Examining the Evolution of Structured Condition Index Using Linear Regression and Automated Classification of Inspection Results by CNN

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Abstract. Monitoring pavement deterioration is a major concern for road network organizations worldwide. If left unaddressed, deterioration can impact safety and incur additional costs. This is why continuous monitoring of pavement condition is one of the most important management methods. Deterioration is reflected in various performance indices, including the Structured Condition Index (SCI), which is used in Morocco. This study aims to analyses how the condition of the structure layer has changed and to predict possible variations in the surface indicator on Road 16 in the Oriental Region between 2010 and 2024. The data comprises images of pavement deterioration collected from the General Directorate of Roads' archive in Morocco. These include records of deflection, pavement uniformity and the distribution of the three most prevalent types of pavement deterioration. The images of pavement deterioration were automatically classified using the DenseNet121 architecture with 92% accuracy. A second classification of the images was then performed using DenseNet201 and a grid ranging from A to D to quantify the severity of the degradation. An analysis of the SCI variation curves was conducted, followed by regression-based prediction. This research continues to support road managers in their decision-making processes.

1 Introduction

Building road infrastructure is an investment with a very high rate of return. This is why road and highway departments allocate very high budgets to maintaining these networks in order to preserve this heritage. However, maintenance costs also represent a challenge, due to the significant increase in repairs required to address road degradation [1]. [2] Showed that pavement maintenance costs related to maintenance activities could reach $90 per square

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meter for the wearing course. The maintenance procedures follow a rigorous technical protocol: information collection, either manually or automatically, is first carried out, then information relating to the distribution, classification, positioning and severity of the deterioration is processed; finally, the decision regarding the methods for initiating repair work is made [3]. However, manual work has a negative impact on the quality of data collection. Road examiners use their human vision to detect and classify deterioration, which can lead to wasted time, miscalculations, and accidents, as they have to walk on the road to carry out their work. However, recent techniques using vehicles equipped with imaging systems make it possible to automate this process and speed up this task. For example, ARAN is a vehicle perfectly suited to measuring rutting using the laser transverse profiler technique. It is also equipped with an imaging system capable of capturing the condition of the road with high precision by recording the coordinates of each deterioration using an integrated geographical positioning system [4]. Another vehicle widely used worldwide is the LASER RST®, manufactured by the Swedish National Institute, which can capture the transverse profile of the roadway [5]. On the other hand, using human vision to classify deterioration after the collection phase is a major additional constraint. This requires the use of sophisticated methods, such as deep learning algorithms [6]. Several models have been used in the literature to detect and classify pavement deterioration . For example, To address the question of establishing an improved pavement crack classification algorithm based on VGG, [7] conducted a comparative study between several architectures such as GoogLeNet, ResNet18, AlexNet and VGG, in order to extract the characteristics of road degradation images. [8] designed an neural network model for road type classification, based on a road surface data collection system they developed themselves. The model's classification accuracy was greater than 96%.

The objective of classifying and detecting pavement conditions remains the evaluation of their performance according to well-defined parameters. The literature lists several tools for describing the current situation of the road, defining priority interventions, predicting its performance and performing an economic analysis. However, depending on the tool adopted, specific input database are required. These are distinguished by varying degrees of accuracy obtained by various methods. These data contribute to determining overall performance and maintenance costs. The Pavement Condition Indicator (PCI), for example, is employed to assess the condition of the pavement surface [9]. In Morocco, the Surface Indicator (SUI) is an indicator similar to the PCI which consists of classifying sections of roadway according to their level of severity, according to the number of degradations observed [10] [11]. The Structured Condition Index (SCI) is also used to quantify pavement structure. As shown in Fig. 1, it is an indicator that requires data on the pavement uniformity, pavement deflection, and the class of cracking present on the pavement, such as longitudinal, transverse, or crazing cracks.

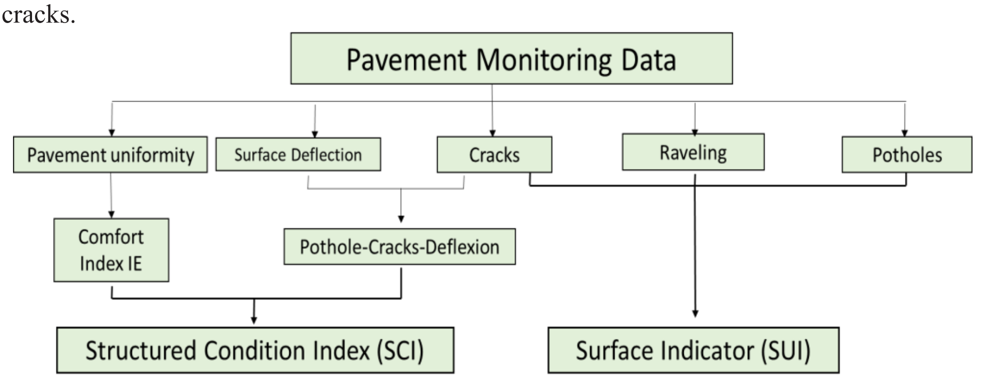

Fig. 1. Structured Condition Index (SCI) assessment method.

Assessing the condition of the road is a very important step in helping road managers make decisions, and predicting its future condition is also essential to optimize the efforts made. From the indicators obtained by classification, it is possible to predict future indicators for the coming years. Linear regression is an effective tool for making this prediction in a linear manner [12]. This approach makes it possible to define the level of degradation to which the pavement can reach and to predict in advance the technical measures necessary to remedy it and improve road safety [13]. The objective of this work is to assess pavement condition using PSI, starting by automatically classifying the different existing types of degradation using the DeneNet201 architecture. The results of this classification, along with deformation and pavement uniformity, will be used to assess PSI between 2010 and 2024, and then to begin graphical linear regression modeling to predict this indicator through 2026.

The second section provides a state-of-the-art review of pavement image classification and prediction methods using CNNs (Convolutional Neural Networks). The third section describes the methodology and a description of the dataset. Section 4 presents the results and discussions, and the fifth section provides conclusions.

2 Pavement data processing method

2.1 Using deep learning in pavement management

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that aims to automate decision-making processes. The goal is to create algorithms capable of learning and predicting from datasets. Increasingly used in many sectors, these techniques can process large amounts of data and adapt to constantly changing patterns, such as pavement data [14]. Several works have been carried out in the literature for the classification of pavement deterioration . [15] used 128 x 128 pixel images to classify pavement deterioration using a random forest classifier, an unsupervised artificial neural network. The accuracy rate obtained was very high, which demonstrates the effectiveness of this method. In 2023, Li et al. [16] used 1,863 pavement images collected by the Luxin-CT616 vehicle to classify six types of pavement deterioration using the ResNet50 model, achieving an accuracy of 96.24%. Deep learning methods tend to demonstrate high robustness in pavement image classification and detection work.

2.2 Prediction of pavement performance indicators

The literature lists several models for predicting performance indicators. Multivariate linear regression is one of the most common methods for studying the relationship between input and output variables. There are also artificial neural networks, which are computer models inspired by the biological characteristics of the brain. In 2018, [17] conducted a comparative study between traditional statistical models and neural networks. This comparison made it possible to evaluate the predictive effectiveness of these two tools for modeling two critical decisions related to travel. for the simple linear regression used in this study

3 Methodology

3.1 Study context

This work is part of a pilot project by the Moroccan Directorate General of Roads to improve techniques and strategies for collecting and processing pavement data. While data collection by the CNER machines reduces the manual work involved in visual surveys, it does require more time to classify images and produce pavement condition reports. The CNER is always looking for sophisticated ways to help inspectors automate and optimise their pavement inspection work.

3.2 Study area

The section under study is part of the pavement network in Morocco's Oriental region. More precisely, it is located near the city of Saidia on the Moroccan–Algerian border. It is National Road (RN) No. 16. Extending over 28 kilometres between kilometer points 01 and 28, its road surface is asphalt. This route was selected due to its strategic location and importance, as it links the provinces of Berkane and Nador via Rass El Maa. It is one of the busiest routes leading to the RN 17, as illustrated in Fig. 2. The latest road census [18], conducted in 2023, revealed an extremely high volume of traffic, with 4,640 vehicles passing by every day. Additionally, this section is characterized by a high volume of traffic, with 74,240 vehicles passing per kilometer per day. It is therefore essential to analyze and monitor the evolution of this road.

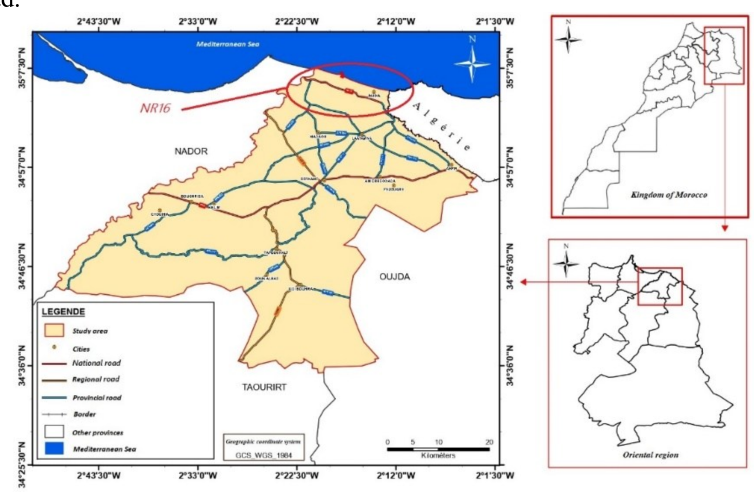

Fig. 2. Study area (road no. 02 from KP 515 to KP 538).

3.3 Data

Data collection is carried out in collaboration with the Moroccan Institute for Pavement and Bridge Studies (CNER), which provides us with data from 2010 to 2024. The dataset includes images of pavement deterioration taken by a vehicle equipped with an imaging system. Thanks to its strobe lights, this vehicle generates high-resolution images that provide sufficient illumination for the cameras, thus improving image quality. The images have dimensions of 640 × 472 pixels, with a resolution of 2.34 mm × 2.12 mm per pixel. These images will serve as initial data to train the DenseNet201 architecture, in order to classify cracks and evaluate the SCI. The results of the longitudinal analysis of the pavement, generated by the Longitudinal Profile Analyzer, are also used to obtain the pavement index values. Finally, the Bump Integrator device is used to measure pavement deformation. The SCI is determined based on these three parameters. All vehicles are shown in Fig. 3.

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a) Pavement imaging vehicle ; b) Longitudinal Profile Analyzer ; c) Bump Integrator

Fig. 3. Intelligent pavement data collection vehicle.

3.4 Data processing

The first task is to automatically detect and classify the different deteriorations present in the images, using a CNN called DenseNet201. DenseNet is a CNN developed by Huang et al. that has several advantages: it eliminates the vanishing gradient problem, significantly reduces the number of parameters, and ensures better feature propagation by connecting each layer to all others. However, it is difficult to distinguish some pavement defects with very similar characteristics (e.g., cracks and tears) after multiple convolution layers. The information may even disappear before reaching the target due to the longer path between the input and output layers. DenseNet was specifically designed to combat these vanishing gradient-induced accuracy drops in high-level neural networks. In this study, DenseNet proves to be a promising choice for pavement degradation recognition. [19].

It uses the Moroccan method of pavement assessment, based on the SCI. This indicator takes into account three types of parameters: cracking, deformation and pavement uniformity. Each parameter is quantified according to its severity over a kilometer of length. Each kilometer is rated A (that's excellent), B (excellent), C (inferior) or D (very bad) depending on the total number of grades assigned and the values retained. The general condition of the pavement network is measured according to the proportion of SCI retained for each kilometer (see Table 1 and Table 2). The image classes trained in the DenseNet201 model are presented in Fig. 4. Once each section is quantified, the SCI is modeled by linear regression to predict the results in the coming years.

Cracked Pavement **Uncracked pavement**

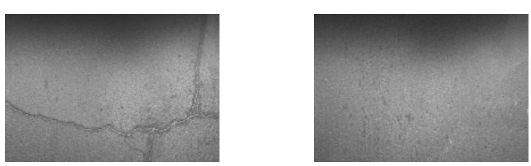

Fig. 4. The input classes for training the DenseNet201 model.

Table 1. Decision matrix for quantifying road sections as a function of deflection.

Deflection (1/100 mm)				
Class	**T0**	**T1**	**T2**	**T3-T4**
A	<80	<100	<120	<140
B	[80,120[	[100,140[	[120,160[	[140,180[
C	≥120	≥140	≥160	≥180

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Table 2. Decision matrix for quantifying road sections based on road surface roughness.

	Roughness Index (mm / km)			
IE	**T0**	**T1**	**T2**	**T3-T4**
A	<2000	<2300	<3000	<3200
B	[2000,2500[	[2300,2800[	[3000,3500[	[3200,3700[
C	[2500,3000[	[2800,3300[	[3500,4000[	[3700,4200[
D	≥3000	≥3300	≥4000	≥4200

4 Results and discussion

As shown in Fig. 5, the analysis of the training results of the DenseNet2021 architecture for the classification of pavement crack images reveals a clear progression of learning. Over the 20 iterations, the training loss decreases rapidly to a value close to 0.21 at the end, while the validation loss follows a parallel trend, but remains slightly higher, around 0.25. This difference indicates a solid performance, but also suggests a slight overfitting. Furthermore, the accuracy curves show a constant improvement: the training accuracy increases from about 82% at the beginning to more than 92%, while that measured on the test set also stabilizes around 92%. These results indicate that the network achieves good generalization.

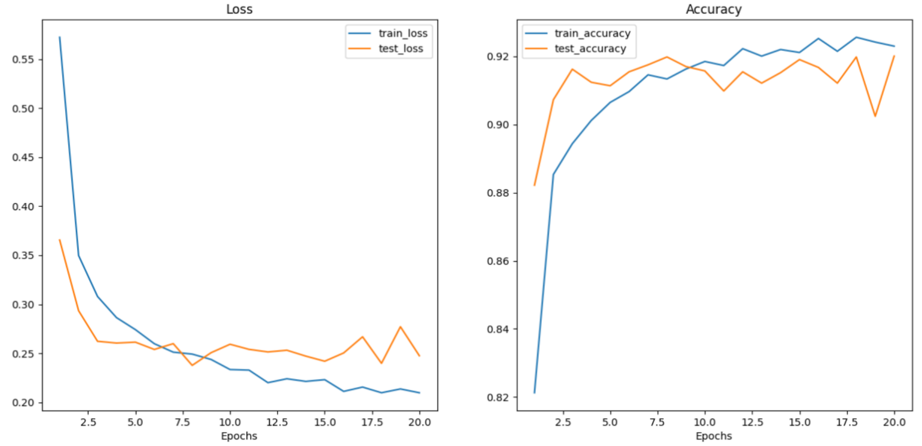

Fig. 5. DenseNet201 accuracy and loss results.

The analysis of the SCI assessed at national road No. 16 reveals a favorable evolution of the condition of the surface over the period 2010–2022. The sections classified as being in good condition (level A) show a continuous progression, going from approximately half of the network in 2010 to almost the entirety in 2022. In contrast, the share of sections in very poor condition (level D) decreases significantly, practically disappearing after 2016. The intermediate classes B and C remain in low numbers, reflecting a one-off need for corrective interventions. However, a phase of stability is noted between 2016 and 2020, before a further improvement during the last years of monitoring (see Fig. 6).

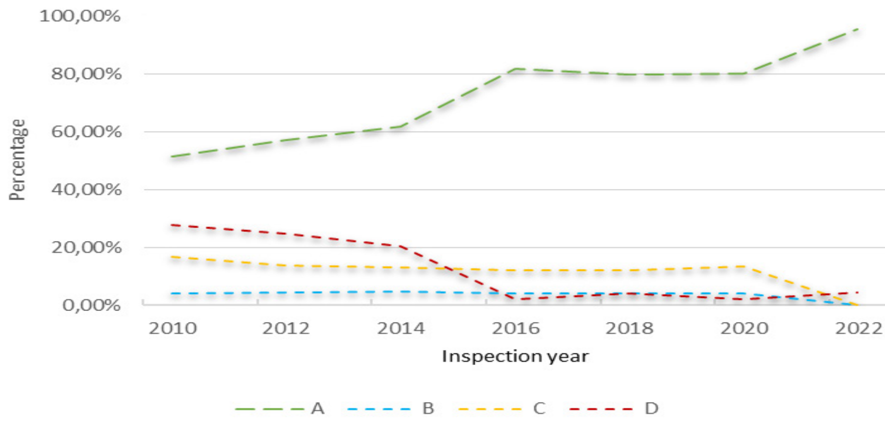

Fig. 6. Evolution of different pavement condition levels of SCI.

The projection made using linear regression highlights a continuous improvement in the condition of National Road No. 16 by 2026. The share of sections in good condition (class A), which represented approximately half of the network in 2010 and nearly 95% in 2022, is expected to continue to grow to cover almost the entire roadway by 2026. Conversely, sections classified as very poor condition (class D), estimated at more than a quarter of the network in 2010, have experienced a rapid decline and disappeared after 2016, a trend that the prediction confirms until 2026. Level C roadways are also following a downward trend: close to 15% in 2010, they are expected to fall to a residual threshold below 5% at the end of the period studied. As for class B, it retains a marginal presence, with a slightly decreasing trend but is difficult to model precisely. Overall, the forecasts corroborate the positive dynamics observed during the inspections, reflecting a clear reduction in critical sections and a lasting strengthening of the structural performance of the network (see Fig. 7).

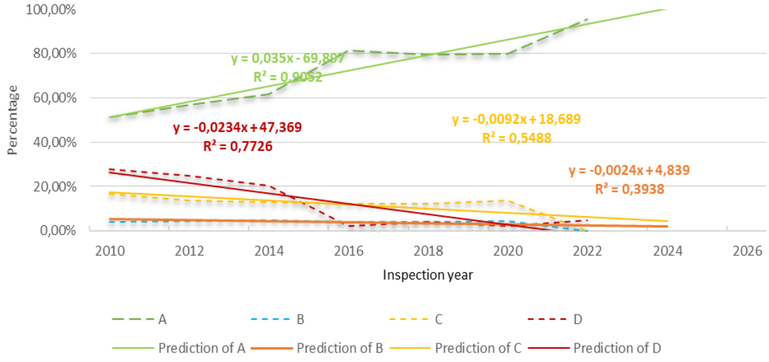

Fig. 7. Evolution of different pavement condition levels of SCI.

5 Conclusions and prospects

This research presents a study of pavement image classification using deep learning, as well as a prediction of SCI values. The dataset used comes from the Ministry of Equipment of Morocco and includes pavement images, values on pavement evenness and on deformation. These three parameters are necessary to quantify the condition of the pavement using the SCI. The results obtained show that DenseNet201, chosen for the classification task, offers good performance in terms of accuracy. In addition, prediction by linear regression demonstrated the effectiveness of this statistical method in predicting future values. Despite these very encouraging results, this study is limited by the need to compare it with other CNN in order to optimize accuracy and avoid errors. The next steps of the research will focus on comparative studies between several CNN architectures and on the modeling of other pavement performance indicators.

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