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A New Concrete Crack Detection based on Deep Feature Extraction

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Abstract: **Concrete is one of the most intensively used materials in the construction industry. This building material, which is basically obtained by mixing additives such as cement, sand and water, is used extensively in the construction industry. In this paper, we propose a new machine learning method that can automatically classify cracks on the surface of concrete material that is frequently used in the construction industry. For this purpose, a feature vector was obtained using deep and textural feature extraction methods. The most significant features are selected from this feature vector using neighborhood component analysis method. The selected features are classified using support vector machines. Deep feature extraction was achieved using the AlexNet architecture, which is a well-known method in the literature. The developed model has reached 99.9% accuracy in classifying crack images and the results obtained clearly demonstrate the performance of the model in automatic concrete crack classification.**

Keywords: **Automatic classification, Concrete crack detection, Deep feature extraction, Artificial intelligence.**

1. Introduction

Concrete, a robust construction material, is primarily composed of cement, sand/gravel, and water [1]. Through the gradual solidification process, this mixture yields a high-strength building material. Notably, this cost-effective construction material affords flexibility in design while demonstrating remarkable resistance to fire [2], [3]. A multitude of concrete types have been documented in the existing literature, encompassing classifications such as normal concrete, high-strength concrete, and waterproof concrete [4], [5]. Nevertheless, concrete stands as the fundamental building material extensively employed in the majority of contemporary construction projects. Consequently, any deformation transpiring within this material can engender irreversible consequences [6], [7]. The occurrence of cracks, particularly in critical components such as columns and beams, which endure substantial usage of concrete, can significantly compromise the structural integrity [8]. Consequently, severe structural impairments or even complete collapse may ensue. Another pivotal aspect emphasizing the importance of concrete strength pertains to seismic activities, whereby concrete surfaces become susceptible to crack formation [9]. The automated detection of such cracks assumes paramount significance in ensuring the safety and well-being of individuals residing within these structures [10]. Hence, special attention must be given to the identification and assessment of deep cracks on reinforced concrete surfaces of buildings.

Nowadays, artificial intelligence technologies show a great acceleration in terms of development [11]. This remarkable progress can be attributed to the rapid advancement of technological resources, thereby facilitating the widespread application of these techniques across diverse fields. An extensive review of the existing literature reveals a prevalent utilization of artificial intelligence-supported classification methodologies, particularly within the healthcare domain [12]-[14]. Nonetheless, it is imperative to acknowledge the vast potential for deploying these technologies across numerous other disciplines. One such domain ripe for exploration is the construction industry [15]. Capitalizing on the capabilities of artificial intelligence, which furnishes indispensable solutions in automated detection and classification, a plethora of methodologies and techniques have emerged to facilitate the early diagnosis and assessment of structural concerns, including the detection of concrete cracks [16]. These methodologies encompass image processing, deep learning approaches, acoustic analysis, and structural modeling, among others. The incorporation of such methodologies presents profound opportunities for the detection and prevention of structural anomalies, yielding invaluable solutions in this realm.

In the present study, we propose a novel machine learning approach aimed at automating the detection and classification of concrete cracks, a critical structural concern. The proposed method encompasses three key steps: feature extraction, feature selection, and classification. In the feature extraction phase, we leverage the power of the AlexNet [17] architecture, a deep network structure, to extract deep features. Furthermore, we incorporate local binary patterns [18] to extract textural features. This hybrid approach enables a comprehensive representation of the input data. Moving on to the feature selection phase, we employ the neighborhood component analysis [19] algorithm to identify the most salient features for subsequent classification tasks, effectively reducing the dimensionality of the feature vector. Lastly, in the final phase of our machine learning model, the selected features undergo classification using support vector machines [20], a widely

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recognized methodology in the literature. To evaluate the efficacy of our model, we conducted experiments on an openly accessible dataset and achieved an outstanding classification accuracy of 99.9%.

The rest of the paper is organized as follows: Section 2 summarizes the literature studies on concrete cracking. Section 3 presents the material details. Section 4 of the paper describes the proposed methodology. Section 5 presents the results obtained. The sixth and last section presents conclusions and future work.

2. Literature Review

This manuscript encompasses the advancement of an automatic crack classification method founded on machine learning principles. To provide context, we summarize relevant machine learning studies on automatic crack classification from the literature in Table 1.

As demonstrated in Table 1, the literature review encompasses diverse investigations on crack detection. The predominant focus of these studies lies in the domain of artificial intelligence, with an emphasis on deep learning methodologies. It is worth noting that deep learning techniques, while computationally intensive, have exhibited remarkable classification prowess. However, in our study, we adopt a distinct approach by employing transfer learning for deep feature extraction, as opposed to employing end-to-end training logic in deep learning. To facilitate feature extraction within the realm of classical machine learning methods, our research leverages the AlexNet deep network architecture, utilizing the last fully connected layer for feature extraction.

3. Materials

In this study, we utilize an open access dataset comprising concrete crack images collected from buildings within the Middle East Technical University Campus. The dataset encompasses two distinct classes: crack and non-crack, encompassing a total of 40,000 images, with each class containing 20,000 images. Notably, this dataset stands as one of the largest in the literature, as no data augmentation techniques were applied. The images in the dataset were obtained and cropped from a pool of 458 master images, resulting in crop image sizes of 227x227. The original dimensions of the master images are 4032x3024. The dataset was obtained from these main images.

The model developed in this research adopts the holdout-validation strategy, wherein the dataset is partitioned into training and test sets. The division between these sets is determined using a randomized approach, with 80% of the images allocated for training and the remaining 20% for testing. Testing process was carried out according to this principle.

4. Proposed Method

In this research, a new machine learning approach for automatic crack classification is developed. The developed model uses the METU crack dataset [29], which is an open access dataset. The proposed method consists of feature extraction, feature selection and classification steps. A block diagram summarizing this method is given in Figure 1.

As depicted in Figure 1, the model takes the image dataset as input and proceeds with the subsequent stage of feature extraction. This phase encompasses both deep feature extraction and textural feature extraction. For deep feature extraction, we employ the renowned AlexNet deep network architecture. Specifically, the "fc8" layer, constituting the last fully connected layer of the AlexNet architecture, is utilized to generate the feature vector, encompassing 1000 distinctive features. Furthermore, the model incorporates local binary patterns (LBP) as an additional method for textural feature extraction, yielding 256 features from each image. Consequently, a comprehensive feature vector with a total dimensionality of 1256 (=1000+256) is obtained. Subsequently, the model proceeds to feature selection, where the most informative features are chosen to optimize the classification outcome. This process results in a reduction in feature vector

Table 1
Machine learning based studies on concrete cracking in the literature

Author(s)	Year	Dataset	Method	Result(s)
Silva and Lucena [21]	2018	Own dataset	Transfer learning based deep learning model (VGG16)	Acc.=92.27
Dung and Anh [22]	2019	METU crack dataset	Fully convolutional network (VGG16)	Acc.=97.8 FScr.=89.3 Ap.=89.3
Park et al. [23]	2020	Own dataset	Data augmentation, YOLO v3 based real time classification	Acc.=94.67
Han et al. [24]	2022	Own dataset	Image segmentation with Otsu, AlexNet based deep CNN	Acc.=98.26
Golding et al. [25]	2022	METU crack dataset	Edge detection, Grayscale image conversion, Custom designed CNN	Acc.=99.43 FScr.=99.54
Xiang et al. [26]	2022	DIV2K	Super-resolution reconstruction, Crack segmentation, ResNet based network architecture	Pre.=84.51 FScr.=84.86 Rec.=85.22 IoU=73.57
Priyadharshini et al. [27]	2023	SDNET2018, METU crack dataset, Historical-crack18-19	Quaternionic wavelet transform and Custom designed CNN	SDNET18 Acc.=98.44 METU Acc.=99.80 Historical Acc.=94.67
Laxman et al. [28]	2023	METU crack dataset	Custom designed CNN, CNN based feature extraction, Random Forest and XGBoost	Acc.=93.7

*Acc.=Accuracy, FScr.=F1-Score, Pre.=Precision, Rec.=Recall, IoU=Intersection Over Union, Ap.=Average Precision, CNN=Convolutional Neural Network size, effectively mitigating computational complexity. Specifically, we select the 500 most significant features during this phase. The final stage of our developed model entails classification, wherein we employ support vector machines (SVM), a shallow classifier. The algorithmic steps of our developed model are outlined in Algorithm-1, while additional insights into the methods employed in the model development process are expounded upon in the respective sub-headings.

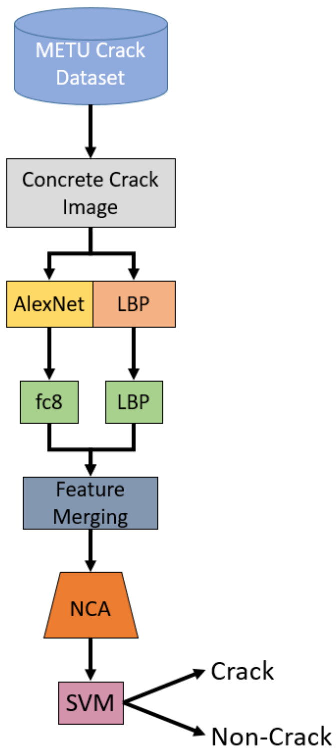

Fig. 1. Proposed method

Algorithm 1. Pseudocode of the proposed method

Input: METU crack image dataset
Output: Predicted results

00: Load crack dataset.
01: Get crack image.
02: Deep feature extraction using the last fully connected layer of the AlexNet architecture.
03: Textural feature extraction using LBP algorithm.
04: Combine features obtained in steps 2 and 3.
05: Obtain a feature vector of size 1256.
06: Repeat from step 1 until all images are complete.
07: Select the 500 most meaningful features using the NCA algorithm
08: Apply the holdout validation method in the classification process.
09: Classify the selected most significant features using the SVM algorithm.

A. Feature Extraction

The initial phase of our model revolves around feature extraction, wherein we employ two distinct feature extractors. The first is an AlexNet-based deep feature extractor, while the second is an LBP-based textural feature extractor. Detailed descriptions of these methods can be found in the respective subsections.

1) AlexNet based Deep Feature Extraction

AlexNet [17] stands as a prominent deep network architecture widely recognized in the literature. Originally designed for image classification tasks, this convolutional neural network was trained using the expansive ImageNet image library. Its notable success has inspired numerous methodologies and approaches found in the literature.

In this research, AlexNet architecture is used as a deep feature extractor. Specifically, we focus on the utilization of the "fc8" layer, which represents one of the fully connected layers within AlexNet. As the last fully connected layer of the network, it yields 1000 distinctive features. To provide a comprehensive overview of the feature generation process utilizing the AlexNet architecture, we present a concise block diagram in Figure 2.

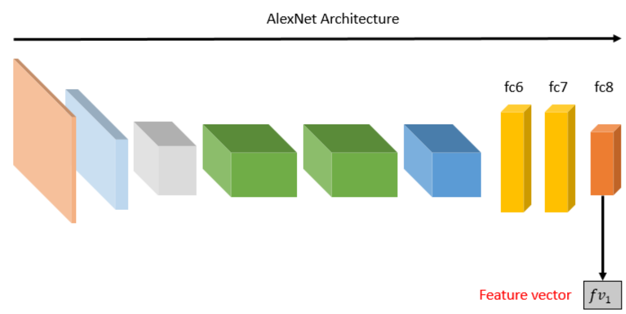

Fig. 2. Feature generation process based on AlexNet architecture

As depicted in Figure 2, the AlexNet architecture comprises three fully connected layers denoted as "fc6," "fc7," and "fc8" correspondingly. In our study, we conduct feature extraction specifically utilizing the "fc8" layer, resulting in a feature vector size of 1000.

Step 1: Extract feature from concrete crack images using AlexNet “fc8” layer.

$$fv_1 = AlexNet(images, fc8) \quad (1)$$

where, $AlexNet$ is the deep learning network images concrete images, $fc8$ is the feature extraction layer and fv_1 is the first feature vector calculated.

2) LBP based Textural Feature Extraction

The LBP (Local Binary Patterns) [18] method serves as a prevalent textural feature extraction approach extensively employed in the literature. Fundamentally, this method entails comparing the center pixel of an image with a threshold value, enabling the assessment of the intensity relationships between the center pixel and its neighboring pixels. With its linear time complexity and straightforward implementation, the LBP method has proven highly effective in real-time applications as documented in the literature. Widely utilized in various domains including face recognition, object recognition, and texture analysis, LBP adeptly captures the local intensity relationships, rendering it a favored choice particularly in image processing and pattern recognition applications.

Another feature extractor used in this study is the LBP method. Using this method, the texture features of the relevant images are obtained. At this stage, a feature vector with a total size of 256 is obtained. A block diagram summarizing the LBP method is given in Figure 3.

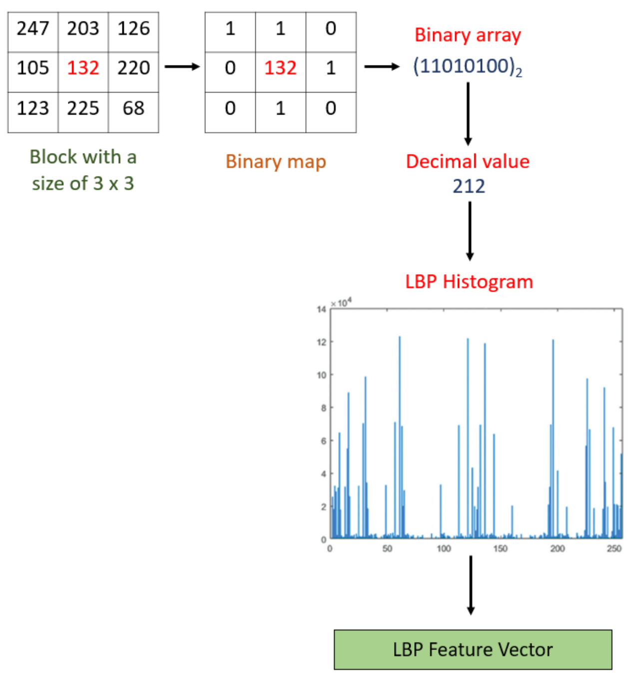

Fig. 3. LBP based feature extraction method

Illustrated in Figure 3, the LBP (Local Binary Patterns) approach partitions the image into blocks, wherein each pixel within a block is compared to the center pixel. This comparison yields a binary number representation. Subsequently, the binary number is converted to decimal form, generating the LBP histogram. The resulting histogram distribution serves as the feature vector for analysis. In our methodology, the image is primarily divided into overlapping 3x3 blocks. From each block, a decimal number ranging from 0 to 255 is calculated. Consequently, the LBP histogram encompasses values within the 0-255 range. Given that the histogram distribution curve is employed as the feature vector, this process yields a total of 256 ($=2^8$) distinctive features.

Step 2: Extract features from concrete crack images using LBP algorithm

$$fv_2 = LBP(images) \tag{2}$$

where LBP is the local binary pattern function and fv_2 is the second calculated feature vector.

B. Feature Merging

In this phase of the model, the feature vector obtained by deep feature extraction and the feature vector obtained by textural feature extraction are combined. In this phase, the size of the combined feature vector is 1256 (=1000 deep features+256 textural features). The feature vector obtained by this process is given as input to the Neighborhood Component Analysis (NCA) algorithm.

Step 3: Concatenate two feature vector to obtain final vector.

$$mfv = merge(fv_i), i \in 1{,}2 \tag{3}$$

Herein, $merge$ is the combine function and mfv represents the final combined feature vector.

C. Feature Selection

Another phase of the machine learning model proposed in this study is feature selection. Feature selection is a frequently used method in classical machine learning approaches. The aim of these methods is to select the most meaningful features for the classification process. In other words, meaningless features are eliminated from the feature vector. In the developed model, the NCA [19] algorithm is used as a feature selector.

The NCA algorithm calculates a weight value for each feature in the feature vector. A high weight value indicates the importance of the feature. In the developed model, the weight values calculated using the NCA algorithm are ranked in descending order and the first 500 features with the best weight are selected. This process reduces the size of the feature vector and minimizes the computational complexity. The optimum number of features is determined by trial-and-error method. The steps of the NCA algorithm and the mathematical equations used are given below.

Step 4: Apply min-max normalization.

Step 5: Calculate the weights for each feature.

Step 6: Select the 500 features with highest weight.

$$nmfv = norm(mfv) \tag{4}$$

$$id = NCA(nmfv) \tag{5}$$

$$sfv(i,j) = nmfv\big(i, id(j)\big), i \in \{1,2, \dots NI\}, j \in \{1,2, \dots, 500\} \tag{6}$$

where, $norm$ represents the normalization function, $nmfv$ represents the normalized feature vector, id denotes the weight values calculated using the NCA algorithm, sfv indicates the selected feature vector, and NI defines the number of images in the study. Using Equations (4)-(6), the weight of each feature vector is calculated and the selection process is performed according to this weight value.

D. Classification

The last phase of the model is classification. In this phase, support vector machines (SVM) [20], a well-known and classical method in the literature, is used. This method is a lightweight classifier. This contributes positively to the computational complexity of the developed model.

Step 7: Calculate final prediction vector by using SVM to the selected features.

$$pfv = SVM(sfv) \tag{5}$$

Herein, SVM is the classification function and pfv is the prediction vector calculated as a result of classification.

5. Experimental Results and Discussion

The model proposed in this research was implemented in the MATLAB programming environment. The test operations were performed on a server. Detailed specifications regarding the server configuration utilized in the experiments are presented in Table 2.

Table 2
Machine specifications used in test operations

Feature	Value
CPU	Intel Xeon 2.70 GHz
Ram	256 GB
Hard disk	1 TB
Operating System	Windows Server 2019
Programming Environment	MATLAB 2021b

The performance metric values, which are well known in the literature, are used to observe the performance of the proposed method. For this purpose, a confusion matrix is calculated using the actual label values and the prediction vector. Performance metric values were determined using this matrix. The mathematical expressions representing the performance metric values, as determined within this study, are given in Equations (7)-(10).

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$Pre = \frac{TP}{TP + FP} \quad (8)$$

$$Rec = \frac{TP}{TP + FN} \quad (9)$$

$$FScr = \frac{2xTP}{2xTP + FP + FN} \quad (10)$$

where Acc is accuracy, Pre is precision, Rec is recall, $FScr$ is F1-Score, TP is true positive, TN is true negative, FP is false positive and FN is false negative.

To validate the model, a holdout cross-validation strategy was employed, involving the division of the dataset into two distinct groups: the training set and the test set. In accordance with a ratio of 80:20, the dataset was partitioned accordingly. The resulting confusion matrix, derived from this validation process, is depicted in Figure 4.

Table 3
Calculated performance metric values

Metric	Result (%)
Acc.	99.88
Pre.	99.85
Rec.	99.90
FScr.	99.88

As depicted in Table 3, the test set, comprising 8000 images, was accurately classified with an impressive 99.9% accuracy through the utilization of the SVM algorithm. These findings precisely demonstrate the outstanding performance of the proposed method. Furthermore, as indicated in Table 3, the proposed model attains exceptional metric values exceeding 99% in all performance metric, underscoring its reliability.

The model devised in this study combines deep feature extraction and textural feature extraction methods, forming a hybrid approach. Additionally, the model incorporates feature selection and classification steps. In the feature selection phase, the NCA algorithm effectively reduces the number of features, thereby mitigating the computational complexity inherent to the proposed method. The resulting reduced feature vector is subsequently subjected to successful classification using SVM, a shallow classifier prominently employed in this research.

Numerous studies and methodologies in the literature have employed the same dataset. To facilitate comparison, Table 4 presents the comparative results obtained from these studies.

As depicted in Table 4, the proposed method in this study attains a very high classification success. Previous studies in the literature primarily focus on deep learning methodologies, which exhibit high classification performance but entail significant computational complexity. In contrast, the model developed in our study demonstrates reduced time complexity relative to these methods.

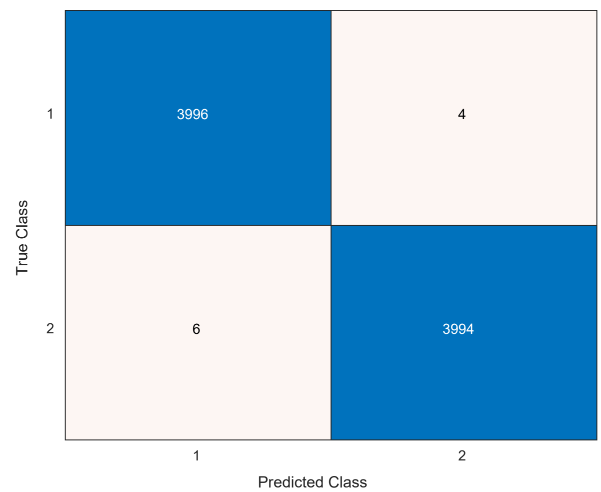

Fig. 4. Calculated confusion matrix for our crack detection model

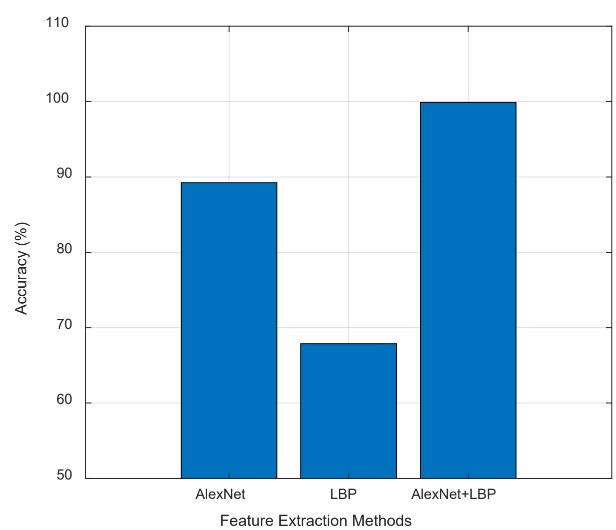

Fig. 5. Comparison results between feature extraction methods

To assess the performance of the developed model, we conducted individual tests for the feature extraction, feature selection, and classification phases. Initially, a comparison was

Table 4
Machine learning based studies on concrete cracking in the literature

Author(s)	Year	Dataset	Method	Result(s)
Dung and Anh [22]	2019	METU crack dataset	Fully convolutional network (VGG16)	Acc.=97.8 FScr.=89.3 Ap.=89.3
Yang et al. [30]	2020	METU crack dataset, SDNET2018, BCD dataset	End-to-end training with deep CNN	METU Acc.=99.83 Pre.=99.50 AUC=100 SDNET2018 Acc.=97.07 Pre.=99.80 AUC=99.58 BCD Acc.=99.72 Pre.=96.46 AUC=99.9
Ali et al. [31]	2021	SDNET2018, METU crack dataset	Custom designed CNN	Acc.=98.50 Pre.=100 Rec.=97.30 FScr.=98.60
Golding et al. [25]	2022	METU crack dataset	Edge detection, Grayscale image conversion, Custom designed CNN	Acc.=99.43 FScr.=99.54
Priyadharshini et al. [27]	2023	SDNET2018, METU crack dataset, Historical-crack18-19	Quaternionic wavelet transform and Custom designed CNN	SDNET18 Acc.=98.44 METU Acc.=99.80 Historical Acc.=94.67
Laxman et al. [28]	2023	METU crack dataset	Custom designed CNN, CNN based feature extraction, Random Forest and XGBoost	Acc.=93.7
Our Method		METU crack dataset	AlexNet based deep feature extraction and LBP based textural feature extraction, NCA and SVM	Acc. 99.88 Pre. 99.85 Rec. 99.90 FScr. 99.88

made between deep feature extraction and textural feature extraction approaches. The outcomes of this comparative analysis are presented in Figure 5.

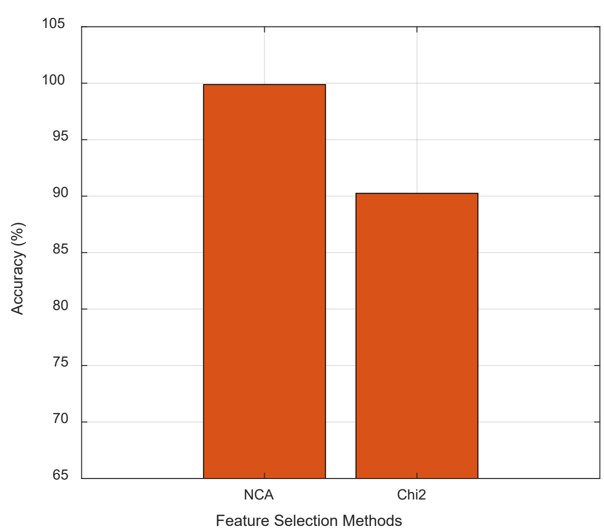

Fig. 6. Performance comparison of NCA and Chi2 algorithms

As evident from the figure, the combination of AlexNet and LBP yields the highest classification outcome. For this particular test, NCA was employed as the feature selector, and SVM served as the classifier. In the subsequent phase of the model, feature selection, two distinct feature selectors were evaluated: NCA and Chi2 methods. The comparative analysis of these methods is illustrated in Figure 6.

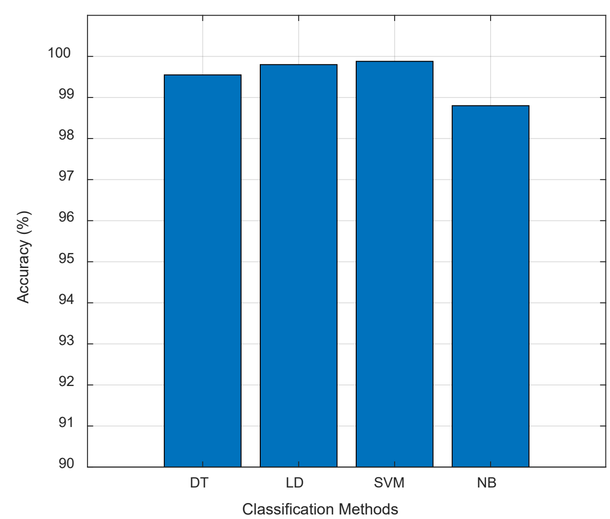

Fig. 7. Performance comparison of DT (Decision Tree), LD (Linear Discriminant), SVM (Support Vector Machine) and NB (Naïve Bayes) algorithms

The comparison process depicted in Figure 6 evaluates the feature vectors obtained from AlexNet and LBP. Furthermore, the SVM classification algorithm is employed for this comparative analysis. The final phase of the model is classification. In the classification process, decision trees, linear discriminant and SVM methods were compared. In this process, the features extracted using AlexNet and LBP are selected using the NCA algorithm. These selected features are then subjected to testing with the aforementioned classification algorithms. The outcomes of this testing process are presented in Figure 7.

The results obtained with the classification process are very close to each other. These calculated results show that the feature extraction and selection phase works with high performance. In other words, the features selected in the developed model are highly discriminative. In this context, the advantages and limitations of the developed model are given below.

Advantages:

- The developed model boasts a low computational complexity.
- The proposed method utilizes classical methods known in the literature. Therefore, it is easy to implement and test.
- The utilization of one of the largest datasets available in the literature contributed to achieving a remarkably high classification success rate (99.9%).

Limitations:

- Other open access crack image datasets in the literature have not been tested.
- The exploration of additional validation techniques commonly employed in the literature, such as k-fold cross-validation, is necessary.

6. Conclusions and Future Works

Nowadays, artificial intelligence-based solutions are used in many different disciplines. One of the most important of these disciplines is the field of health. These systems, which generally use inputs such as audio, image and text, provide successful results in many fields with automatic interpretation and classification mechanisms. Artificial intelligence technology offers various solutions that can be used interdisciplinary. In this paper, an example of this is demonstrated. Detection of concrete cracks, which has an important place in the construction industry, has been automated with the model developed in this study. Cracks, which are an important problem in concrete buildings according to their location and type, are automatically classified with the machine learning model developed in this study.

The model developed in this research consists of feature extraction, feature selection and classification phases. Deep feature extraction and textural feature extraction were applied for this purpose. Deep feature extraction is achieved using the last connected layer of the AlexNet architecture and textural feature extraction is performed using the LBP method. The model developed in this research is different from the classical CNN approaches in the literature. Instead of end-to-end training, the proposed model generates features using the "fc8" layer, one of the AlexNet deep network layers. This feature vector is then combined with the feature vector generated by the LBP algorithm. In this way, a hybrid feature extraction methodology was created. The model uses NCA algorithm for feature selection and SVM method for classification. The proposed model was tested on an open access dataset and achieved a classification success rate of over 99%. The calculated performance metric values reveal the success of the proposed method.

In this context, it is planned to use the proposed method in real field research for future studies. In addition, it is also aimed to be validated using other open access concrete crack datasets in the literature.

References

[1] A. Surahyo, Surahyo, and Luby, *Concrete Construction*. Springer, 2019.

[2] M. Amran, S.-S. Huang, S. Debbarma, and R. S. M. Rashid, "Fire resistance of geopolymer concrete: A critical review," *Construction and Building Materials,* vol. 324, p. 126722, 2022.

[3] Y. H. M. Amran, N. Farzadnia, and A. A. A. Ali, "Properties and applications of foamed concrete; a review," *Construction and Building Materials,* vol. 101, pp. 990-1005, 2015.

[4] G. F. Huseien, K. W. Shah, and A. R. M. Sam, "Sustainability of nanomaterials based self-healing concrete: An all-inclusive insight," *Journal of Building Engineering,* vol. 23, pp. 155-171, 2019.

[5] M. G. Richardson, *Fundamentals of durable reinforced concrete*. CRC Press, 2002.

[6] M. Amran, S.-S. Huang, A. M. Onaizi, G. Murali, and H. S. Abdelgader, "Fire spalling behavior of high-strength concrete: A critical review," *Construction and Building Materials,* vol. 341, p. 127902, 2022.

[7] P. T. L. Yee, A. B. Adnan, A. K. Mirasa, and A. B. A. Rahman, "Performance of IBS precast concrete beam-column connections under earthquake effects: a literature review," *American Journal of Engineering and Applied Sciences,* vol. 4, no. 1, pp. 93-101, 2011.

[8] A. S. Kiremidjian, E. G. Straser, T. Meng, K. Law, and H. Soon, "Structural damage monitoring for civil structures," 1997: SHM, pp. 371-382.

[9] M. S. Chalhoub, "Effect of reinforced concrete deterioration and damage on the seismic performance of structures," 2015: Springer, pp. 77-95.

[10] T. Yamaguchi and S. Hashimoto, "Automated crack detection for concrete surface image using percolation model and edge information," 2006: IEEE, pp. 3355-3360.

[11] M. Baygin, "An accurate automated schizophrenia detection using TQWT and statistical moment-based feature extraction," *Biomedical Signal Processing and Control,* vol. 68, p. 102777, 2021.

[12] M. Baygin, O. Yaman, P. D. Barua, S. Dogan, T. Tuncer, and U. R. Acharya, "Exemplar Darknet19 feature generation technique for automated kidney stone detection with coronal CT images," *Artificial Intelligence in Medicine,* vol. 127, p. 102274, 2022.

[13] S. G. Kobat *et al.*, "Automated diabetic retinopathy detection using horizontal and vertical patch division-based pre-trained DenseNET with digital fundus images," *Diagnostics,* vol. 12, no. 8, p. 1975, 2022.

[14] N. Baygin *et al.*, "Automated mental arithmetic performance detection using quantum pattern-and triangle pooling techniques with EEG signals," *Expert Systems with Applications,* vol. 227, p. 120306, 2023.

[15] S. G. Ozkaya *et al.*, "Most complicated lock pattern-based seismological signal framework for automated earthquake detection," *International Journal of Applied Earth Observation and Geoinformation,* vol. 118, p. 103297, 2023.

[16] M. Baygin, S. G. Ozkaya, M. A. Ozdemir, and I. Kazaz, "A new approach based on image processing for measuring compressive strength of structures," *International Journal of Intelligent Systems and Applications in Engineering,* pp. 21-25, 2017.

[17] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM,* vol. 60, no. 6, pp. 84-90, 2017.

[18] M. Heikkilä, M. Pietikäinen, and C. Schmid, "Description of interest regions with local binary patterns," *Pattern recognition,* vol. 42, no. 3, pp. 425-436, 2009.

[19] W. Yang, K. Wang, and W. Zuo, "Neighborhood component feature selection for high-dimensional data," *J. Comput.,* vol. 7, no. 1, pp. 161-168, 2012.

[20] W. S. Noble, "What is a support vector machine?," *Nature biotechnology,* vol. 24, no. 12, pp. 1565-1567, 2006.

[21] W. R. L. D. Silva and D. S. D. Lucena, "Concrete cracks detection based on deep learning image classification," 2018, vol. 2: MDPI, 8 ed., p. 489.

[22] C. V. Dung, "Autonomous concrete crack detection using deep fully convolutional neural network," *Automation in Construction,* vol. 99, pp. 52-58, 2019.
[23] S. E. Park, S.-H. Eem, and H. Jeon, "Concrete crack detection and quantification using deep learning and structured light," *Construction and Building Materials,* vol. 252, p. 119096, 2020.
[24] X. Han *et al.*, "Structural damage-causing concrete cracking detection based on a deep-learning method," *Construction and Building Materials,* vol. 337, p. 127562, 2022.
[25] V. P. Golding, Z. Gharineiat, H. S. Munawar, and F. Ullah, "Crack Detection in Concrete Structures Using Deep Learning," *Sustainability,* vol. 14, no. 13, p. 8117, 2022.
[26] C. Xiang, W. Wang, L. Deng, P. Shi, and X. Kong, "Crack detection algorithm for concrete structures based on super-resolution reconstruction and segmentation network," *Automation in Construction,* vol. 140, p. 104346, 2022.
[27] R. A. Priyadharshini, S. Arivazhagan, and M. Arun, "Crack recognition on concrete structures based on machine crafted and hand-crafted features," *Expert Systems with Applications,* vol. 228, p. 120447, 2023.
[28] K. C. Laxman, N. Tabassum, L. Ai, C. Cole, and P. Ziehl, "Automated crack detection and crack depth prediction for reinforced concrete structures using deep learning," *Construction and Building Materials,* vol. 370, p. 130709, 2023.
[29] Ç. F. Özgenel, "Concrete crack images for classification," *Mendeley Data,* vol. 1, no. 1, 2018.
[30] Q. Yang, W. Shi, J. Chen, and W. Lin, "Deep convolution neural network-based transfer learning method for civil infrastructure crack detection," *Automation in Construction,* vol. 116, p. 103199, 2020.
[31] L. Ali, F. Alnajjar, H. A. Jassmi, M. Gocho, W. Khan, and M. A. Serhani, "Performance evaluation of deep CNN-based crack detection and localization techniques for concrete structures," *Sensors,* vol. 21, no. 5, p. 1688, 2021.