Asphalt pavement cracking classification using convolutional neural networks

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Abstract. *Asphalt pavements on roads are subject to cracking due mainly to overload and weather over time. Detecting the presence of cracking is an essential part of road maintenance systems. Traditional road defect detection methods are time-consuming, dangerous, labor-intensive, and subjective. An alternative is to use digital images of roads, collected by cars or unmanned aerial vehicles, to feed automated asphalt damage identification models. Thus, automated defect detection systems could quantify the quality of road surfaces and help prioritize and plan road network maintenance, thereby preserving and extending the useful life of roads. This work aims to investigate the use of machine learning for detecting and classifying cracking in road pavements using convolutional neural networks. Transfer learning and data augmentation techniques were used to build classification models. The results indicated that the model was able to identify cracking in the images of roads with an accuracy of 99%. When using the model to classify the cracking subtypes, the model presented an overall accuracy of 78%.*

Keywords: machine learning, image processing, convolutional neural networks, road damage.

1. Introduction

Roads are essential in Brazil as they are the primary means of transporting goods and passengers. According to the National Department of Transport Infrastructure (DNIT), most roads in Brazil are paved with asphalt, with over 60% of the country's road network being paved [1,2]. Like any other engineering structure, asphalt pavements must exhibit robustness and durability throughout their life cycle. Pavement should provide a surface that is durable and safe for traffic and suitable for a variety of weather conditions.

High costs are invested in road construction, so maintenance of these roads is necessary to maintain the capital invested. Damages in road pavements, such as cracking, potholes, and exudation, reduce road performance and threaten road safety. Figure 1 illustrates the main defects categorized by the technical standard DNIT 005/2003, which deals with defects in flexible and semi-rigid pavements, establishing the terms and definitions used in this area [2]. Among all damages in asphalt pavements, potholes and cracking are the two most prevalent types of road surface damage, significantly affecting vehicle performance and driving quality. Furthermore, cracking in pavements can lead to a cascade of other issues if not addressed promptly. Over time, cracking allow water to penetrate among the pavement layers. This infiltration can weaken the underlying base and subbase materials, leading to further deterioration and the formation of potholes. Cracking can also expand due to changes in temperature (thermal expansion and contraction) and traffic loads effects, exacerbating the damage. The damaged pavement structure can result in uneven surfaces, reduced load-bearing capacity, and ultimately, higher maintenance costs. Therefore, it is crucial to address roads cracking early to prevent more severe and costly damage to the pavement.

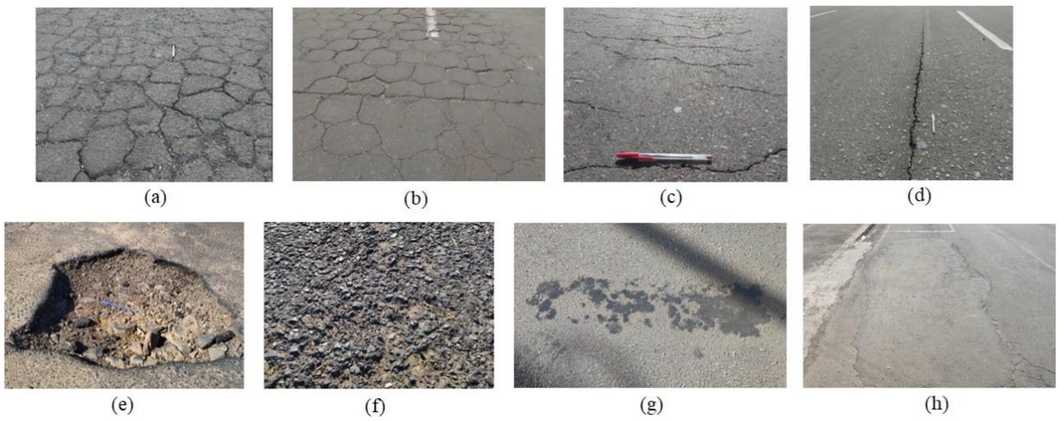

Figure 1. Damage types in roads: (a) alligator cracking, (b) Block cracking, (c) transverse cracking (d), longitudinal cracking, (e) pothole, (f) exudation (h) patch

Companies and governments have concentrated efforts to achieve the objective of building a high-quality road network, which involves high costs [3]. Good and effective road maintenance not only reduces vehicle operation cost and accident rates but also improves service life of the roads by reducing the rate of deterioration of pavements. Therefore, there is a need for constant inspection and maintenance. Cracking detection is an essential part of road maintenance systems and has attracted interest from researchers in the fields of engineering and computing [4].

Traditional road damage detection methods are time-consuming, dangerous, labor intensive and subjective [5]. Automated defect detection systems can quantify the quality of road surfaces and help prioritize and plan road network maintenance and thus preserve and extend the useful life of roads. Recently, computer vision and machine learning algorithms, using images as input to train classification algorithms, have been studied to detect defects in road pavements [6, 7]. In this approach, images of road sections can be captured using cameras, installed in vehicles, or handled by humans. These images can then be fed into classification models, which can detect and classify pavement damage.

Different approaches to detecting defects through image processing and computer vision have been investigated [8]. The Sobel algorithm, approaches based on thresholding, Gabor filtering and local binary patterns have been used to acquire descriptors using local characteristics of images [9, 10, 11]. However, these methods are often sensitive to noise or cannot distinguish (or filter) damage types from the image background. Convolutional neural networks (CNNs) have been presented as an alternative to solving computer vision problems, due to their ability to extract features directly from raw image data [12].

This paper evaluates convolution neural networks for classifying cracking in asphalt pavements. Pavements images from Internet and from the LabPavi system [13, 14] were used as input to build classification models using convolutional neural networks.

2. Pavement Cracking Detection and Classification

Cracking are discontinuities that occur on the asphalt surface. A damage is called crack when it is perceptible at distances smaller than 1.5 meters. Cracking can be subdivided into isolated and interconnected. Isolated cracking in turn are divided into transverse, longitudinal, and retraction cracking. Interconnected cracking can be described by the alligator or the block types [2].

Studies on pavement crack classification using digital image processing have been conducted. Traditional image processing methods, including pixel thresholding and image segmentation, have also been investigated [4,9,15, 16]. Also, deep learning and convolution neural networks (CNN) have been studied, due to limitations of the tradicional image processing techniques when dealing with noise and brightness differences in pavement images [17]. A CNN can be seen as a hierarchical and multi-layer feature extractor: each neural network layer performs a convolution operation. The result of the convolution operation are forwarded to the next layer. Also, normalization on data is performed on the output of the convolutional layers, whereby the extracted features are normalized by adjusting and scaling the artificial neuron activations. Aiming to reduce the feature maps, max pooling operations are also used. On the top of the network, a fully connected layer computes the score of each class and infers the class of the input image.

A pavement cracking detection method that uses convolutional neural networks are presented in [3]. Instead of using all pixels from the digital images, the authors used patches from pavement pictures, taken using smartphone cameras. They compared machine learning with convolutional neural network models. The influence of the number of convolution network layers on damage identification were investigated in [18]. The authors concluded that increasing the network depth can improve the classification accuracy. Road damage dataset was presented in [19] and [13]. In [19], images were used aiming for detecting cracking in Moroccan pavements using convolutional neural networks. The authors investigated two types of road cracking (alligator crack and longitudinal crack types) and concludes that is its important have a large dataset of images, mainly to detect longitudinal crack types. The longitudinal crack, transverse crack, alligator crack and pothole classes of damage were addressed in [20], using a CNN network architecture is used for detecting damage in roads. The authors used the road damage dataset presented in [21].

2. Methods

Images from asphalt pavements were used in this study aimed to evaluate the classification performance of Convolutional networks when detecting pavement damage. A subset of images from the LabPavi system [11] were used. This dataset was expanded, using images collected from the Internet. Also, data augmentation was used to generate new images from the original images.

Two main experiments were conducted. In the first experiment, a CNN model was evaluated considering the problem of identifying cracking in asphalt pavements images, regardless the subtype of crack. For this, a dataset composed of 1020 images of pavement cracking were used. This dataset contains 510 images of various subtypes of cracking and 510 images of crack-free. A total of 306 images (60%) were used for train, and 204 images for each class were used in the model validation (40%).

In the second experiment, the goal was to evaluate the model performance when identifying the subtype of pavement cracking. For this classification problem, a dataset composed of samples of four subtypes of pavement crack was used: alligator, transverse, longitudinal and block (Figure 2). In this scenario, 300 images for each subtype of pavement crack are included the dataset. The total number of images was equal to 1200. In a similar fashion, 60% of the images were used for training and the remaining 40% of the images for validating the results.

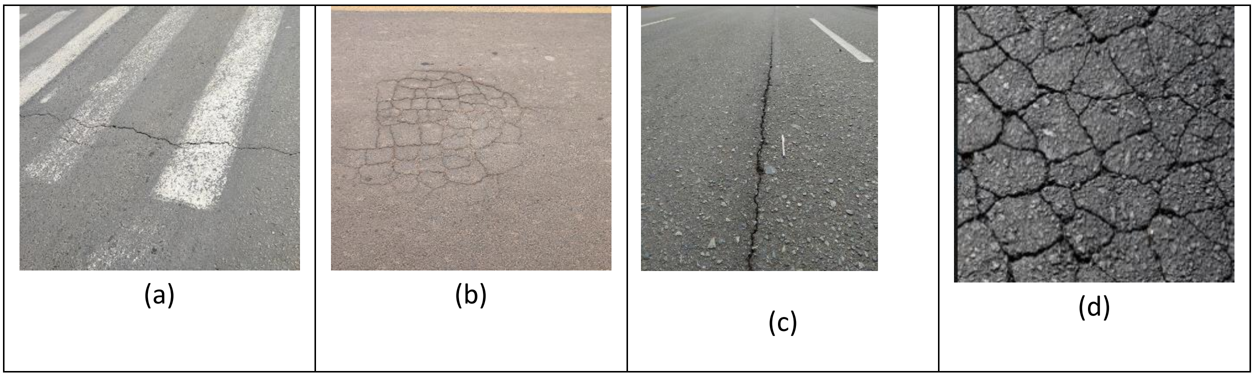

Figure 2 – Samples of the subtypes of pavement crack images in the dataset: (a) transverse, (b) alligator, (c) longitudinal and block (d).

The VGG16 model [22], available in Keras and TensorFlow 2.9.1, was used. The VGG16 was extended using 3 additional Dense type networks layers and transfer learning was used in the training. Transfer learning focuses on keeping previous knowledge in a CNN while applying it to another problem. When using transfer learning, the most CNN layers lack their network weights updated on training, thus preserving the previous model knowledge representation.

The accuracy, loss function, recall, precision, and f1-score measures were used to evaluate the results. The accuracy and the loss function values were observed during the models training, and thus, the overall correctness of the model was evaluated using the accuracy values. The accuracy is the ratio of the number of correct predictions and the total number of predictions. A loss function measures how well the model is performing during training. The loss measures the discrepancy between the predicted values and the actual ground truth labels. The Precision metric evaluates how often the model is correct when predicting a target class. The precision is evaluated by dividing the number of correct positive predictions (true positives) for a class by the total number of instances the model predicted as positive, considering both true and false positives samples. Precision values near to 1, in a 0 to 1 scale, are achieved when the model makes fewer false positive errors. The recall or sensitivity indicates the performance of the model when finding all objects of a target class. High recall values indicates that the model captures most of the positive instances. The F1-score is the harmonic mean of precision and recall. The F1-score provides a single metric that evaluates both false positives and false negatives.

3. Results

The VGG16 model learning curves, aiming to classifying crack and crack-free road images are illustrated in Figure 3. For the same classification problem, the related performance metrics of the VGG16 model are presented in the Table 1. The results show that the model distinguished images with and without cracking with an accuracy of 99%. The precision and recall values indicate that the model's performance was the same, regardless of the class.

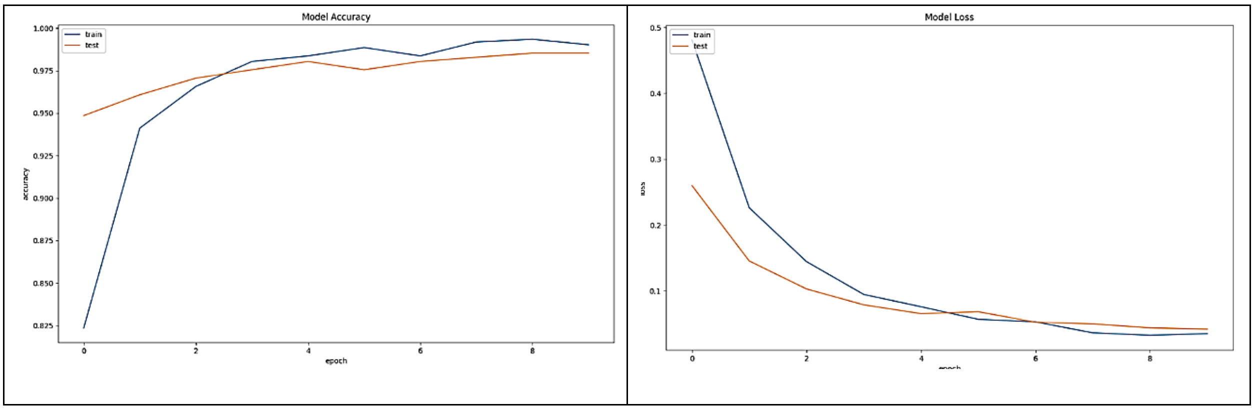

Figure 3 – Crack and crack-free images learning curves.

Table 1 – VGG16 model results when identifying pavement images with cracking.

	Precision	Recall	F1-Score	Support
Non-crack	0.99	0.99	0.99	204
Crack	0.99	0.99	0.99	204
Accuracy			**0,99**	408
Macro avg	0.99	0.99	0.99	408
Weighted avg	0.99	0.99	0.99	408

The Figure 4, and the Tables 3 and 4, show the results when using the model to classify the type of asphalt pavement cracking. In this classification problem, the model achieved the best precision (98%) when classifying the blocking crack class (Table 2). Considering the precision values, the model presented the worst performance for the alligator cracking class, with a precision of 76%. This indicates that the model obtained a greater number of false positives for the alligator cracking. In the case of the alligator crack subtype, the model classified 16 images as longitudinal and 10 images as transverse cracking (Table 3). In terms of sensitivity, the model also presented the best performance for the block cracking class, and the worst performance for the alligator cracking, with recall values of 95% and 76%, respectively. According to the confusion matrix (Table 3), the model incorrectly classified alligator cracking images examples as longitudinal or transverse (12 and 10 samples, respectively).

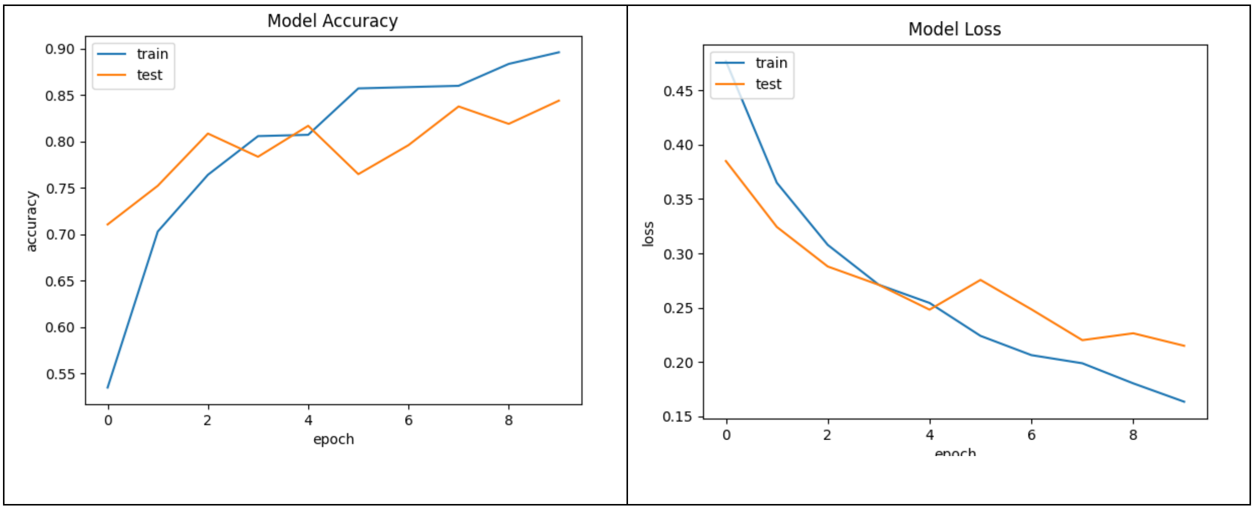

Figure 4 – Learning curves when using the VGG16 model for classifying the four pavement crack types available in the dataset.

Table 2 – VGG16 model results when classifying the subtype of pavement cracking.

Crack Subtype	**Precision**	**Recall**	**F1-Score**	**Support**
Longitudinal	0.78	0.87	0.82	120
Transverse	0.88	0.82	0.84	120
Block	0.98	0.93	0.95	120
Alligator	0.76	0.77	0.76	120
Accuracy			**0.84**	480
Macro avg	0.85	0.84	0.85	480
Weighted avg	0.85	0.84	0.85	480

Table 3 – VGG16 model confusion matrix when classifying the subtype of cracking.

True/Predicted	**Longitudinal**	**Transverse**	**Block**	**Alligator**
Longitudinal	**104**	4	0	12
Transverse	12	**98**	0	10
Block	2	0	**111**	7
Alligator	16	10	2	**92**

Conclusion

This paper presented an evaluation of the VGG16 convolutional neural network for detecting road cracking. The results indicated that the model was able to identify asphalt pavement cracking in the images, with an accuracy of 99%. When classifying the four classes of damage by cracking, the model presented an overall accuracy of 78%. Improvements can be done in the image's dataset, aiming to achieve better accuracy values. In future work, extensions in the classification model can also be evaluated. For instance, the inclusion of new layers in the network topology and the use of fine tuning can be studied. Furthermore, other network models can also be evaluated, in addition to the presented in this paper.

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