

INTELLIGENT ROAD MAINTENANCE: A MACHINE LEARNING APPROACH FOR SURFACE DEFECT DETECTION

Research paper

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Abstract

The emergence of increased sources for Big Data through consumer recording devices gives rise to a new basis for the management and governance of public infrastructures and policy design. Road maintenance and detection of road surface defects, such as cracks, have traditionally been a time consuming and manual process. Lately, increased automation using easily acquirable front-view digital natural scene images is seen to be an alternative for taking timely maintenance decisions; reducing accidents and operating cost and increasing public safety. In this paper, we propose a machine learning based approach to handle the challenge of crack and related defect detection on road surfaces using front-view images captured from driver's viewpoint under diverse conditions. We use a superpixel based method to first process the road images into smaller coherent image regions. These superpixels are then classified into crack and non-crack regions. Various texture-based features are combined for the classification model. Classifiers such as Gradient Boosting, Artificial Neural Network, Random Forest and Linear Support Vector Machines are evaluated for the task. Evaluations on real datasets show that the approach successfully handles different road surface conditions and crack-types, while locating the defective regions in the scene images.

Keywords: Road surface image analysis, Crack detection, Surface defect detection, Machine learning

1 Introduction

The processes of digitalization and datafication have been affecting various aspects of society (Kitchin, 2014), including research practices (Abbasi et al., 2016; Shmueli and Koppius, 2011) and decision making in business environments (Abbasi et al., 2016). With ubiquitous recording devices increasingly becoming sources for big data (Yoo, 2010), data-driven management and governance of public infrastructures and policy design has emerged (Rabari and Storper, 2014). The resulting ubiquitous rich image data enables the use of analytics to gain insights into situations and processes in public areas, such as planning and road maintenance (Tang and Sun, 2012; Yang and Lin, 2013). Consequently, we identify research opportunities regarding the development of analytics-based solutions that can leverage visual data to support public planning decisions. Therefore, we present a machine learning (ML) approach in this paper for processing two-dimensional (2D) road and scene images to automatically detect cracks and related surface defects. The images that we use in this study are captured using commodity cameras mounted on pedelecs and e-bikes. We propose that an intelligent road surface defect detection system can improve the effectiveness of maintenance and decrease manual labour associated with the inspection of road conditions.

Roads are the vital infrastructure and asset for economic growth, at the same time it also requires periodic checks and maintenance which are time and resource intensive. A comprehensive research by

Gleave (2014) studied the effect of the untimely maintenance of roads on different factors such as: (1) Increased maintenance costs, (2) Vehicle operating costs, (3) Environmental degradation from CO₂ emissions, fuel consumption and pollution from difficult rehabilitation works, (4) Increased safety issues related to accidents and health impacts. Automation in road defect and distress detection is an ongoing research area and is crucial for road infrastructure management as it detects surface conditions such as cracks, potholes, patches (Koch et al., 2015; MnDOT, 2009). However, automated decision making in public infrastructure management of roads or bridges are yet to be realized on a large scale. They are still predominantly surveyed and assessed manually or in a semi-automatic manner to a great extent (Chambon and Moliard, 2011; Gavilan et al., 2011; Radopoulou et al., 2016). Distress detection is currently done by manual visual detection, through large specialized vehicles or robotic carts to cover for the aspects of data acquisition and processing (BaSt, 2008; MnDOT, 2009; Prasanna, 2012; Zalama et al., 2013) and by citizen reports. However, such specialized vehicles are much larger in size and come fitted with multiple cameras, artificial lighting, friction sensors, laser profilers, radars, etc., making them costly (could be around \$800,000 (Radopoulou et al., 2016)) – unaffordable for most road authorities or agencies and used infrequently. This results in major maintenance backlogs (Gleave, 2014) and an inability to run on inner-city roads, narrower roads, bike paths and sidewalks.

To discuss more on the objectives that could be achieved through increased automation using the power of data, we can look at the findings in Gleave (2014). Based on their study of the roads in European countries, poor pavements and road surface leads to a 34% and 12% increase in the fuel consumption of light vehicles and heavy vehicles, respectively, leading to higher CO₂ emissions. Furthermore, deficient road surface could also increase the vehicle maintenance cost by 129% for heavy vehicles and 185% for light vehicles. In addition, poor road surfaces decrease the life of the vehicle tires by approximately 10% for heavy vehicles and 66% for light vehicles. Further, poor road conditions are directly responsible for increased accidents, affecting public security and safety. Automated systems providing timely monitoring could thus contribute toward enhanced environmental sustainability (Gholami et al., 2016; Melville, 2010). Thus, the need for a cost-efficient, scalable, flexible and intelligent system that can inspect roads for defects from simple images with reduced human intervention is undebatable.

We see that digital image analysis based road maintenance provides cheaper solutions and better resistance to movements than sensors (Chambon and Moliard, 2011; Yang and Lin, 2013). Given the increased usage of surrounded digital technologies and cameras, or aerial vehicles (Zakeri et al., 2016), scene images are easily acquirable nowadays by consumer devices (Henfridsson and Lindgren, 2005; Yoo, 2010). In turn, this requires robust processing for intelligent decision making. Hence, this research deals with the automatic detection of cracks, the most common form of surface defects, and related surface degradations from scene images using ML techniques.

However, to the best of our knowledge, most 2D image-based approaches work with the images taken by cameras from a close distance facing downwards directly towards the road (allowing an easier control of external conditions. Artificial lighting is also often used for image acquisition). Moreover, most of the approaches for crack detection are image-processing and segmentation based, with very limited usage of ML for detailed analysis (Koch et al., 2015; Mohan and Poobal, 2017; Varadharajan et al., 2014). Such image-processing based methods are particularly sensitive to noise like thresholds and cannot be directly applied to different locations (Gavilan et al., 2011). On the contrary, images captured from the driver's front viewpoint under normal daylight presents the challenges of varied illumination and surface conditions, lack of closer or focused view on image regions, cracks and defects occupying only smaller area in the whole image, and the presence of scene and surface elements (cars, road markings, buildings, grass, etc.). In spite of these, they are much easily acquirable and have more coverage of the area to be inspected for quick first-hand analysis, thereby reducing future search spaces. However, there is a lack of a systematic insight related to: (1) Most relevant features to be used and the ML approach to follow, (2) Developing similar techniques for handling different crack-types such as single, network, cracks near edges, block cracks and related degraded surface areas (BaSt, 2008), (3) Avoiding noisy thresholding based techniques, (4) Handling front-view images for a majority of the detections and defect localization in images. Thus, in order to achieve increased automation for intelligent infrastructure management, we aim to attend the below research questions in this work:

RQ1: What are the most relevant feature types that can be used and selected using ML based classifier's performance, in order to detect surface cracks and related degraded surface areas on roads from the scene images captured through a driver's front-faced camera's viewpoint?

RQ2: How can state-of-the-art ML techniques be applied to crack and defect detection using front-view scene images for handling different crack-types, locations and surface conditions?

Figure 1 shows examples of images handled by us and our approach for data collection. Unlike many existing methods, we use front-view scene images which are more cluttered and less structured. We do not use the commonly followed edge detection, thresholding or segmentation based methods, thereby making our work challenging. We take complete scene images as input and output the recognized crack and degraded surface area on roads as shown in Figure 3 (c). We use extracted features from superpixels and supervised ML-based classifiers for the task at hand. Moreover, we use the classifier performance for tuning the parameters of different feature extraction algorithms. Figure 2 shows the approach that we follow in this study. The remainder of this paper is organized as follows: in next sections we state the related works, data collection and data preparation processes, the features used and the classifier design for road surface defect detection. Finally, we present our evaluations and the discussion.



Figure 1. (Left- most) Our approach for data collection using a simple HD camera mounted on a pedelac taking scene images from front viewpoint. Rest of the images show examples of pre-processed road images that are used in our approach. Few crack-types are shown.

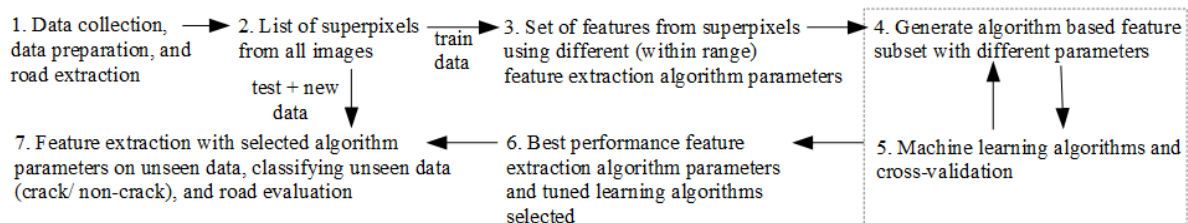


Figure 2: ML-based crack and defect detection approach for road condition evaluation and categorization using labeled superpixels and scene images.

2 Related Work

Some of the common automatic visual inspection methodologies for road surface evaluations are based on radar, laser, accelerometer or vibration, 3D reconstruction, remote sensing and 2D image-based techniques (BAST 2008; Koch et al., 2015; MnDOT, 2009; Salari, 2012; Staniek, 2014; Zakeri et al., 2016). These approaches have both advantages and disadvantages, with approaches other than image-based ones being more expensive as they require more equipment and computation. However, image-based techniques pose many challenges for increased automation such as varied viewpoint, lighting, shadows, texture, surface-types, less or more distress coverage area within images. The techniques for 2D road surface crack detection could be broadly classified into either more image-processing based (Mohan and Poobal, 2017) or a combination of image-processing and ML (Koch et al., 2015). Further, these detection techniques could be classified into either using downward view-images or front-view images.

One of the common approaches in road or pavement defect evaluation is seen to be based on thresholding techniques, binarization, mathematical morphology (Teomete et al., 2005). Most image-processing

based approaches assume that crack pixels are darker than non-crack pixels and use different thresholding or histogram based techniques (Mohan and Poobal, 2017) depending on it. Statistical measure based approach using variance and standard deviation solely is also be seen in many works (Sinha and Fieguth, 2006, Huidrom et al., 2013). A matrix operation based approach using residuals, followed by probabilistic and thresholding techniques, is used by Day et al. (2012) for analysing durability cracking. Edge detection based systems using local curves, along with their combination with SVM, is also seen (Prasanna et al., 2012). A good overview of parametric and non-parametric ML approaches for crack detection is presented in Oliveira and Correia (2009) and the authors used mean and standard deviation as features. Li et al. (2014) used features such as rectangle area around cracked area and cracking rate (i.e. number of defect pixels in an image) with Artificial Neural Network (ANN) for crack-type recognition (longitudinal, transverse, linear and network cracks). However, for crack detection or extraction it used Otsu's and other thresholding approaches as the first step. In Rababah et al. (2005) thresholding based crack detection was followed by crack classification using Hough space features and edge detection, Genetic Algorithm, Self-Organizing Maps and Multilayer Perceptron; with Multilayer Perceptron outperforming the rest. An adaptive seed based approach is also seen to be used where pavement type is first classified using Support Vector Machine (SVM) prior to crack detection (Gavilán et al., 2011). Features are extracted here based on histogram shape descriptor that gives difference between crack and non-crack objects, and classifying them using SVM, after morphology is used. Line scan cameras were used in it. A Wavelet Transform based approach is seen in Nejad and Zekeri (2011) that uses Dynamic NN and gives good results for network cracks (cluster of cracks). A Deep Learning based approach using Convolutional Neural Network can also be seen in some literatures (Pauly et al., 2017; Ruoxing et al., 2018; Zhang et al., 2016). An AdaBoost based system using Gabor filter features like, frequency, was also used for crack-type classification into transverse or longitudinal by Zalama et al. (2014). Wu et al. (2016) showed an ANN based approach for crack recognition, where the crack extraction and grouping is done using thresholding and morphology. As it is seen, most studies used downward-view images (with closer view) or specialized vehicle acquisition method. Furthermore, ML is seen to be used more for crack-type (like, linear, network, etc. using coverage area properties) classification (Li et al., 2014) or recognition, after considerable image-processing based approaches such as thresholding or morphology have been employed as the main step for crack detection or extraction (Koch et al., 2015; Moon and Kim, 2011); making them sensitive toward noise.

On the contrary, few recent studies show growing interest in using ML extensively for crack or defect detection using front-view images, which are similar to the image types we use in this work (Varadharajan et al., 2014). In Radopoulou et al. (2016), the camera was placed much lower, closer to the license plate and the authors used the Wavelet Transform and Semantic Texton Forest ML approaches to analyse the data. Varadharajan et al. (2014) presented a Multiple Instance Learning based SVM technique for crack detection using a combination of Local Binary Pattern (LBP) texture, position and colour giving 138 features, with the camera placed on the car's windshield. The approach in it helped handle subjective and weakly labelled images produced by people. However, the model missed distributed or lighter cracks and displayed similar and brightly lit surface conditions. As can be seen, the features used in various such approaches does not have easy discriminative abilities (Pauly et al., 2017). Gavilan et al. (2011) stated that location dependent results is a bottleneck in crack detection. Further, a lack of benchmark or publicly available datasets (Koch et al., 2015), along with difficult and costly image acquisition systems (Radopoulou et al., 2016), make the progress in automation slower. Thus, for an improved road surface management and increased digitalization, one should aim to procure HD images in an easier way and make digital image data availability more reachable. Using digital images for most of the major first-hand surface analysis will enhance road quality and reduce search space for follow-up intensive analysis. Furthermore, the development of intelligent techniques for handling various defects across different locations and conditions, instead of using more surface conditions and location specific approaches for enabling cross-applications has become a necessity.

3 Data Collection and Preparation

In this work, we collected high definition natural scene videos and images, along with their GPS values, in Germany over a period of 1 year by mounting a camera on pedelecs and e-bikes. We collected around 75 videos, each being 40 minute long, giving a large repository of images. We obtained images of 1242×720 resolution from the video clips. The images that we selected in this work belong to varied scenes such as rural and urban, varied road width and varied times such as morning and afternoon. They were all taken under normal daylight. As we process scene images taken from such front-view cameras, we first extract our region-of-interest in the scene image, i.e. road area needs to be extracted, as shown in Figure 3, for preparing the data for crack detection. From now on, we use the term "scene image" to refer the complete captured scene, while "road image" refers to the image with only extracted road area. The steps of pre-processing are as follows: (1) Road area extraction to generate "road images" from "scene images", (2) Segmenting the road image into superpixels (groups of pixels) from which features are to be extracted, (3) CLAHE usage. Data preparation is shown in Figure 2 (steps 1 and 2). Figure 3 shows different aspects of our data preparation.

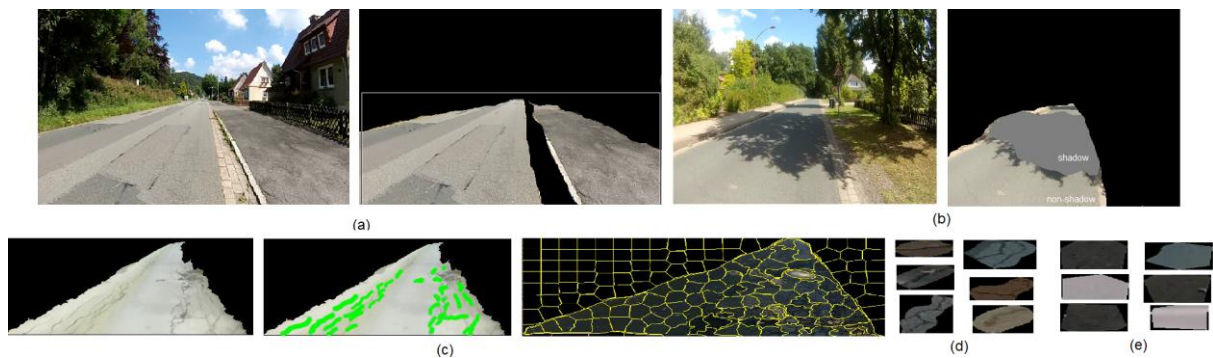


Figure 3: Data preparation: (a) Generated road images and region of interest (box) from scene images. (b) Basic shadow handling (shadow in gray color). (c) Annotated cracks on the image and SLIC superpixels (in yellow) over road images. Background superpixels with black color are avoided. (d) Sample superpixels belonging to crack category. (e) Sample superpixels belonging to non-crack category.

3.1 Generating road images from scene images

A scene contains various elements like, cars, buildings, trees, etc. and needs to be removed before the road area is extracted and used for surface defect detection. In this work, we used the approach in Chatterjee et al. (2017) to extract the road area region from the complete scene. We selected this approach as it helped us achieve the following: (1) The method is applicable to a wide range of scene types such as, rural and urban. So, we can use the same algorithm for different scene types that we handle in this work, (2) The algorithm detects the major shadow areas that could be avoided or handled accordingly, thus reducing false positives in the crack or surface defect detection step. The used approach is based on the Gaussian kernel based hybrid distance metric, linear optimization with Hungarian Algorithm and pairwise assignment from a distance matrix for hierarchical clustering. Once the road area is clustered, it is extracted as the road image as shown in Figure 3 (a-b).

3.2 Pre-processing of road images and superpixel generation

Once the road images are generated by extracting the road area from scene images, we used Hough lines to demarcate the road-side edges. Such lines are thus not considered as cracks in later stages. Following this, we resized the road images to 300×150 size and then divided the image into s_n (here, $s_n = 150$) superpixels, to group similar pixels. We used Simple Linear Iterative Clustering (SLIC) (Achanta et al., 2012) to generate the superpixels by clustering the red, green, blue colour values of the

pixels, along with their (x, y) location values. Furthermore, followed by the superpixel segmentation of each image, each of the superpixel undergoes histogram equalization. General histogram equalization (Gonzales and Woods, 2002) provides the possibility to enhance the contrast of an image. An image with enhanced contrast is a much better input for a feature extraction algorithm. General histogram equalization might suffer losses due to over-brightness or over-darkness. To solve the information loss in general transformation we used Contrast Limited Adaptive Histogram Equalization (CLAHE) (Zuiderveld, 1994). CLAHE transforms the image by calculating the histogram of each region instead of one histogram over the whole image. In this work, the original image is divided into smaller blocks called "tiles" having the size of 8x8. Then these blocks are histogram equalized. Thus, no data has been lost by extreme general histogram transformation, yet the crack region's colour intensity has improved.

3.3 Final road image dataset for defect detection

As our approach is based on supervised learning, it is a requirement to train the classifier models with samples. In our case, each sample is one superpixel, i.e. groups of pixels, as in Figure 3 (d-e). We selected 30 manually annotated images under diverse conditions. Every image is divided into s_n superpixels. Each superpixel sample belongs to one of the two categories - crack (positive) and non-crack (negative) at the broadest level. In this work, a dataset of images under diverse lighting and surface conditions have been used for annotation, as required for training and ground truth comparison. Figure 3 (c, second image) shows an example of an annotated image. Out of the superpixels those with black colour values are not used as they are the background, as shown in Figure 3 (c). For every remaining valid superpixel, features are extracted and are labeled as crack (output as 1) or non-crack (output as 0) for the training. So, the regions are now encoded in terms of the feature space and we have a task of binary classification to be solved. It should be noted that the sample dataset is highly unbalanced, i.e., for every image, there are more superpixels which are non-crack than crack. One way of solving this is to generate more such data samples or superpixels belonging to diverse crack conditions. However, this requires more annotated images. Another way could be to drop some non-crack samples as many of them might have similar features. Accordingly, we balance our data by dropping similar non-crack samples and finally selected 1215 samples (containing samples for non-crack to crack in 50:50 ratio). Out of these, we used 1000 samples for training and 215 samples for testing and comparison to the annotated ground truth. We also report successful crack defect detection on 80 additional test images (i.e. 8828 more non-black valid test superpixel samples) with varied conditions and crack-types.

4 Problem Formulation

Each superpixel is a data point and we characterize it by a feature vector x . We denote the set of all feature vectors by X . Here, $x = [x_1, x_2, \dots, x_m]$ with m being the total number of features per data point. For training, marked superpixels have a label $y \in Y$, where, $Y = \{0,1\}$. The aim of the research is to find a ML approach with the combination of input features and the model, $f: X \rightarrow Y$, which maximizes the overall accuracy. The learned function, f , is the classifier which is then used to predict the label of unseen data into either class 1 (superpixel with positive condition having crack or defect) or class 0 (superpixel with negative condition having no crack or defect). In the next section we state how the m features are tuned (using steps 1 -3 of Figure 2) and selected by the classifier's accuracy.

We use the following four classifiers in this work- Gradient Boosting (GB) (Friedman, 1999), Random Forest (RF) (Breiman, 2001), Artificial Neural Network (ANN) (Rojas, 1996), and Linear Support Vector Machine (LSVM) (Cortes and Vapnik, 1995). They are shortly described here. GB and RF are typical examples of ensemble learning. For ensemble classifiers, in general, weak learners are used to form a strong learner. RF works in a parallel manner using independent classifiers following a bagging approach, while GB works sequentially following a boosting approach. Compared to RF, gradient boosted trees makes use of very small decision trees (tree stumps) (Hastie et al., 2009). The ground truth in GB is modelled by incrementally adding more trees where each tree tries to minimize the loss function evaluated on the previous model. On the other hand, RF uses many classification trees and it chooses majority vote concept to classify an object aggregating the result of these trees. ANN mimics the biolo-

gical neuron characteristics and gives the non-linear function approximation. It typically consists of multiple layers with nodes known as input layers for receiving signals and data, hidden layers, and output layer that provide final results. The layers are inter-connected and weights are learned to adjust the flow of input signals across layers for minimizing the error. Binary SVM classifier works on the concept of decision hyperplane that separates a set of objects within two different classes by maximizing the margin between them. The objects lying on the hyperplane are called support vectors.

5 Feature Extraction

Following our research approach in Figure 2, we use extracted features from image regions, i.e. superpixels, to classify them as regions containing defect or no defect. Features are the image descriptors which help encode regions. The texture and edge features could be intuitively understood to be more relevant than other kind of features, as cracks are inherently regions of anomalies or discontinuities. We experimented with state-of-the-art features, such as statistical measures, Grey Level Co-occurrence Matrix (GLCM) (Haralick, 1979), Gabor (Daugman, 1985; Gabor, 1946), Histogram of Oriented Gradients (HoG) (Dalal and Triggs, 2005), Local Binary Patterns (LBP) (Silva et al., 2015), different colour channel (Gonzales and Woods, 2002) variants and histograms (e.g. HSV, RGB, LSV), as well as, Sobel and Canny edge features (Canny, 1986; Gonzales and Woods, 2002). Selection of these algorithms was motivated by their varied use in the literature and that a crack in essence is an edge or a typical change in gradient. Using classifier's accuracy metric and incremental subset feature selection process (step1 - step 3 in Figure 2), we selected the following 40 features for each of the superpixels: variance, skewness, 6 GLCM features and 32 features from a newly defined feature variant called Variance-of-Gabor (VoG).

To start discussing the features, variance and skewness are calculated using the flattened array of gray scale pixel values, say Gx , within a superpixel S . This array contains $\#(Gx)$ elements. In grayscale, every image pixel gets a weighted average of $0.29 R + 0.56 G + 0.11 B$ from its R, G, B individual colors. Variance simply measures the spread or variability in the data and skewness measures the asymmetry or imbalance within the data distribution, which in this case could be defined for a superpixel as: $Var(S) = \frac{1}{\#(Gx)} \sum_{i=1}^{\#(Gx)} (Gx_i - \overline{Gx})^2$. Similarly, $Skew(S)$ is obtained.

Apart from these, we also use GLCM second-order statistical properties of an image region (superpixel in our case) as texture features. Unlike first-order properties like variance, GLCM properties or features consider spatial relationship between neighbouring pixels. The GLCM matrix is calculated on the grayscale image and six features of homogeneity (g_h), angular second moment (g_{asm}), energy (g_{e2}), correlation (g_c), contrast ($g_{contrast}$) and dissimilarity (g_d) are extracted from each of the superpixel as in equations (1-5). Energy g_{e2} is square of g_{asm} . The GLCM matrix is derived from frequency of each reference pixel and the neighbouring one.

$$g_h(\theta, d_o) = \sum_{i,j} \frac{1}{1 - (i - j)^2} p(i, j), \quad (1)$$

$$g_{e2}(\theta, d_o) = \sum_{i,j} p(i, j)^2, \quad (2)$$

$$g_c(\theta, d_o) = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)}{\sigma_i \sigma_j} p(i, j), \quad (3)$$

$$g_{contrast}(\theta, d_o) = \sum_{i,j} p(i, j)(i - j)^2, \quad (4)$$

$$g_d(\theta, d_o) = |i - j| p(i, j), \quad (5)$$

where, the probability of change from graylevel i to j at a distance d_o and directional angle θ is given by

$p(i, j)$. Distance should be small to consider closer pixels. Moreover, using the feature importance ranking of the RF classifiers, these features could be ranked as follows: correlation, homogeneity, contrast, dissimilarity, energy and angular second moment. GLCM is parameterized by (d_o, θ) i.e. angle θ (giving direction for the spatial relationship) and an offset d_o (neighbour pixels to be considered). The number of graylevel is taken as 256. Here, $\theta = \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$ and $d_o = \{1, 2, 3, \dots, 8\}$ are the used ranges for the parameters for tuning using the classifier's accuracy metric to select their best combination of (d_o, θ) . Figure 4 provides example of the effect of parameter tuning on final ANN classifier's accuracy.

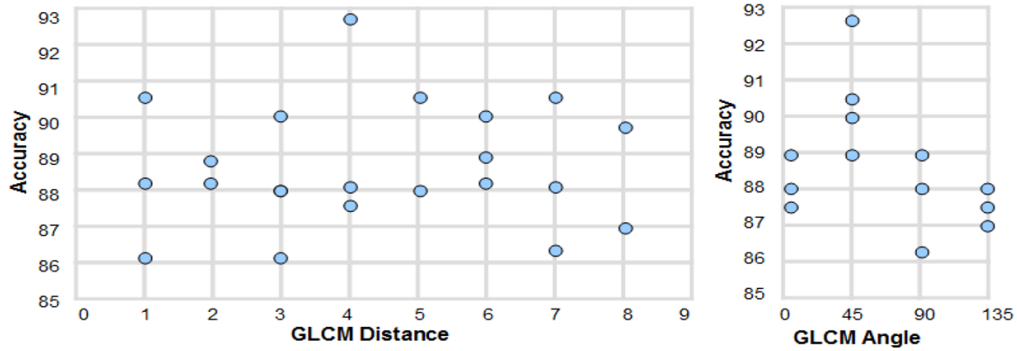


Figure 4. Effect of GLCM parameters on ANN classifier's performance. Seven percent variation can be seen in accuracy (in percent) depending on GLCM parameters. For each value of x-axis, multiple dots show accuracy for it when combined with other parameters.

5.1 Variance-of-Gabor (VoG) features

Gabor filter based approaches are widely applied for a variety of computer vision use cases such as object detection, texture analysis, edge detections, to name a few, owing to their similarity to human visual system characteristics. When Gabor filters are overlaid on an image, useful edge and texture features could be extracted as the filters respond to pixel positions where a major change in texture or edge takes place. Gabor filter is built as a product of Gaussian and sinusoid functions. The parameters of it are: α (controls the orientation of the filters), k (Gabor filter kernel size), σ (the scale parameter of the Gaussian function g), λ (controls the wavelength of the Gabor filter sinusoid s) in pixels. α is one of the most important parameters and for each of the α , a filter is produced, thus giving a series of filter bank. α also determines the angular response of the Gabor filter. For instance, $\alpha = 0^\circ$ indicates that the Gabor filter only responds to horizontal features. Here, α is taken in the range of 0° to 180° (to avoid symmetry and directional redundancy) and 32 filter orientations are defined at an equal interval of 5.625° in order to get the features at different angles. Thus, $\alpha = [\alpha, \alpha_{i+1}, \dots, \alpha_{i+31}]$ with $i = 1$ and $\alpha_{i+1} - \alpha_i = 5.625^\circ$. At the end, a filtered image is generated for each of the α orientation, as in Figure 5.

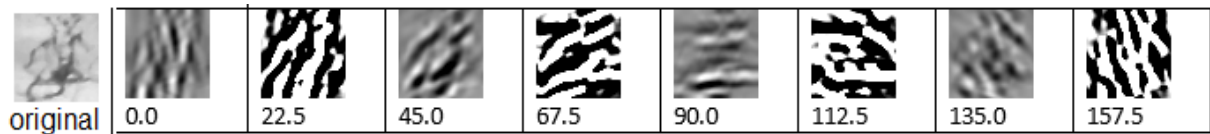


Figure 5: Sample Gabor filtered images of a superpixel for each corresponding orientation.

We define Variance-of-Gabor (VoG) features of any superpixel following equation (6). Thus, for every superpixel having b Gabor filter bank, i.e. orientations for the θ , a VoG feature set of size b is obtained using the corresponding Gabor filtered images as follows:

$$VoG(S) = [Var(G_1), \dots, Var(G_b)]. \quad (6)$$

Here, S is the superpixel and G_i is the i^{th} Gabor filtered image with $i = 1 \dots b$. $Var(G_i)$ is the variance of the i^{th} Gabor image. We take $b = 32$ as it gives the best performance. For generating VoG features, we need to generate Gabor filtered images of the superpixels for each of the α using the filter parameters: $k, \sigma, \lambda, \theta$. We automatically tune k, σ and λ using classifier's accuracy metric and obtain α with 32 orientations, $k = 11, \sigma = 15, \lambda = 10, \theta = 0$ for generating 32 VoG features. It has been noticed that larger σ and λ fade away the edges and make the filtered image blurred. As an example, Figure 6 show the tuning process for two of these parameters, σ and λ .

In order to tune the parameters of the feature extraction algorithms we used, i.e., GLCM and Gabor filter, we first took algorithm-specific feature subsets with different parameters and tuned the parameters using classifier's accuracy, as shown in steps 1 – 3 of Figure 2. Once the tuned parameters of feature extraction algorithms are obtained, the classifier's hyperparameters are extensively tuned using the complete feature set. 10 fold cross-validation has been used for all the tuning. Finally, we have well-tuned 40 features, as given in Table 1, for each superpixel. The development platform in this work is Python 2.7 and we used libraries of OpenCV 3.3.0, SciPy, scikit-image and scikit-learn.

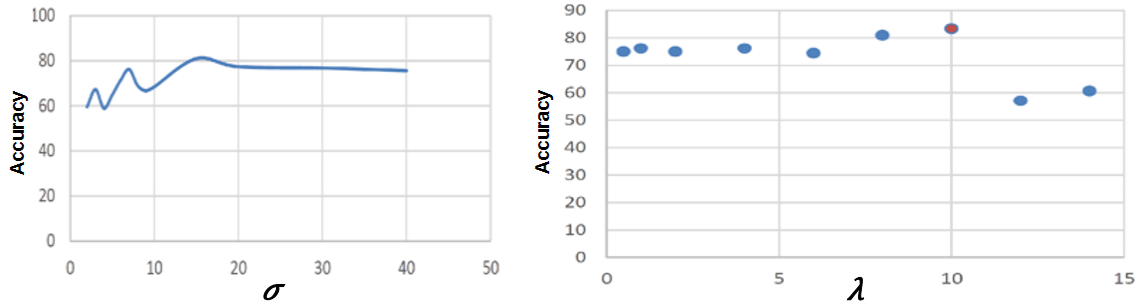


Figure 6. Parameter tuning of the Gabor filter for VoG features using classifier's performance.

Variance, skewness, 32 VoG features with $k = 11, \sigma = 15, \lambda = 10$ for Gabor filter and 6 GLCM features ($g_c, g_h, g_{contrast}, g_d, g_{asm}, g_{e2}$) with best combination of (d_o, θ) as $\theta = 45^\circ, d_o = 5$.

Table 1. List of features extracted from each superpixel using the tuned parameters.

6 Evaluations

We used here precision (P), recall (R), F1-measure for comparing the four classifiers as follows: $P = \frac{TP}{TP+FP}$, $R = \frac{TP}{TP+FN}$, $F1 = 2 \frac{P \cdot R}{P+R}$, $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$. Here, TP gives true positives (crack detected as crack), TN gives true negatives (non-crack detected as non-crack), FP gives false positive (detecting non-crack area as crack), FN gives false negative (detecting crack as non-crack). All evaluations are at the superpixel level. In total, we used 1000 data points for training, 215 first test data, and 8828 additional new test data from 80 test images. The results are given in Table 2 and Table 3.

| Classifier | Accuracy (%) | P (%) | R (%) | F1 (%) | TP | FP | TN | FN |
|------------|--------------|--------------|--------------|--------------|-----------|----------|------------|-----------|
| GB | 91.16 | 92.38 | 89.81 | 91.08 | 97 | 8 | 99 | 11 |
| ANN | 90.24 | 93.94 | 86.11 | 89.86 | 93 | 6 | 101 | 15 |
| RF | 90.69 | 94.85 | 85.98 | 90.61 | 92 | 5 | 103 | 15 |
| L-SVM | 74.88 | 75.96 | 73.15 | 74.53 | 79 | 25 | 82 | 29 |

Table 2. Performance of the classifiers on 215 test data.

| Classifier | Accuracy (%) | P (%) | R (%) | F1 (%) |
|------------|--------------|-------|-------|--------|
| GB | 92.77 | 87.62 | 94.88 | 91.11 |
| ANN | 90.63 | 81.37 | 93.91 | 87.19 |
| RF | 91.82 | 88.81 | 93.02 | 90.87 |

Table 3. Performance of the classifiers on additional 8828 test data from various locations, surface conditions and crack-types.

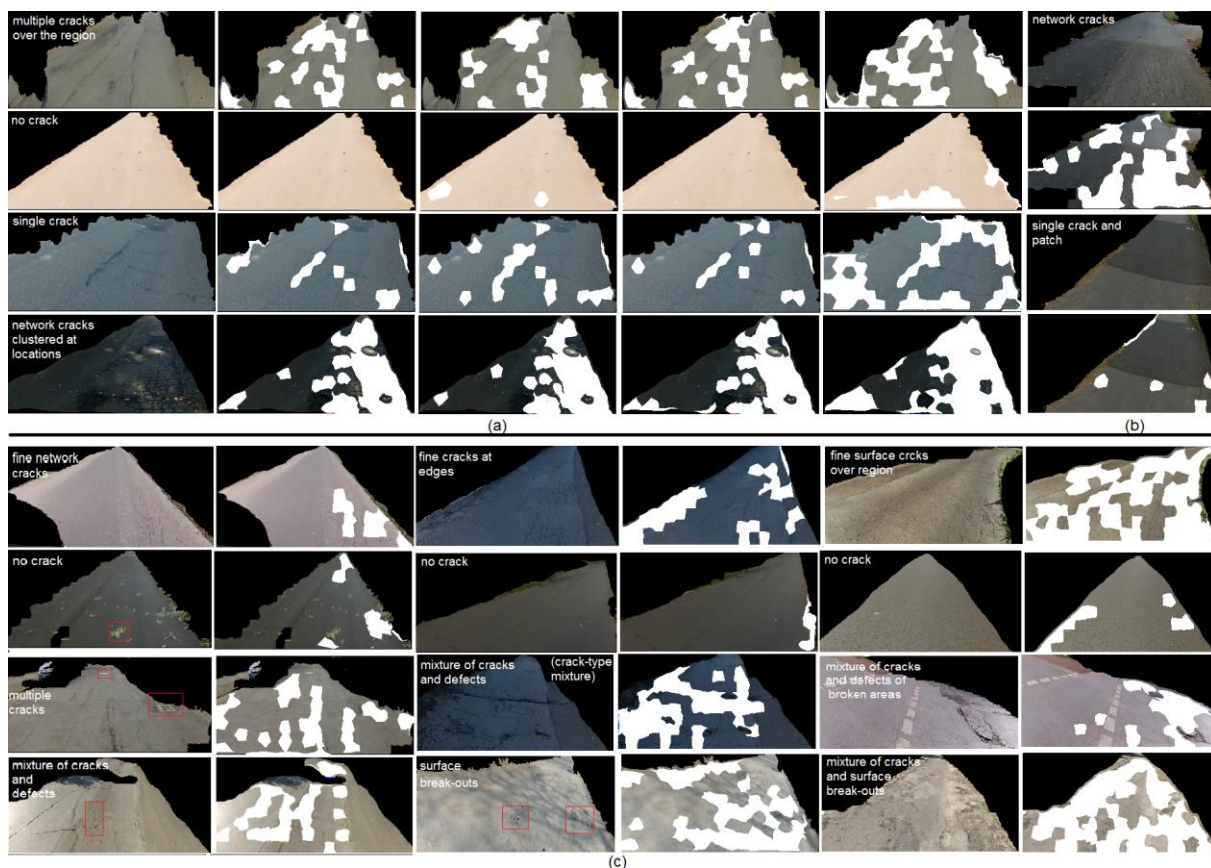


Figure 7. Detected crack areas on images marked in white. (a) First image is the original image, second image shows marked area (superpixels) detected to contain cracks using RF, third image using ANN, fourth using GB, fifth using L-SVM. (b-c) Crack detections with RF for given original images. Few crack-types and conditions are marked.

The hyperparameters of all four classifiers are selected using grid search and a 10 fold cross-validation. For GB classifier, an ensemble of weak learners of Decision Trees are considered and Logistic function is taken as the loss function; while, hyperparameters like maximum depth of the estimator is taken to be 7 and minimum required samples for splitting at the internodes nodes is taken to be 8. For ANN construction, features are standardized prior to the learning process, along with the input layer size of 41 nodes (with a bias), 1 hidden layer, and a learning rate of 0.001 being used. For RF, maximum depth of trees is taken as 18 and minimum samples for splitting at internal nodes is taken to be 8. The number of estimators with 300 showed convergence for it. Finally, L-SVM learner with a linear kernel having the regularization penalty parameter set to 0.01 has been used for comparison. Once we obtain the learned predictions, we generate two outputs for visualization of the results: an auto-annotated image showing location of detected cracks and defective areas, as shown in Figure 7, and percentage of superpixels detected as crack. This helps to rank road surfaces, thus helping to come up with maintenance strategies. Higher percentage indicates that the road has severe defects and needs attention.

7 Discussion and Future Work

Digitalization in today's time has given rise to unprecedented traces of data (Goes, 2014). Leveraging the process of datafication, through which consumer devices are being turned into sources of big data (Galliers et al., 2015), one may derive significant value for society through ML techniques, using data generated by portable and connected devices during consumers' everyday activities (Günther et al., 2017). In this work, we provided evidence for the effectiveness of data analytics based on data gathered through commodity devices (i.e., electric bikes equipped with cameras) that can be operated by standard consumers. More specifically, we successfully developed a ML approach for detecting cracks and related defects in normal scene images to facilitate road maintenance process. We used state-of-the-art feature extraction algorithms and tuned their parameters using ML, along with incremental subset feature selection method. Finally, we used ML to classify the image regions into crack and non-crack using tuned feature extraction algorithms and classifiers. Figure 7 shows different illumination, surface conditions, locations, crack-types (such as single, network, cracks at edges, etc.) and related surface defects or distresses that are handled by our approach for defective region detection.

This research contributes to research streams of decision support systems (Banker and Kaufmann, 2004) by helping in intelligent decision making using automated tools for road maintenance and monitoring. The way front-view images are handled in this study for crack detection using the developed ML-based approach in Figure 2 shows the technical possibilities of a future modular and flexible decision support system, based on the algorithms developed in this work. This could help pavement management systems (BASt, 2008; FHWA, 2016) to come up with a pavement condition index (e.g. bad, medium, good, etc.) (BASt, 2008) in an automated manner and with reduced human interventions, for example using percentage of cracks detected.

Moreover, as we work with front-view images, image acquisition and analysis becomes cheaper and easier because simple everyday devices such as smartphones, car and traveller's cameras could be used, contributing toward a decentralized crowdsourcing-based system for road condition assessment (Laubis et al., 2016). In this context, individual cars for example could be employed for crack detection and quick monitoring. GPS-based mapping systems may be used to combine different or same road segments that are analysed separately in such cases. Additionally, autonomous vehicles can detect cracks and avoid such areas, thus incurring lower vehicle operating costs and select safer routes, consequently affecting road safety (Stilgoe, 2017). Lately, using commodity devices, big data and crowdsourcing approaches for decision making in maintenance services is observed to be on a rise (Galliers et al., 2015; Nitsche, 2014). This helps in timely maintenance of roads to have less backlog and come up with strategies for efficient resource planning and monitoring (Laubis et al., 2017; Tang and Sun, 2012). Additionally, citizens could be engaged in activities involving road monitoring such as voluntary data acquisition (e.g. from traveller's or cars). Intelligent decision making could also help in developing alert systems to notify citizens for surface defects and cracks so that they can select safer routes. Thus, it enhances collaboration between citizen and government for inclusive information technology-based societal development and smart services (Fink, 2010). For such services one needs to develop approaches for analysing road surface condition for defects automatically, timely, and quickly; motivating us to develop the ML-based approach in this work for intelligent decision making.

The ML approach for defect detection in this work shows robust behaviour when first-order statistical features of variance and skewness are extensively used, along with GLCM second-order statistical features and Gabor filtering for feature extraction. While, first-order features showed variabilities over an image area or region, second-order features considered more local and neighbourhood properties. Additionally, defining the new feature variant called Variance-of-Gabor (VoG) helped us to process crack and non-crack superpixels at different orientations. Table 1 gives the final set of features and their parameters. Here, we followed the incremental subset feature selection process and tuned feature extraction algorithm's parameters automatically using ML algorithm's performance metric; moving towards a systemic approach for feature mapping. Texture related features show more adaptability to various illumination conditions than edge-based features. To discuss their effectivity, GLCM features alone, along with standard deviation or variance features, were found highly discriminative, while Gabor filters

helped to make the system more generalized and adaptable by extracting interesting edges. Similarly, VoG features alone also show a high accuracy, as seen in Figure 6, whereas the best combination of identified features provided a higher accuracy of around 91.16 %, as given in Table 2. However, only non-filtered texture features showed more sensitivity to lighting, roughness, or acquisition distance.

It is seen from the evaluations in Table 2 and Table 3 that RF and GB perform better following highest accuracy, good F1 and lowest false positives. LSVM did not perform well. ANN's performance decreased for the dataset with varied conditions in Table 3, with a specific decrease in precision. This is because, it has been noticed that for surfaces with very little crack area and single cracks ANN gives more false positives (as in Figure 7 (c - first row, first image set)) or absolutely no crack (as in Figure 3 (a – second row), Figure 3 (c second row, second image set)). RF and GB can handle both single or network cracks and does not give many false positives even if crack does not exist. Overall performance shows better fit of ensemble ML techniques such as RF and GB for the task at hand, even when images from different location than those used for training were used. It is noted that lower false positives are an important criteria for defect detection, while not compromising the overall accuracy, and Random Forest shows highly consistent detections for all the datasets. The presented approach is applicable across different locations and crack-types.

In comparison to other related works for crack defect detection, we did not use downward-view images under controlled external conditions, thresholding or morphological approaches as a major detection step, or costly equipment systems with lasers or radars (MnDOT, 2009; Wu et al., 2016; Zalama et al., 2014). Moreover, we provide a systematic approach for ML based crack and related defect detection using feature selection and tuning feature extraction algorithm's parameters and a thorough comparison among different ML techniques. It is also seen that unlike this work, in most related works crack-type (e.g. linear, network) classification or recognition is done using ML using features such as crack angle, covered area, whereas the major crack detection or extraction step still uses noisy thresholding based approaches; making the overall approach sensitive toward cross-location application. Finally, as we used simple 2D images which are easily acquirable, our approach is flexible, cost-efficient and scalable for either wider or narrower roads. The presented approach also makes data acquisition for such image-based maintenance easier as many service vehicles such as public transportation systems like busses and taxis, or patrolling cars could be fitted with front-view cameras to gather necessary images and data (Mertz, 2011). This effects directly the increased automation for timely maintenance on local and urban roads which are seen to experience the highest safety issues (Gleave, 2014). We can thus see that the immense use fullness of increased automation for infrastructure management using big data and ML can reduce human effort and increase the timeliness of maintenance. Moreover, as detection of defects is delayed, the defects (e.g. cracks) become worse and often need more time and money to rehabilitate and repair them. For example, if network cracks are not timely attended they could develop into potholes over time. This clearly shows the positive impacts of data-driven innovations (Abella et al., 2017) to create value using simple image data for continuous detection, monitoring and road maintenance. Thus, the approach for intelligent analysis of 2D images in this study could bring about quicker monitoring of road maintenance, lower costs, provide safer routes and an enhanced traveling experience for the public.

Limitations and future work

One of the major limitations of the proposed approach is the lack of information on the depth of visual entities arising from the 2D nature of the images. Nevertheless, detecting cracks and defects from these images and obtaining GPS locations of defective roads are major first steps towards automating road maintenance. Thereby, most of the road inspection tasks can be performed automatically and search spaces can be reduced drastically. Rather than using expensive sensors and 3D analysis systems in general, images can be supplemented with 3D information only at these specific defective search locations. The need to invest in costly equipment or systems at a larger scale can thereby be eliminated. Additionally, external elements such as drainage, manholes, as marked in Figure 7 (c) (third row, first image set), could cause false detections. Another limitation is that the approach suffers if the surface contains weathering, swelling, or rough edges (as in Figure 7 (c), last row), then the crack gets detected at the junctions although no explicit crack is visible. In future, we plan to handle these defects by incorporating pavement-type categorization technique, as defects or crack-types depend on pavement surface-type and ma-

terial. Additionally, we aim to extend our approach for detecting other defects such as potholes, patches and classify cracks into types, e.g., linear or network category. Finally, it can be stated that the approach developed in this paper constitutes a technology artifact (Lee et al., 2015) comprising ML models that process constant inputs of image and video data to automatically detect road surface defects. While we sketch the shape of the information flow and the social dynamics required to apply the system, we have not formally designed an information and social artifact that, along with the technology artifact, are necessary to form an information systems artifact (Lee et al., 2015). Therefore, we encourage researchers to further study the requirements for applying ML-based, crowdsourced surface defect detection in everyday life and – based on our technical contributions – develop a solution by considering the interaction of different actors, data sources and processes of data analysis

8 Conclusion

In this work, we presented an ML-based approach for crack detection on road surfaces of natural 2D scene images taken from a driver's viewpoint under normal daylight. We propose the usage of simple images with regard to the automation in defect detection, given their cost-efficiency, quickness and flexibility. In addition, this simplicity provides scalable solutions that could reduce manual efforts and long-term costs for maintenance, while increasing public safety. We used state-of-the-art feature extraction algorithms at the superpixel level, such as, GLCM, statistical measures of variance and skewness, and defined a new feature variant called Variance-of-Gabor using the Gabor filters. Tuning of important parameters of these feature extraction algorithms and incremental feature selection were automatically done in a systematic manner using ML algorithm's performance metric. It has been noticed that texture based features, after being filtered, are highly effective for the task of crack and defect detection in such images. We compared state-of-the-art classifiers like, Gradient Boosting, Artificial Neural Network, Random Forest and Linear Support Vector Machines, along with various feature extraction algorithms for the task at hand. Random Forest and Gradient Boosting show the best overall performance with the lowest false positives and high accuracy. As a result, crack regions belonging to different crack-types, such as single or network, and related defects are successfully detected on road images belonging to varied external conditions and locations. In this way, identified defects are located on road images; thereby helping in road surface condition evaluation by inspecting the defective area within an image.

References

- Abbasi, A., S. Sarker and R. H. Chiang (2016). "Big Data Research in Information Systems: Toward an Inclusive Research Agenda." *Journal of the Association for Information Systems* 17 (2).
- Abella, A., M. Ortiz-de-Urbina-Criado and C. De-Pablos-Heredero (2017). "A Model for the Analysis of Data-driven Innovation And Value Generation In Smart Cities Ecosystems." *Cities* 64, 47-53.
- Achanta, R., A. Shaji, K. Smith, A. Lucchi, P. Fua and S. Susstrunk (2012). "Slic Superpixels Compared to State-Of-The-Art Superpixel Methods." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 34(11), 2274–2282.
- Banker, R. and R. Kauffman (2004). "The Evolution of Research on Information Systems: A Fiftieth-Year Survey of the Literature." *Management Science*, 281-298.
- BASt. (2008). *Road Monitoring and Assessment (ZEB - Verfahrensbeschreibung)*. Report. Federal Highway Research Institute (Bundesanstalt für Straßenwesen - BASt). <http://www.bast.de>.
- Breiman, L. (2001). "Random Forests." *Machine Learning* 5(1), 5-32.
- Canny, J. A. (1986). "Computational Approach to Edge Detection." *IEEE Trans. Pattern Analysis and Machine Intelligence* 8(6), 679–698.
- Chambon, S. and J. Moliard (2011). "Automatic Road Pavement Assessment with Image Processing: Review and Comparison." *International Journal of Geophysics*. 1–20.
- Chatterjee, S., B. Hildebrandt, L.M. Kolbe (2017). "Understanding the Scene Data – Pavement Area Grouping in Images." In: *Proceedings of the 38th International Conference on Information Systems (ICIS)*. South Korea: Seoul.

- Cortes, C. and V. Vapnik (1995). "Support-vector Networks." *Machine learning*, 20(3), 273-297.
- Dalal, N. and B. Triggs (2005). "Histograms of Oriented Gradients for Human Detection." In: *Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*. USA: Washington, DC. Volume 1, pp. 886-893.
- Daugman, J.G. (1985). "Uncertainty Relation for Resolution in Space, Spatial Frequency, and Orientation Optimized by Two-dimensional Visual Cortical Filters." *JOSAA* 2(7), 1160-1169.
- Day, D., A. McGath and B. Natarajan (2012). "Image Based Detection of D-cracking In Pavements." In: *Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition. The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp)*.
- FHWA. (2016). *Long-Term Pavement Performance Program - Pavement Performance Measures and Forecasting and the Effects of Maintenance and Rehabilitation Strategy on Treatment Effectiveness*. Report No: FHWA-HRT-16-046.
- Fink, D. (2010). "Road Safety 2.0: Insights and Implications for Government." In: *23rd Bled eConference eTrust: Implications for the Individual, Enterprises and Society*. Slovenia.
- Friedman, J. (1999). *Greedy Function Approximation: A Gradient Boosting Machine*. IMS 1999 Reitz Lecture.
- Gabor, D. (1946). "Theory of communication. Part 1: The analysis of information." *Journal of the Institution of Electrical Engineers-Part III: Radio and Communication Engineering* 93(26), pp.429-441.
- Galliers, R., S. Newell, G. Shanks and H. Topi (2015). "Call for papers for the special issue: The Challenges and Opportunities of 'Datification'; Strategic Impacts of 'Big'(and 'Small') and Real Time Data—for Society and for Organizational Decision Makers." *Journal of Strategic Information Systems* 24 (3).
- Gavilán, M., D. Balcones, O. Marcos, D.F. Llorca, M.A. Sotelo, I. Parra, M. Ocana, P. Aliseda, P. Yarza and A. Amirola (2011). "Adaptive Road Crack Detection System by Pavement Classification." *Sensors* 11(10), 9628–9657.
- Gholami, R., R. Watson, H. Hasan, A. Molla, Alemayehu and N. Bjorn-Andersen (2016). "Information Systems Solutions for Environmental Sustainability: How Can We Do More?" *Journal of the Association for Information Systems* 17 (8), Article 2.
- Gleave, S. D. (2014). *EU Road Surfaces: Economic and Safety Impact of the lack of Regular Road Maintenance—Study*. Report- Policy Department Structural and Cohesion Policies. European Parliament.
- Goes, P.B. (2014). "Big Data and IS Research." *MIS Quarterly* 38 (5), 3–8.
- Gonzales, R. C. and R. E. Woods (2002). *Digital Image Processing*. 2nd. Edition. New Jersey: Pearson Education.
- Günther, W. A., M. H. R. Mehrizi, M. Huysman and F. Feldberg (2017). "Debating Big Data: A Literature Review on Realizing Value from Big Data." *The Journal of Strategic Information Systems*.
- Haralick, R.M (1979). "Statistical and Structural Approaches to Textures." *Proceedings of the IEEE* 67(5), 786–804.
- Hastie, T., R. Tibshirani and J. Friedman (2009). "Boosting and additive trees." *The elements of statistical learning*, 337-387.
- Henfridsson, O. and R. Lindgren (2005). "Multi-contextuality in Ubiquitous Computing: Investigating the Car Case through Action Research." *Information and Organization* 15, 95–124.
- Huidrom, L., L.K. Das and S.K. Sud (2013). "Method for Automated Assessment of Potholes, Cracks and Patches from Road Video Clips." *Procedia- Social and Behavioral Sciences* 104, 312-321.
- Kitchin, R. (2014). "Big Data, New Epistemologies and Paradigm Shifts." *Big Data and Society* 1(1).
- Koch, C., K. Georgieva, V. Kasireddy, B. Akinci and P. Fieguth (2015). "A Review on Computer Vision Based Defect Detection and Condition Assessment of Concrete and Asphalt Civil Infrastructure." *Advanced Engineering Informatics* 29, 196-210.

- Laubis, K., V. Simko and A. Schuller (2016). "Road Condition Measurement and Assessment: A Crowd Based Sensing Approach." In: *Proceedings of the 37th International Conference on Information Systems (ICIS)*. Ireland: Dublin.
- Laubis, K., V. Simko, A. Schuller and C. Wienhardt (2017). "Road Condition Estimation Based on Heterogeneous Extended Floating Car Data." In: *Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS)*. Hawaii.
- Lee, A., M. Thomas and R. Baskerville (2015). "Going Back to Basics in Design Science: From the Information Technology Artifact to the Information Systems Artifact." *Information Systems Journal*, 25, 5-21.
- Li, L., L. Sun, G. Ning and S. Tan (2014). "Automatic Pavement Crack Recognition Based on BP Neural Network." *Swarm Intelligence in Transportation Engineering, PROMET - Traffic and Transportation* 26(1),11-22.
- Li, R., Y. Yuan, W. Zhang and Y. Yuan (2018). "Unified Vision-Based Methodology for Simultaneous Concrete Defect Detection and Geolocalization." *Computer-Aided Civil and Infrastructure Engineering*.
- Melville, N. (2010). "Information Systems Innovation for Environmental Sustainability." *MIS Quarterly* 34 (1), 1-21.
- Mertz, C. (2011). "Continuous Road Damage Detection Using Regular Service Vehicles." In: *Proceedings of the ITS World Congress*.
- MnDOT. (2009). *Pavement Condition Executive Summary*. Report No. MnDOT/OMRR-PM--2009-01. Minnesota Department of Transportation.
- Mohan, A. and S. Poobal (2017). "Crack Detection Using Image Processing: A critical Review and Analysis." *Alexandria Engineering Journal*.
- Moon, H. and J. Kim (2011). "Intelligent Crack Detecting Algorithm on the Concrete Crack Image Using Neural network." In: *Proceedings of the 28th Int. Symposium on Automation and Robotics in Construction*. South Korea: Seoul, pp.1461-1467.
- Nejad, F.M., H. Zakeri (2011). "An Expert System Based on Wavelet Transform and Radon Neural Network for Pavement Distress Classification." *Expert Systems with Applications* 38(6), 9442–9460.
- Nitsche, P., C. Van Geem, R. Stüt., I. Mocanu and L. Sjögren, (2014). "Monitoring Ride Quality on Roads with Existing Sensors in Passenger Cars." In: *Proceedings of the 26th ARRB Conference*. Sydney.
- Oliveira, H. and L. Correia (2009). "Supervised Crack Detection and Classification in Images of Road Pavement Flexible Surfaces." *Recent Advances in Signal Processing*, 159-184.
- Pauly, L., H. Peel, S. Luo, D. Hogg and R. Fuentess (2017). "Deeper Networks for Pavement Crack Detection." In: *Proceeding of 34th Int. Symposium on Automation and Robotics in Construction*. Taipei, pp. 479-485.
- Prasanna, P., K. Dana, N. Gucunski and B. Basily (2012). "Computer-vision Based Crack Detection and Analysis." In: *Proceedings of SPIE Smart Structures and Materials, Nondestructive Evaluation and Health Monitoring, International Society for Optics and Photonics*, pp.834.
- Rababahh, H., D. Vrajitoru and J. Wolfer (2005). "Asphalt Pavement Crack Classification: A comparison of GA, MLP, and SOM." In: *Proceedings of Genetic and Evolutionary Computation Conference*.
- Rabari, C. and M. Storper (2014). "The Digital Skin of Cities: Urban Theory and Research in the Age of the Sensored and Metered City, Ubiquitous Computing and Big Data." *Cambridge Journal of Regions, Economy and Society* 8, 27–42.
- Radopoulou, S., I. Brilakis, K. Doycheva and C. Koch (2016). "A Framework for Automated Condition Monitoring." In: *Proceedings of Construction Research Progress*. Puerto Rico: San Juan.
- Rojas, R. (1996) *Neural Networks*. Springer-Verlag, Berlin.
- Salari, E. (2012). *Pavement Distress Evaluation Using 3d Depth Information from Stereo Vision*. Report No: MIOH UTC TS43 2012-Final. Michigan Ohio University Transportation Centre.
- Shmueli, G. and O. R. Koppius (2011). "Predictive analytics in information systems research." *MIS Quarterly*, 553–572.

- Silva, C., T. Bouwmans and C. Frelicot (2015). “An Extended Center-symmetric Local Binary Pattern for Background Modeling and Subtraction in Videos.” In: *Proceedings of the 10th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*. Germany: Berlin, pp. 1-9.
- Sinha, S. and P. Fieguth. (2006) “Automated Detection of Cracks in Buried Concrete Pipe Images.” *Automation in Construction* 1, 58–72.
- Staniek, M. (2014). “Neural Networks in Stereo Vision Techniques of Road Pavement Evaluation.” In: *Proceedings of the International Symposium- Non Destructive Testing in Civil Engineering*. Germany: Berlin.
- Stilgoe, J. (2017). “Machine Learning, Social Learning and the Governance of Self-Driving Cars.” *Social Studies of Science*, 48(1).
- Tang, J. and B. Sun (2012). “An Integrated Digital Image Processing Pavement Management Information System.” *ICLEM 2012: Logistics for Sustained Economic Development—Technology and Management for Efficiency*.
- Teomete, E., V: Amin, H. Ceylan, O. Smadi (2005). “Digital Image Processing for Pavement Distress Analyses.” In: *Mid-continent Transportation Research Symposium*. Iowa.
- Varadharajan, S., S. Jose, K. Sharma, L. Wander and C. Mertz (2014). “Vision for Road Inspection.” In: *Proceedings of the IEEE Winter Conference on Application of Computer Vision (WACV)*. USA: Colorado, pp.115-122.
- Wu, L., S. Mokhtari, A. Nazef, B. Nam (2016). “Improvement of Crack Detection Accuracy with Novel Crack Defragmentation Technique in Image-based Road Assessment.” *Journal of Computing in Civil Engineering* 30 (1).
- Yang, C.C. and J.D. Lin (2013). “Establishment of Pavement Information Decision Management Platform via Cloud Computing Technology.” *Advanced Materials Research* 723, 829–837.
- Yoo, Y. J. (2010). “Computing in Everyday Life: A Call for Research on Experiential Computing,” *MIS Quarterly* 34 (2), 213–231.
- Zakeri, H., F. M. Nejad and A. Fahimifar (2016). “Image Based Techniques for Crack Detection, Classification and Quantification in Asphalt Pavement: A Review.” *Archives of Computational Methods in Engineering* 24 (4), 935-977.
- Zalama, E., J. Gómez-García-Bermejo, R. Medina and J. Llamas (2013). “Road Crack Detection Using Visual Features Extracted By Gabor Filters.” *Computer-Aided Civil and Infrastructure Engineering* 29 (5), 342-358.
- Zhang, L., F. Yang, Y.D. Zhang and Y.J. Zhu (2016). “Road Crack Detection Using Deep Convolutional Neural Network.” In: *Proceedings of IEEE Int. Conf. on Image Processing (ICIP)*, pp. 3708-3712.
- Zuiderveld, K. (1994). *Contrast limited adaptive histogram equalization*. Graphics gems IV. USA: Academic Press Professional, Inc. pp. 474-485.