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A Deep-Learning-Based Road Deterioration Notification and Road Condition Monitoring Framework

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Abstract: Road deteriorations threaten people 'safety as they are considered one of the major causes of road accidents leading to significant human and material losses. Automatic detection of road deteriorations can help massively in avoiding the tragic consequences. However, this task represents a real challenge. This work describes an attempt to tackle this issue by establishing a crack notification and road condition monitoring system. The proposed system will help drivers to avoid dangerous cracks and enable authorities to supervise and manage the road surface. In order to automatically detect and classify the road surface images, a convolutional neural network (CNN) is used, as this model has proven to be more suitable for this task than traditional methods due to its ability to extract features implicitly. The novelty in this paper consists on finding the optimal CNN model architecture for crack detection and classification into 10 distinguished classes. The proposed CNN model is trained and tested using historical 3D pavement images and can perform the classification with a high accuracy (above 95%). To evaluate and supervise each road segment condition, a novel method for severity indexes computation that uses the resulting classes is suggested as well as the generation of a weighted road graph in which the edge weights evolve according to the severity indexes. All data processing tasks are performed over a Hadoop-based framework using HBase and MapReduce.

Keywords: Convolutional neural network, Deep learning, Road cracks, Big data, Hadoop/map reduce.

1. Introduction

One of the most used types of road surface is asphalt pavement structure, which is characterized by its low investment cost and easy manufacturing process, corresponding to the constraints of the majority of developing countries economic status. However, after a period of use, distress starts to occur in the asphalt pavement structure, mainly due to the dry environment and temperature decreases. This threatens the safety of road users, and can be considered one of the primary accident-causing factors after reckless behavior by drivers. The transportation departments are responsible for ensuring a safe driving experience for road users. In order to repair the damaged roads and to maintain the cities' roads in a good state, periodical road monitoring should be scheduled.

The detection and classification of road deterioration are mandatory steps for road surface management [1-3]. The purpose is to gather data on pavement conditions for further maintenance. Cracking is the most common type of pavement distress to be tracked, since it can be easily absorbed by other types of pavement distresses. The study in [4] revealed that the presence of road cracks can decrease the road surface quality by up to 40% during its first 75% of life, and with no treatment at all, this affects it by another 40% in the subsequent 12% of its life. Cracks are generally divided into six types [5]: block, alligator, edge, reflection, longitudinal and transverse cracks.

Visual inspection is the most common traditional method for crack detection and classification. This method has not been very effective mainly due to the time and money costs and the lack of objectivity. The overall objective of this study is to evaluate and increase the quality of roads condition by automatically detecting and classifying the three most frequent crack types present in the cities' roads (longitudinal, transversal and alligator cracks) and to estimate the severity of distress of each road segment for further maintenance.

The proposed system takes advantage of the Convolutional neural networks (CNN) for the automatic detection and classification of road cracks. The CNN models approved high efficiency in the processing of visual data such as images and videos which prompt us to choose it. It transforms raw input data from the lowest layer and transforms it by performing a series of basic calculation units in order to obtain representations which have intrinsic values for classification in the upper [6].

In this study, we are particularly focused on elaborating an integrated system for crack notification and road condition monitoring that meets both road users and authorities' expectations. This is done by conducting periodical scans of the road network which allow the collection of road surface images and other additional data. The images gathered from each road scan will undergo a few pre-processing steps before being passed as input to a novel CNN-based detection and classification method. This CNN has already been trained and experimented with several combinations of layers and finally selected the optimal CNN architecture. The detection and classification results are then used to measure the severity indices of the road segments based on a novel method that takes into consideration more than one crack indicator. The road network graph is generated and then weighted with the severity indices. The big data paradigm is adopted to deal with the huge volume of periodically gathered data. Hadoop/MapReduce is chosen for this, due to its simple programming models for the distributed processing and storage of a large volume of data. An online analytical processing tool, OLAP[7], is used for data analysis.

The main contributions in this work are:

- A CNN based approach that distinguish between images with crack and non-crack and further recognize cracks into precise types which are: transversal, longitudinal and alligator cracks with variety of severities while respecting processing time. To our knowledge, no previous work has classified cracks in the same manner.
- The cracks classification has grant us the possibility to establish a novel method for road severity computation that takes into account multiple crack indicators.
- The generation of a spatio-temporal map with the computed severity indices and offering a friendly crack notification interface for road users.
- The use of big data tools for storage, processing and analyzing the collected data and proving a road monitoring service for authorities to supervise the road condition.

This paper is organized into several sections: research survey is described in Section 2; Section 3 provides a detailed overview of the proposed crack notification and road condition monitoring framework, the proposed CNN-based crack detection and classification method and the novel road severity computation approach are presented in Sections 4 and 5 respectively; Section 6 describes the case study and results; and a discussion and conclusion are presented in Sections 7 and 8, respectively.

2. Research survey

In this section, a brief review on the existing crack detection methods is presented. First, the traditional approaches including visual inspection and image processing-based thresholding methods. Second, the machine learning based approaches for detection and classification of road cracks.

2.1 Traditional approaches for crack detection

Visual inspection is adopted in most traditional crack detection methods: a trained expert evaluates the condition of the road structure depending on the coordinates and the width of the observed crack. This task is considered too time consuming, intensive and expensive to be done manually. Since each expert evaluates the state of a road surface depending on his or her own experience, the results of traditional detection methods are subjective, and this process is also dangerous for the evaluator due to traffic Hazards. The weakness of the manual inspection approach has led to the study of image-based automated crack detection methods. The efficiency, objectivity, safety and low cost of these techniques can highly improve the road surface maintenance process.

Automatic distress detection by thresholding relies on using image processing methods followed by thresholding in order to extract the structure of road deterioration. To achieve this, image pre-processing is necessary, which consists of reducing non-uniform illumination. Following this, thresholding is carried out in the image space by assuming that crack regions in an image are slender, connected and darker compared to the background of the image [8]. The road distress image can then be refined using morphological operations and connected component searching methods. The authors of [9,10-11] present approaches to the thresholding of road distress images using the CrackIT toolbox, which is a closed-source but publically available toolbox. The advantage of this automated approach arises from the use of well-chosen image pre-processing techniques and image edge detection. Unfortunately, the characteristics to be extracted vary from one pavement surface to another, and can be influenced by light, noise and other factors.

2.2 Machine learning based approaches

For more accurate image-based crack detection methods, approaches based on machine learning have been considered[12]. Artificial neural networks (ANNs) and supervised machine learning algorithms have been deployed in order to detect whether or not a crack is present in an image [13]. The work in [14] represents an example of a neural-network-based approach that use a multi-layer perceptron network. However, only simple ANN structures can be put into practice to detect road cracks, due to the limitations of its computational capability. Fortunately, in the last decade, the evolution of deep learning and distributed computations utilizing graphic processing units [15] has made it possible to exploit convolution neural networks (CNNs) in image recognition [16]. This approach classifies images based on fewer computations compared to conventional neural networks thanks to its use of partial connections and sharing weights between neurons, and the pooling process used. The two main steps in deploying CNNs are the design of the architecture and the training of the CNN using an adequate data set.

The detection and further classification of the pavement cracks attracted the attention of multiple researchers. Authors in [17] proposed four supervised CNNs with different sizes of receptive fields to automatically classify image patches cropped from 3D pavement images into 5 classes which are: no cracks, transverse, longitudinal and alligator with acceptable classification accuracy.

In this paper [18], a fully automated crack detection and classification using deep convolution neural network (DCNN) architecture is suggested in order to classify cracks into the same types as [17] and using two different filter sizes: 3x3 and 5x5.

Authors in [19] proposed a method of convolution neural networks-based crack detection that was designed through fine-turning an existed CNN architecture. The classification of a large number of images into cracks and non-cracks was conducted and the results showed high accuracy and performance.

Taking insight of the aforementioned research studies, the present research uses CNN for crack detection and classification into 10 different classes. The opted classification made it possible to propose a novel severity computation method and further suggest a notification and road condition monitoring framework. The following sections will describe in details our contribution. In the discussion, a comparison with previous studies based on the accuracy evaluation metric will be presented.

3. Overview of the proposed crack notification and road condition monitoring framework

3.1 Framework architecture

Fig. 2 gives an overview of the proposed framework structure. The main goal of this structure is the automatic handling of road distress detection and classification issues. The proposed approach consists of the collection of road surface data using cameras embedded in a dedicated car, and road network data from urban management centers. These data should be fed into the system database. The data processing module uses this database to launch its services, analyses and extracts knowledge based on the algorithms used and OLAP analysis. This advanced computational module mainly consists of the following stages:

1) The pre-processing of the collected road surface images consists firstly of data normalization in order to ensure that each input image has a similar data distribution and to avoid the influence of high- and very low-frequency noises. The second step of pre-processing is the augmentation of both training and testing datasets in order to expose the CNN to a wide variety of image types for better learning.

2) Image classification consists of using a CNN-based module to detect and classify road cracks. The module is trained and tested using the existing public image data sets (SDNET2018 [20], CIFIA-10 and CIFAR-100[21], MNIST[21]). The images represent non-cracked areas, longitudinal cracks (with low, medium and high severity), transverse cracks (low, medium and high severity) and alligator cracks (low, medium and high severity). Furthermore, the trained CNN can be used to predict the classes of new images gathered in a series of road scans.

3) The severity index computation unit combines three indexes: the alligator crack index (ACI), the transverse crack index (TCI) and the

longitudinal crack index (LCI). These indexes are computed based on the numbers of each type of crack detected in the collected images.

4) The road network generation step consists of generating the graph of the road network using the gathered road network data.

5) The weighted network generation step uses the obtained severity indices in conjunction with the road data to create a weighted graph. The edge weights of the road network are the computed severity indices.

6) Our solution provides a crack notification system that can help road users to avoid severe road cracks that can affect their safety or that of their vehicles, by providing a map representing the condition of the road surface and sending notifications when approaching a road with an unsafe level of distress. The proposed solution is also a road surface condition monitoring system for the authorities, which can provide analysis, reports and statistics and severity indices to give a clear view of road surface conditions and to determine which road segments most need maintenance.

3.2 Data storage

To realize our proposed framework, the use of big data tools is required in order to store, analyse and process the large amounts of data fed to the system from the periodical road network scans. A data warehouse is therefore developed using Hadoop Hbase in order to store all the gathered data. The choice of Hadoop HBase was not arbitrary; this is a data management system that is dedicated to a distributed environment and runs on top of Hadoop file manager. It is an open-source and column-oriented storage model inspired by the principles of Google's BigTable. It permits the storage of the collected data on clusters of servers spread over multiple data centers. The overall aim at this stage is to transform the required relational conceptual model into a column-oriented schema.

The manipulated data are stored within large tables called HTables, which are composed of rows and families of columns, in their turn, the column families are composed of columns. An HTable contains a series of row records and is organized as a key-value entity. Fig. 3 illustrates the star schema of the data warehouse, which consists of a fact table

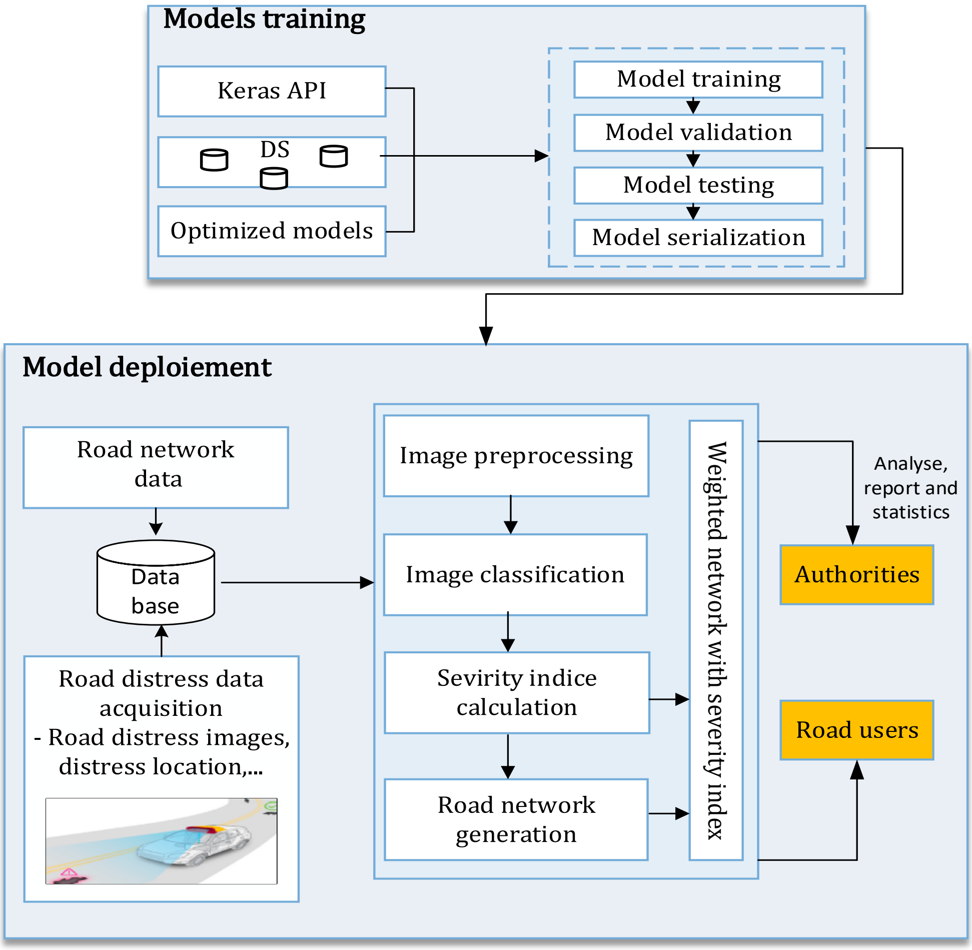

Figure. 1 Architecture of the proposed crack notification and road condition monitoring system

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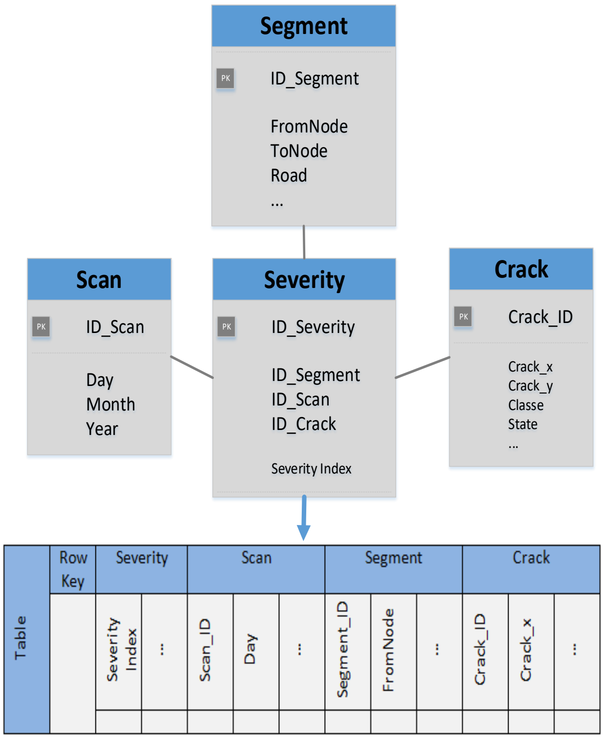

Figure. 2 Part of the conceptual/logical schema of the database

entitled "Severity" and three dimensions (segment, crack, and scan). Each dimension is translated into a column family in the HTable. The fact table is also represented by a column family in the target table.

3.3 Data storage

In this study, the parallel distributed programming model MapReduce was adopted. This was introduced by Google Labs and is dedicated to the treatment of large data sets and the effortless writing of applications. It has the capability to compute a vast amount of data clusters in parallel. MapReduce performs two essential functions: it distributes the tasks to several nodes within the cluster (the Map function), thereafter, in order to provide a response to a request, it organizes and aggregates the results of each of the nodes (the Reduce function). In our case, both the input and the output of the functions are stored in a Hadoop HBase. In order to carry out the clustering algorithm, the initial set of clusters with their centers and the data to be clustered need to be suitably structured in the input directory and then passed to the master node.

The manipulated data include road surface images and GPS data. large amounts of storage and high computing power is required to analyze this data. Using the MapReduce processing model of Hadoop, a weighted graph with the severity indices can now be generated. The MapReduce process shown in Fig. 4 has the objective of generating the weighted road network. This phase combines the image classes with the road network data in order to compute a severity index for each road segment of the network. At this stage of the MapReduce process, the method described in Section 5 is applied to compute the severity indices.

3.4 Data acquisition and network modeling

The first step of this stage consists of collecting the road surface data (see Fig. 5). Multiple image-based techniques can be used to achieve this, and several factors need to be considered in order to choose the most suitable technique. In this study,

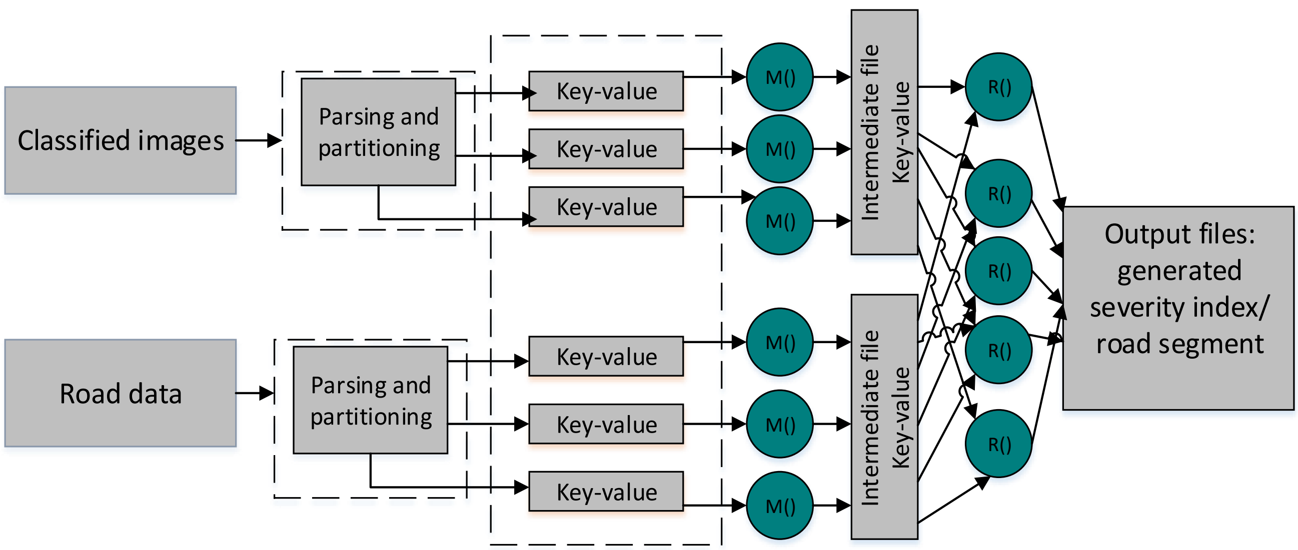

Figure. 3 The MapReduce process

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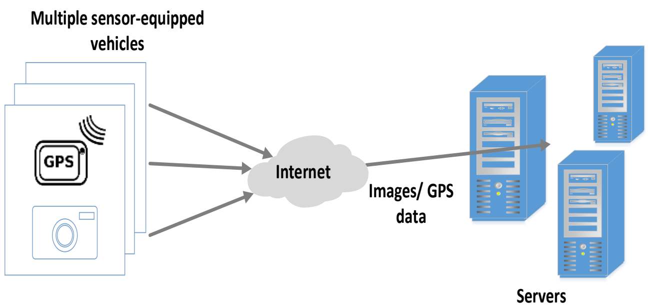

Figure. 4 The data acquisition process

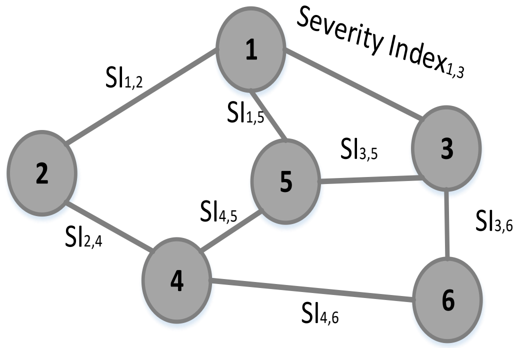

Figure. 5 An example of a weighted graph

factors such as image clarity, accuracy, processing speed and implementation costs should be considered. High-quality images of size 4096 × 2048 representing the road surfaces are required and can be collected using a camera in dedicated vehicles. These vehicles, equipped with cameras and other embedded sensors such as GPS, periodically travel the entire road network to provide the system with images of the actual road surface conditions, locations etc.

The road network is formed using a planar graph G = (V, E) with a set of vertices V and a set of edges E, in which the roads appear as the set of arcs, characterized by parameters such as the number of each crack type, length, etc. The road segments are the links between two nearby vertices, and are represented by either one or two directed edges. The edge weight W_{ij} between two vertices V_i and V_j is a dynamic factor that is used to represent properties related to the edge (V_i, V_j) (see Fig. 6). The severity indices are calculated based on the gathered data that includes images of the road surface and their location. These severity indexes are associated with the arcs modeling the road network and are used to generate the weighted graph (more details on the arc weights are given in Section 5).

3.5 Image pre-processing

The main idea behind CNNs is that they learn features implicitly. However, building an effective neural network model requires careful consideration of the network architecture as well as the input data format. The preprocessing of the input data refers to all the transformations applied to it before it is fed to deep learning algorithms. For instance, training a convolutional neural network on raw images will probably lead to poor classification performance, according to[22]. Preprocessing techniques, such as centering and scaling techniques, also helps to faster the training[23]. The two main preprocessing techniques used in this study are normalization and augmentation.

It is mandatory to ensure having similar data distribution and data normalization for each input parameter (in this case, pixel). It also removes the influence of high- and very low-frequency noise. This makes convergence faster while training the network. The input data are normalized as follows:

$$N_I = \frac{I - mean(I)}{max(I) - min(I)} \quad (1)$$

where N_I denotes the normalized data and I denotes the input data.

Data augmentation is another common preprocessing technique that involves augmenting the existing data set with perturbed versions of the existing images. Scaling, rotation and other affine transformations are also typical; these are done to expose the neural network to a wide range of variations. A data set was built based on pavement images from existing public image data sets ((SDNET2018 [20], CIFIA-10 and CIFAR-100[21], MNIST[21]). We selected 1,000 images randomly from the database. The size of each image was 4096 × 2048, representing a pavement surface roughly 4 m by 2 m. In order to augment the input data, the proposed CNN was trained on square image patches, which were created by dividing the original pavement images into patches of size 512 × 512. Image rotations were also adopted to increase the variation in the data set used to train the classification model, as shown in Fig. 7.

4. The CNN-based crack detection and classification module

In training and test data sets, small patches are classified into ten classes: uncracked class, each type of cracks (longitudinal transverse and alligator) is classified into three classes: cracks with low, medium or high. Figure 3 presents a subset of the training data set.

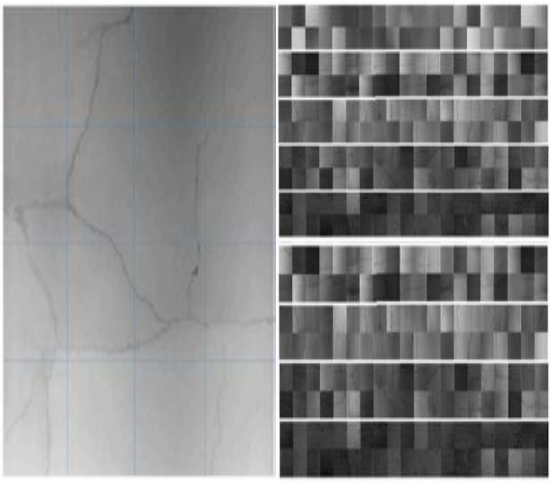

Figure. 6 original 3D pavement image divided into patches (Left); a subset of the training dataset (right)

In this classification problem, the target value is a

$$W(K+1) = W(K) - \alpha \frac{\partial E}{\partial W'} \quad (2)$$

10-dimensional column vector containing values of ‘0’ or ‘1’. Each item of training data and testing data is labeled with a vector, as shown in Table 1. The sufficiency and diversity of the training data set are fundamental to the success of training CNNs. Hence, more than 28,000 patches and corresponding target vectors were used to make up the training and testing data sets. The composition of these data sets is given in Table 2.

Stochastic gradient descent (SGD): The goal of training a CNN is to find the values of all the parameters W that can minimize a loss function E. The loss function E(i)=D(D(i), F(W, Z(i))) measures the discrepancy between D(i), the ‘correct’ or desired output for input Z(i), and the output F(W, Z(i)) generated from the function F, that is, the CNN. The general problem of minimizing a function with respect to a set of parameters is at the root of many issues in the field of computer science and mathematics.

The SGD algorithm has proven to be a predominant methodology [24]The loss function can be minimized by estimating the impact of small variations in the parameter values in the CNN. The simplest minimization procedure using SGD is

where α is the learning rate, which is a constant less than 1, and k is the iteration time.

Since the proposed CNN is a multi-layer feed-forward network, the relationship between the CNN parameters and the implicit loss function E is complex. Hence, the chain rule of calculus is applied to calculate the derivatives. In this way, the gradients at the mth layer are computed from the gradients at the (m+1)th layer, and the backpropagation algorithm derives its name this process.

Table 1. Target values for 10 types of data

Type of crack	**Target value**
Class 1	[1000000000]T
Class 2	[0100000000]T
Class 3	[0010000000]T
Class 4	[0001000000]T
Class 5	[0000100000]T
Class 6	[0000010000]T
Class 7	[0000001000]T
Class 8	[0000000100]T
Class 9	[0000000010]T
Class 10	[1000000001]T

Table 2. Composition of the data set

Type of crack	**Number of training data**	**Number of testing data**
Class 1	5552	300
Class 2	2323	130
Class 3	2323	136
Class 4	2324	134
Class 5	2401	132
Class 6	2403	134
Class 7	2401	134
Class 8	2410	136
Class 9	2410	132
Class 10	2411	132

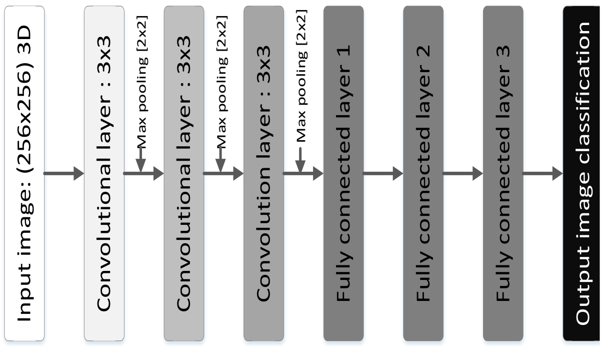

Figure. 7 The optimal CNN architecture

To maximize the performance of classification, it is essential to compose the layers of the CNN in an optimal way. The use of more hidden layers may improve the performance of classification, but the speed of training may be reduced. On the other hand, a high-complexity CNN with many layers and parameters may lead to overfitting. Fig. 8 illustrates the optimal CNN architecture chosen in this study.

The loss function E is the mean square error, which is defined as:

$$E = \frac{1}{Q}\sum_{i=0}^{Q}(D^{(i)} - O^{(i)})^{2} \quad (3)$$

where D(i) is the ith target vector, and O(i) is the ith output vector.

ReLu and log-sigmoid are applied as the activation functions in the convolutional layers and fully connected layers, respectively. Before feeding the CNN with our training data set, each patch is resized to 256 × 256 in order to save computing time. Once convergence is achieved, the training process is terminated, as illustrated in Fig. 9.

The CNN was implemented using Python with the Tensorflow library. Tensorflow is an open-source Python library developed by Google that helps users to implement deep learning algorithms in a more efficient way.

5. The proposed method for computing crack severity

In this section, we present the types of surface distress handled in this study and the proposed method for computing the crack severity index for each road segment. Three types of surface distress are considered: transverse, longitudinal and alligator cracks.

5.1 Alligator crack

Alligator cracking may be considered a combination of fatigue and block cracking, and consists of a series of interconnected cracks at various stages of development. Alligator cracking develops into a many-sided pattern that resembles chicken wire or alligator skin, and may exist at any part of the road segment. The severity levels of alligator cracks range from low to high (see Fig. 10).

- Low severity: characterized by the absence or very few interconnecting cracks, cracks are <= 6 mm in mean width, and the distance between the cracks doesn't exceed 0.328 m. This kind of cracks can be so tight which makes it hard or even impossible to determine its width.
- Medium severity: The suffering road area forms a complete interrelated pattern of cracks. Crack widths range from 6 mm to 19 mm, it can be also associated to any crack with an average width under 19 mm and close to a pattern of low-severity cracking. Distance between this category of Cracks doesn't exceed 150 mm.
- High severity: The crack pattern in the road area is made of joined cracks moderately or badly formed. High severity can be associated to cracks with a width higher than 19 mm or any crack having a width under 19 mm but near medium to high-severity random cracking.

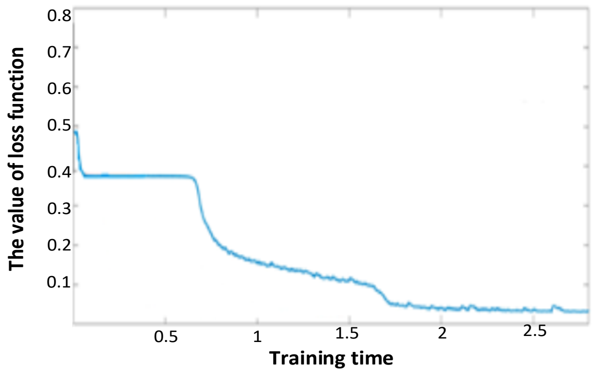

Figure. 8 Values of the loss function versus training time

Figure. 9 Examples of different severity levels of alligator cracking

Table. 3 Severity levels of alligator cracking

Alligator cracking severity levels		Crack pattern: LOW	Crack pattern: MED	Crack pattern: HIGH
Crack width	LOW	L	M	H
	MED	M	M	H
	HIGH	H	H	H

For an efficient severity determination of alligator cracks, it is mandatory to observe the cracks width and pattern. Based on the above description of each severity, the highest level of the crack width and crack pattern determines the overall severity (see Table 3).

5.2 Transverse crack

Transverse cracking mainly takes place anywhere within the road lane and perpendicularly with the centerline of the road. The severity levels of transverse cracks range from low to high (see Fig. 11).

- Low severity: Cracks are qualified with a mean width lower than 6 mm. confined cracks having a good state sealant and difficulty to determine the width.

Figure. 10 Examples of different severity levels of transverse cracking

- Medium severity: Cracks mean width ranges from 6 mm to 19 mm, or any crack with a mean width under19 mm but joined to random low-severity cracking.
- High severity: Cracks mean width over19 mm, or any crack with a mean width under 19 mm and linked to random medium- to high-severity cracking.

5.3 Longitudinal crack

It mainly takes place anywhere within the road segment and parallel to the centerline of the road. Longitudinal cracks principally take place in the wheel trajectory. The severity levels of longitudinal cracks range from low to high (see Fig. 12).

- Low severity: Cracks mean width is lower than 6 mm. tightly closed cracks having good state sealant and difficulty to measure the width.
- Medium severity: Cracks mean width ranges from 6 mm to 19 mm, or any crack with a mean width under 19 mm but near random low-severity cracking.
- High severity: Cracks with a mean width over 19 mm, or any crack with mean width under 19 mm but near random medium to high severity cracking.

5.4 Computation method for the road segment severity index

Eq. 4 represents the road segment severity index (SI), which is a combination of three indices: the ACI (Eq. 5), the TCI (Eq. 6) and the LCI (Eq. 7) of that same segment. Each of the three indices considers the number of detected cracks present in a road segment and their severity level, which is made possible by the proposed CNN-based detection and classification method described in the previous section.

$$SI(i) = \frac{ACI(i) + TCI(i) + LCI(i)}{3} \tag{4}$$

Figure. 11 Examples of different severity levels longitudinal cracks

$$ACI(i) = \frac{Cf_1 \times LAC + Cf_2 \times MAC + Cf_3 \times HAC}{\sum_{j=1}^{3} Cf_j} \tag{5}$$

where LAC, MAC and HAC are the counts of low-, medium- and high-severity alligator cracks present in road segment i, respectively.

$$TCI(i) = \frac{Cf_1 \times LTC + Cf_2 \times MTC + Cf_3 \times HTC}{\sum_{j=1}^{3} Cf_j} \tag{6}$$

where LTC, MTC and HTC are the counts of low-, medium- and high-severity transverse cracks present in road segment i, respectively.

$$LCI(i) = \frac{Cf_1 \times LLC + Cf_2 \times MLC + Cf_3 \times HLC}{\sum_{j=1}^{3} Cf_j} \tag{7}$$

Where LLC, MLC and HLC are the counts of longitudinal cracks of low, medium and high severity present in road segment i, respectively. Cf1, Cf2 and Cf3 in each equation separately are coefficients linked to each cost parameter. Experts in the field are responsible for checking the values of these coefficients for better optimization of the weight calculation function.

6. Experimentation and results

In this section, we present the crack notification service and discuss its benefits in terms of drivers' journeys on the roads. In addition, the road surface condition monitoring service is illustrated by presenting some results of analysis that demonstrate the importance of our solution in making short- and long-term decisions on the amelioration of road conditions. Due to lack of data availability and resources to conduct the periodical road scans, we reserved an amount of data from the existing public road surface datasets to test our proposed framework. Table 4 illustrates the overall classification of the images using a conventional neural network.

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Table 4. Example of the classification results of a particular road scan

Image class	Count
Non-cracked	58,225
Low-severity alligator crack	3,601
Medium-severity alligator crack	3,532
High-severity alligator crack	3,508
Low-severity transversal crack	3,832
Medium-severity transversal crack	4,774
High-severity transversal crack	4,694
Low-severity longitudinal crack	6,182
Medium-severity longitudinal crack	8,493
High-severity longitudinal crack	7,309

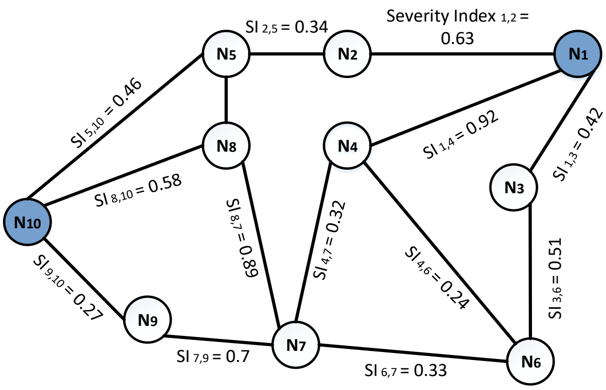

Figure. 12 Example of the road graph generated

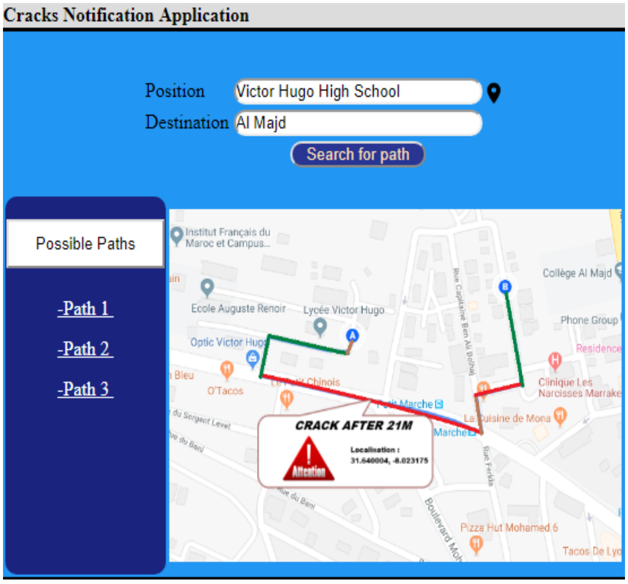

Figure. 13 Crack notification application for road users

Using a web application, drivers can start the road notification service and travel between a given start and end point. In return, they receive notifications whenever they are close to road distress that could affect their safety or that of their vehicle. To test this service, we randomly assigned road surface data to a road network. The system generates a weighted graph where the computed severity indices represent its weights. Fig. 13 represents an example of a graph generated.

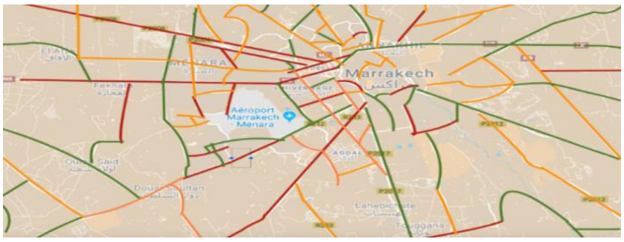

Figure. 14 Example of a road network with the severity state of each segment

Our solution has a user-friendly interface that requires a form to be filled out by the user. The information requested includes the position and destination of the driver. The position is automatically retrieved from the users' devices after permission has been granted. As a result, a map containing the trajectory of the user appears, with severity indices corresponding to each segment, and notifications are sent to the user by text and voice alerts whenever the car approaches a segment with a high severity index (see Fig. 14).

7. Discussion

The aim of this study is to evaluate road conditions in terms of the presence of deterioration in a city road network. Our proposed solution involves the automatic detection and classification of the three most frequent types of road degradation: longitudinal, transverse and alligator cracks. The focus on these types is not arbitrary, and is due to the fact that these types of cracks are easily absorbed by other categories of road distress. Timely maintenance of road segments suffering from one or more of these three detected categories reduces the cost to the city authorities. Based on the detected and classified cracks, our framework computes a severity index for each road segment using a novel method that combines several parameters to provide a genuine view of the road surface conditions.

Our proposed framework represents a crack notification and road surface condition monitoring service based on a CNN that is dedicated to road users and authorities. Road surface data collection using vehicles equipped with a GPS and camera is suggested. This data gathering allows the proposed framework to be suitable for data analytics; however, the storage and processing of progressively higher volumes of data presented a significant challenge in this study. To overcome this issue, the use of big data tools was considered. We chose the Hadoop/MapReduce framework as a big data management tool due to its high flexibility, reliability and scalability.

Our goal is to detect and classify road surface images, and a CNN was adopted to achieve this since it has the ability to extract image features implicitly and to predict image classes based on training and testing datasets. The size of the training data set has a strong influence on the accuracy of the model. Our CNN model was trained on data sets with different sizes and the largest of these increased the accuracy of the model to its maximum due to the high number of iterations used, which gives a more accurate output. In this study, several CNN architectures were proposed and we experimented with these to find the optimal composition of the CNN model. The use of a higher number of hidden layers can lead either to higher performance with a slower training speed or to overfitting. Figure 8 represents the selected CNN architecture that offered the best performance in terms of classifying road surface images into 10 classes. Table 5 shows the classification accuracies of the selected CNN. A high accuracy classification

Table 5. Accuracies classification of the selected CNN

Crack type	Accuracy (%)
Class1	98.00
Class2	96.68
Class3	96.66
Class4	96.67
Class5	96.31
Class6	96.33
Class7	96.35
Class8	92.67
Class9	93.65
Class10	93.65

Table 6. performance comparison of previous deep learning methods

Reference	Mean accuracy (%)	Size of image input	Number of image classes
[17]	94%	512x512	5 classes
[18]	99%	32x32	5 classes
[19]	99.39 %	224x224	Cracked, non-cracked
Our proposed method	95%	256x256	10 classes

performance was achieved compared to other architectures, and the mean accuracy of all 10 classes was higher than 95%.

Table 6 presents a performance comparison of deep learning methods reported in section 2. In general, these methods work on pavement crack classification and show high performance in classification using CNNs. The study in [17]reached lower accuracy in classifying 5 types of cracks. In [18], 99% accuracy is achieved by using a CNN to classify 5 types of defect images; however, the input image size used was 32 × 32, meaning that fewer parameters were needed to train the model. The authors of [19] adopted methods based on CNNs to classify pavement patches into two categories, cracked or non-cracked, and hence the output layers of their CNNs contained only two nodes, meaning that their networks were less complex than others. Our proposed method can obtain 95% accuracy, and is reliable in classifying pavement patches into the 10 categories discussed above.

8. Conclusion

The approach discussed in this paper represents a road crack notification and road condition monitoring solution based on big data and deep learning concepts. The proposed framework uses distributed data gathered from four vehicles equipped with a camera and GPS. The collected data will be then managed using Hadoop to ensure fast data loading, fast query processing and efficient storage.

The contributions of this work lie within the use of deep CNN based method for automatic crack detection that classifies pavement patches into 10 categories as mentioned in previous sections. The comparison between several CNN architectures with different parameters setting on concrete crack image datasets is done in order to find an optimal model. subsequently, and based on the results provided by the cracks classification model, we tried to measure the severity of the road by calculating the severity index, which is according to our knowledge, it is never calculated in this way.

The case study illustrates the crack notification service for drivers and presents the road condition monitoring service for authorities based on data analysis. Our experimental results show that the data processing operations and algorithms deployed in the large-scale data processing system are feasible and efficient. The use of a system based on Hadoop improves the performance and significantly decreases the processing time.

The limitations of our solution are apparent in the abilities of our proposed classification model. Although it allows for high-accuracy classification, it is restricted to a binary categorization at a patch level of 256 × 256 pixels, and produces slow convergence over around 17,000 training iterations. In addition, since our classification model reflects the knowledge used in its training, human expertise is needed to supervise and correct the model in order to develop an appropriately evolving tool. To address these limitations, we intend to carry out complementary studies and to implement a model that is capable of identifying cracks at any pixel level, to optimize the training time of the model and enable a feedback system with corrections from an expert in the field of road structure inspections.

Conflicts of Interest

By respecting the rules and policy of the journal IJIES and our responsibility as researchers, we declare that we do not have any related financial and/or commercial interests on these matters, and do not receive funding from a company likely to be affected by the research reported in this research paper.

Author Contributions

The paper Conceptualization, methodology, software, and formal analysis, investigation, resources, data curation, writing—original draft preparation, writing-review and editing, visualization have been done by the first author. The supervision, project administration and validation have been the second and third authors.

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