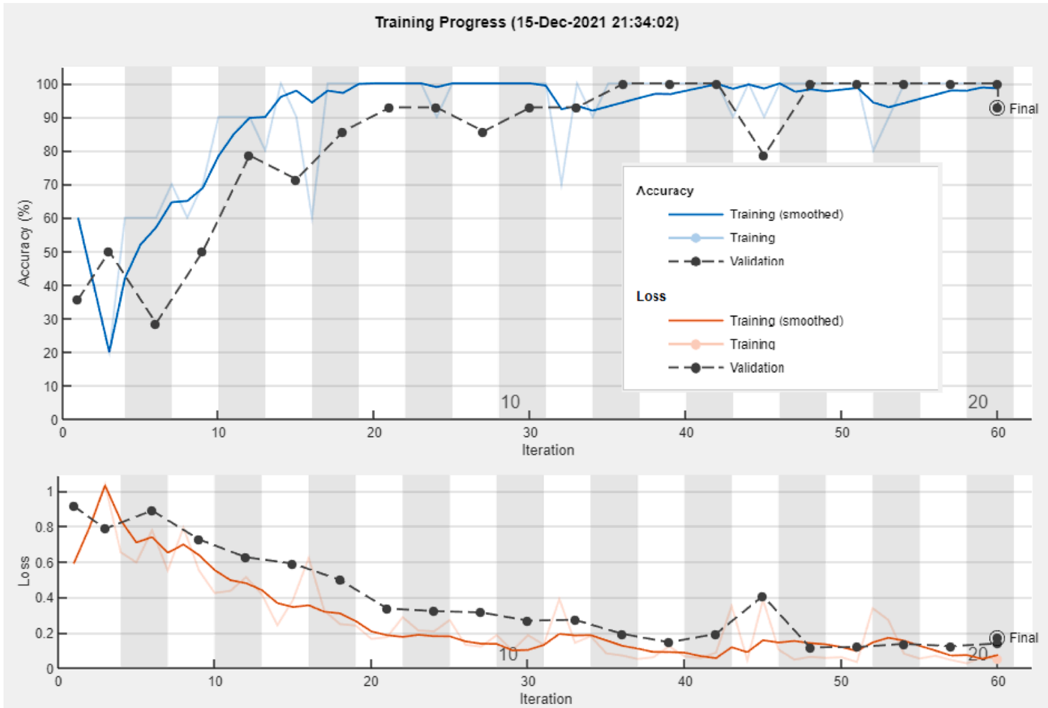

Fig. 8. Training progress of the AI-based defect detection algorithm using Resnet50 network and gray images (classification accuracy of 92.5%, MATLAB Figure).

Table 1
Summary of the prediction scores of the proposed algorithm using different configurations for the Resnet-50 pre-trained deep learning network (max. score value (probability) = 1, false classification in bold).

	Network	**Resnet50(Grayscale)**		**Resnet50(RGB-10)**		**Resnet50(RGB-20)**	
s	**Correct classification**	**Defected**	**Good**	**Defected**	**Good**	**Defected**	**Good**
1	Defected	0.999777	0.000223	0.997401	0.002599	0.995054	0.004946
2	Defected	0.996647	0.003353	0.9989	0.0011	0.998887	0.001113
3	Defected	0.996065	0.003935	0.9989	0.0011	0.998887	0.001113
4	Defected	0.997214	0.002786	0.997646	0.002354	0.99979	0.00021
5	Defected	0.999807	0.000193	0.999736	0.000264	0.99979	0.00021
6	Defected	0.999033	0.000967	0.999736	0.000264	0.996606	0.003394
7	Defected	0.999033	0.000967	0.983785	0.016215	0.996606	0.003394
8	Good	0.157906	0.842094	0.445953	0.554047	0.008165	0.991835
9	Good	0.157906	0.842094	0.445953	0.554047	0.008165	0.991835
10	Good	0.100307	0.899693	0.005074	0.994926	0.007689	0.992311
11	Good	**0.654957**	**0.345043**	0.026837	0.973163	0.154789	0.845211
12	Good	0.143291	0.856709	0.124696	0.875304	0.154789	0.845211
13	Good	0.143292	0.856708	0.039926	0.960074	0.195046	0.804954
14	Good	0.447808	0.552192	0.039841	0.960159	0.011282	0.988718
	Max. Error	0.654957		0.445953		0.195046	
	RMSE	0.323043	0.002282	0.244138	0.006299	0.111022	0.002674

network configurations, and image types; namely, Resnet50 using different weight learn rate factors, Googlenet, VGG19, RGB images, and grayscale images. The performances of the addressed pre-trained deep learning algorithms were evaluated using RGB (R) and grayscale (G) input images. Fig. 10 depicts the results of the comparative study. The VGG19 pre-trained network yielded a correct image classification of 100 % when trained using grayscale images. The RMSE and maximum image classification/prediction scores were used for classification performance evaluation. VGG19 produced an RMSE value and a classification score of 0.33 % and 0.87 %, respectively. This means that the average certainty of the correct classifications is 99.63 %. The score value provides a negated average binary loss per class, and each class is a support vector machine (SVM) multiclass classifier.

Various pictures with various concrete column-based concrete cover conditions, which were not used for training, were utilized to test the performance of the proposed algorithm. For example, the images shown in Fig. 11 were taken from a site in Qatar using a Nikon D610 digital camera. The algorithm successfully managed to binary classify all images with a classification rate of 100 %.

7. Conclusion

This paper employs the Internet of Things (IoT) and Artificial Intelligence (AI) technologies to develop an efficient algorithm for the automated health monitoring of concrete column base covers. The algorithm is developed for automated facility management as it has the capability to monitor the health of a large number of concrete column bases simultaneously. This is achieved by providing the column barcode and location information, binary classifying their health conditions (good or defected), and then sending notifications to the facility maintenance team.

The state-of-the-art deep learning framework, Convolutional Neural

Table 2
Summary of the prediction scores of the proposed algorithm using Googlenet and VGG19 pre-trained deep learning networks (max. score value (probability = 1).

	Network	Googlenet (RGB)		Googlenet(Grayscale)		VGG19(RGB)		VGG19(Grayscale)	
s	Correct classification	Defected	Good	Defected	Good	Defected	Good	Defected	Good
1	Defected	0.969243	0.030757	0.997918	0.002082	0.999836	0.00014	0.99174	0.007883
2	Defected	0.969243	0.030757	0.99951	0.00049	0.869828	0.127292	1	2.53E-09
3	Defected	0.929899	0.070101	0.999455	0.000545	0.999943	5.63E-05	0.999998	5.38E-07
4	Defected	0.980153	0.019847	0.93933	0.06067	0.99996	3.89E-05	1	8.81E-08
5	Defected	0.991365	0.008635	0.93933	0.06067	1	1.07E-08	0.999996	1.42E-06
6	Defected	0.77988	0.220121	0.996861	0.003139	0.996789	0.000976	0.999989	6.3E-06
7	Defected	0.929097	0.070904	0.951068	0.048932	0.998301	0.00046	0.999964	7.71E-06
8	Good	0.004074	0.995926	0.040438	0.959562	7.31E-08	0.99999	8.26E-08	0.999999
9	Good	0.004074	0.995926	0.00663	0.99337	2.65E-07	0.999962	3.39E-08	0.999998
10	Good	0.001514	0.998486	0.041824	0.958176	7.68E-07	0.999998	0.008741	0.989347
11	Good	0.0124	0.9876	0.041824	0.958176	2.34E-07	0.999991	5.11E-07	0.999994
12	Good	0.075749	0.924252	0.002568	0.997432	9.58E-07	0.999889	3.71E-10	0.999999
13	Good	0.271405	0.728595	0.077213	0.922787	1.03E-08	0.999986	1.02E-08	0.99999
14	Good	0.271404	0.728596	0.077213	0.922787	5.06E-07	0.999999	4.57E-07	0.999997
	Max. Error	0.220121		0.077213					
						0.127292		0.008741	
	RMSE	0.147961	0.093163	0.049437	0.037361	5.2E-07	0.048114	0.003304	0.002979

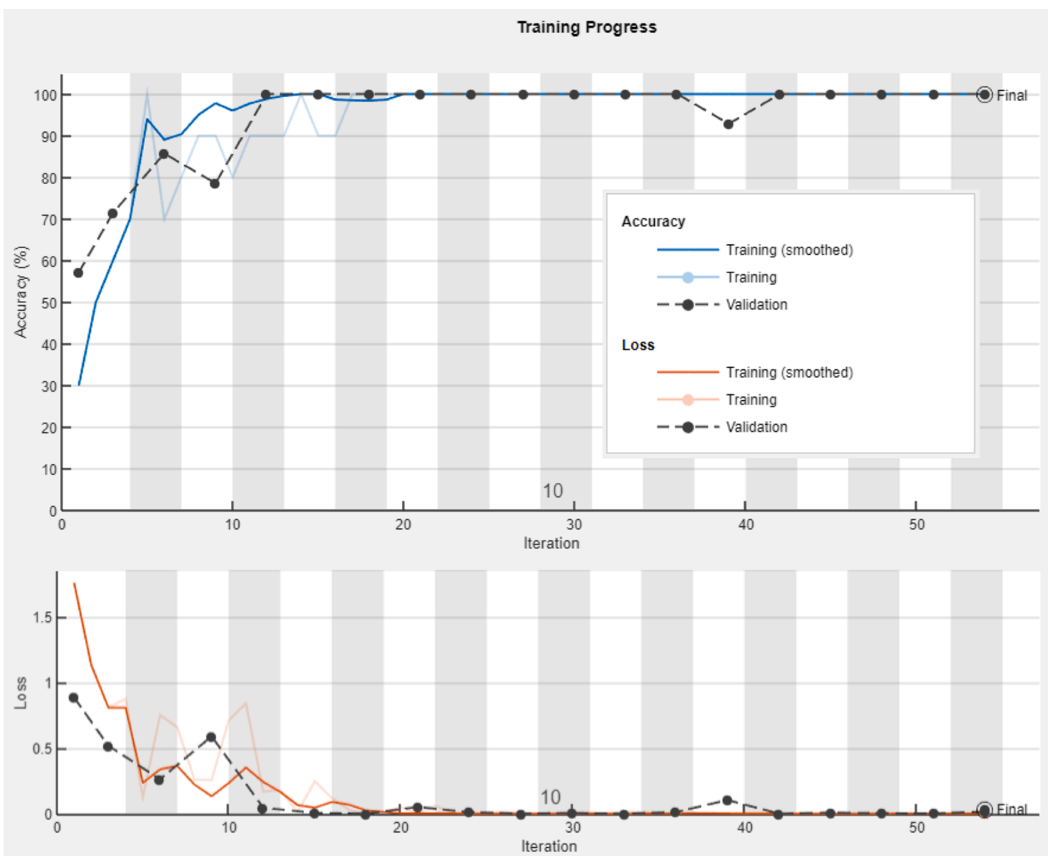

Fig. 9. Training progress of the AI-based defect detection algorithm using VGG19 network and gray images (classification accuracy of 100%, MATLAB Figure).

Network (CNN) was used to develop an instance detection and localization of the major types of column base defects; namely spalling and rebar exposure. Resnet-50, Googlenet, and VGG19 pre-trained deep neural networks were used for training and transferring learning to maximize classification performance and certainty. Resnet-50 pre-trained deep learning network with standard configurations yielded an image classification accuracy of 92.5, as shown in Table 1 and Fig. 8. Various pre-trained networks were used for training with the objective to not only improve the binary classification accuracy but the certainty of the classification. Although the certainty of the classification is important, a few research articles researched it. VGG19 network outperformed the rest of the addressed network configurations yielding a binary classification accuracy of 100 % with an RMSE error and a maximum classification error score of 0.33 % and 0.87 %, respectively, as shown in Table 2. Despite the slight differences between healthy and defective columns, the introduced method proved its effectiveness and certainty.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

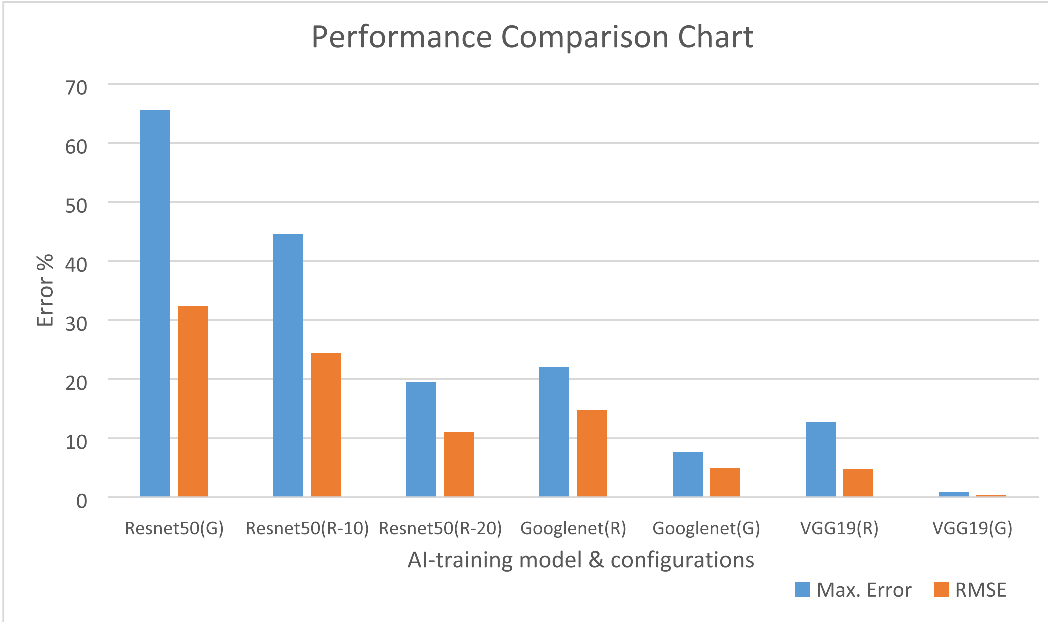

Fig. 10. Performance comparison chart for the addressed deep learning pre-trained algorithms.

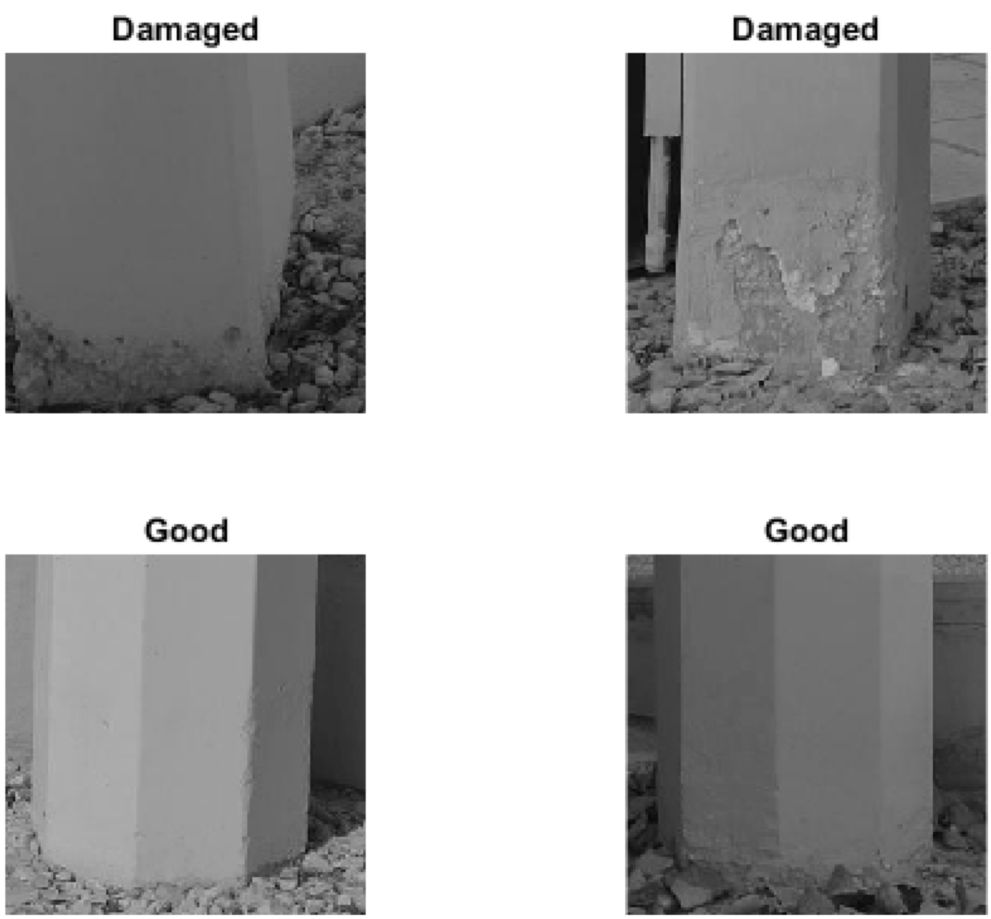

Fig. 11. An example of image classification of 4 column covers taken from a site in Qatar.

the work reported in this paper.

References

[1] Kim B, Cho S. Automated Multiple Concrete Damage Detection Using Instance Segmentation Deep Learning Model. Appl Sci, MDPI 2020;10:8008.

[2] Grosse C, Glaser S, Kruger M. Condition monitoring of concrete structures using wireless sensor networks. Proceedings of SPIE - The International Society for Optical Engineering, p. DOI: 10.1117/12.657303, 2006.
[3] Davis AM, Mirsayar MM, Hartl DJ. A novel structural health monitoring approach in concrete structures using embedded magnetic shape memory alloy components. Constr Build Mater 2021;311:125212.
[4] Cheng Yu, Gao F, Hanif A, Lu Z, Li Z. Development of a capacitive sensor for concrete structure health monitoring. Constr Build Mater 2017;149:659–68.
[5] e. a. Kocherla, Embedded PZT sensors for monitoring formation and crack opening in concrete structures. Measurement, vol. 182, p. 109698, 2021.
[6] "Types and causes of concrete deterioration," Portland Cemenet Assosiation, vol. PCA R&D Serial No. 2617, p. IS536, 2002.
[7] Zhao YX, Wang YZ, Dong JF. Experimental Study and Analytical Model of Concrete Cover Spalling Induced by Steel Corrosion. J Struct Eng 2020;146(6).
[8] Bélanger P. Report of the Elliote Lake Commision of Inquiry: The Events Leading to the Collapse of the Algo Center Mall. Commissioner of the Elliot Lake Inquiry, 2014.
[9] Cao et al. Automatic recognition of concrete spall using image processing and metaheuristic optimized LogitBoost classification tree. Adv Eng Softw. vol. 159, p. 103031, 2021.
[10] Perez H, Tah JHM, Mosavi A. Deep Learning for Detecting Building Defects Using Convolutional Neural Networks. Sensors 2019;19(16):3556.
[11] Kim B, Cho S. Automated Multiple Concrete Damage Detection. Appl Sci 2020;10:8008.
[12] Gowid S, et al. Experimental investigation and Artificial Intelligence- Based Modeling of the Residual Impact Damage Effect on the Crashworthiness of Braided Carbon/Kevlar Tubes. Compos Struct. vol. 243, p. 112247, 2020.
[13] Haggag M, et al. An Intelligent Hybrid Experimental-Based Deep Learning Algorithm for Tomato-Sorting Controllers. IEEE Access, vol. 7, no. 1, pp. 106890–106898, 2019.
[14] Li J, et al. Automatic pixel-level multiple damage detection of concrete structure using fully convolutional neural network. Comput. Aided Civ Infrastruct Eng. vol. 34, p. 616–634, 2019.
[15] Perez H, Tah J, Mosavu A. Deep Learning for Detecting Building Defects Using Convolutional Neural Networks. Sensors 2019;19(16):3356.
[16] Zeeshan M, Adnan S, Ahmad W, Khan F. Structural Crack Detection and Classification using Deep Convolutional Neural Network. Pakistan J Eng Technol 2021;4(4):50–60.
[17] Bhavani D, Adhikari A, Sumathi D. Detection of Building Defects Using Convolutional Neural Networks. In: Proceedings of Second Doctoral Symposium on Computational Intelligence; 2021. p. 839–55.
[18] Elghaish F, Talebi S, Abdellatef E, Matarneh ST, Hosseini MR, Wu S, et al. Developing a new deep learning CNN model to detect and classify highway cracks. J Eng, Design Technol 2022;20(4):993–1014.
[19] Ostankovich VaAI. Illegal Buildings Detection from Satellite Images using GoogLeNet and Cadastral Map. 9th IEEE International Conference on Intelligent Systems 2018At: Madeira, Portugal, p. DOI: 10.1109/IS.2018.8710565, 2018.
[20] Saha S. A Comprehensive Guide to Convolutional Neural Networks, 2018. [Online]. Available: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53. [Accessed 12 2021].

Further reading

[21] MathWorks, Deep Learning Toolbox, 2021. [Online]. Available: https://www.mathworks.com/help/deeplearning/. [Accessed 12 2021].

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