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Remote Sensing and Neural Network-Driven Pavement Evaluation: A Review

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Abstract
This review paper aims to evaluate the remote sensing and neural network-driven pavement evaluation (RSNNPE) techniques. The collected studies were published in recent years and mainly relate to pavement distresses detection, classification, and quantification. The data collections were conducted by remote sensing and non-destructive techniques, including photography, hyperspectral imagery, satellite imagery, photogrammetry, laser scanning, ground penetrating radar, and laminography. The data analysis was conducted by neural network (NN) modeling, image filtering, threshold segmentation, template matching, SVM, and random forest. The NN architectures include MLP, RNN for structured data; CNN, Faster R-CNN, NIN for 2D/3D imagery patch-wise or object-orientated pavement distresses detection; and FCN, U-net, SegNet, PSPNet, DeepLabv3+, Mask-RCNN, DeepCrack, CrackSeg, FPHBN, CrackGAN for 2D/3D imagery pixelwise segmentation. Moreover, this paper discusses drone photogrammetry-based data acquisition, data preparation, and NN architecture selection for pavement evaluation. Based on the results of the review, future research recommendations are proposed.

Keywords
Pavement Distress Detection, Remote Sensing, Neural Network Modeling, Photogrammetry, Literature review.

1. Introduction

Using destructive testing techniques to evaluate pavement conditions is still necessary for some specific objectives, such as inspecting the source of the problematic layer or layers and to acquire materials for further laboratory testing, however the engineering, construction and operation community (ECO) has adopted and developed several remote sensing and neural network-driven pavement evaluation (RSNNPE) approaches to conduct pavement evaluation in non-contact and non-destructive ways with advantages of cost-effectiveness, staying up-to-date, and limited traffic regulation requirements. Previous reviews summarized well the flexible pavement cracking detection, classification and quantification (Zakeri et al., 2017), pavement distress classification and detection (Ragnoli et al., 2018), and pavement asset management systems (Peraka & Biligiri, 2020). In this review, the reviewed studies include 1 technical report, 1 Ph.D. dissertation, 1 preprinted article, 28 peer-reviewed journal articles and 5 peer-reviewed conference papers. The majority of journal articles are from ECO's research publications, such as *Automation in Construction*, *Journal of Computing in Civil Engineering*, and *Construction and Building Materials*. Moreover, the computer science and electronic engineering, remote sensing and geoscience, and biomedical engineering communities are continually improving and developing image processing algorithms and neural network (NN) models for crack detection in surfaces of buildings, structures, and pavements.

2. Objectives for Pavement Evaluation

The reviewed studies have 156 author keywords. Fig. 1 shows a 20-category clustering results of the author keywords, based on the character lengths of the 1st, 2nd, 3rd , and 4th words. In the reviewed studies, "crack detection" occurred 12 times and is the most common keyword of the research objective, which is not only specific to pavement cracks, but also contains a wide variety of concrete surfaces, such as bridge structures, building walls, and sidewalks. After combining "convolutional neural network" (Dung & Anh, 2019; Ji et al., 2020; Kearney et al., 2020; Zou et al., 2019), "CNN" (Augustaukas & Lipnickas, 2019), "convolutional neural network (CNN)" (Ali et al., 2019),"convolutional neural networks" (Protopapadakis et al., 2019), "deep convolution neural network" (Q. Yang et al., 2020), and "deep convolutional neural network" (Huyan et al., 2019; Zhou & Song, 2020a), the "convolutional neural network" is the second most common keyword, occurring 10 times, and is the most common keyword of the data analysis method, but some of them did not exactly fit with the utilized or developed NN model in these studies. Other common keywords include: "deep learning"-7 times, "pavement crack detection" and "UAV" (unmanned aerial vehicle, or drone)-4 times, " fully convolutional network," "machine learning," "photogrammetry" (or structure from motion, SfM)-3 times, "3d mesh model," "computer vision," "image processing," "laser-scanned range image," "non-destructive testing," "pavement crack," "pavement distress," "remote sensing," "terrestrial laser scanning (TLS)," "U-net"-2 times.

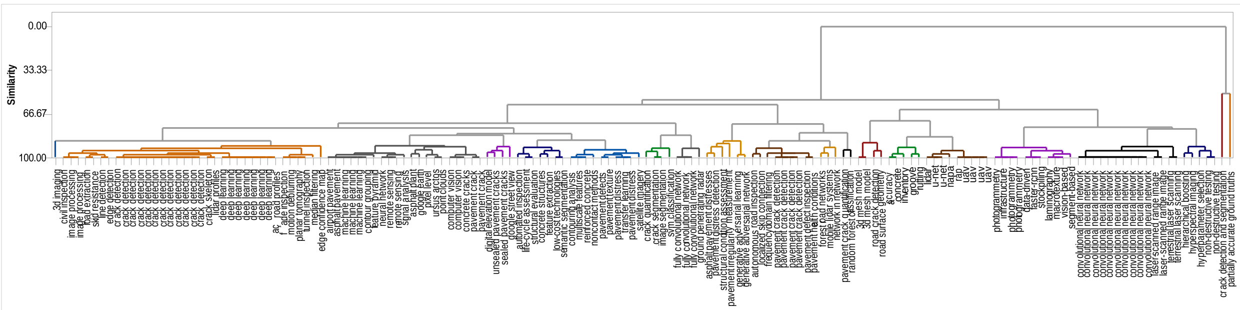

Fig. 1. Keywords relation.

Based on those keywords of research objectives, data collection and analysis methodology, it is safe to conclude that the RSNNPE research objectives are still focused on 2D imagery based pavement distress inspection, while starting to move to pavement performance evaluation (Puppala & Congress, 2019) and pavement irregularity measurement (Barbarella et al., 2019) with 3D models. The pavement distresses detection is still focused on cracking detection, while starting to move to crack segmentation (Alipour et al., 2019; Dung & Anh, 2019; Ji et al., 2020; Kalfarisi et al., 2020) and cracking quantification (Ji et al., 2020; Kalfarisi et al., 2020; Weng et al., 2019). The 3D data collection methods were not limited to terrestrial laser scanning and SfM, which also includes non-destructive techniques, such as ground penetrating radar (GPR) (Sukhobok et al., 2019; Tong et al., 2020) and planar tomography (Moosavi et al., 2020). The use of Google Street View (Maniat, 2019) and satellite imagery (Ashtiani et al., 2019; Kearney et al., 2020) started to develop cost-effective pavement evaluation tools. Furthermore, the detailed relationships between pavement evaluation objectives and data sources are summarized in ***Section 3***, and data analysis methods are summarized in ***Section 4***.

3. Remote Sensing Data Acquisition Techniques for Pavement Evaluation

The reviewed studies have achieved various pavement evaluation objectives with the remote sensing and non-destructive testing techniques in pavement surface properties evaluation, pavement geometrical properties evaluation, and other related objectives. There were different types of data sources used in different pavement evaluation objectives, while the most common two types are: a) 2D imagery that was captured by digital cameras (smart phones) that were carried by operators, mounted on vehicles, and carried by drones (Ali et al., 2019; Dadrasjavan et al., 2019; Dorafshan et al., 2019; Y. Liu et al., 2020); b) 3D imagery that was directly generated from laser line profile sensors (Edmondson et al., 2019; A. Zhang et al., 2019; Zhou & Song, 2020a, 2020b), and converted from point clouds by 3D laser scanner (Edmondson et al., 2019) and SfM photogrammetry (Edmondson et al., 2019; Roberts et al., 2020).

3. 1 Digital Camera and Photogrammetry

Digital Camera. Digital Camera is the most common technique in pavement cracking detection in the reviewed studies. 2D images contain crack and non-crack backgrounds that can be captured by a hand-held or vehicle mounted digital camera with its movement over the target area of a roadway, such as the data sets of pavement crack images collected from the campuses of Harbin Institute of Technology (Ji et al., 2020), Huazhong University of Science (Z. Liu et al., 2019), and Temple University (F. Yang et al., 2020). Another approach is capturing 2D images through a drone mounted digital camera (Ali et al., 2019; Dadrasjavan et al., 2019; Dorafshan et al., 2019; Y. Liu et al., 2020), which can minimize manual operation in most conditions, but is not a safe choice for surveying a roadway with a high traffic volume. Moreover, when the timeliness does not matter, according to studies (Maniat, 2019; Mohammed, 2017), extracting roadway images from Google Street View (images are captured by vehicle mounted 360° digital cameras) could get the accurate pavement cracking detection results without traffic regulation. 2D imagery typically has Red/Green/Blue (RGB) 3 channels and can be converted to 1-channel grayscale images. In a crack image, crack regions have higher pixel intensity standard deviation values and lower mean intensity values than the non-crack regions (Oliveira & Correia, 2013).

SfM Photogrammetry. 2D images can be used to create a 3D point cloud with the SfM method, such as using a commercial photogrammetry software, Agisoft PhotoScan (Edmondson et al., 2019; Roberts et al., 2020). The photogrammetric point cloud would be converted to digital elevation model (DEM) (Puppala & Congress, 2019) (for roadway and ground surface) and 3D mesh model (Kalfarisi et al., 2020; Roberts et al., 2020) (for other objects), and be translated to 3D imagery that is named as surface height plot (Edmondson et al., 2019), depth map (Roberts et al., 2020). The pixel value of a 3D image represents the elevation information instead of the intensity value of a 2D image. Then, pavement geometrical information, such as the longitudinal slope and transverse slope of a roadway, would be determined (Puppala & Congress, 2019), the detailed surface shape and profiles of the pavement would be reconstructed (Edmondson et al., 2019; Roberts et al., 2020), and the crack dimensions (width, length and depth) would be measured from a scale aligned 3D mesh model (Kalfarisi et al., 2020). However, to set the ground sampling distance (GSD) around 0.5-mm, the camera or the drone should be at close-range (about 1.5-m) to the target objects' surfaces (Kalfarisi et al., 2020; Roberts et al., 2020). That means the drone-carried camera is unable to complete the roadway image acquisition tasks without traffic regulation. Otherwise, flying a drone at an altitude of 60-m (with GSD=3.6-cm) would be suitable for cracking detection (Dadrasjavan et al., 2019) but not precise enough for measuring a crack's width.

Hyper Spectral Camera. Hyper spectral cameras (HSC) are generally used to measure the spectral range of 350nm-2500nm, which contains spectra beyond the human vision range (400nm-700nm). In the range of 450nm-550nm, the spectral response is sensitive to the change of metal oxides, thus the areas of cracking and potholes (where the interior materials of pavement, including minerals and hydrocarbons, are exposed) have a different spectral response from the areas of undamaged pavement surfaces (which contains metal oxides). The accurate HSC imagery should be captured when pavement surfaces are clean, such as rushed by rains (Abdellatif et al., 2019). The resolution of the HSC, like 1000×1000-pixel in (Abdellatif et al., 2019), is much smaller than cost-effective optical digital cameras, which leads to the HSC not being suitable for cracking quantification beyond close-range as well. In addition, infrared thermography has low resolution; otherwise, it can be carried by a drone to survey a highway at midnight when the traffic volume is low.

Satellite Imagery. High resolution satellite imagery, such as the RapidEye satellite imagery (5-m resolution), is useful in road network evaluation and has been used to extract road networks from forested areas in Western Canada (Kearney et al., 2020). In addition, one study (Ashtiani et al., 2019) utilized Google Earth DEM to estimate the reclaimed asphalt pavement (RAP) stockpiles volume in Washington State. Google Earth contains satellite and aerial images and has the resolution range from 15-m to 15-cm (Google, 2020; Wikipedia, 2020), which makes it a suitable data source for pavement evaluation if the high-resolution images are available at the target areas.

3. 2 Laser Scanner

Terrestrial Laser Scanner and UAV LiDAR. Laser scanner technique is based on light detection and ranging technology (LiDAR). The most commonly used system is the terrestrial laser scanner (TLS), which extends its coverage area with multiple scanning stations on the target area (Barbarella et al., 2019; Puppala & Congress, 2019). Another approach is using mobile LiDAR systems without the setting-up procedures of TLS at each singular scanning station, such as the vehicle mounted mobile LiDAR with an accuracy of 10-mm (Gézero & Antunes, 2019), and the UAV LiDAR with an accuracy of 15-mm when flight altitude is at 30 m (Li et al., 2019).

The scanned results from LiDAR systems are point clouds (Barbarella et al., 2019; Edmondson et al., 2019; Gézero & Antunes, 2019; Li et al., 2019; Puppala & Congress, 2019), which can be used in measuring distances between two aligned point clouds for monitoring vertical deformations on bridge approach and deck (Puppala & Congress, 2019). In addition, a point cloud can be used to create 3D mesh models, including triangulated irregular network (TIN) (Li et al., 2019) and DEM (Barbarella et al., 2019), for extracting pavement geometrical features, translated to 3D imagery that are named as surface height plot (Edmondson et al., 2019) for extracting pavement textural features, and used to extract the road cross-section profiles for identifying pavement rutting (Gézero & Antunes, 2019).

Laser Line Profile Sensor. Laser line profile sensor technique is ideal for quickly getting high precision range information between pavement surfaces and the sensor, which is the core module for commercially available laser crack measurement systems, such as PaveVision, Pathway, Dynatest, and Fugro-Roadware (Serigos et al., 2012, 2015;

A. Zhang et al., 2019). The laser line profile sensor can be mounted on a vehicle, about2.13-m above ground (Zhou & Song, 2020a, 2020b), to have lane-wide coverage (about 4-m) (A. Zhang et al., 2019; Zhou & Song, 2020a, 2020b). The sensor has a depth (range) resolution of 0.1-mm, and the generated range image has a transverse spacing of about 1-mm, and a longitudinal spacing of about 2-mm (Zhou & Song, 2020a, 2020b).

3. 3 Other Non-destructive Techniques

Ground Penetrating Radar. Ground penetrating radar (GPR) has been widely used as a non-destructive testing technique for pavement thickness measurement (Sukhobok et al., 2019) and pavement distress detection (Tong et al., 2020). A GPR system transmits electromagnetic waves with a specific frequency that can penetrate pavement structures. Portion of the waves are reflected when it hits pavement distresses such as cracks, water-damage pits, and uneven settlements; then, these reflected waves are received by an antenna and present abnormal GPR signals differently from the background of undamaged pavement (Tong et al., 2020).

The GPR system can be mounted on vehicles and UAVs too, but a GPR imagery (covers a pavement section with multiple GPR signals) is only able to show either longitudinal or transverse profiles of the pavement structures. Moreover, due to GPR sensors relying on close proximity, the UAV requires operation at a very low level and at a very consistent altitude (VulcanUAV, 2018).

Planar Tomography. Planar tomography is a special case of laminography in which the X-ray source and the detector move synchronously and parallel to the object, whereas the object remains stationary. A 3D volume data of the studied object can be reconstructed by a fast shift-average algorithm (Moosavi et al., 2020). Cracks can be detected with the template matching method (Ehrig et al., 2011). However, this technique is not a reasonable approach for pavement crack detection, because the detector was unable to be installed under a roadway without destruction.

4. Neural Network Modeling for Pavement Evaluation

The pavement surface of a roadway section is a relatively flat plane, which makes it feasible to use 2D imagery, such as top-view and drone photogrammetric orthophoto (Dadrasjavan et al., 2019), to represent the pavement spectral features (Red, Green, Blue), and 3D imagery, such as surface height plot (Edmondson et al., 2019), depth map (Roberts et al., 2020), and range image (Zhou & Song, 2020a, 2020b), to represent the pavement elevation feature. 2D and 3D images can be aligned to the same pixel coordinate, and merged as integrated features (Dadrasjavan et al., 2019; Li et al., 2019). Based on those 2D/3D data sources, the NN modeling approaches, CNN-based classification(Ali et al., 2019; Fan et al., 2019; Maniat, 2019; Protopapadakis et al., 2019; Q. Yang et al., 2020; Zhou & Song, 2020a), and fully convolutional network (FCN)-based pixelwise segmentation(Alipour et al., 2019; Augustaukas & Lipnickas, 2019; Dung & Anh, 2019; Ji et al., 2020; Z. Liu et al., 2019; Song et al., 2020; Zou et al., 2019) are the most common data analysis methods in the reviewed studies for achieving the pavement evaluation objectives of cracking detection, classification and quantification.

4.1 Patch and Object Classification-based NNs

1D Structured Data Approach. Artificial neural network (ANN), or neural network (NN) is an approach to implement machine learning, which has the architecture of multiple layers, including an input layer, hidden layers, and an output layer. By using different hidden layers to connect the input and output layers, the NN can generate anything from numerical values to free-form elements like images, texts, and sounds, while other machine learning methods, such as support vector machine (SVM) (Dadrasjavan et al., 2019; Li et al., 2019) and random forest (RF) (Li et al., 2019), only output numerical values as classification results.

Multilayer perceptron (MLP) is a class of feedforward ANN, which typically has 1D vector input data, such as a GPR trace with 128 samples (Tong et al., 2020) or 300 samples (Sukhobok et al., 2019). The hidden layers usually are fully connected layers (FC or dense layers), dropout layers, and activation functions. The output layer contains a SoftMax activation function to generate a 1D binary class vector for classification tasks, where the size of the output vector depends on the number of classes, such as normal signal and abnormal signal-2 classes (Tong et al., 2020), and pavement thickness (equal to the samples)-300 classes (Sukhobok et al., 2019). Then, the additional Argmax function is required to return the index of the maximum value in the binary class vector as the final numerical value (classification) output (Jiang et al., 2020).

Furthermore, one study (A. Zhang et al., 2019) developed a recurrent neural network (RNN) termed “CrackNet-R” for fully automated pixel-level crack detection on 3D imagery of asphalt pavement. Its key idea is generating a pixel sequence (with the minimum average elevation) as a timely sequence for each pixel in a 3D image, which means the kth input pixel (u,v) is the kth time step; each pixel's probability (of being an element of crack) is determined based on timely probabilities predicted for all pixels' sequences; then, the crack detection result is generated from the mapped pixel probabilities.

2D Imagery Data Approach. Beyond structured data, the most common type of input data for NNs in the reviewed studies is 2D imagery data , which results in CNNs and FCNs being the most widely used data analysis method for pavement evaluation. A CNN starts with a convolutional layer, while its hidden layers contain multiple max-pooling layers, convolutional layers and FCs. A CNN typically ends with a FC with SoftMax activation function for conducting classification tasks, which generates the numerical value (classification) output as the same as MLP (Jiang et al., 2020). That is the major difference from FCNs, because a FCN typically does not contain FC, but it uses a convolutional layer with Sigmoid activation function as the network's end layer for generating the same sized output results as the input images (Jiang & Bai, 2020).

CNNs can be used with sliding window scheme (or overlapping small patches (Jiang et al., 2020; Protopapadakis et al., 2019)) to perform crack and non-crack binary classification tasks (Ali et al., 2019; Maniat, 2019; Protopapadakis et al., 2019; Zhou & Song, 2020a) and pavement cracking categories classification tasks(Maniat, 2019) in each small-patch of a large resolution 2D/3D image. Moreover, when the size of the window patches are very small, like 13×13-pixel (Protopapadakis et al., 2019), the CNN-based image patch classification results would be properly annotating cracks on the large resolution images (Protopapadakis et al., 2019; Zhou & Song, 2020a). Moreover, one study (Fan et al., 2019) also utilized the bilateral filter to smooth 227×227-pixel small patches with cracks, and implemented a k-means clustering based image segmentation algorithm to achieve a pixel accuracy of 98.70%.

Object-oriented Approach. Faster region-based convolutional network (Faster R-CNN) is a NN architecture proposed for object detection (Ren et al., 2017), which has been used for crack detection (Huyan et al., 2019; Kalfarisi et al., 2020). The Faster R-CNN has a similar design as Fast R-CNN (Girshick, 2015), both use the regions of interest (RoIs) to find the target object alternative to the brute force approach of searching all window patches in the whole image (Girshick, 2015). The difference is that in Fast R-CNN RoIs are extracted from the original input image, while in Faster R-CNN RoIs are derived from the feature-maps with a region proposal network (Girshick, 2015; Ren et al., 2017). These networks have two output vectors per RoI, the SoftMax probability which is the same as CNNs to indicate the probability of a RoI being a crack, and the bounding-box regression offset (Girshick et al., 2014) which indicates the location and region of the detected crack object. With the post-process, such as the structured random forest edge detection (Dollar & Zitnick, 2013), the crack can be annotated in Faster-RCNN (Ren et al., 2017) detected cracking regions (Kalfarisi et al., 2020).

Moreover, the network in network (NIN) architecture (Lin et al., 2013) has similar SoftMax and regression ending branches as Faster R-CNN and Fast R-CNN, which has been utilized in studies (Tong et al., 2020) for crack, water-damage pit, and uneven settlement abnormal signals detection on 1-m pavement GPR signals (like 2D images). In this NIN, the FC with SoftMax function is used to classify the abnormal signals; and, the (fully connected) regression layer is used to obtain a crack's peak location and width, water-damage pit's depth, width, and length, and uneven settlement's depth, width and length.

4.2 Pixelwise Segmentation-based NNs

Classical FCNs Approach. The reviewed studies adopted several classical FCN architectures in identifying cracks with digital images, such as FCN (Shelhamer et al., 2017), U-net (Ronneberger et al., 2015), SegNet (Badrinarayanan et al., 2017) and DeepLabv3+ (Chen et al., 2018), which were designed for image semantic segmentation tasks. Study (Alipour et al., 2019) developed the "CrackPix" for pixelwise crack detection based on FCN and reached a pixel accuracy of 92.1% for detecting concrete cracks in images of bridge surfaces, building walls and slabs, and sidewalk surfaces. U-net is a FCN architecture for biomedical image semantic segmentation, which has been adopted in concrete crack detection (Z. Liu et al., 2019), and pavement crack detection that reached a pixel accuracy of 98.92% and an Intersection of Union (IoU) of 0.4850 (Augustaukas & Lipnickas, 2019); U-net has been used as the generator for "CrackGAN" (K. Zhang et al., 2020); and, U-net has the advantage of reaching higher accuracy with smaller training data sets (image and manually annotated ground truth cracks) (Z. Liu et al., 2019; K. Zhang et al., 2020). SegNet is a deep convolutional encoder-decoder architecture for pixelwise segmentation, which has been adopted in identifying road networks in the large forested area from the RapidEye satellite imagery; and, the segmentation results are a pixelwise annotated road and non-road binary image (Kearney et al., 2020). Moreover, DeepLabv3+ has been utilized for crack detection on asphalt pavement (Ji et al., 2020).

FCNs have more complex architecture than CNNs, especially in hidden layers. FCNs may: use convolutional and deconvolutional layers to generate and explain feature-maps; use max-pooling and up-sampling layers to resize feature-maps and keep the main features after convolutional and deconvolutional layers; use activation function ReLU in hidden layers for faster model training; use dropout layers to prevent overfitting; and, use merging layers to combine the feature-maps (tensors) from two different layers as a new feature-map (tensors) (Chollet, 2020; Jiang et al., 2020; Jiang & Bai, 2020), such as the element-wise addition layers used in FCN (Shelhamer et al., 2017) and channel concatenation layers used in U-net. Considering the limitation of GPU memory, the modern FCN models would still be trained with small size image data sets, but on model prediction stages, the well-trained model could process images of any size. For image segmentation, using SoftMax function in the ending convolutional layer of a FCN achieves the probability of each pixel belonging to the predefined classes, such as crack and non-crack (Badrinarayanan et al., 2017; Song et al., 2020). Thus, the sliding window scheme used along with CNNs is unnecessary, and the additional filtering and segmentation post-processes after crack patches and objects are detected by CNNs and Faster-RCNN would be skipped. For example, the Mask region-based CNN (Mask-RCNN) (He et al., 2020) completed crack detection and segmentation simultaneously (Kalfarisi et al., 2020), because the Mask-RCNN has an additional branch of fully convolutional layers than Faster-RCNN and Fast-RCNN for generating crack instance segmentation results.

Modified FCNs Approach. Beyond adopting classical FCNs, the reviewed studies also developed several FCNs by modifying classical FCNs. One study (Dung & Anh, 2019) developed a convolutional encoder-decoder for concrete crack image semantic segmentation with an average precision of 89.3% in testing. The encoder block contains convolutional and max-pooling layers, while the decoder block contains up-sampling layers and both convolutional and deconvolutional layers, which is different from DeconvNet (Noh et al., 2015) (only use deconvolutional layers in decoder) and SegNet (only use convolutional layers in decoder). The end convolutional layer using SoftMax function is the same as SegNet.

"DeepCrack" developed in study (Zou et al., 2019) is based on SegNet, but is different from the original SegNet. It added skip-layer fusion (contains channel concatenation, convolutional, deconvolutional, and crop layer) to connect the encoder and decoder network. Its output is a 1-channel prediction map that indicates the probability of each pixel belonging to the crack by using a cross-entropy loss.

"CrackSeg" developed in (Song et al., 2020) is focused on road crack detection and achieved a precision of 98.0% and a mean IoU of 73.5%. This network has a multiscale dilated convolution module (Yu & Koltun, 2015) for generating rich crack features, and also has an up-sampling module to restore crack feature-maps to the input image size, and then predict the crack spatial distribution with the SoftMax function. The comparisons of "CrackSeg" and other methods on the same "CrackDataset" (Song et al., 2020) showed the "CrackSeg" has the best performance in pavement crack detection followed by DeepCrack, DeepLabv3+, PSPNet (Zhao et al., 2017), U-Net, and SegNet.

Novel NNs Approach. Study (F. Yang et al., 2020) proposed a novel network architecture named feature pyramid and hierarchical boosting network (FPHBN) for pavement crack detection. FPHBN contains four modules: a bottom-up module for hierarchical feature extraction, a feature pyramid module (using top-down architecture) for merging context information to lower layers, a hierarchical boosting module to adjust sample weights, and a side networks module for supervision learning (F. Yang et al., 2020). Moreover, beyond the "CrackGAN" (K. Zhang et al., 2020), the generative adversarial network architecture (GAN) also has been utilized in study (Y. Liu et al., 2020) to enhance motion blurred concrete crack images (captured by drone on high-rise building façades).

5. Literature Review Summary, Discussion and Recommendations

5.1 Summary

The reviewed RSNNPE studies conducted research in identifying pavement distresses of cracking, rutting, pothole, subsidence, water-damage, and uneven settlement with 2D/3D imagery acquired by remote sensing and non-destructive testing techniques. Among them, the cracking detection attracted the attention of most researchers, because it can be conducted by using the most cost-effective and convenient device, smart phones (Huyan et al., 2019;Roberts et al., 2020), to capture pavement surface images which can be used to create 3D mesh model by SfM and TIN for pavement distresses visualization and quantification as the building walls cracking study in (Kalfarisi et al., 2020). That will have the same effect as using LiDAR technique to acquire 3D point cloud and converting to 3D meshmodel in (Li et al., 2019).

Additionally, the reviewed cracking detection research (using optical cameras) has the limitation that only focuses on identifying cracks themselves from 2D images, but skipped the task of pavement assessment in flexible pavement visual survey. The pavement longitudinal cracking needs to be measured in linear feet per 100-ft. station, and the transverse cracking needs to be measured in terms of number of transverse cracks per 100-ft. station (Stacks, 2019).

Furthermore, compared to pavement crack image data sets collected from university campuses (Ji et al., 2020; Z. Liu et al., 2019; F. Yang et al., 2020), the "CrackDataset" (Song et al., 2020) that consists of pavement images of 14 cities in the Liaoning Province, China, is much better to present all pavement distresses features with a high traffic volume.

5.2 Discussion and Recommendations

Drone Photogrammetry based Data Acquisition. The reviewed study (Dadrasjavan et al., 2019) showed a feasible approach of using key frames extracted from a drone's video to generate an orthophoto of the surveyed roadway and then detecting cracks using the generated orthophoto. The coverage of an orthophoto is much larger than a single frame image, detecting and annotating pavement cracking on orthophotos would yield out a better visualization results, and it would be more feasible to conduct project level or network level pavement evaluation. In addition, when the high-resolution satellite images or aerial images are available for the target road project or network in Google Earth imagery (or other free access satellite imagery), the pavement cracking assessment would be more efficient with them by skipping the time-consuming and labor-consuming aerial imagery acquisition operations by the infrastructure management agency-self. For example, study (Jiang et al., 2021a) presented the experimental results of using Google Earth imagery for visual condition surveying of Interstate 43 (I-43) in Milwaukee County. Moreover, Google Street View is a good data source for road network pavement cracking detection, which has been verified in studies (Maniat, 2019; Mohammed, 2017).

For obtaining the detailed shape of pavement surfaces, such as accurate depth resolution (0.1-mm), transverse and longitudinal spacing resolution (1 to 2 mm) as the laser line profile sensor technique (Zhou & Song, 2020a, 2020b),the drone should be flying in close-range to pavement surfaces. According to the online GSD Calculator (Propeller Aero, 2018), a drone's (DJI Phantom 4 Pro V2.0, build in camera) flight height at 2, 4, 7, 14, 18, and 36-m, have the corresponding GSDs of 0.5, 0.11, 0.19, 0.38, 0.49, and 0.99-cm/px, respectively. Thus, the minimum altitude for guaranteeing cracking quantification accuracy needs to be determined for different types of sensors, including optical camera, HSC, thermal imaging camera or infrared night vision camera. The safest altitude for minimizing impacts to drivers needs to be evaluated in future research. Otherwise, the cracking quantification is hard to be conducted without traffic regulation when using drone photogrammetry.

Data Preparation. The reviewed studies with NN modeling are either input spectral features (RGB imagery), or input elevation features (3D imagery) (A. Zhang et al., 2019), then convolutional layers are used to generate complex feature-maps based on the input images. However, the traditional method, SVM classifier, is preferred to input structured combination features. In study (Dadrasjavan et al., 2019) a set of spectral features (RGB, and mean), textural features (contrast, correlation, energy, and homogeneity), and geometrical features (extent, eccentricity, minor axis length major axis length, and orientation) were generated from the drone photogrammetric orthophoto. The results showed using the combination features had an accuracy of 92% in crack/non-crack classification. Only using textural features had the lowest accuracy of 81% as cracks are not significantly different from non-cracks in asphalt pavement. Using spectral and structural features separately had the accuracy of about 85%, because cracks in color and shape are different from non-cracks (Dadrasjavan et al., 2019). The CrackForest (Shi et al., 2016) is a RF classifier for road image crack detection, which used an integral channel feature (3 color, 2 magnitude and 8 orientation channels). In addition, a RF classifier used multiple features to reach an accuracy of 92.3% in potholes/subsidence/undamaged pavement classification (Li et al., 2019), where multiple features were extracted from the UAV LiDAR point cloud, which include point cloud elevation, reflection intensity, multiscale roughness index, multiscale Gaussian curvature, and several object-oriented geometric features. Thus, for NN modeling methods, concatenating RGB 3-channel and an elevation 1-channel to form a 4-channel input image may have better performance in pavement distress detection, classification, and segmentation. For example, study (Jiang et al., 2021b) showed the experimental results of adding features of points' elevation or points' normal directions to the RGB feature can increase the performance of U-Net-based pixelwise segmentation in pavement cracking detection compared to the RGB feature alone. Moreover, the detectable pavement distresses would not be limited to cracking, and could also include potholes, subsidence, rutting and others, because the geometrical features are available in the integrated 4-channel images.

The crack image deblurring approach proposed in (Y. Liu et al., 2020; Nishikawa et al., 2012) could be considered when the images are captured with camera movement. In addition, when the pavement evaluation data source is satellite imagery, such as Google Earth Imagery, applying SRGAN (Ledig et al., 2016), a GAN for image super-resolution (SR), to enhance the satellite imagery should be considered, where the high quality image can be captured by drone for training the SRGAN.

NNs Selection. The output of NNs would be a pixel probability (of classification of pavement distresses) map (using SoftMax function in the ending convolutional layer), and the additional post-process is required to annotate the class labels to each pavement distress object in the original input image (as pixelwise semantic segmentation results). In addition, NNs' output would be a pixel probability (of damaged/undamaged, which is referred to a specific pavement distress) map (using Sigmoid function in the ending convolutional layer), then the post-process is required to classify the pixel probability map by clustering (Oliveira & Correia, 2013) or threshold segmentation (Shao et al., 2019). The quantification can be conducted by measuring the pavement distress objects' width, length, and area (if the image is captured in close-range with a small GSD cm/px), and depth (if elevation in 3D imagery is available). Moreover, the image processing methods proposed in the reviewed studies can be used to refine crack skeletons by the weighted median filtering (Shao et al., 2019), edge detection (Roberts, Prewitt, Sobel, and Laplacian of Gaussian) and frequency (Butterworth and Gaussian) domain techniques (Dorafshan et al., 2019), and measure crack width with a high accuracy of 93.7% by the segment-based method (Weng et al., 2019).

Furthermore, the differences of overall accuracy between the CrackSeg, DeepCrack, DeepLabv3+, PSPNet, U-Net, and SegNet are not significant in pavement crack segmentation. Thus, using U-Net to conduct pavement cracking detection in road network is better as U-net requires much fewer model training data sets than other FCNs, which can be separately trained for concrete and asphalt pavements, different weather and illuminate conditions, and different photography devices.

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