International Journal of
Science and Engineering Investigations vol. 10, issue 117, October 2021
Received on October 12, 2021 ISSN: 2251-8843

Hybrid Machine Learning Model for Crack Identification in Concrete Surface

Déborah Santos[1], Alcineide Pessoa[2], Gean Sousa[3]
[1,3]Federal University of Maranhão
[2]Federal University of Pará
[3]Professor in Federal University of Maranhão
([1]bricialopes.dl@gmail.com, [2]alcineidedutra@hotmail.com, [3]gean_mat@yahoo.com.br)

Abstract-The deterioration of concrete structures occurs gradually over the years, requiring periodic monitoring so that it reaches the useful life for which it was designed. The objective of this work is to identify cracks in concrete surface using K-means and SVM machine learning techniques. The classification results reached values above 95%, demonstrating the ability to combine Machine Learning methods.

Keywords- *Concrete, Cracks, Machine Learning*

I. INTRODUCTION

Since the beginning of civilization, man has sought to create structures that are synonymous with safety and comfort for his life. The search for materials and techniques that supply such conveniences was necessary, thus emerging the reinforced concrete, in which many buildings are designed with this element, making it essential to monitor the element, as every structure over time its use deteriorates. Occurring gradually and usually appear through pathological manifestations, such as fissures, which can damage the entire structure [1]. And based on the Brazilian standard NBR 15.575/2013, civil construction has to meet quality, safety and performance requirements to reach the useful life of the structure.

To assess the quality of concrete structures, there are techniques that help in this process, such as Structural Health Monitoring (SHM), which aims to recover the behavior of structures, evaluating the performance of materials during the lifetime of the structures. SHM encompasses the integration of sensors, intelligent materials, data transmission, computational power and processing within the framework [2].

The simulation tools suggest providing a reliable framework for assessing the energy distribution of buildings, aiding in understanding the importance of building and climate parameters. However, when taking into account the decision-making process during the project cycle, running numerous simulations can lead to complex scenarios, in addition to the possibility of being time-consuming. In order to avoid these disadvantages, machine learning techniques can be used to forecast energy demand [3]. These techniques require as little time as possible to model a complete building and are becoming commonly used for preliminary estimates [4].

These tools help identify cracks in concrete surfaces and in conjunction with machine learning techniques, this work aims to identify cracks in concrete through a hybrid model of feature extraction and image classification.

II. MACHINE LEARNING TECHNIQUES: K-MEANS AND SVM

Machine Learning (MA) based computational methods have been widely used in several recent applications. These methods include the clustering method known as k-means and the SVM (Support Vector Machine) classification method. The following subtopics provide a conceptual approach to these two AM techniques.

A. *K-Mens*

The K-Means algorithm is a widely used technique that deals with simple grouping in data mining. An unsupervised learning algorithm used in solving well-known cluster problems, which groups objects based on their data into k distinct sets among their data group classifications [5].

The algorithm seeks to find k divisions that satisfy a certain criterion, in order to obtain an optimized result, where k is a positive integer responsible for specifying the number of clusters and must be provided in advance. This method proposes that a data be used as a reference in the space of the set to search for patterns, measuring the distances of locations of k sets of data considering its center. For location, a representative is selected, the centroid, which is intended to serve as a model for the grouping [6].

The result of the K-Means algorithm is very close to each data point in each data group. In K-Means, data groups are originated even before calculating the distance between the centroid and each data point, thus obtaining the initial classification, and if the classification is not reasonable, it will be modified and iterated until a reasonable classification is obtained, that is, this process continues several times, until each data point is solely a group [7].

B. *Support Vector Machines SVM*

Support Vector Machines (SVM) is a classification technique based on supervised machine learning with a Mathematical Optimization algorithm through the implementation of a limit derived from Statistical Learning Theory. The SVM stands out for having solid theoretical foundation and for achieving great performance in practical applications, where learning theory accurately identifies the elements that must be considered for successful learning and for the construction of complex models [8].

The SVM can be used to separate spectrally similar classes, mapped to a multidimensional feature space, and with a high degree of accuracy, in which the algorithms are not parametric using the automatic learning technique [9].

According to Nascimento et al. [10], the SVM algorithm aims to train a classifier that can do a mapping by example and make it possible to classify a sample not yet seen with the same probabilistic distribution.

III. MATERIALS AND METHODS

A. *Data base*

The database used in this article consists of a set of 40,000 concrete surface images. Each image in this set has a dimension of 224 x 224 pixels and RGB channels. These images correspond to cracks in the concrete of several buildings on campuses of the Middle East Technical University [11]. Two groups of images make up this base, namely, cracked and uncracked images. Fig. 1 exemplifies such characterization.

(a) (b)

Figure 1. Example of images that make up the database: A) Image with crack, B) Image without crack.

B. *Feature Extraction and Classification*

Some machine learning techniques, such as SVM, require a step prior to classification. This step is commonly called feature extraction. Some authors see this step as a problem [11].

In this article, it is proposed that the image feature extraction step used in the classification process be automated through the AM technique known as K-means. In other words, the methodology for identifying cracks in images proposed in this work consists of the combination of two AM methods, one for feature extraction (K-means) and one for classification (SVM), fig. 2.

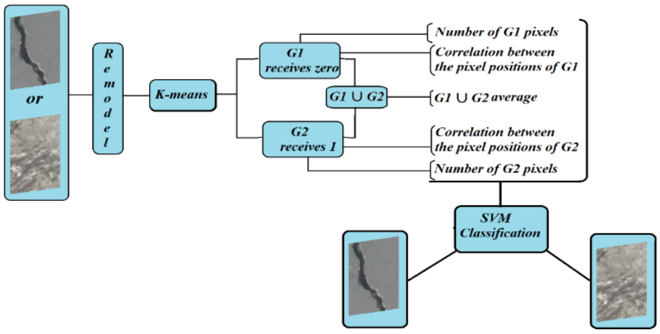

Figure 2. Proposed hybrid model for feature extraction and image classification.

C. *Performance Metrics*

The performance of a ranking process is verified using some metrics. Islam and Kim [11], who developed work using the same database described in subsection 3.1, proposed that the rating be evaluated based on the following metrics: Structural Accuracy (SA), Precision (P) Recall (R) e F1-Score. Mathematically, the metrics are defined as follows:

$$SA = \frac{TP+TN}{TP+TN+FP+FN}. \quad (1)$$

$$P = \frac{TP}{TP+FP}, \quad (2)$$

$$R = \frac{TP}{TP+FN}. \quad (3)$$

and

$$F1 - score = 2\,x\,\frac{P*R}{P+R}. \quad (4)$$

on what:

- TP corresponds to the number of positive observations predicted, by a given classifier, as positive, also known as True Positives. In this work, TP represents the number of images with cracks classified correctly.
- TN, by definition, is the number of negative observations predicted to be negative. These are the real Negatives. In this work, TN is the number of images without rac that are correctly classified.
- FP is the number of false positives, that is, the number of negative observations predicted to be positive. In our case, FP quantifies the number of uncracked images classified as cracked.
- FN consists, then, of the number of positive observations predicted as negative, that is, they are false negatives. In the problem addressed in this work, FN is the number of cracked images classified as uncracked. In the problem addressed in this work, FN is the number of cracked images classified as uncracked.

D. *Cross validation*

An AM model must present, in addition to good results, a good generalization capacity, that is, it must be able to repeat its performance in new data or in new situations. To measure the generalizability of classification algorithms, some techniques are used, including cross-validation [12].

Validation techniques are premised on establishing strategies to partition the data in such a way that the generalizability is more reliable. Among these techniques [12], three stand out: the holdout method, the leave-one-out or k-fold method. Among these techniques [12], three stand out: the holdout method, the leave-one-out, the k-fold. This last technique (k-fold) will be used in this work.

According to Varoquaux [13], the realization of the k-fold consists of dividing the dataset into k subsets of approximately equal sizes. The k - 1 objects are used in classifier training and the remaining k-th partition is used for model validation. Fig. 3 illustrates the described process.

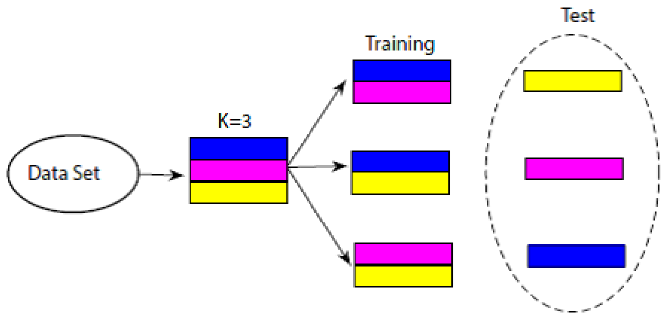

Figure 3. Cross Validation method (k folds)

It can be seen from Figure xx that the training and testing processes are repeated k times (k folds), until all partitions have been used both in training and in the classifier test. The performance is then evaluated from the mean and standard deviation of the evaluation metrics of all "folds".

IV. Results and Discussion

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by IJSEI for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

A. Authors and Affiliations

The computational experiments carried out in order to test the proposed methodology were carried out according to three different strategies. The first strategy followed what was done in the works of Islam and Kim [11], that is, the data set was divided into three groups: training (40%), test (40%) and validation (20%). This strategy was performed in order to compare our results with those obtained by Islam and Kim [11]. The results of the first computational tests are finally shown in Table I.

TABLE I. COMPARISON BETWEEN THE PROPOSED METHOD AND THE LITERATURE

Método	Prec. (P)	Rec. (R)	F1-Score	S.A
SVM	68,75	73,33	70,96	71,87
CNN	88,75	78,02	83,04	81,87
FCN	91,30	94,10	92,7	92,8
Proposta	95,54	96,00	95,77	95,78

The strategy of dividing the dataset into test and validation training may imply the so-called overfitting. For this reason it is common to use cross-validation techniques. In this work, the k-folds methodology was applied in the second and third experiments, in order to overcome the possibility of overfitting. In the first one, a "k=5" was used, that is, 5 folds. The results of each fold and the means of these results are shown in Tables II and III.

TABLE II. CLASSIFICATION RESULTS FOR 5 FOLDS

Fold	Prec. (P)	Rec. (R)	F1-Score	S.A
1	95.16	95.09	95.12	95.13
2	95.44	95.67	95.56	95.56
3	95.44	95.80	95.62	95.62
4	95.51	95.83	95.67	95.67
5	95.70	95.93	95.81	95.81

TABLE III. AVERAGE AND STANDARD DEVIATION OF PERFORMANCE METRICS (5 FOLDS)

	Prec. (P)	Rec. (R)	F1-Score	S.A
Média	95.44	95.66	95.56	95.55
Desvio Padrão	0.19	0.33	0.26	0.25

In addition to the results listed in the tables, another analysis methodology was applied in order to complement and confirm the findings. This analysis consists of evaluating the area under the roc curve (AUC). In this case, the closer to 1 this value is, the better the classifier performance. In fig. 4 there is a graph of the ROC curve in each fold and the respective area under it.

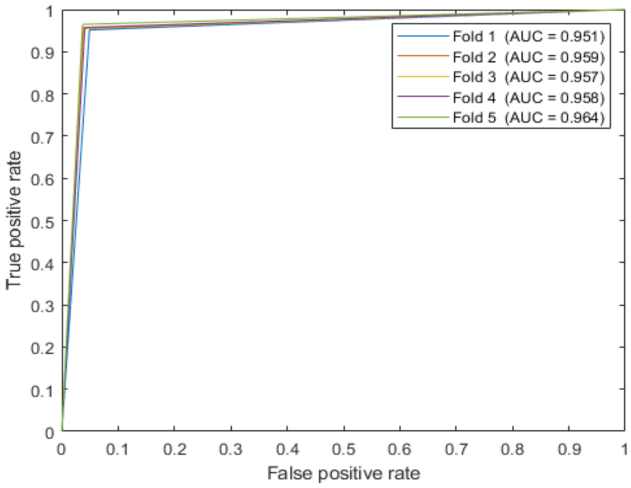

Figure 4. ROC Curves Graphs for each fold (k=5)

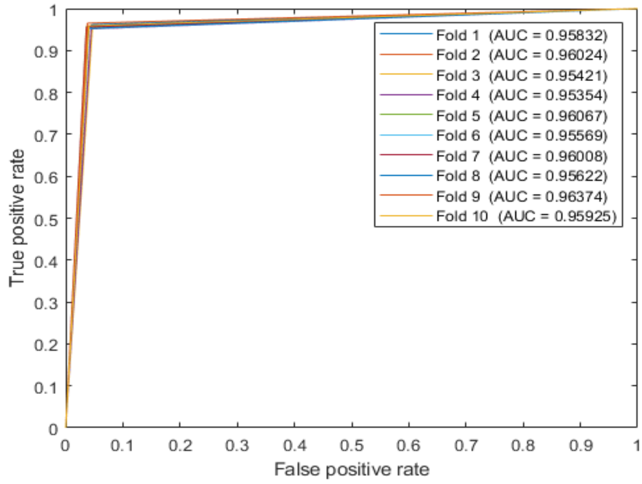

Figure 5. ROC Curves Graphs for each fold (k=5)

In the third experiment we also followed the k-folds cross-validation strategy. In this case we use 10 folds (k=10). The results of each fold, the means and standard deviation of these results are shown in Tables IV and V.

TABLE IV. CLASSIFICATION RESULTS FOR 10 FOLDS

Fold	Prec. (P)	Rec. (R)	F1-Score	S.A
1	95.36	95.68	95.52	95.52
2	95.73	95.35	95.55	95.54
3	95.83	95.72	95.78	95.78
4	95.82	95.83	95.83	95.83
5	95.72	95.81	95.77	95.76
6	95.81	95.77	95.80	95.79
7	95.74	95.80	95.77	95.77
8	95.75	95.91	95.83	95.83
9	95.67	95.86	95.77	95.76
10	95.66	95.87	95.77	95.76

TABLE V. AVERAGE AND STANDARD DEVIATION OF PERFORMANCE METRICS (10 FOLDS)

	Prec. (P)	Rec. (R)	F1-Score	S.A
Média	95.71	95.76	95.74	95.73
Desvio Padrão	0.13	0.15	0.11	0.10

As in the second experiment, here we also perform an analysis considering the area of the ROC curve. Fig. 5 shows the graphs for each fold and the respective area under the curve.

V. CONCLUSION

After the computer simulations using the proposed model, it can be seen that the classification results reached, on average and homogeneously, values above 95%, which demonstrates the ability of the combination of Machine Learning methods to identify images that contain cracks in concrete.

In addition to the accuracy percentages achieved, the proposed methodology indicated the possibility of intelligently automating the process of extracting features in image processing. In this article, this automation took place through the use of the method known as k-means. Thus, the proposed methodology proved to be as effective as high computational cost methodologies such as those based on Convolutional Networks.

REFERENCES

[1] E.A.Jiya, N.S.N. Anwar and M.Z. Abdullah, "Detection of Cracks in Concrete Structure Using Microwave Imaging Technique". Int. J. Microw. Sci. Technol. 2016, 2016, doi:10.1155/2016/3195716.

[2] Mosbeh R. Kaloop, Jong Wan Hu, Emad Elbeltagi and Ahmed El Refai , " Structural Health Monitoring and Assessment: Sensors and Analysis ", Journal of Sensors , vol. 2018 , Artigo ID 9834958 , 2 páginas , 2018 . https://doi.org/10.1155/2018/9834958.

[3] G. R. Duarte, L. G. da Fonseca, Goliatt, P. V. Z. C and A. C. De C. Lemonge, "Comparison of machine learning techniques for predicting energy loads in buildings". Built Environment, Porto Alegre, v. 17, no. 3, p. 103-115, Jul./Sep. 2017. ISSN 1678-8621 National Association for Built Environment Technology.

[4] A. Melo, et al, "A Novel Surrogate Model to Support Building Energy Labelling System: a new approach to assess cooling energy demand in commercial buildings". Energy and Buildings, v. 131, p. 233–247, 2016.

[5] S. Jigui, L. Jie and Z. Lianyu, "Clustering algorithms Research. Journal of Software". Vol. 19, No. 1, pp. 48-61, 2008.

[6] Luciano Vieira Dutra, “Selection of candidates: A Strategy for Incorporating Mahalanobis Distance into the K-Means Algorithm”, 7° Brazilian Conference on Dynamics, Control and Applications- FTC-Unesp at Presidente Prudente,SP, Brasil, 2008.

[7] K.A.A. Nazeer, M.P. Sebastian, “Improving the Accuracy and Efficiency of the k-means Clustering Algorithm”, Proceeding of the World Congress on Engineering, vol 1, Londres, Julho, 2009.

[8] Eulanda Miranda dos Santos, “Theory and Application of Support Vector Machines to Appearance-Based Object Learning and Recognition”, Thesis (Master's degree), Federal University of Paraiba, Campina Grande, 2002.

[9] ENVI, “Envi Guide in Portuguese”, Visual Information Solutions: SulSoft Data Processing Services LTDA, 2007.

[10] R.F. Nascimento, E.H. Alcantara, M. Kampel, J.L. Stech, E.M.L.M. New, L.M.G. Fonseca, “The Support Vector Machines (SVM) algorithm: Evaluation of the optimal class separation in CCD-CBERS-2 images”, Annals, Natal, Brazil, 2009, p. 079-2086.

[11] M. M. Islam, Jong-Myon Kim, “Vision-based autonomous crack detection of concrete structures using a fully convolutional encoder–decoder network”, Sensors, v. 19, n. 19, p. 4251, 2019.

[12] Ron Kohavi, et al, “A study of cross-validation and bootstrap for accuracy estimation and model selection”, In: Ijcai, 1995, p. 1137-1145.

[13] Gaël Varoquaux, Cross-validation failure: Small sample sizes lead to large error bars, *NeuroImage* http://dx.doi.org/10.1016/j.neuroimage.2017.06.061.

Déborah Fabrícia Lopes Santos, Bachelor in science and technology and major in Civil Engineering at the Federal University of Maranhão.

Alcineide Dultra Pessoa, Bachelor in science and technology and major in Civil Engineering at the Federal University of Maranhão. Master in Civil Engineering from the Federal University of Pará. Doctoral Student in Civil Engineering from the Federal University of Pará.

Gean Carlos Lopes de Sousa, Graduated and Master in Mathematics from the Federal University of Pará, with experience in Numerical Analysis of Differential Equations. He is currently a professor atthe Federal University of Maranhão and PhD student in the Graduate Program in Electrical Engineering, Federal University of Maranhão.

How to Cite this Article:

Santos, D., Pessoa, A. & Sousa, G. (2021). Hybrid Machine Learning Model for Crack Identification in Concrete Surface. International Journal of Science and Engineering Investigations (IJSEI), 10(117), 12-16. http://www.ijsei.com/papers/ijsei-1011721-02.pdf