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Concrete Pavement Crack Detection and Classification Using Deep Convolutional Neural Network with Grid Search Optimization

Oumaima Khlifati[1*] and Khadija Baba[2]

[1]*Civil Engineering and Environment Laboratory (LGCE), Mohammadia School of Engineers, Mohammed V University in Rabat, Morocco*

[2]*Civil Engineering and Environment Laboratory (LGCE), High School of Technology, Mohammed V University in Rabat, Salé, Morocco*

***Correspondence to:**
Oumaima Khlifati
Civil Engineering and Environment Laboratory (LGCE),
Mohammadia School of Engineers,
Mohammed V University in Rabat, Morocco.
E-mail: khlifatioumaima@gmail.com

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Abstract

Pavement distress is the main element impacting the stability of roads and the comfort of drivers. It is crucial to identify and fix road damage promptly to prevent greater harm and decrease expenses associated with rehabilitation. Pavement deterioration identification has been carried out through manual means, resulting in significant time and labor requirements. Consequently, an automated method for detecting cracks is necessary to streamline this procedure. Multiple approaches exist for the automated identification of deterioration, ranging from image processing to the implementation of deep learning techniques. The process of identifying deterioration using image processing techniques often involves edge detection and threshold segmentation methods, which primarily emphasize feature extraction but remain susceptible to variations in image texture. Traditional machine learning techniques have demonstrated favorable outcomes, but they lack dependence on the features that are extracted. The application of deep learning techniques has yielded successful results in the field of distress detection, surpassing the performance of traditional methods. This research paper introduces an innovative algorithm for the identification and categorization of pavement deterioration, formulated as a multi-label classification task. In this study, images of concrete pavements were utilized as the training and test data for the models. Various types of pavement deterioration are identified and categorized, including longitudinal cracks, transversal cracks, oblique cracks, and no cracks. Moreover, in order to attain optimal performance for our algorithm, we fine-tune the hyperparameters that compose the deep convolutional neural network model through the utilization of the grid search technique. The grid search explores every conceivable combination and selects the one that attains the greatest accuracy. Once the optimization process is finished, the effectiveness of the enhanced model is assessed using diverse evaluation metrics, including accuracy, precision, recall, and F1 score.

Keywords

Concrete pavement, Crack detection and classification, Deep learning, Grid search

Introduction

Pavements are a major component of transportation. After a period of use of the pavement which can be either concrete or asphalt, diseases will appear such as cracks which are considered the predominant defect. Cracks on the pavement not only reduce driving comfort, they also adversely affect the function of the pavement. With increased traffic, cracks easily spread, leading to structural defects in the pavement and shortening its service life. Hence, once the road is cracked, it must be repaired quickly to effectively slow the spread of cracks and minimize pavement maintenance costs. Accordingly, the pavement surface condition should be detected as early as possible to establish a preventive repair basis [1].

Road distress detection was done by manual ways which are labor-intensive and time consuming. The results of these inspections depend on the competence, experience, and subjectivity of the examiner [2]. Therefore, automatic methods are needed to accelerate the crack detection process. Traditional automatic methods for pavement crack detection can be classified into two main categories: image processing techniques [3], traditional machine learning approaches [4]. The image processing techniques include threshold method, edge detection method [5], and minimal path selection method [6].

Fujita et al. apply filters from the Hessian matrix to extract the line structures attached with cracks, then they use the threshold approach to distinguish between the cracks and the background [7]. Other researchers have proposed an approach to extract crack by computing the intensity gap between every pixel and the averaged intensity of each line in concrete pavement image [8]. The main disadvantage of threshold method is the issue of choosing an appropriate threshold for crack feature extraction.

Various edge detection algorithms are employed in concrete crack detection, such as Canny [9], Prewitt [8], Sobel [10], and Robert [11]. Despite Sobel's edge detector detects more edges and has a higher computational dynamic than the Canny edge detector, it finds more false edges [5]. The Prewitt and Robert detectors are able to identify the various edges but are not suitable for detecting small edges with inadequate thresholds [5]. Although the edge detection methods can obtain the crack defect edge distribution and draw the crack contour, it cannot describe the internal pixel information of the cracks.

Minimal path selection is a successful method for continuous crack detection. Amhaz et al. have applied minimal path selection to detect cracks from a global point of view, which significantly improves the continuity of fractured cracks [12]. Despite the fact that the minimum path selection method can detect cracks from a global point of view, it remains unsatisfactory when it detects cracks with disorderly forms or poor contrast.

The most used traditional machine learning methods for classification and prediction are support vector machine [13], random forest [14], artificial neural networks [15]. These methods apply a pre-defined feature extraction process prior to training the models. However, they are unable to handle large amounts of datasets. Traditional machine learning has a limitation in learning from complex features and cannot process complicated information in images, especially background with different illumination [16].

The irregular textures, inconsistent directions and unequal shapes make the cracks difficult to detect. Furthermore, the pavement images include a lot of noise such as shadow, changes in illumination and dust which have a significant impact on the results. Therefore, these traditional techniques are inadequate to analyze all the characteristics of the cracks. These traditional methods compare unfavorably with the convolutional neural network (CNN) when utilizing large-scale data. CNN has achieved considerable technical success in the field of automatic pavement crack detection. In this paper, we propose an innovative method for identifying and categorizing pavement damages, formulated as a multi-label classification task. The concrete pavement distress images are identified and categorized as follows: longitudinal crack, transversal crack, oblique crack, and no crack.

In this paper, we present the dataset adopted for our study, followed by a presentation of the proposed method. Furthermore, we introduce the hyper parameters optimization, and we provide a comprehensive analysis of the experimental results obtained for the optimized model.

Materials and Method

Materials

The dataset is composed of public images of concrete pavements from SDNET2018 [17]. This dataset is intended to be used in automatic concrete crack detection studies based on deep convolution neural networks (DCNN) and image processing [18]. SDNET2018 concludes more than 56,000 images of concrete pavements, walls and bridge which are captured by 16 MP Nikon digital camera. The size of each image RGB is 256*256 which is annotated as cracked images and no-cracked images. All the cracks in this dataset have a width between 0.06 mm and 25 mm. Additionally, the dataset contains some obstructions such as shadows, edges, surface roughness, holes, and flakes. All used materials are nanoscale materials.

In this paper, the classification study is concentrated in the concrete pavement dataset. The total of 1023 images are labeled into four classes: Longitudinal crack, transverse crack, oblique crack, and no crack. The quantity of images for each category is illustrated in table 1. After the labeling procedure, the data sets are resized to 224*224.

Table 1: Number of images in each class.

Image classification	Number of images
Longitudinal crack	225
Transverse crack	420
Oblique crack	125
No crack	253

Method

CNN is the most commonly employed model in deep learning. Generally, CNN mainly consists of three layers: convolution layers, pooling layers, and fully connected layers. Convolution layers are considered the high power of the convolution neural network, which is employed to perform convolution on the input and produce distinct feature maps. The pooling of layers aims to simplify the spatial dimensions of the feature maps. There are two types of pooling layer, namely max-pooling and average pooling. In this study, max-pooling

[19] was chosen because it is the most used and the fastest. The outcome of the final max-pooling layer is flattened and fed into the fully connected layers. Convolution layers and fully connected layers are followed by an activation function to improve the model accuracy [20]. A dropout layer is also used to avoid overfitting during the training of the CNN model.

This paper proposes a CNN model using a multi-classification method to identify and categorize the image pavement into four classes: Longitudinal crack, oblique crack, transverse crack and intact. In order to optimize our model, the hyper parameters of the CNN model are adjusted using a grid search approach. In this study, the CNN model concludes 25 weighted layers: one input, six convolution layers, six max-pooling layers, two fully connected layers, one flatten layer, one dropout and eight activation function as illustrated in figure 1. The last layer (output) is composed of four neurons, as the CNN model is aimed to classify the pavement image into four classes.

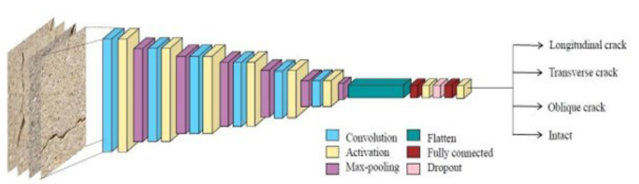

Figure 1: The architecture of proposed CNN model.

Results and Discussion

Performance evaluation metrics

The evaluation of classification performance is required in image classification to justify the results of this work. Numerous performance evaluation indicators have been adopted for image classification and considered as standard metrics in many studies. These evaluation metrics include accuracy (Acc), precision (Pr), and F1 score (F1) and recall (Re). The following formulas represent the equations for these metrics:

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

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

$$F1 = \frac{2 * Pr * Re}{Pr + Re} \quad (3)$$

$$Re = \frac{TP}{TP + FN} \quad (4)$$

Where, FN (False Negative), TP (True Positive), TN (True Negative), and FP (False Positive) are defined in table 2.

Grid search optimization

Recently, the application of CNNs in pavement detection and classification has increased, which has led to the emergence of some challenges in their use. The CNN architectures are designed to get more performance results by becoming deeper and using higher quality input images, leading to more computing costs increase. The implementation of robust hardware and optimization of hyperparameters is essential to reduce these computing costs and achieve more performance results. Accordingly, all main hyper parameters of the CNN models are adjusted through the utilization of a grid search approach. Grid search optimization is one of the appropriate methods for hyper parameter optimization whose purpose is to find the optimal combinations for the CNN model.

Table 2: Definition of FN, TP, TN, and FP.

		Ground truth	
		Positive	Negative
Prediction	Negative	**FN**	**TN**
	Positive	**TP**	**FP**

CNN models contain several hyper parameters which can be separated into two categories: the fine adjustment hyper parameters and the structural hyper parameters. The fine adjustment hyper parameters include batch size, epoch and learning rate. The structural hyper parameters contain optimizer, number of convolution layers, filter sizes, number of filters, and activation function. The optimizers used in this study conclude: RMSprop (Root Mean Square Propagation), Adam (Adaptive Moment Estimation), Adadelta, Adagrad (Adaptive Gradient Algorithm), Nadam (Nesterov-accelerated Adaptive Moment Estimation), Adamax, Ftrl (Follow-the-Regularized-Leader), and SGD (Stochastic Gradient Descent). RMSprop is an optimizer proposed by Geoff Hinton that incorporates a running average of squared gradients to adjust the learning rate. RMSprop has demonstrated successful applications in computer vision domains, including tasks like image classification, object detection, and semantic segmentation, where it has shown effective performance. The Adam optimizer is widely recognized as one of the most favored algorithms for optimizing gradient descent. By integrating the principles of momentum and RMSprop, the Adam optimizer adjusts the learning rate for each parameter independently by taking into account both the historical gradients' average and their square roots. Adadelta is a derivative of RMSprop that eliminates the necessity of manually setting a global learning rate by automatically adapting the learning rate for each parameter during training, providing a more flexible and dynamic approach. Adagrad adjusts the learning rate for each parameter based on the inverse proportionality to the square root of the cumulative sum of squared gradients. Nadam synergistically integrates the Nesterov accelerated gradient method with Adam's adaptive moment estimation, harnessing the advantages of both techniques to expedite convergence and enhance generalization, making it particularly effective for deep learning models. Adamax, derived from Adam, is specifically designed to handle large gradients and sparse updates more effectively. This characteristic makes Adamax particularly suitable for models involving embeddings or natural language processing tasks. Ftrl, a widely adopted optimizer in domains like online advertising, is especially favored for large-scale linear models due to its exceptional efficiency and capability to handle sparse data. SGD, a popular and fundamental optimizer, iteratively adjusts the model's parameters by taking into account the gradient of the loss function concerning a randomly sampled subset of training examples at each iteration, enabling efficient parameter updates in large-scale machine learning tasks.

We applied a variety of activation functions such as ELU (Exponential Linear Unit), SELU (Scaled Exponential Linear Unit), ReLU (Rectified Linear Unit), GELU (Gaussian Error Linear Unit), PReLU (Parametric ReLU), and Leaky ReLU. ELU is a smooth activation function that ensures non-linearity in neural networks by providing a continuous and differentiable gradient for both positive and negative values. SELU is an activation function designed to maintain the statistical properties of input data, such as mean and variance, as it passes through different layers of a neural network, thereby aiding in self-normalization. ReLU is a widely used activation function that adds non-linearity to neural networks by producing the input value as output if it is positive, and zero otherwise, effectively enabling selective activation of neurons. GELU is an activation function that closely approximates the Gaussian cumulative distribution function, featuring a smooth curve and behaving like ReLU for positive inputs, while introducing a differentiable transition for negative inputs. PReLU is an extended version of ReLU that incorporates a trainable parameter responsible for determining the slope of the negative portion of the function. Leaky ReLU is a variant of the ReLU activation function that mitigates the issue of "dying ReLU" by allowing a small, non-zero gradient for negative inputs, rather than completely discarding them, thus enabling improved information flow, and preventing the saturation of neurons.

In this study, algorithm 1 is used to optimize fine adjustment hyper parameters. Algorithm 2 is applied to enhance the structural hyperparameters. In algorithm 1, we apply the grid search algorithm for training which is set by three tune adjustment hyper parameters as shown in figure 2. 1023 pavement images are randomly separated into training, testing with 0.70:0.30 ratio. The grid search tries all potential parameter value even obtaining the combination which has the highest accuracy. The total combinations to betray is 4 x 7 x 4 = 112. Table 3 displays the hyperparameters that have been optimized through the grid search approach to achieve the optimal tuning adjustments.

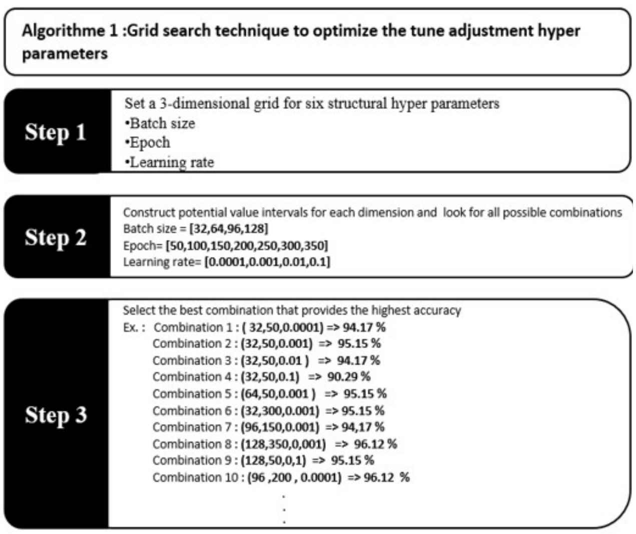

Figure 2: Grid search for tune adjustment hyper parameters.

Table 3: Optimum tune adjustment hyperparameters results obtained by grid search.

Tune adjustment hyper parameters	Possible values	Best value
Batch size	[32,64,96,128]	32
Epoch	[50,100,150,200,250,300,350]	50
Learning rate	[0.0001,0.001,0.01,0.1]	0.001

Similarly, in algorithm 2, the structural hyper parameters are optimized using the grid search as presented in figure 3. In this case there are 4800 possible combinations to check: 8 x 5 x 4 x 5 x 6. As there are 4800 combinations to be processed through the threefold procedure, the CNN model will be run 14400 times. Table 4 showcases the optimal structural hyperparameters attained through the grid search technique.

Results achieved by optimized CNN model

Once the optimization process is done, the CNN model will be tested to justify its performance by different reliable methods. Evaluation of model performance is carried out using loss, accuracy, recall, precision and F1 score. In this work,

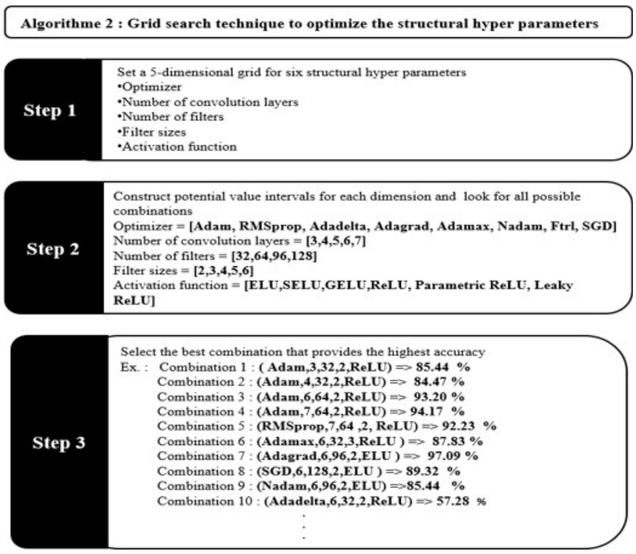

Figure 3: Grid search for structural hyper parameters.

Table 4: Optimum structural hyperparameters results obtained by grid search.

Structural hyper parameters	Possible values	Best value
Optimizer	[Adam, Adadelta, RMSprop, Adagrad, Nadam, Adamax, Ftrl, and SGD]	Adagrad
Number of convolution layers	[3,4,5,6,7]	6
Filter sizes	[2,3,4,5,6]	2
Number of filters	[32,64,96,128]	96
Activation function	[ELU, SELU, GELU, ReLU, Parametric ReLU, and Leaky ReLU]	ELU

cross-entropy is employed as the loss function because it's very suitable for multi-classification tasks [20]. Figure 4 represents the loss plot of the optimized model in training and validation. It can be clearly observed that the loss plot decreases quickly from the second epochs, then it is stabilized at 0.09 for training and reaches 0.3 for validation at 50 epochs. Figure 5 presents the accuracy graph of the optimized model during both the training and validation phases. From the result, it's obvious that the performance of the model increases with time, which means that the model learns and gets better with experience and achieves more than 96% accuracy in the training and validation. It can be affirmed that the optimized model achieved significantly higher accuracy and lower loss values, beginning from the 30th epoch, which reflects a good convergence of the model at a high-speed. According to the confusion matrix classification shown in figure 6, the longitudinal crack class achieves 96% accuracy, 100% of the transverse crack class, 87% of the oblique crack class and 100% of the intact class. To further confirm the performance of the optimized model, the precision, F1 score, and recall are calculated for each class as illustrated in table 5.

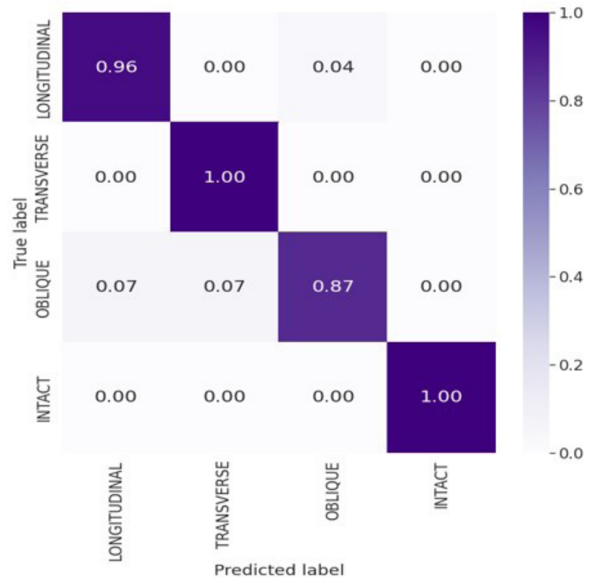

Figure 6: The confusion matrices of the different type of pavement crack.

Table 5: Precision, recall, and F1 score of the different types of pavement crack classification.

	Pr (%)	Re (%)	F1 (%)
Longitudinal crack	92.86	100	96.29
Transverse crack	97.22	100	98.59
Oblique crack	100	80	88.89
Intact	100	100	100

Conclusion

This paper proposes the multi-classification of concrete pavement using CNN models which are automatically adjusted using grid search technique. Almost all the hyper parameters constituting the CNN model have been adjusted to obtain the best combination that ensures a good performance of the model. Using a public dataset, a robust CNN model is created to classify concrete pavement into four classes: longitudinal crack, transverse crack, oblique crack, and intact. To confirm the performance of the optimized model, many evaluation indicators have been adopted such as recall, precision, and F1 score. The optimized model has an accuracy of 96%, 100%, 87%, and 100% respectively for longitudinal crack, transverse crack, oblique crack, and intact. The classification of the concrete pavement model achieved 97.09% accuracy.

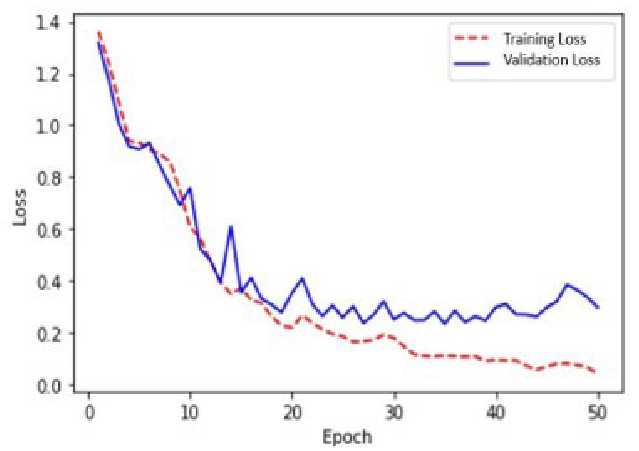

Figure 4: The loss curves for training and validation of the optimized model.

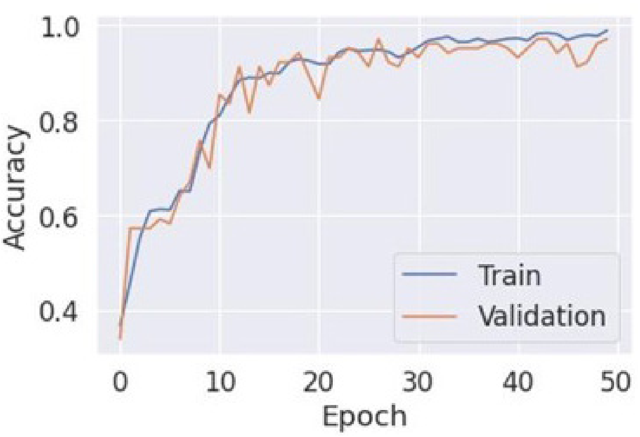

Figure 5: The accuracy of the optimized model in training and validation.

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Conflict of Interest

The authors state that they have no competing interests pertaining to the publication of this article.

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