DETECTING DAMAGE IN ROADS USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract. *Roads are subject to damage such as cracks and potholes, mainly due to overload and weather over time. To ensure the longevity of roads, to prevent economic losses, and to improve safety, damage detection is crucial in pavement conditions monitoring. Damage detection is usually performed in the field by surveying and is a time-consuming and unsafe task. This paper presents an experimental study using machine learning and convolutional neural networks for detecting damage in roads. Transfer learning and data augmentation techniques were used to build classification models. Three models were evaluated, and the accuracy results on average were near 80%. Best accuracy results were achieved on detecting potholes, exudation, raveling and patches. The models did not perform well when distinguishing among subtypes alligator, transversal, and longitudinal of crack damage. For these types of damage, the models achieved an average accuracy bellow to 70%.*

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

1. Introduction

In Brazil, roads are wide used in transportation systems and enable the carrying of passengers and goods across the country. The pavement technology is used to build roads composed of multiple layers to resist to vehicle traffic and weather, aiming to provide comfort and safety to users [1]. The asphalt overlay used in roads is subject to stress, overload, weather conditions and deterioration over time. When the asphalt pavements are exposed to these events and without suitable schedule maintenance, damage can arise, such cracks and potholes. The detection and correction of these problems is a crucial process to ensure the longevity of the pavement, prevent economic losses, and improve safety [2].

To detect damage in pavements, visual inspection is performed by specialized agents. In this task, agents proceed with visual inspection and acquire digital images from the asphalt pavements to feed road condition monitoring systems. During surveying, traffic blocking is required, to ensure safety to the agents and users. Such operations are risky to agents and related to harm users, such as delays and economic losses [3].

Recently, computer vision and machine learning algorithms, using asphalt images as input to train classification algorithms, have been studied to detect damage in road pavements [4,5]. In this approach, images from road sections can be captured through cameras, installed either in vehicles or handled by humans, and then these images can be submitted to classification models, which can detect and classify pavement distress.

Detecting damage by using image processing and computer vision has been investigated [4,5,6]. The Sobel algorithm, thresholding-based approaches, Gabor filtering, and local binary patterns have been used to acquire descriptors using local features from images [7, 8,9,10]. However, these methods are often sensitive to noise or cannot distinguish (or filter) types of damage from image background [4]. Convolution neural networks (CNNs) have been presented as an alternative to solving computer vision problems, due to its ability to build features directly from raw image data [4]. This paper evaluates convolution neural networks for detecting and classifying damage in asphalt pavements. Images from the LabPavi system [11] were used as input to build classification models using convolutional neural networks.

2. Background

In Brazil, to classify damage in asphalt pavements, the DNIT 005/2003 – TER technical standard must be used [12]. The types of damage addressed by this standard are crack, pothole, raveling and patch (Figure 1). Some of these damage categories can be expanded. For instance, cracks can also be classified into different types of the following cracks: alligator, transverse, block and longitudinal [4].

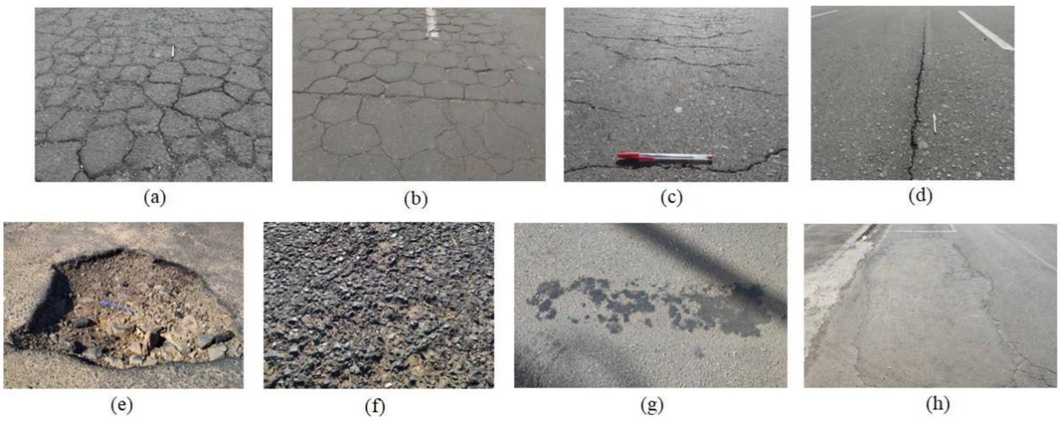

Figure 1 – Types of damage in asphalt pavements: (a) alligator crack (b) block cracks (c) transverse cracks (d) longitudinal crack (e) pothole (f) raveling (h) patch (some images were taken with a pen image next to the pavement distresses to understand the size of damage).

Cracks are discontinuities that occur on the asphalt surface that can be classified as fissures or cracks. A damage is called crack when they are perceptible at distances smaller than 1.5 meters, in addition, they do not present functional problems to the coating, otherwise, when they reach larger dimensions, consequently their visibility is greater, they are called cracks. Cracks can be subdivided into isolated and interconnected. Isolated cracks in turn are divided into transverse, longitudinal, and retraction cracks. Interconnected cracks can be described by the alligator or the block types [2].

Potholes are cavities formed in the coating, resulting from localized disintegration and accelerated by the action of traffic, excessive humidity, and failure in priming. *Raveling* occurs when the surface aggregates come off, thus the asphalt becomes rough. *Exudation* is the damage resulting from excess binder on the asphalt surface, evidenced by dark spots. Finally, the *patches* are related to the typical technique of treatment of a pothole damage. Pothole patching is used to hold the pavement damage until a more effective treatment can be placed.

Road damage detection using digital image processing have been study in the last years. Among all classes of damage, cracks are gained interest from researchers since it can lead, in the lack of road maintenance, to severe damage, as potholes. Intensity thresholding and filtering-based methods were studied in the past. For instance, a pavement crack detection method based on the Gabor filter is proposed in [7], and local binary patterns are investigated in [10,14]. Pixel thresholding is investigated in [15] and [3]. In [16], structural information is used to characterize cracks in pavements.

Due to problems in distinguishing noise or to filter background information from images, deep learning and convolutional neural networks (CNNs) have been widely used in the field of computer vision [17]. A CNN is a hierarchical and multi-layer feature extractor: each convolutional layer performs a convolution operation on the image input and passes the extracted features to the next layer [2, 5]. Batch normalization is performed on the output of the convolutional layers, whereby the extracted features are normalized by adjusting and scaling the artificial neuron activations. Max pooling operations shorten the input representations, and a softmax function translates a feature vector into a probability distribution. Lastly, a fully connected layer computes the score of each class and infers the category of the input image.

Zhang *et al.* [2] presented a pavement crack detection method that uses convolutional neural networks. Using patches from pavement pictures, taken using smartphone cameras, machine learning classifiers were compared with convolutional neural network models. Pauly *et al.* [18] investigated the influence of the number of layers (depth) of convolution networks and concluded that increasing the network depth can improve the classification accuracy. A road damage dataset aimed to deep learning tasks was proposed [19]. Zhu and Song [20] used the deep learning and transfer learning method to improve a pre-trained VGG16 model. Hammouch et al. [21] proposed a model for detecting cracks in Moroccan pavements using convolutional neural networks. The authors investigated two types of road cracks (alligator crack and longitudinal crack types) and concludes that is its important have a large dataset of images, mainly to detect longitudinal crack types. In [22], a CNN network architecture is used for detecting damage in roads. The authors used a road damage dataset [23] to train an CNN and the following classes of damage were addressed: longitudinal crack, transverse crack, alligator crack and pothole. In [3], the authors concluded that the classification performance of pavement crack detection algorithms is limited to images with a simple background and a single type of damage.

3. Methods

Damage images from asphalt pavements of Ponta Grossa City 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] was used. The LabPavi system[1] is a repository of images of pavement damage and related maintenance tasks. This repository was built using images from roads of Ponta Grossa City and is frequently updated by student engineers and researchers from Ponta Grossa State University (UEPG). All damage pavement images in this repository are associated with labels (such as crack, pothole or patch) and to a related set of maintenance tasks. Civil engineering students and their coordinators performed the labeling of the images [11].

Also, aiming to improve the accuracy of the classification algorithms, techniques were used to generate new images from the original images, a technique commonly known as data augmentation. The data set size is 333 samples, distributed by the following classes: pothole (83 images), crocodile crack (75 images), transverse crack (37 images), longitudinal crack (35 images), raveling (25 images), exudation (43 images), and patch (35 images). In this study, the

[1] LabPavi system is available at https://lcad.deinfo.uepg.br/labpavi

use of data augmentation techniques increased the number of samples to 700. The figure 2 illustrates a data augmentation process when using a pothole class of damage. All images were converted to grayscale and resized to 224x224 pixels in the last step of the image preprocessing.

(a) (b)

Figure 2 – A pothole type of damage image and an its corresponding image artificially generated using data augmentation.

Pre-trained models of artificial neural networks available in Keras and TensorFlow 2.9.1 were used. The Resnet50V2 and MobileNetV3 pre-trained convolutional networks were used to build classification models. Also, a modified version of the Resnet50V2 architecture was evaluated. In this modified version, three new convolutional dense layers and two dropout layers were included in the original topology, as illustrated in the code fragment in Figure 3.

```
model = tf.keras.Sequential([
    pretrained_model_without_top_layer,

    tf.keras.layers.Dense(28, activation='relu'),
    tf.keras.layers.Dropout(0.1),
    tf.keras.layers.Dense(14, activation='relu'),
    tf.keras.layers.Dropout(0.1),
    tf.keras.layers.Dense(num_of_classes),
])
```

Figure 3. Resnet50V2 architecture with additional layers in this topology. The object `pretrained_model_without_top_layer` represents the pre-trained network from tensorflow/Keras.

Transfer learning was used when training the CNN models. 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.

After training the classification models, some additional images from road damage were used to illustrate the capabilities of the final classification model. All machine learning experiments were carried out using a computer with a Ryzen 5 5600H processor, 16Gb of RAM and with RTX3050 video card with 4GB of memory.

4. Results

The performance metrics of the MobileNetV3 and the ResNet50 networks are presented in Tables 1 and 2. These results were obtained after 15 epochs. The Resnet50V2 network obtained better accuracy values (76%) than the accuracy values from the MobileNetV3 large network (68%). The learning curves for the outputs of the models are presented in Figures 4 and 5.

The performance metrics of the changed version of the RestNet50v2, named as RestNet50V2(M), are presented in Table 3. This network architecture achieved the better accuracy values compared with the MobileNetV3 and the Resnet50V2 architectures, mainly due to the additional dense and dropout layers.

All network models achieved better accuracy results for raveling, exudation, and pothole types of damage. When classifying cracks, all networks presented accuracy values near 50% and were unable to distinguish among distinct types of cracks with better accuracy values.

Table 1 – MobileNetV3 performance metrics for each class

Type of damage	**Accuracy**	**Recall**	**F1-score**
Pothole	0.70	0.78	0.74
Crocodile cracking	0.53	0.56	0.54
Transverse crack	0.60	0.57	0.59
Longitudinal crack	0.50	0.53	0.51
Raveling	0.85	0.88	0.87
Exudation	0.79	0.71	0.75
Patch	0.73	0.65	0.69
Macro avg	*0,67*	*0.67*	*0.67*
Weighted avg	*0.68*	*0.68*	*0.68*
Accuracy average	**68%**		

Table 2 – Resnet50 model performance metrics for each class

Type of damage	**Accuracy**	**Recall**	**F1-score**
Pothole	0.83	0.83	0.83
Crocodile cracking	0.77	0.56	0.65
Transverse crack	0.55	0.86	0.67
Longitudinal crack	0.62	0.53	0.57
Raveling	0.96	0.92	0.94
Exudation	0.94	0.71	0.81
Patch	0.74	0.82	0.78
Macro average	*0.77*	*0.75*	*0.75*
Weighted average	*0.78*	*0.76*	*0.76*
Accuracy average	**76%**		

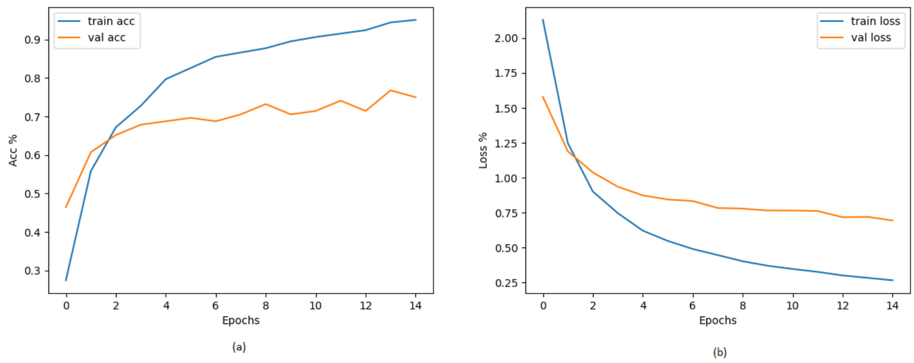

Figure 4. MobileNetV3 learning curves.

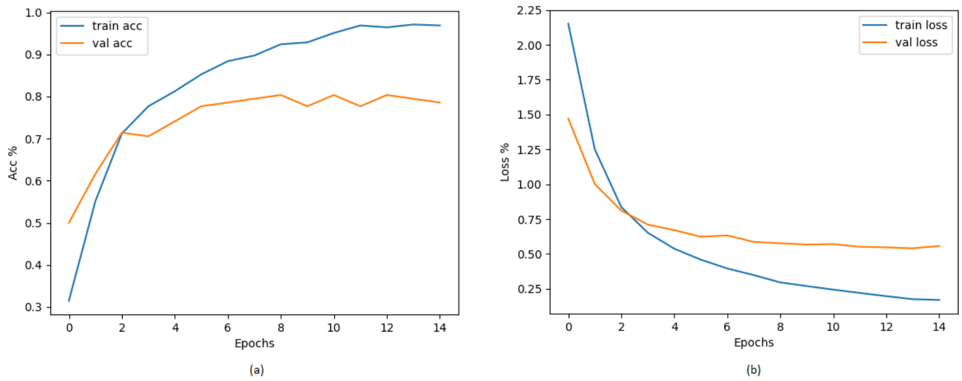

Figure 5: ResNet50 learning curves.

Table 2 – ResNet50(M) performance metrics

Type of damage	**Accuracy**	**Recall**	**F1-score**
Pothole	0.88	0.83	0.86
Crocodile cracking	0.69	0.61	0.65
Transverse crack	0.64	0.76	0.70
Longitudinal crack	0.68	0.68	0.68
Raveling	0.96	0.92	0.94
Exudation	0.90	0.86	0.88
Patch	0.83	0.88	0.86
Macro average	*0.80*	*0.79*	*0.79*
Weighted average	*0.81*	*0.80*	*0.80*
Accuracy average	**80%**		

The results of the classification of five images of road damage are presented in Figure 6. Images not used when training and validating the RestNet50(M) model were applied as input to the final classification model. The images (a), (b) and (c) correspond to hits, while figures (d) and (e) represent classifier errors since the first corresponds to a longitudinal crack and was classified as a fatigue crack and the second corresponds to a patch, classified as a pothole. The model classified all images correctly, except for the patch image. For this image, the model made a mistake and returned the classification as a pothole. Another problem verified was the difficulty of the model to differentiate the types of cracks; sometimes, when a crack image was presented, it could identify it, but was unable to differentiate its nature – crocodile, longitudinal, or transverse.

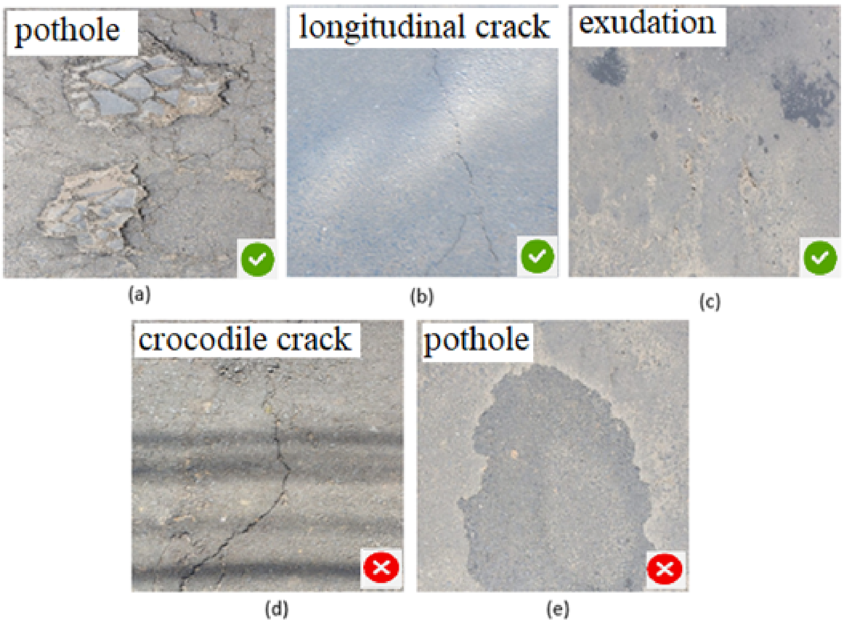

Figure 6: Testing the model with images not in training.

5. Conclusion

This paper presented an evaluation of convolutional neural networks aiming to detect road damage. The results indicated that the Resnet50V2 classifier was better than the MobileNetV3 Large model for the LabPavi dataset, achieving an accuracy of 77%, when classifying the seven types of damage addressed in this dataset. The MobileNetV3 model presented an accuracy of 69%. The changed model proposed in this paper, named as Resnet50V2(M), achieved an accuracy of 80%, better than the other models. The final model was saved, and not previously presented images were used as input. The model almost correctly classified the classes of damage. It was observed that for the crack classes, the model had difficulty in differentiating their types, for the patch class the model was unable to classify those that did not present similarity with the images contained in the training set.

Therefore, based on the experimental results, the Resnet50V2(M) model can be employed to detect damage in roads. The model presented values of accuracy over 80% for five classes of damage. The accuracy values for all crack damage subtypes were near 50%. Despite this, improvements can be done in the model and in the image's dataset, aiming to achieve better accuracy values. In future work, extensions in the classification model can 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 those presented in this paper.

6. References

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