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Classification of Surface Pavement Cracks as Top-down, Bottom-up, and Cement-Treated Reflective Cracking Based on Deep Learning Methods

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ABSTRACT: The treatment and repair strategies of reflective and fatigue cracking that initiate at the pavement surface (i.e. top-down cracking) and at the bottom of the asphalt concrete layer (i.e. bottom-up cracking) are noticeably different. However, pavement management engineers are facing difficulties in identifying these cracks in the field as they usually appear in visually identical patterns. The objective of this study was to develop Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) applications to differentiate and classify top-down, bottom-up, and cement-treated reflective cracking in in-service flexible pavements using deep-learning models. The developed CNN model achieved an accuracy of 93.8% in the testing and 91% in the validation phases and the ANN model showed an overall accuracy of 92%. The ANN classification tool was

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developed based on variables related to pavement and crack characteristics including pavement age, Average Daily Traffic (ADT), thickness of Asphalt Concrete (AC) layer, type of base, crack orientation, and crack location.

Keywords: Artificial Neural Network, Convolutional Neural Network, Cement-treated Reflective Cracking, Bottom-up cracking, Top-down cracking

INTRODUCTION

Pavement condition evaluation is an essential component of Pavement Management System (PMS) in order to plan for necessary maintenance and rehabilitation activities and to maintain the road network in acceptable conditions (Tsai and Lai 2002). The timely detection and accurate quantification of pavement distresses also assist PMS engineers to forecast future pavement deterioration and to plan for needed repair strategies. Non-destructive pavement evaluation methods such as Ground Penetrating Radar (GPR) and laser technologies are powerful, efficient, and safe for highway agencies. Road surveying vehicles, which are equipped with computers, sensors, cameras, and lasers, are commonly used to automatically collect high definition pavement images and have found wide acceptance by highway agencies (Attoh-Okine and Adarkwa 2013). Using these vehicles, distresses such as cracking, rutting, faulting, and roughness are identified automatically from pavement images through computer vision and machine learning techniques (Tsai and Lai 2002; Attoh-Okine and Adarkwa 2013; Jang et al. 2017).

Cracking is a major failure mechanism in flexible pavements. Based on the initiation and propagation phases of the cracks, pavement cracks can be classified as bottom-up or top-down cracks, which have different treatment and repair strategies.

Therefore, the accurate and up-to-date identification and classification of pavement cracks allow pavement management engineers to allocate the required budget and to schedule the needed repair strategies. Recent advancements in machine learning methods including Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) have been used as effective and promising tools to evaluate flexible pavement conditions in terms of pavement cracking (Hoang et al. 2018).

ANNs are widely recognized as effective computational modeling tools to solve engineering problems because of the distinctive features such as data generalization capability, non-linearity, noise tolerance in the input data, and adaptability with complicated data patterns. These benefits of ANNs allow complex data fitting and facilitates model applicability to unlearned data (Elseifi and Elbagalati 2017). Recently, researchers have developed different image-based CNN models to efficiently classify pavement cracking. CNN is a powerful machine learning technique, which extracts different features as outputs from the input images for accurate classification (Tong et al. 2017). The CNN structure is typically architected with three layers including convolutional, pooling, and fully connected layers to examine the shape change complexity of pavement cracks (Li et al. 2018; Tong et al. 2017).

OBJECTIVES

The objective of this study was to develop ANN and CNN applications to identify and differentiate pavement surface cracks as top-down, bottom-up, and cement-treated reflective cracking using pavement characteristics and surface images. This will provide highway agencies intuitive tools for successful classification of the visually identical cracking patterns. Variables including pavement age, Asphalt Concrete (AC) thickness,

Average Daily Traffic (ADT), type of base, and orientation and location of cracks were used to develop the ANN classification tool. The CNN classification tool was developed to classify surface cracks solely based on pavement surface images.

BACKGROUND

Cracking Mechanisms in Flexible Pavements

Cracks in flexible pavements are either top-down or bottom-up based on the location of initiation and mode of propagation. In the past, pavement cracking was assumed to be bottom-up crack, i.e., initiate at the bottom of AC layer and propagate upwards to the surface. Yet, many studies were conducted in recent years to identify the time-frame of initiation, location, and major causes of the opposite mode of crack initiation and propagation, i.e., top-down surface-initiated crack. Studies have identified high surface horizontal tensile stresses due to tire loading as the major cause of top-down cracking and these cracks usually appear as longitudinal surface cracks in the wheel paths (Myers et al. 1988, Svasidisant et al. 2002). The identification of top-down cracking in the field and their consideration in pavement design methods are problematic compared to fatigue cracking, which is assumed to initiate from the bottom of the AC layers. Maintenance and rehabilitation programming for pavement asset management at the network-level can benefit significantly from the identification of TDC as a part of pavement condition surveys and evaluation. Myers et al. reported that pavement surface cracks appear as longitudinal cracks in the wheel paths and propagate to a depth ranging from just under the top surface to the full depth of the AC layer (Myers et al. 1988). Uhlmeier et al. noted that top-down cracking initiates after 3 to 8 years following construction in pavement sections that satisfy

structural requirements and that are properly designed for the projected traffic loads (Uhlmeier et al. 2000).

Park and Kim (2013) applied a viscoelastic finite element continuum modeling approach for the investigation of two sections in North Carolina, which exhibited top-down cracking (TDC). Field cores were used to measure the mechanical properties of the asphalt layers using the dynamic modulus test for linear viscoelastic characterization and the controlled crosshead cyclic direct tensile test for damage characterization. Results showed that the simulation prediction correlated positively with field performance as predicted from the level of damage in the field sections (Park and Kim 2013). Furthermore, Dhakal et al. (2021) investigated the mechanisms of TDC in flexible pavements using three-dimensional finite element (FE). The FE model was validated using stress and strain measurements obtained from the Louisiana Accelerated Loading Facility (ALF). Results showed that the initiation of surface cracking is due to the vertical shear strain within the AC layer exacerbated by high tensile strain at the surface due to loading. Furthermore, the incorporation of transverse tangential stresses increased the surface tensile strains by more than 50% regardless of the asphalt concrete (AC) layer thickness. However, longitudinal tire contact stresses had minimum effect (less than 10%) on the surface and bottom AC tensile strains (Dhakal et al. 2021). Similarly, Ling et al. developed a 3D FE model to simulate the propagation of TDC and to calculate the fracture parameter J-integral associated with the complex stress field in the pavement structure. Results showed that the J-integral is not uniform throughout the thickness of the asphalt layer and reaches its maximum value at a third of the thickness of the surface layer, which indicated that TDC can propagate rapidly until it reaches a third of the depth of the top layer (Ling et al. 2017).

Reflective cracking from CTB is another form of flexible pavement cracking, which initiates at the surface of the cement-treated base or subgrade layers and propagate through the AC layer as reflective cracking. CTB reflective cracks can be often confused with top-down and bottom-up fatigue cracking due to the similar mode of appearance. Shrinkage due to hydration of cement (autogenous shrinkage), chemical reactions of cement compositions with carbon dioxide (carbonation shrinkage), and drying of hardened concrete (drying shrinkage) are typical categories of shrinkage in CTB materials (Gribniak et al. 2008). The diffusion of water from CTB material into the surrounding environment causes volumetric change in the base layer, resulting in the development of tensile stresses. When these tensile stresses exceed the tensile strength of the material, shrinkage cracks start to appear, which subsequently propagate to the pavement surface as CTB reflective cracking.

Artificial Neural Network (ANN)

Artificial neural networks are parallel computing schemes that functions similarly to the mechanism of the human biological nature of neurons and can model complex problems (Elseifi and Elbagalati 2017). Generic and accurate ANN models can be developed with high accuracy to simulate numerical model components and to solve complex engineering problems (Karlaftis and Vlahogianni 2011). The learning ability of genetic flexible training algorithm in ANNs allows it to make decisions based on given inputs (Kim et al. 2014). ANNs provide robust models that can be continuously updated with new data and that are more accurate with large databases (Plati et al. 2015).

The neural network (NN) models have been considered powerful, cost-effective, and versatile computational approaches and have been widely used to identify the existing

pavement conditions including pavement roughness, cracking, rutting, and ride quality and to determine the future deterioration rates and maintenance strategies. Owusu-Ababio concluded that neural networks outperform multi-linear regression (MLR) models in predicting pavement conditions in terms of the pavement distress index (PDI) based on input variables including thickness of AC and base layers, pavement age, subbase conditions, and traffic level (Owusu-Ababi 1998). Van der Gryp et al. evaluated the performance of ANN to determine the visual condition index and estimate the overall pavement conditions; a multilayered feed forward ANN comprising of one hidden layer and 12 processing elements with a back propagation learning rule was used. The sigmoid function was used for the transfer learning, which presents the output between '0' and '1'. The pavement condition determination was based on distresses including cracking, patching, bleeding, pumping, and patching (Van der Gryp et al. 1998).

Owusu-Ababio performed a comparative analysis of back-propagation neural networks (BPNN) with one, two, and three hidden layers in predicting pavement cracking based on three input variables; namely, pavement age, AC thickness, and equivalent single axle load (ESAL). The author found that the use of one hidden layer BPNN was sufficient to achieve satisfactory results in cracking prediction (Owusu-Ababi 1998). Another study utilized back-propagation algorithm to train 16 ANN models with different transfer functions and varying hidden layers and neurons to forecast roughness, rutting, raveling, and cracking for low volume roads. The ANN models were observed to be efficient in forecasting pavement distresses with high goodness of fit of 0.98 and 0.97 in the testing and validation phases, respectively (Thube 2012).

Gajewski and Sadowski estimated the cracking behavior in flexible pavements using Radian Basis Function (RBF) and Multi-layer Perceptron (MLP) neural networks based on AC layer thicknesses, load value, and the elasticity modulus of each layer. The MLP neural network with seven hidden layers outperformed RBF neural network in terms of learning quality and crack propagation estimation (Gajewski and Sadowski 2014).

Convolutional Neural Networks (CNN)

In recent years, an increased number of studies investigated the application of computer vision techniques such as deep learning (DL) and machine learning (ML) to identify and classify pavement distresses. The four main DL architectures include Autoencoder (AE), Deep Convolutional Neural Networks (DCCNs or Deep ConvNets), Deep Belief Networks (DBNs), and Restricted Boltzman Machines (RBMs) (Gopalakrishnan et al. 2017). The convolutional neural networks are typically structured with three layers as convolutional layer, pooling layer, and fully connected layer. The local patches in the feature maps of the input images and the feature maps of convolutional layer are connected through a set of weights known as filter bank for accurate training of the model. The pooling layers are used to (i) select the spatial invariance by reducing the resolution of feature maps, and (ii) receive the maximum of a local patch of units in each feature map. The classification is finally performed by the fully connected layers, which connects together all units in the feature maps in form of a vector as in the traditional multi-layer perceptron (Gopalakrishnan et al. 2017; Li et al. 2018).

Fan et al. trained and tested CNN model to detect pavement cracks based on two databases consisting of 118 RGB images and 38 gray-level images, where 72 and 38 images were respectively used for training and testing of the database with RGB images,

and 24 and 14 images were respectively used for training and testing of the database with gray-level images. The developed CNN was modeled with 4 convolutional layers, 2 max-pooling layers, and 3 fully connected layers. The classification effectiveness was tested by conducting three experiments; training with RGB images and testing on gray-scale images, training with gray-scale images and testing on RGB images, and training and testing on a hybrid database. The authors observed the better generalization ability of CNN when trained and tested on different databases and highlighted the high potential of CNN to classify pavement images compared to the state-of-art methods (Fan et al. 2018). Wang and Hu developed CNN model to detect the pavement cracks and Principal Component Analysis (PCA) to classify the detected cracks as longitudinal, transverse, and alligator. The image pre-processing was achieved by converting the RGB images to gray-scale and segmenting the images into non-overlapping grids. The CNN consisted of two sets of convolutional and pooling layers with each consisting of 16 and 32 numbers of feature maps, and one fully connected layer. The developed approach of crack detection and classification achieved an approximate accuracy of 90%, 97%, and 98% to classify alligator, transverse, and longitudinal cracks, respectively (Wang and Hu 2017).

Nhat-Duc et al. conducted a study that compared the performances of edge detection techniques and CNN to detect pavement cracks. The models were trained and validated with 400 images of crack and non-crack labels. The accuracy of CNN, Sobel algorithm, and Canny algorithm were observed to be 92.1%, 79.9%, and 76.7%, respectively (Nhat-Duc et al. 2018). The use of ‘off-the-shelf’ features of well-established DCNN such as AlexNet, resnet, VGG-16, and GoogLeNet have proven to be a useful tool in the classification of domains where acquisition of large dataset is difficult as these

networks are pre-trained using large-scale annotated natural image datasets (Gopalakrishnan et al. 2017). This approach, also known as transfer learning, enables the learning ability of pre-existing models trained on large data to deploy on a new domain consisting of a smaller size dataset. Li and Zhao successfully implemented AlexNet to detect pavement cracks; the authors modified the pre-trained AlexNet with five convolutional layers, three max-pooling layers, and three fully connected layers. The CNN also employed dropout after first two fully-connected layers and local response normalizations after first two pooling layers (Li and Zhao 2019).

Contribution of the Study

The literature review has identified neural network-based technologies as promising methods to evaluate existing pavement conditions based on identification and classification of different pavement distresses. The present study was conducted to address some limitations in the existing state of art with respect to surface cracking as follows:

- Even with huge advancement in the field of distress detection and classification through deep learning techniques using pavement images, none of the previous studies have classified surface pavement cracks as top-down, bottom-up, and CT reflective cracks. Hence, this study developed neural network models to classify surface cracking into these categories.
- Limited studies have developed accessible applications that can be routinely used by pavement engineers and highway agencies to classify pavement distresses. This study developed implementation-ready windows-based and software-based

applications to classify pavement cracking by integrating sophisticated algorithms that can be used by agencies without advanced knowledge of these algorithms.

METHODOLOGY

Data Description

In-service flexible pavements that developed top-down, bottom-up, and cement-treated reflective cracking were first identified to extract the pavement images for each class. The acquired images were pre-processed using different techniques to train, test, and validate the CNN model. Furthermore, variables representing pavement and crack characteristics including age of the pavement, thickness of AC layer, ADT, base type, and orientation and location of crack, were also collected to train, test, and validate the ANN model. The data collection and image pre-processing procedures adopted in the study can be found elsewhere (Dhakal 2020).

Images for CNN Classification

The Louisiana Department of Transportation and Development (LaDOTD) employs the Automatic Road Analyzer (ARAN) system to survey the pavement network every two years and to collect continuous high definition pavement right of way and surface images. These images, which are stored in the PMS inventory, were used to develop the CNN model. Top-down cracks were validated in the field with coring before images were collected for the model development. The characteristics of these cracks including orientation, location, and years of appearance were taken into consideration for the accurate identification of the sections with top-down cracks before validating with pavement cores. The video survey tool available in PMS was used to first identify the sections with typical

cement-treated reflective and bottom-up cracking. The identified sections that developed the cracks at specific locations were then projected back to previous years' surveys for the same locations to collect the images during early development phase of the cracks. The details on identification and verification of pavement sections with cracking can be found elsewhere (Dhakal 2020).

Field Validation of Pavement Cracking

Pavement cores were obtained along the wheel path to validate the sections with top-down cracking. The location coordinate of the sections with top-down cracks was first identified from the project maps in PMS such that these locations corresponded to the pavement images locations obtained from PMS for image analysis. The cores were extracted at the tip of the longitudinal cracks such that the orientation and propagation of the cracks could be verified, see Figure 1. The drilled holes at the sites were carefully investigated to validate the top-down propagation of the cracks for the cores that fragmented during coring. As shown in the figure, the cracks started at the pavement surface and propagated downward through the AC layer.

Pavement Data for ANN Classification

The ANN input layer was fed with the simplest inputs set consisting of six different variables that are readily available to the PMS engineers and that would provide acceptable accuracy. Different classes were defined for each input variable and assigned a numerical value for each class. The classes and assigned numerical values for the input sets is presented in Figure 2; the assigned numerical values are represented by the numbers in front of each class.

ANN Classification Model

The ANN crack classification model for this study was built using MATLAB programming language because of its latest technology, computational efficiency, and simplicity in coding. Figure 3 presents the structure of the feed forward ANN model, which is frequently used for non-linear data modeling. As shown in this figure, ANN consisted of the input layer with six neurons to incorporate six different inputs and the target layer consisted of three neurons to incorporate the corresponding prediction classes. The adequate correlations between the inputs and targets were established with ten neurons in the hidden layer that connected each neuron in the input and target layers. An iterative process was used to select the number of neurons in the hidden layer such that the network performance is not affected and the least number of hidden neurons are selected. The error optimization in the learning and training phases of ANN was achieved using a back-propagation algorithm, which calculates the weights and biases to match the desired output (Elseifi and Elbagalati 2017). Equation (1) presents the error function (E) that was used to calculate the error from the network output (y).

$$E = \frac{1}{2} (t - y)^2 = \frac{1}{2} [t - f(w, b, x)]^2 \quad (1)$$

where 't' is the target value, 'w' and 'b' are the weights and biases respectively, and 'x' represent the independent variables.

The weighted sum at each neuron was converted into a new input value and transferred to the next layer using an activation function. The transfer functions are the differentiable non-linear functions, which allow the neural network to acquire non-linearity. In this study, the sigmoidal function, which presents the output value between 0 and 1, was used for all

the layers. The steps of the ANN back propagation process using a single hidden layer with the sigmoid activation function can be summarized as follows (Mitchell 1997):

1. Create a feedforward network with input nodes (n_i), hidden nodes (n_h), and output nodes (n_o);
2. Initialize all weights to small random numbers;
3. For each training iteration:
  - a. Compute the output values of each output node using the feedforward network.
  - b. Propagate the error backwards through the network:
    - i. For each output node (k), calculate delta, defined as follows:

$$\delta_k = o_k(1 - o_k)(t_k - o_k) \quad (2)$$

where:

δ_k = delta term for each output node, k

o_k = output value for each output node, k , predicted deflection

t_k = target value for each output node, k , measured deflection.

- ii. For each hidden node, calculate its delta, defined as follows:

$$\delta_h = o_h(1 - o_h) \sum_{k \in out} w_{kh} \delta_k \quad (3)$$

where:

δ_h = delta term for each hidden node, h ;

o_h = output value for each hidden node, h ;

w_{kh} = weight between hidden node, h , and output node, k ;

δ_k = delta term for each output node, k .

- iii. Update each weight in the network as follows:

$$w_{ji} = w_{ji} + \eta \delta_i x_{ji} \quad (4)$$

where:

w_{ji} = weight between node i and node j;

η = learning rate;

δ_j = delta term for each node, j;

x_{ji} = output value from node i to node j.

CNN Classification Model

The CNN classification model was developed using DL technology using the transfer learning and domain adaptation approach. The classification model was developed based on a pre-existing CNN model; the pre-trained AlexNet (Krizhevsky et al. 2012) model, which was trained and validated with an extensive image database. The model was modified to consist of 5 convolutional layers, 3 max-pooling layers, and 3 fully connected layers as shown in Figure 4. Equation (5) and Equation (6) present the mathematical expressions to represent the convolutional and pooling operations (Sugomori et al. 2017):

$$z_{ij}^{(k)} = \sum_{c=1}^C \sum_{s=0}^{m-1} \sum_{t=0}^{n-1} w_{st}^{(k,c)} x_{(i+s)(j+t)}^c \quad (5)$$

where,

$m \times n$ = filter size of the convolution;

C = the number of channels of the image;

W = filter weight; and

k = index of the filter.

$$y_{ij}^{(k)} = \max (a_{(l_1, i+s)(l_2, j+t)}^{(k)}) \quad (6)$$

where,

l_1 and l_2 = the size of pooling filter; and

$s \in [0, l_1]$, $t \in [0, l_2]$.

The pavement images were first labelled as top-down, bottom-up, or CT reflective cracking before training the pre-trained classifier to identify the surface cracks. The training process generates a CNN classifier which classifies the surface cracking using the sliding window

(Li and Zhao 2019). The feature sets for each crack class in the developed CNN model are generated automatically based on the training images to classify the pavement cracks accordingly.

ANN and CNN Applications

Application Formulation

The commercial MATLAB, which provides a design toolbox (MATLAB App designer) to develop standalone windows-based and MATLAB-based applications, was used in this study. The required dependencies for the developed applications were assembled using the MATLAB compiler, which also generates the installation file for the end users. The ANN and CNN applications were developed in MATLAB 2019a platform in a computer with Intel Core i5-4590S microprocessor and 8GB of RAM. The procedure adopted to formulate the applications is explained in this section.

Create Input and Output Components

The input and output components were created by using app designer component library that provides sliders, push buttons, drop down lists, numeric edit fields, and components to present figures, which can be easily dragged and dropped into the canvas. These components allow the user to define the inputs and the application to present the results.

Create a Callback Function

The user interface (UI) components created in the first step were then assigned with specific functions known as callbacks, which are executed when the user interacts with the UI components. The application stores the defined inputs once the user interacts with the UI components. The ANN code to classify pavement cracks into three classes was

incorporated using the callback function created for the 'Results' push button component. The neural network is first trained when the user clicks the 'Results' push button. Then, the classification results for the respective inputs defined by the user are displayed in the 'Table' component as shown in Figure 5.

Create Standalone Application

The standalone application was created using MATLAB Compiler, which generates an installation file and incorporates both the standalone application and all the required dependencies. The end users can access the application after running the installer generated by the compiler without the need for MATLAB in their computer. Figure 5(a) presents the interface to classify the pavement cracks using the ANN model. The results of ANN classification are displayed in the table with assigned class and net error with a description in yellow colored boxes.

Create MATLAB-Based Application

An application that presents both CNN and ANN results was also created using the MATLAB compiler by adding a section with 'CNN Result' as presented in Figure 5(b). The CNN classification algorithm was incorporated along with the image processing algorithm in the 'Open Image' push button such that the application processes the image and presents the results of CNN classification for the given image at once. However, this application requires the users to install a licensed version of MATLAB on their computer.

Steps in the CNN and ANN Windows-Based Application

Four major steps are conducted when running the ANN and CNN windows-based application, which are described in this section.

Step 1: Open Image

The 'Open Image' push button allows the users to browse and open the digital pavement image on their computer for image processing; see Figure 6(a).

Step 2: Image Processing

Once the user opens the digital image, the application processes the raw pavement image such that the orientation and location of cracks can be identified and used as input for the CNN model. The image processing algorithms including intensity normalization, median filtering, morphological erosion, and contrast enhancement are incorporated to the 'Open Image' push button directly. Hence, once the user opens the image using the push button, the application automatically processes the image. Figure 6(b) illustrates the image processing procedure in the application.

Step 3: Enter Inputs for ANN Classification

The ANN application requires the users to define six different inputs for the selected pavement section, which are age of the pavement, thickness of AC layer, type of base, ADT, orientation of the crack, and location of the crack. Numeric edit field components were created for pavement age, AC thickness, and ADT, which allows the user to enter the respective values. The user then defines the type of base, and orientation and location of the cracks using the drop-down menu. The base type drop-down menu allows the user to select between cement-treated base, untreated base, and PCC. The crack orientation allows the user to select between longitudinal, transverse, and both longitudinal and transverse. The crack location drop-down menu allows the user to select wheel path or outside wheel

path for longitudinal crack and any location for transverse or transverse and longitudinal crack.

Step 4: Results

The ANN classification code is incorporated in the 'Results' push button in the interface. The corresponding class of the given pavement crack can be obtained with one click of the button. The result of the classification is displayed in terms of number as '1', '2', or '3' where 1 indicates bottom-up, 2 indicates CT reflective, and 3 indicates top-down cracking. The net error is also displayed along with the assigned class, which indicates the chance that a crack with given properties belong to other classes than classified. In case of the MATLAB-based application, the results of the CNN classification are displayed in 'CNN Result' component once the users open the image. The pavement crack classification with CNN and ANN is presented in Figure 6(b).

RESULTS AND ANALYSIS

Classification Accuracy of ANN and CNN Models

The data processing and the development of ANN and CNN classification models were achieved using a computational tool available in MATLAB 2019a. The six input variables for 150 pavement images were divided into 70%, 15%, and 15% for training, validation, and testing, respectively. The training process was halted when the validation set error stopped decreasing to avoid data overfitting. The testing data, which had no effect on the training, were used to provide independent measure of the network performance. The ANN classification model achieved an accuracy of 91.3% in the testing and validation sets with an overall prediction accuracy of 92% indicating its effectiveness to correctly predict the

crack types, which initiate at different locations in the pavement. Figure 7 presents the results for the training, testing, validation, and overall steps for the ANN classification in terms of the confusion matrices. The numbers and percentages of falsely and correctly predicted classes between the output and target classes are respectively represented by the unshaded and shaded areas in the matrices.

The LADOTD PMS inventory was used to create a data set consisting of 350 images of different pavement sections to develop the CNN model. It is relevant to note that the data set was limited by the number of cores that were extracted from the field to validate the type of cracks identified at the surface. These images were pre-processed using an automated preprocessing tool consisting of five major steps namely image acquisition, median filtering, morphological erosion, contrast enhancement, and background subtraction. The images were then randomly divided into 60%, 25%, and 15% for training, validation, and testing, respectively. For the raw pavement images, the model achieved a low accuracy of 61.7% on testing and 73.4% on validation phases. When the images were preprocessed, the developed model achieved an overall accuracy of 93.8% and 91%, respectively, see Figure 8. The increase in accuracy was expected as image processing enhanced the pavement cracks from other factors in the original pavement image including excessive pavement noise, background illumination, pavement marking, and spots and stains.

Case Studies

This section demonstrates the application of the CNN and ANN models along with the Windows application to a number of field sections in order to classify the pavement cracking as either top-down, bottom-up, or cement-treated reflection cracking.

Section 058-02

The pavement section is located on St. Tammany Parish (Parish 52) of Hammond district (District 62). The length of the section was 7.51 miles; the pavement was structured with 8 in. AC and a 6 in. stabilized granular base over a 5 in. clay subbase and clayey subgrade. An asphalt concrete overlay was applied within the pavement preservation program for a sub-section with begin log mile of 0 and end log mile of 7.51. The final inspection date of the project was 12/6/2012. The section carries an ADT of 4,700. Top-down cracking initiated on the pavement section in 2016, which was validated with field coring. The longitudinal cracks appeared on the wheel path as shown by the preprocessed image. Figure 9(a) presents the results of CNN and ANN classification. As shown in the figure, both CNN and ANN successfully classified the pavement cracking as top-down cracking.

Section 011-04

The pavement section is located on Caddo Parish (Parish 09) of Bossier City district (District 04). The length of the section was 14.13 miles and the pavement section was structured with 8 in. AC and a 6.75 in. red sand with gravel base over a clayey subgrade. An asphalt concrete overlay was applied within the pavement preservation program for a sub-section with begin log mile of 0 and end log mile of 5.02. The final inspection date of the project was 10/5/2005. The section carries an ADT of 1,000. The section developed pavement surface cracking at the year 2014. Figure 9(b) presents the results of CNN and ANN classification. The cracks were not clearly visible on the preprocessed image due to excessive noise in the original image. The zoomed-in preprocessed picture showed longitudinal cracks on the wheel path. As shown in the figure, both CNN and ANN classified the pavement cracking as bottom-up cracking.

Section 857-63

The pavement section is located on Vermilion Parish (Parish 57) of Lafayette district (District 03). The length of the section was 10.79 miles; the pavement was structured with 3.5 in. AC and 9.5 in. cement stabilized sand clay gravel base over a clay subgrade. A base stabilization and asphalt overlay were applied for a sub-section with begin log mile of 0.65 and end log mile of 10.85. The final inspection date of the project was 5/28/2013. The section carries an ADT of 2,300. Top-down cracking initiated on the pavement section in 2015, which was validated with field coring. The longitudinal cracks appeared on the wheel path as shown in the processed image. Figure 9(c) presents the results of CNN and ANN classification. As shown in the figure, both CNN and ANN successfully classified the pavement cracking as top-down cracking.

Section 003-10

The pavement section is located on Acadia parish (Parish 01) of Lafayette district (District 03). The length of the section was 11.367 miles; the pavement was structured with 6 in. AC and a 7.5 in. Portland Cement Concrete (PCC) base over a clay subgrade. An asphaltic concrete overlay was applied for a sub-section with begin log mile of 6.28 and end log mile of 11.377. The final inspection date of the project was 8/13/2012. The section carries an ADT of 6,700. The section developed pavement surface cracks in 2016. Figure 9(d) presents the results of CNN and ANN classification. As shown in the figure, both CNN and ANN classified surface cracking as cement-treated reflective cracking.

Section 014-06

The pavement section is located on Rapides Parish (Parish 40) of Alexandria district (District 08). The length of the section was 13.21 miles; the pavement was structured with 9 in. AC and an 8.5 in. cement stabilized sand shell base over 9 in. PCC and a clayey subgrade. A cold planning asphaltic concrete and asphaltic concrete wearing course was applied for a sub-section with begin log mile of 3.44 and end log mile of 10.75. The final inspection date of the project was 5/8/2008. The section carries an ADT of 7,800. Cement-treated reflective cracking initiated on the pavement section in 2016. Figure 9(e) presents the results of CNN and ANN classification. As shown in the figure, CNN successfully classified the pavement cracking as cement-treated cracking while ANN mistakenly classified the cracking as bottom-up cracking.

SUMMARY AND CONCLUSIONS

The study developed and validated ANN and CNN applications to classify pavement cracking into three classes as top-down, bottom-up, and cement-treated reflective cracking. ANN application was developed based on pavement and crack characteristics while the CNN application was developed based on a model that was trained and validated using pavement images. Based on the results of the study, the following conclusions can be drawn:

- The ANN model showed an acceptable decision prediction accuracy of 92% indicating its effectiveness to classify the surface cracks that initiate at different locations in the pavement.

- The CNN model achieved an accuracy of 93.8% in training and 91% in validation phases. Based on these measures, the approach adopted based on the pre-trained CNN model (AlexNet) was found to be effective to classify pavement crack automatically.
- Based on the ANN classification model, a windows-based application was developed that allows the user to perform crack classification without installing MATLAB in their computer.
- An application that presents both CNN and ANN classification results was also developed by incorporating CNN classification algorithm into an UI component; however, this application requires the user to install a licensed version of MATLAB on their computer.

The use of the developed applications was successfully demonstrated for in-service pavement sections. While this study is one of the first attempts to classify pavement cracks with respect to their initiation and propagation, further improvement and training of the models is recommended to increase the crack classification accuracy.

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