IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 40, No. 2, April, 2023, pp. 639-646
Journal homepage: http://iieta.org/journals/ts

Non Invasive Decay Analysis of Monument Using Deep Learning Techniques

Ramani Perumal*, Subbiah Bharathi Venkatachalam

Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai 600089, Tamil Nadu, India

Corresponding Author Email: ramanip@srmist.edu.in

https://doi.org/10.18280/ts.400222

Received: 22 December 2022
Accepted: 10 March 2023

Keywords:
local binary pattern, multi layer neural network, luminance, clustering, non destructive techniques

ABSTRACT

Monuments are a vital part of the heritage of any culture that witnesses the history of our time. These monuments are inherited from previous generations, and it is essential to preserve them through monitoring. The analysis of monument degradation employs a non-destructive method. One of the most effective Non-Destructive Techniques is Deep Learning Technique. The collected images from various monuments are preprocessed and fused with local binary pattern and Luminance. The integrated K-Means clustering used in the proposed approach automatically segments the moss and cracks in monuments, and multilayer neural networks are used to classify the decay. Performance parameters are assessed in terms of precision, accuracy, recall, and F1-Score after the decay parameters are identified using MLNN and validated. The novelty of the proposed work classifies the decay as moss or crack with an accuracy of approximately 97%.

1. INTRODUCTION

Culture in any aspect plays an important role in the growth of a country. The Culture represents the goals and values of a nation. India has a large cultural diversity. In a cultural diversified nation its monuments plays a significant role in providing insights of its rich cultural heritage and architectural past. Indian Culture is represented as one of the most outstanding facets of monuments.

India has a sizable population and a rich global cultural heritage. In India, there are 2,500 000 historic places, and Tamil Nadu alone has 40,000. All of them are centuries old, they are not properly protected against environmental deterioration. These antiquated artifacts contain extremely important knowledge about the culture and wealth of the nation, as well as about music, astronomy, medicine, dance, etc. The architecture and the construction practices of the ancient Indians were so advanced that great heritage structures were built during that period. Nevertheless, the environmental changes over the centuries had severe impact on these monuments and structures.

Though there is a large number of a heritage structure spread across the country, a very limited number of them are maintained by the Archaeological Society of India (ASI). Among the rest, most of them are associated with religious centers where there is no scientific approach to conservation [1]. Scientific interventions are essential in assessing the weathering forms and the extent of damages to cultural heritage structures and provide valuable inputs to restoration and preservation plan. Such interventions need to be non destructive, in situ, less time consuming and cost effective with a graphical map of damage location and distribution [2]. It is not advised to evaluate a monument's state of decay using destructive techniques as it could cause further damage. In this context, the proposed research provides a technological intervention to assess the decay of these monuments using a non-destructive method.

Structural damage in monuments is caused by various weathering factors. There are three types of weathering deterioration namely chemical, physical and biological weathering. Chemical weathering causes replacement of molecular structure in the rocks which collapses the structure of rocks. Biological weathering means that the structure deteriorates because of animals and plants. Damage to the item exposed on the site is caused by the natural process of weathering, which occurs throughout the year and is influenced by each of the four seasons. Peeling, exfoliation, and disintegration may occur in monuments as a result of the impact of rain and wind from the natural environment [3]. The crack and moss are two important factors that causes decaying of the monuments.

Monument decay can be evaluated by two methods such as Destructive and Non-destructive method [4-7]. Destructive methods diffraction analysis of X-ray, microscopy such as Scanning electron and transmitted light microscopy [8]. Methods that include Non-destructive decay are digital image processing, ultrasonic imaging and infrared thermography [9]. A cultural heritage structure is deteriorated due to moss and cracks. In order to assess the structural health and safety, crack detection is a very demanding task [10]. Manual moss and crack research is tiresome and involves making arbitrary decisions, according to investigators. A hybrid crack detection model has been developed by Pansare et al. [11] properties of the crack, such as area and direction, are measured.

It is useful to develop a radar which will automatically detects in concrete and other surfaces by using the images of monuments taken from camera so that the cost for the maintenance will be reduced. It is difficult and tedious to manually find crack and moss by simultaneously acquiring data and information regarding the decay factors. That is why, deep learning technique comes into picture in order to make the work easy and less time consuming.

The classification of cracked and uncracked specimens is proposed using an image-based machine-learning approach. It may be used to objectify and automate crack identification, eliminating sources of uncertainty and inaccuracy from experiment post-processing [12].

There are several methods are used for detection of crack in monuments and specimen. Sankarasrinivasan et al. [13] proposed combined HSV thresholding with Bottom Hat Transform for detection of a crack in civil structures. Medina et al. [14] introduced a novel method to automatically detect the crack in concrete tunnel. The crack had been detected using Gabor filter in multidirectional dimension and thus allowed the detection of crack with 95% accuracy.

From the literature discussed here it is understood that there are various methods to detect cracks and there is a necessity to classify them. It is obvious that CNN is the mostly used for classification and different forms of CNN has been proposed by Saini et al. [15] and Aslam et al. [16]. Both the said methods can achieve accuracies up to 92%. Deep Convoltional Neural Network (DCNN) technology is used to provide an autonomous crack- detecting method based on machine vision. With an accuracy of 92%, pixel-wise segmentation is performed, and the concrete surface is classified as cracked or not [17].

To achieve a greater accuracy a fusion technique has been proposed. The use of LBP, Lumniance, and MLNN fusion to provide higher accuracy of monument decay detection of both moss and crack is proposed in this paper. The proposed method would be helpful in conservation planning and restoration of decaying monuments. It is significant in terms of achieving sustainable monument preservation. The damaged area is identified using a color-coded map, and this would be useful to save the heritage structures from future damage. The proposed work not only detects the crack but also classifies them.

The layout of this paper is as follows. The relevant works are described in Section 2, and the proposed work has been explained in Section 3. The results and discussions are presented in Section 4. Section 5 explains the conclusion and the future work.

2. LITERATURE REVIEW

Stone, and bricks are bounded with mortar in making up of the historic buildings in India, and to varying degrees in different parts of the world. The susceptibility of masonry materials to decay and deterioration and the qualities associated with such materials transformation are widely discussed [18].

Digital image processing, ultrasonic imaging, and infrared thermography (IRT) are non-destructive approaches. In the present work, a deep learning model that automatically detects cracks and moss without damaging the image's structure is presented.

An image segmentation technique based on a multiscale wavelet-based random field model is provided in the paper , and medical images were used for the analysis. The wavelet transform is used to extract boundaries and edges, which serve to detail the non-moving attribute. Used the Bayes theory to classify the images and achieved good efficiency [19].

Using a thermal camera, Brooks et al. [20] developed a model to identify the crack**.** The Camera had been used for distinguishing the impression of an infrared source from the exterior of the crack and the same had been used further to recognize the deformities in huge outside regions.

An algorithm for extracting the local variance feature from an image using fuzzy clustering is presented in the paper [21]. The transitional features are extracted using the OTSU approach. In order to perform the transitional features, hybrid segmentation is used.

A Novel system has developed that detects multiple cracks. In the proposed method the first step was combined edge detection and seed growing. It was then followed by the skeleton optimization process that removed non-crack segments and retrieved the crack properties. The novel method retrieved multiple cracks from the concrete structure [22]. Using a variety of inputs, this model identified the crack and classified the detected segments in accordance with the skeletal information. It was very useful in evaluating the solid structures.

Dare et al. [23] developed a method to perform automatic crack detection in concrete structures. The bilinear interpolation method was used to process the crack pixel values and the sub pixels were measured using DOG filter.

Jung et al. [24] proposed a method to detect the cracks in the pressed board. Edge lines were removed and those outcomes are contrasted with the original sample board. With this technique the speed of crack detection and assessment has been improved a lot.

Feng et al. [25] has developed a model to automatically detect the crack in the dam structures using deep learning techniques. The images were captured from Unmanned aerial Vehicle. The crack regions are detected and classified with the precision approximately 80%.

Shehata, et al. [26] suggested a new method for the estimation of crack depth using the Make3D tool kit. The toolbox had been used to convert 2D images into 3D images. In this method, ground truth values were calculated from the laser scanner, and supervised learning was used to train and classify the model. The impact noise method was used to identify cracks in ceramic plates. The analysis of higher-order spectral data is done. It has been discussed how cracks RMS value, minimum and maximum values, and peaks are calculated [27]. In order to get a more precise crack edge position, the crack edge of a civil structure was retrieved using an interpolation calculation-based subpixel edge detection approach. On the basis of the end-to-end object detection network YOLO, a civil structural fracture was discovered [28].

Ramani et al. [29] developed an image-processing method for the automatic detection of and classification of the crack decay. Crack is detected using combined canny with BHT and extracted the DWT features from the fused method. Crack length, location, width, orientation is measured using proposed method. Performance is measured in terms of selectivity, accuracy, and other factors. This method improves the performance than existing methods.

3. PROPOSED WORK

The factors of decay in the cultural heritage structures are the moss, alveolar, loss of stone, lichen, and crack present in the structures. The detection of crack is work in checking basic well being and security [30-32]. Finding moss and cracks is a challenging task while keeping an eye on a structure's safety. The manual process of this detection is tedious and it expects experts to analyze this decay. The proposed method detect, classify and recognize the type of decay as moss/crack using fused LBP with Luminance and segmented with integrated K-means clustering and multi layer neural network.

3.1 Image acquisition

The images were captured from 9th century chokkeeswarar temple, Kancheepuram and 7th century shore temple, Mahabalipuram, Sivapuram and kooram temple and various other monuments in Tamil Nadu using high resolution DSLR Camera. The captured image pixel dimension is 5184×3456. After the acquisition of image, they are preprocessed using image resizing. The acquired images are resized into 256×256.

3.2 Preprocessing and image enhancement

The resized images are preprocessed using image adjustment. This improves the contrast of the acquired image and also removes the noises which are present in the image. The proposed method of crack/moss detection and classification model is given in Figure 1.

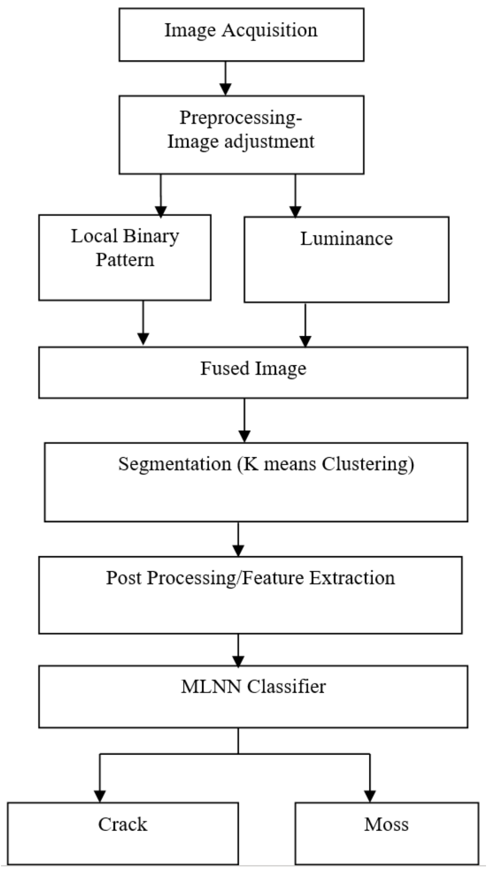


Figure 1. Proposed method of crack/moss detection and classification model

3.3 Local binary pattern and luminance

Then RGB color image is converted into a YCbCr image. The image Y denotes the Luminance of the image that details the information about the brightness in terms of black and white gray shades. The next step is to convert the monument images from RGB color format to grayscale color images in order to get single information. A gray image is a shade of the gray color image.

It has black color at a minimum point and white color at a maximum point. A grayscale image is computed from a weigh sum of red, green, and blue color and it is given in Eq. (1):

$$\text{grayscale}=Rc*0.298+Gc*0.587+Bc*0.114 \quad (1)$$

LBP is a basic method to signify the neighborhood pattern and is utilized in many applications. The LBP is the abstraction type of texture [33] and it determines the nearby contrast of the image. It computes the image of binary pattern by comparing pixels of the neighborhood with that of the pixels present in the center of the image [34]. The LBP (Local Binary Pattern) images are computed by using the succeeding expression.

$$\text{LBP}_{u,v}(w_c)=\sum_{h=0}^{H-1} Y(w_h - w_c)\, 2^h \quad (2)$$

$$Y(s)=\begin{Bmatrix} 1 & s \geq 0 \\ 0 & s < 0 \end{Bmatrix} \quad (3)$$

where, w_c: value of center pixel; w_h: varies from 0 to H-1-neighbor pixel values on a circle radius u; v: quantity of sampled neighbors.

This algorithm works with two dimensional texture analysis. The outline of the nearby image structure is formed by comparing every value and its nearest value. To start with, consider the middle value as the threshold.

Assign 0 when the middle value is less than the neighboring pixels otherwise assign 1. The local binary pattern is determined by the nearby by values in the clockwise direction. The binary code for LBP and weights of a 3×3 image are given in Tables 1 to 3.

Table 1. 3×3 image

33	44	15
17	20	38
47	26	37

Table 2. Binary code

1	1	0
0		1
1	1	1

Table 3. Weights

1	2	4
128		8
64	32	16

Then the local binary pattern images and Luminance images were combined. Then, K-means clustering is utilized to segment this fused image.

3.4 K-means clustering

It is one of the techniques for unsupervised classification**.** It groups the data by iteratively calculating the mean of each group and separating the data by arranging every pixel in the group with the nearest mean [35].

It is one of Artificial Intelligence (AI) technique which is broadly utilized in various applications, for example, data-mining, video processing, and pattern recognition. It is the process which groups data into k-cluster. Based on the intensity level it splits the image into non-overlapping groups [36].

The steps involved to perform the clustering are:

a) Initially, choose the number of clusters randomly
b) Grouping the pixels into K-cluster
c) Then find the average value of the cluster
d) Assigning the objects closer to the cluster after determining the nearest neighboring pixels
e) Reiterate the step c and d until the centroid do not change.

where, K=5.

The monument may be affected by different weathering factors such as moss, crack, and lichen, and Alveolar. In this work, five clusters are considered for the segmentation.

3.5 Post processing and feature extraction

The noise is present in the segmented image. The post-processing removes the noise from it. Eroding is done. Erosion is a morphological operation that diminishes the objects and can be exceptionally helpful amid the preprocessing stage and post-processing stage [32]. Erosion removes the smaller noisy pixels in an image. The statistical features of the proposed method are calculated from the histogram of the fused image.

The gray image of the histogram [37] is defined as:

$$P_r(k_i)=H(k_i)/M \tag{4}$$

where, k: represents an intensity, M: Number of pixel.

Eqns. (4)-(7) provide the first-order statistical features:

Mean

Mean indicates the image brightness level:

$$\text{Mean m}= \sum_{i=0}^{M} k_i P_r(k_i) \tag{5}$$

Standard Deviation

It indicates the contrast:

$$\text{Variance} = \sqrt{\sum_{i=0}^{M}(k_i-\mu)^2} \tag{6}$$

Skewness

It indicates the anti symmetry with respect to the mean in the intensity distribution:

$$\text{Skewness S}=\sum_{i=0}^{M}(k_i-m)^3 P(k_i) \tag{7}$$

where, *m:* mean of the image; *P(k)*: probability of the gray image.

Kurtosis

It shows that the intensity distribution is uniform. It also indicates the relative flatness of the histogram. Uniformity is the texture indicator.

Energy

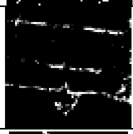
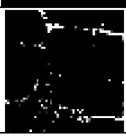
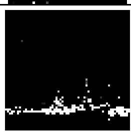
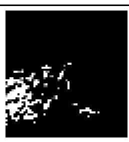
The sum of brightness values of all the pixels present in the object.

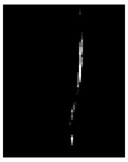
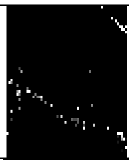
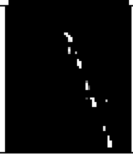
Entropy

The entropy indicates the minimum number of bits required to code the image.

Then the classification is done using the multiclass SVM [38], Multilayer Neural Network [39] with the set of extracted features. The sample feature vectors and the output images are given in Table 4.

Table 4. The sample feature vector of the images

IMAGE	Output Image	Mean	Variance	Skewness	Kurtosis	Entropy
		1.0915	0.0832	2.8929	8.9395	0.8632
		1.08502	0.0777	2.9756	7.8545	0.8444
		1.1226	0.1076	2.3000	6.2900	0.7847
		1.1135	0.1006	2.4367	6.9378	0.7987
		1.1288	0.1195	2.2553	6.0853	0.7799

		1.0258	0.02516	5.9780	31.7365	0.9496
		1.0343	0.03312	5.1174	27.1885	0.9337
		1.03671	0.0353	4.9271	25.2766	0.9292
		1.0605	0.0588	3.6591	20.7076	0.8822

3.6 Multi layer neural network classifier

Second order statistical features are fed to the multilayer neural network training model. Tested images are classified by the model as crack and moss based on the training features. Ten layers are used in hidden layer which train the model for better classification.

4. RESULTS AND DISCUSSION

The work was carried out in MATLAB 2020A with an Intel core 2.5GHz computer and Windows 10. A training set of 93 samples and a test set of 12 samples are used in this analysis. After the segmentation, the image features are extracted.

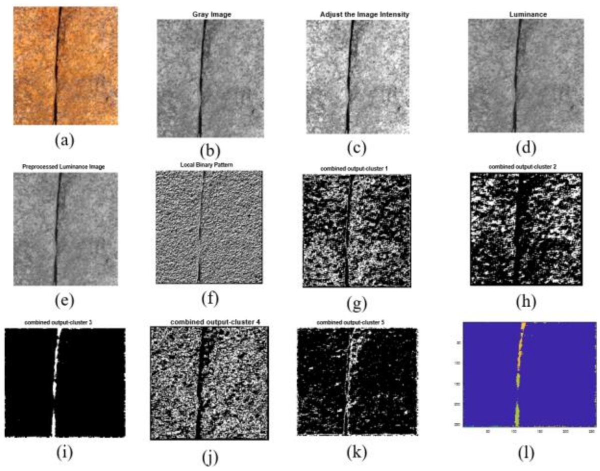


Figure 2. (a) Original-Crack image (b) Gray Image (c) Image enhancement (d) Luminance (e) Preprocessing-Luminance (f) Local binary pattern (g) Segmented cluster-1 (h) Segmented cluster-2 (i) Segmented cluster-3 (j) Segmented cluster-4 (k) Segmented cluster-4 (i) Detected crack image

The acquired images are preprocessed and enhanced using contrast adjustment. The preprocessed Luminance image is fused with the local binary pattern image. K-means clustering is used to segment the resulting image. Then removed the noise from the detected image and color coded map is generated. This color coded map is used to locate the decayed region. Figure 2 describes the various stages of the detected crack image. Figure 3 gives the various stages of the detected moss image.

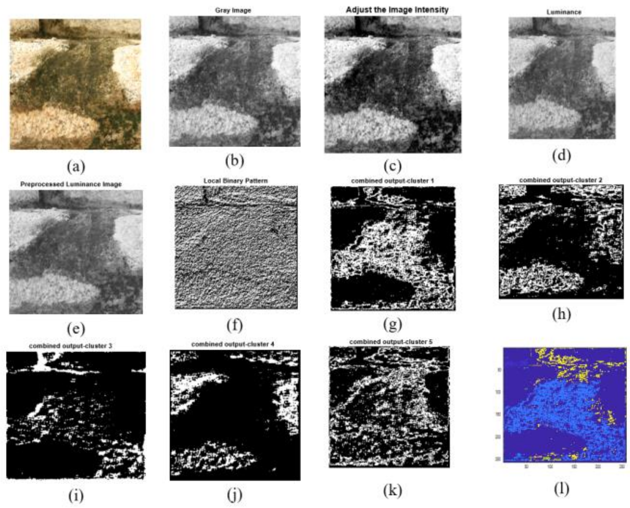


Figure 3. (a) Original-Moss image (b) Gray Image (c) Image enhancement (d) Luminance (e) Preprocessing-Luminance (f) Local binary pattern (g) Segmented cluster-1 (h)- Segmented cluster-2 (i) Segmented cluster-3 (j) Segmented cluster-4 (k) Segmented cluster-4 (i) Detected crack image

The features are extracted from segmented image. During the training process, you will first create and configure a ten-layered neural network, and then you will instruct it to learn about the extracted features of the training set's images. The learning phase, which involves calculating error and altering weights to reduce error, is carried out using the back propagation method. In order to maximize accuracy, this is done. Create a neural network (NN) and configure it as follows: 1000 epochs, a 90% learning rate, and a 0.1% allowable error. This MLNN has been employed to classify the clusters of the tested image features into moss and crack. The confusion matrix of proposed model is given in Table 5.

Table 5. Confusion matrix of training of proposed model LBP+Luminance+MLNN

True Positive - TP 64	False Positive - FP 2
False Negative - FN 1	True Negative - TN 28

The performance of the proposed method is validated and calculated based on the performance metrics. The parameters are Accuracy, Recall, Precision and F1-Score.

The following are the performance indicators:

$$Accuracy=\frac{TP+TN}{(TP+TN+FP+FN)} \tag{8}$$

$$Recall=\frac{TP}{(TP+FN)} \tag{9}$$

$$Precision=\frac{TP}{(TP+FP)} \tag{10}$$

$$F\text{-}score=\frac{(2\times Precision\times Recall)}{(Precision+Recall)} \tag{11}$$

Table 6. Comparison of (Luminance+LBP+MLNN) Proposed method with existing methods (LBP+SVM and LBP+Luminance+SVM)

Methods	Accuracy	Precision	Recall	F1-Score
LBP+SVM	87.1	89.5	92.3	90.8
LBP+Luminance+SVM	92.4	92.5	95	93.4
LBP+Luminance+MLNN	96.8	96.9	98.4	97.6

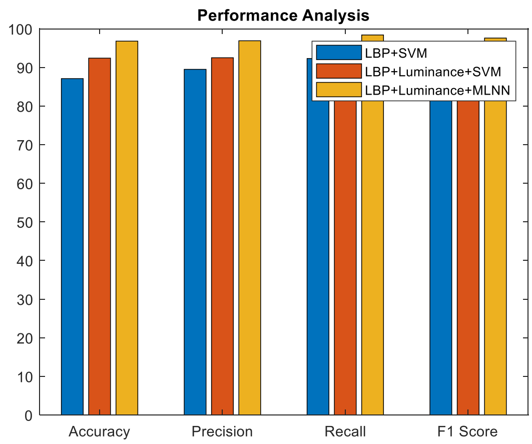


Figure 4. Comparison of performance parameters of existing method with proposed method

Table 6 and Figure 4 compare the proposed method (LBP+Luminance+MLNN) to specified methods LBP+Luminance+SVM) and (LBP+SVM) with accuracy of 96.8%, recall of 98.4%, precision of 96.9%, and an F-score of 97.6%, and the proposed method outperforms the previously mentioned method in terms of accuracy. This technique can be used to assist archaeologists in identifying and locating the type of decay.

Table 7. Comparison existing method with proposed method

Methods	Surface Type	Number of classes	Accuracy (%)
Deep Convolutional Network [25]	Dam surface	2	90
Deep Convolutional Neural Network [17]	Concrete surface	2	92
LBP, BPNN [40]	Wood	3	93.3
LBP, SVM	Ancient monuments	2	87.1
LBP,Luminance,SVM	Ancient monuments	2	92.4
Proposed Method	Ancient monuments	2	96.8

The proposed approach is compared with the existing methods as given in Table 7. The performance of the ancient monument image classification using LBP, luminance, and MLNN is measured for various ancient monument test images. By comparing methods, surface types, and number of classes in Table 7, it is shown that the proposed LBP and Luminance with MLNN yield good accuracy when compared to other methods.

5. CONCLUSIONS

The proposed deep learning technique acts as an automatic detection and classification of crack and moss on the surfaces of the monuments using MLNN. The fused image's segmented features are trained using an MLNN classifier. The performance metrics are evaluated, validated, and recognized. The performance of the proposed methods are Accuracy-96.8% Recall-98.4%, Precision-96.9% and F-score-97.6% gives good results than Luminance with SVM and fused image with SVM and existing methods. This study can be expanded in the future to include the identification of crack and moss in video frames.

ACKNOWLEDGMENT

We are grateful to the Department of Archaeology in Tamil Nadu for granting us permission to collect photographs from different ancient temples.

REFERENCES

[1] Kordatos, E.Z., Exarchos, D.A., Stavrakos, C., Moropoulou, A., Matikas, T.E. (2013). Infrared thermographic inspection of murals and characterization of degradation in historic monuments. Construction and Building Materials, 48: 1261-1265. https://doi.org/10.1016/j.conbuildmat.2012.06.062

[2] Fais, S., Casula, G., Cuccuru, F., Ligas, P., Bianchi, M.G. (2018). An innovative methodology for the non-destructive diagnosis of architectural elements of ancient historical buildings. Scientific Reports, 8(1): 1-11. https://doi.org/10.1038/s41598-018-22601-5

[3] Hatir, M.E., Barstuğan, M., İnce, İ. (2020). Deep learning-based Weathering type recognition in historical stone monuments. Journal of Cultural Heritage, 45: 193-203. https://doi.org/10.1016/j.culher.2020.04.008

[4] Sýkora, M., Diamantidis, D., Holický, M., Marková, J., Rózsás, Á. (2018). Assessment of compressive strength of historic masonry using non-destructive and destructive techniques. Construction and Building Materials, 193: 196-210. https://doi.org/10.1016/j.conbuildmat.2018.10.180
[5] Costamagna, E., Quintero, M.S., Bianchini, N., Mendes, N., Lourenço, P.B., Su, S., Paik, Y.M., Min, A. (2020). Advanced non-destructive techniques for the diagnosis of historic buildings: The Loka-Hteik-Pan temple in Bagan. Journal of Cultural Heritage, 43: 108-117. https://doi.org/10.1016/j.culher.2019.09.006
[6] Uchida, E., Watanabe, R., Cheng, R., Nakamura, Y., Takeyama, T. (2021). Non-destructive in-situ classification of sandstones used in the Angkor monuments of Cambodia using a portable X-ray fluorescence analyzer and magnetic susceptibility meter. Journal of Archaeological Science: Reports, 39: 103137. https://doi.org/10.1016/j.jasrep.2021.103137
[7] Rahimi Jafari, F., Habibi, F., Moazen, S. (2021). Introducing the non-destructive method of photogrammetry in the study and servey of historical monuments. Journal of Research on Archaeometry, 7(2): 135-158. http://jra-tabriziau.ir/article-1-285-en.html
[8] Fitzner, B., Heinrichs, K. (2004). Photo atlas of weathering forms on stone monuments, Geological Institute, RWTH Aachen University–Working Group Natural stones and weathering.
[9] Clemente, P. (2018). Extending the life-span of cultural heritage structures. Journal of Civil Structural Health Monitoring, 8: 171-179. https://doi.org/10.1007/s13349-018-0278-3
[10] Hoang, N.D. (2018). Detection of surface crack in building structures using image processing technique with an improved Otsu method for image thresholding. Advances in Civil Engineering, 2018: 3924120. https://doi.org/10.1155/2018/3924120
[11] Pansare, D., Panchwadkar, A. (2022). Crack detection using image processing. AIP Conference Proceedings, 2653(1): 030007. https://doi.org/10.1063/5.0116894
[12] Müller, A., Karathanasopoulos, N., Roth, C.C., Mohr, D. (2021). Machine learning classifiers for surface crack detection in fracture experiments. International Journal of Mechanical Sciences, 209: 106698. https://doi.org/10.1016/j.ijmecsci.2021.106698
[13] Sankarasrinivasan, S., Balasubramanian, E., Karthik, K., Chandrasekar, U., Gupta, R. (2015). Health monitoring of civil structures with integrated UAV and image processing system. Procedia Computer Science, 54: 508-515. https://doi.org/10.1016/j.procs.2015.06.058
[14] Medina, R., Llamas, J., Gómez-García-Bermejo, J., Zalama, E., Segarra, M.J. (2017). Crack detection in concrete tunnels using a gabor filter invariant to rotation. Sensors, 17(7): 1670. https://doi.org/10.3390/s17071670
[15] Saini, A., Gupta, T., Kumar, R., Gupta, A.K., Panwar, M., Mittal, A. (2017). Image based Indian monument recognition using convoluted neural networks. International Conference on Big Data, IoT and Data Science (BID), pp. 138-142.
[16] Aslam, Y., Santhi, N., Ramasamy, N., Ramar, K. (2020). Localization and segmentation of metal cracks using deep learning. Journal of Ambient Intelligence and Humanized Computing, 1-9. https://doi.org/10.1007/s12652-022-04018-1
[17] Islam, M.M., Kim, J.M. (2019). Vision-based autonomous crack detection of concrete structures using a fully convolutional encoder–decoder network. Sensors, 19(19): 4251. https://doi.org/10.3390/s19194251
[18] Douglas-Jones, R., Hughes, J.J., Jones, S., Yarrow, T. (2016). Science, value and material decay in the conservation of historic environments. Journal of Cultural Heritage, 21: 823-833. https://doi.org/10.1016/j.culher.2016.03.007
[19] Tang, W., Wang, Y., He, W. (2016). An image segmentation algorithm based on improved multiscale random field model in wavelet domain. Journal of Ambient Intelligence and Humanized Computing, 7: 221-228. https://doi.org/10.1007/s12652-015-0318-3
[20] Brooks, A.J., Hussey, D.S., Yao, H., Haghshenas, A., Yuan, J., LaManna, J.M., Jacobson, D.L., Lowery, C.G., Kardjilov, N., Guo, S., Khonsari, M.M. (2018). Neutron interferometry detection of early crack formation caused by bending fatigue in additively manufactured SS316 dogbones. Materials & Design, 140: 420-430. https://doi.org/10.1016/j.matdes.2017.12.001
[21] Parida, P., Bhoi, N. (2018). Fuzzy clustering based transition region extraction for Image segmentation. Engineering Science and Technology, an International Journal, 21(4): 547-563. https://doi.org/10.1016/j.jestch.2018.05.012
[22] Tian, Q.G., Luo, Q.J., Ge, B., Li, Y. (2019). A methodology framework for retrieval of concrete surface crack′s image properties based on hybrid model. Optik, 180: 199-214. https://doi.org/10.1016/j.ijleo.2018.11.013
[23] Dare, P., Hanley, H., Fraser, C., Riedel, B., Niemeier, W. (2002). An operational application of automatic feature extraction: the measurement of cracks in concrete structures. The Photogrammetric Record, 17(99): 453-464. https://doi.org/10.1111/0031-868X.00198
[24] Jung, H., Lee, C., Park, G. (2017). Fast and non-invasive surface crack detection of press panels using image processing. Procedia Engineering, 188: 72-79. https://doi.org/10.1016/j.proeng.2017.04.459
[25] Feng, C., Zhang, H., Wang, H., Wang, S., Li, Y. (2020). Automatic pixel-level crack detection on dam surface using deep convolutional network. Sensors, 20(7): 2069. https://doi.org/10.3390/s20072069
[26] Shehata, H.M., Mohamed, Y.S., Abdellatif, M., Awad, T.H. (2018). Depth estimation of steel cracks using laser and image processing techniques. Alexandria Engineering Journal, 57(4): 2713-2718. https://doi.org/10.1016/j.aej.2017.10.006
[27] Akgun, O. (2020). Spectral and statistical analysis for damage detection in ceramic materials. Traitement du Signal, 37(1): 9-16. https://doi.org/10.18280/ts.370102
[28] Luo, W.M. (2022). Research on the real-time detection method for image processing – Based civil structure crack. Traitement du Signal, 39(6): 2223-2228. https://doi.org/10.18280/ts.390638
[29] Ramani, P., Subbiah Bharathi, V. (2020). Detection and classification of crack in heritage structures using machine learning techniques. Journal of Critical Reviews, 7(19): 1595-1600. https://doi.org/10.31838/jcr.07.19.195
[30] Fujita, Y, Hamamoto, Y. (2011). A robust automatic crack detection method from noisy concrete surfaces. Machine Vision and Applications, 22(2): 245-254.

https://doi.org/10.3390/s20072069
[31] Zou, Q., Cao, Y., Li, Q., Mao, Q., Wang, S. (2012). Automatic crack detection from pavement images. Pattern Recognition Letters, 33(3): 227-238. https://doi.org/10.1016/j.patrec.2011.11.004
[32] Gil, J.Y., Kimmel, R. (2002). Efficient dialation, erosion, opening, and closing algorithms. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(12): 1606-1617. https://doi.org/10.1109/TPAMI.2002.1114852
[33] Wicaksono, Y., Wahono, R.S., Suhartono, V. (2015). Color and texture feature extraction using gabor filter-local binary patterns for image segmentation with fuzzy C-means. Journal of Intelligent Systems, 1(1): 15-21.
[34] Ojala, T., Pietikainen, M., Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture Classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7): 971-987. https://doi.org/10.1109/TPAMI.2002.1017623
[35] Khan, M.Q., Hussain, A., Rehman, S.U., Khan, U., Maqsood, M., Mehmood, K., Khan, M.A. (2019). Classification of Melanoma and Nevus in Digital Images for Diagnosis of Skin Cancer. IEEE Access, 7: 90132-90144. https://doi.org/10.1109/ACCESS.2019.2926837
[36] Kaushink, P., Sharma, Y. (2012). Comparison of different image enhancement techniques based upon PSNR & MSE. International Journal of Applied Engineering Research, 7(11): 2010-2014.
[37] Devesh, R., Jha, J. (2019). An efficient approach for monuments image retrieval using multi-visual descriptors. Proceeding of the Second International Conference on Microelectronics, Computing & Communication Systems (MCCS 2017), pp. 281-293.
[38] Khare, V., Kumari, S. (2022). Performance comparison of three classifiers for fetal health classification based on cardiotocographic data. Acadlore Transactions on AI and Machine Learning, 1(1): 52-60. https://doi.org/10.56578/ataiml010107
[39] El Rejal, A.A., Nagaty, K., Pester, A. (2023). An end-to-end CNN approach for enhancing underwater images using spatial and frequency domain techniues. Acadlore Transactions on AI and Machine Learning, 2(1): 1-12. https://doi.org/10.56578/ataiml020101
[40] Zhang, Y.X., Zhao, Y.Q., Liu, Y., Jiang, L.Q., Chen, Z.W. (2016). Identification of wood defects based on LBP features. IEEE 35th Chinese Control Conference (CCC), pp. 4202-4205. https://doi.org/10.1109/ChiCC.2016.7554010