Pavement Automated Condition Assessment Model Using Unmanned Aerial Vehicle and Convolutional Neural Network

Vinay Chawla, Carol Massarra, Husam Sadek, Zhen Zhu and Mohammed Sadeq

February 17, 2023

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Paper ID:28

Vinay Chawla
vinay.chawla@e2.com
E2 Consulting Engineers, Inc.
Los Angeles, CA, USA

Carol Massarra
massarrac19@ecu.edu
East Carolina University
Greenville, USA

Husam Sadek
husam.sadek@seeroeng.com
SEERO Engineering Consulting LLC.
Doha, Qatar

Zhen Zhu
zhuz@ecu.edu
East Carolina University
Greenville, USA

Mohammed Sadeq
mohammed.sadeq@seeroeng.com
SEERO Engineering Consulting LLC.
Doha, Qatar

ABSTRACT

Assessing pavement condition is essential in any efforts to reduce future economic losses and improve the pavement performance. The resulting data are used as a record to evaluate pavement performance and assess their functionality and reliability. Traditional pavement condition assessment approaches rely on expert visual inspection and observational information along with testing using specialized equipment. However, these approaches are challenging because of the cost associated with assessment, safety issues, and the accessibility restrictions, especially after natural hazard events. This paper aims to develop an automated classification model to rapidly assess pavement condition by classifying pavement distresses using image classification that is based on Convolutional Neural Network (CNN) model. High-resolution aerial images representing alligator and longitudinal cracks for flexible pavements are collected using Unmanned Aerial Vehicle (UAV) images. The results of the developed model indicate an accuracy of 96.7% in classifying the two categories of pavement distress, while the use of UAV provides flexibility and manoeuvrability to capture the necessary data without risking personal safety and provides operational benefits in relatively lesser time. The methodology behind the developed model will help to reduce the need for on-site presence, increase safety, and assist emergency response managers in deciding the safest route to take after hurricane events. Additionally, application of the model will enable pavement engineers in rapidly assessing the pavement damage, aid in making quick decisions for road rehabilitation and recovery and devise a restoration or repair plan.

Keywords: Unmanned Aerial Vehicle (UAV), Convolutional Neural Network (CNN), Flexible Pavement.

1 INTRODUCTION

Transportation, more importantly, road networks, are significant components of infrastructure, which greatly impact the economic and social well-being of a region as people heavily depend on them for their daily activities. Asphalt (or flexible) pavements are a vital part of the transportation networks. Acquiring critical information on the pavement damage through pavement condition assessment is essential, especially after hurricane events. This information helps gain knowledge about the underlying physical phenomena, examines the impact of a natural hazard on the pavement, assesses and mitigates the damage, determines the need for external assistance (Lindell et al., 2003), and aids in rehabilitation and alternative hazard management practices. However, pavement condition assessment is a very challenging process because it is expensive, protracted, and laborious, especially after hurricane events when access to the disaster-struck area is restricted (Morton et al., 2011).

Conventional ground-based approaches for pavement condition assessment mainly rely on expert human visual inspection and observational information along with testing using specialized equipment (Aksamit et al., 2011;Weinmann et al., 2004). These techniques are labor-intensive and time-consuming and require both field and laboratory testing, which may cause further damage to the pavements. Recent technological advancement in the form of Unmanned Aerial Vehicles (UAVs) has proven to aid in rapid data collection through aerial reconnaissance, provide emergency responses and humanitarian relief, facilitate aerial monitoring and damage evaluation (Estrada et al., 2019; Restas, 2015), especially for inaccessible areas (Floreano et al., 2015), and provide operational and economic benefits (Adams et al., 2010; Ezequiel et al., 2014).

Several studies have used image classification approaches to assess pavement conditions. These studies used either images collected from UAVs or from high- resolution cameras. (Ersoz et al., 2017; Gopalakrishnan et al., 2017; Ibragimov et al., 2020; Li et al., 2019; Zakeri et al., 2016) . A general deficiency within current pavement condition assessment approaches is twofold 1) limitation of image classification applications to either specific distress (cracking) or binary distress (crack or no crack), and 2) relying on image pre-processing to extract relevant information for the model. The advancement in technology and computer vision has made several progresses to reduce human effort in various fields, including civil infrastructure, creating possibilities for automatic pavement distress detection and classification. Hence, to rapidly identify and classify pavement distresses, novel non-traditional pavement condition assessment methods that use aerial images and are based on machine or deep learning classification algorithms are needed to be developed. In this paper, a convolutional neural network (CNN) is developed to classify two distress types of flexible pavements (i.e., alligator and longitudinal cracking) using aerial images collected from UAVs. The aerial images are captured using DJI Mavic Mini UAV and used in their raw form without pre-processing. Model performance is validating using a cross validation, and the model accuracy is expressed in terms of cross-classification rate (CCR).

2 METHODOLOGY

2.1 Data

The field data collection consisted of the acquisition of aerial images for pavement distress using Unmanned Aerial Vehicles (UAVs). Streets shown in Figure 1 with flexible pavements at East Carolina University (ECU) campus in Greenville, United States were selected with two types of distress (i.e., alligator and longitudinal cracks). The UAV flight was manually operated, and the recorded videos for the streets were captured in segments of single flights in one direction. Still, images were then extracted from the collected videos and cropped to represent the distresses in post-processing. The aerial images were manually labeled and classified into the two categories before inputting them into the model for training.

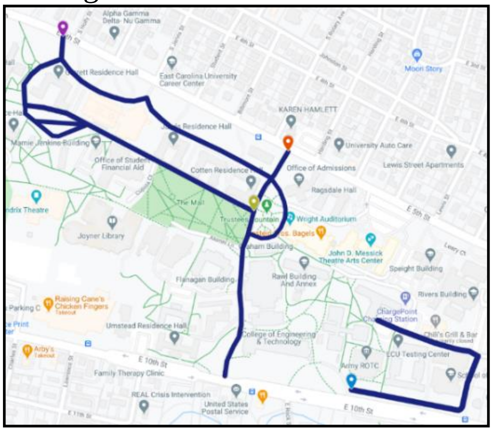

Figure 1: Locations of surveyed streets with pavement distresses on ECU campus

The resulting dataset consists of 100 high-resolution aerial images of two types of pavement distress (i.e., alligator and longitudinal cracking) and is randomly divided into training and validation sets. The training set comprises 70% of the original dataset and is used to train the model, and the validation set comprises 30% of the original dataset and is used to validate the model. Table 1 shows the pavement distress categories and number of images for the training and validation sets.

Table 1. Pavement distress categories and frequency of collected data for training and validation

Categories	**Training Set**	**Validation Set**	**Total**
Alligator Cracks	35	15	50
Longitudinal Cracks	35	15	50
Total	70	30	100

2.2 Model Training

To assess the pavement condition, image classification approach named Convolutional Neural Network (CNN) (Xie et al., 2017) is used. CNN classifies images by perceiving information from the raw input data (i.e., aerial images) and then learning from the features of these data. CNNs are being widely used for structural and road damage detection, pavement crack analysis, and pavement distress detection (Abdeljaber et al., 2018; Nie et al., 2018; Wang et al., 2018; Wang et al., 2017). Two primary operations, named as convolutions and pooling operations, and three secondary operations, named as ReLU activation, normalization, and dropout operations, take place in the feature extraction part. The rationale behind the primary operations is extracting features of the input images, while the rationale behind the secondary operations is enhancing the network performance. For features with two categories, probabilities of being in one of the two categories are calculated using logistic regression. For the two categories of pavement distress, the probabilities of being in one of the two categories are calculated as $p(\theta) = \frac{1}{1+exp^{\theta_j}}$, where; *p* is the probability associated with the class *j* during the observation *n*, and θ are the model parameters.

Due to a sample size restriction, a transfer learning approach using AlexNet, a pre-trained CNNs, is adopted and modified to match the smaller dataset (Gopalakrishnan et al., 2017). All the feature layers are considered for the modified network except the last two layers of the network (i.e., final fully connected and the softmax layers), which are initially configured to classify 1,000 objects. Therefore, to enable detection of the new two categories, the properties of these layers are modified. The fully connected layer is modified with new learning rate factor, and the softmax layer is customized using a logistic regression model. The input images are resized to 227×227 to fit the network requirements and prevent model overfitting.

The model is then trained using a stochastic descent gradient (SGD) algorithm with momentum. SGD updates the network parameter after each input during the training process to increase accuracy (Li et al., 2019). The mini-batch size is set to 35 images, which is number of images used per update during training. The maximum number of epochs , which is the number times that the learning algorithm will work through the entire training dataset, is set to 6, which is the number of complete updates of the entire dataset during training. The initial learning rate is set to 0.0001, and the feature layer is specified as drop 7. This layer extracts the distress features for the CNN model.

2.3 Model Validation

After the CNN model is trained, the predictive performance of the model is validated using cross-validation. Cross-validation is a technique to estimate the accuracy at which the model will perform in practice, illustrating the model's ability to predict new or unseen data. The validation set comprising 30% of the original dataset is used to perform the cross-validation. Model performance is assessed by finding the cross-classification rate (CCR), which indicates the percentage of pavement distress where the predicted distress class corresponds to the observed distress. The percentage of the correctly classified distress is calculated as $CCR = \frac{\sum_{d=1}^{D} F_{dd}}{\sum_{d=1}^{D}\sum_{c=1}^{C} F_{cd}}$, where F_{dd} are observations along the diagonal of the error matrix, and F_{cd} are all observations in the error matrix.

3 RESULTS

The CNN model was trained using a training set that counts for 70% of the original dataset. A randomly generated array of images for model training is shown in Figure 2

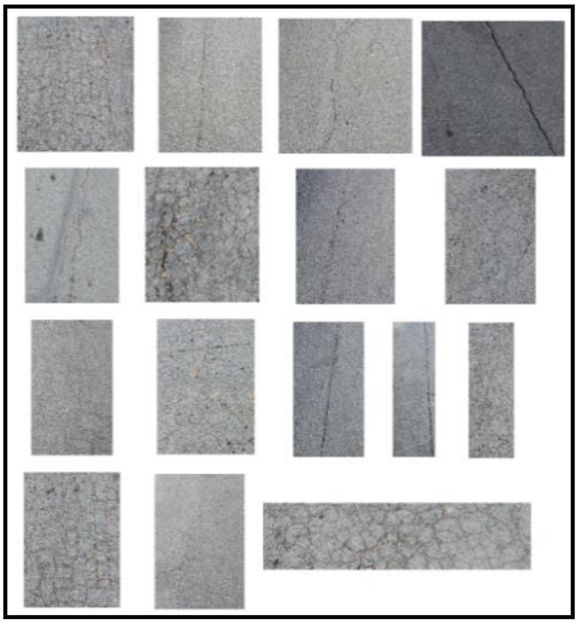

Figure 2: Array of random images of pavement distress used for model training

Results of model training are illustrated in Figure 3. The accuracy and loss during training are indicated with the blue and orange lines in the graph, respectively. The training accuracy gradually increases (i.e., from approximately 58% to 97%) as the algorithm passes through the dataset, with each epoch updating the parameters and learned features. Simultaneously, the loss during the training is reduced over the epochs increases (i.e., from approximately 1.1 to 0.18). The dotted line represents the accuracy and loss based on the validation data set for which a similar trend is observed (i.e., an increase in accuracy and decrease in loss) over the subsequent epochs.

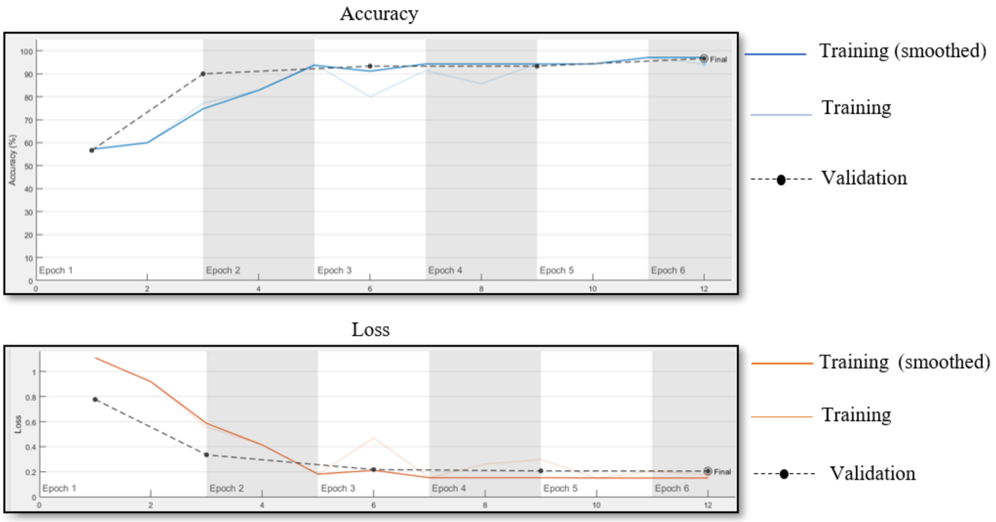

Figure 3: Traces of training and validation accuracy (top) and loss (bottom) during model training

The predictive performance of the CNN model was validated using a validation set that counts for 30% of the original dataset. The validation accuracy was represented every three iterations during the training in Figure 3. The overall model accuracy is represented by the confusion matrix (Table 2) and was found to be 96.7%, misclassifying only one image for a single class during model validation which indicated a satisfactory model performance.

Table 2 Target vs. output model confusion matrix and CCR for the pavement classification model

		Target Class		
Output Class		Alligator	Longitudinal	CCR 96.7%
	Alligator	14 (46.7%)	0 (0%)	
	Longitudinal	1(3.3%)	15(50%)	

The output class refers to the prediction from the model, whereas the target class refers to the actual label of the input image. The diagonal from left to right represents the correctly classified quantity (the number on top) and the correctly classified percentage (the percentage on bottom) of the corresponding categories.

4 CONCLUSION

The major contribution includes the use of advanced technology (Unmanned Aerial Vehicle) to collect aerial imagery for flexible pavement distresses and development of a deep learning classification model (Convolutional Neural Network) for the classification of the two pavement distresses (alligator and longitudinal cracks) in MATLAB.

The specific conclusions of this paper are:

- Based on the overall model accuracy, the developed CNN classification model proved to be a successful approach for automated pavement distress classification.

- The use of computer vision resulted in a reduction of human effort and time spent in the field for assessing pavement conditions.
- The finding from this research will aid transportation engineers in rapidly assessing the damages to pavements and devise a restoration or repair plan for pavements in a quick, effective, and economic manner.
- Application of the developed model will provide a platform to minimize the damage to the pavements, which is sometimes caused by traditional approaches for pavement assessment and make the examination process efficient and rapid.

Collecting data for various distresses and types of pavements and using techniques such as LIDAR or multispectral camera and creating 3D models for pavement distresses will aid in more realistic and improved evaluation of the pavement distresses. Expanding the methodology to a road network level and geo-referencing the location of pavement distress will provide an exact record of distress locations, which enable emergency responders to locate the safe routes for relief, especially after natural hazards and aid in decision-making regarding immediate repair and maintenance.

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