

# Deep Learning-based Wear and Tear detection in Smart roads

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**Abstract:** Roads transportation is a vital feature of any human settlement and they are prone to wear and tear leading to cracks, due to day-to-day usage and environmental factors. Manual inspection methods are often time-consuming and require extensive human effort. Smart roads are an important cog in the overall scheme of things as far as the vision of smart city development is concerned. Early detection of wear and tear detection of roads goes a long way in minimizing cost involved in road restoration as well as in preventing accidents and improving the quality of life of city dwellers. In this paper, we have presented a crack alert and road condition monitoring system. The system to be developed will help drivers avoid dangerous cracks and enable officials to view and manage the road surface. We have used a CNN model that classifies the road crack and based on the output, sends alert message to the users and the road maintenance department, so that preventive measures such as detouring and immediate repairing of roads can be performed.

**Keywords:** Smart Road, CNN model, Road crack

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## Introduction

Asphalt pavement structure is one of the most popular forms of road surface and is distinguished by its easy manufacture and inexpensive initial investment cost. process, matching the limitations of the economic standing of the vast majority of emerging nations. But after some time of usage, the dry climate and temperature drops cause the asphalt pavement structure to begin to suffer. This puts road users' safety at risk and is perhaps one of the main causes of accidents, second only to drivers' carelessness. The transportation departments are in charge of making sure that drivers have a safe driving experience. Regular road monitoring should be planned in order to fix any damaged roads and keep the cities' roads in good condition.

Road surface management requires the identification and categorization of road deterioration [1–3]. The goal is to compile information on pavement conditions for future upkeep. Because it can be readily absorbed by other pavement distress kinds, cracking is the most prevalent type of pavement distress to be monitored. According to the study in [4], road cracks can reduce the quality of the road surface by up to 40% over the first 75% of its life, and by an additional 40% during the next 12% of its life if treatment is not applied. Block, alligator, edge, reflection, longitudinal, and transverse cracks are the six general categories into which cracks are classified [5].

The suggested approach uses convolutional neural networks (CNN) to automatically identify and categorize cracks in roads. Our decision is prompted by the CNN models' demonstrated great processing efficiency when handling visual data, including pictures and movies. In order to create representations with inherent values for categorization in the upper layer, it converts raw input data from the lowest layer using a number of fundamental calculation units [6]. Each road scan's collected photos will go through a few pre-processing stages before being fed into an innovative CNN-based approach to classification and detection. The best CNN architecture has already been chosen after this CNN has been trained and tested with a number of layer combinations. In order to handle the massive amount of data that is periodically collected, the big data paradigm is used. Because of its straightforward programming models for the distributed processing and storing of massive amounts of data, Hadoop/MapReduce is used for this. Data analysis is done using OLAP, an online analytical processing tool [7]. This work's primary contribution is a CNN-based method that, while maintaining processing speed, can differentiate between images with and without cracks and further identify cracks into specific categories, such as transversal, longitudinal, and aligner cracks with a range of severities. To the best of our knowledge, no prior research has categorized cracks in this manner.

## Literature Survey

In order to recover the structure of road deterioration, automatic distress detection by thresholding uses image processing techniques followed by thresholding. Image pre-processing, which involves lowering uneven lighting, is required to perform this task. The next step is thresholding in the picture space, which is done by assuming that the crack regions in an image are thin, linked, and darker than the image's background [8]. Morphological operations and linked component searching techniques can then be used to improve the road distress image. Road distress image thresholding techniques are presented by the authors of [9,10–11] utilizing the CrackIT toolbox, a publicly accessible but closed-source toolbox. Machine learning-based techniques have been explored for more precise image-based fracture detection techniques [12]. Networks of artificial neurons. To determine whether a crack is present in a picture, supervised machine learning methods and artificial neural networks (ANNs) have been used [13]. An illustration of a neural network-based strategy that makes use of a multi-layer perceptron network may be found in the work in [14]. Unfortunately, because of its computational constraints, only basic ANN architectures may be used to identify road cracks. Thankfully, convolution neural networks (CNNs) may now be used for image recognition [16] thanks to advancements in deep learning and distributed computations using graphic processing units [15] over the past ten years.

This method uses partial connections and requires less calculations to classify images than traditional neural networks. Neurons share weights, and a pooling procedure is employed. CNN deployment involves two primary steps: architecture design and CNN training with a sufficient data set. Several studies were interested in the identification and subsequent categorization of the pavement cracks. Four supervised CNNs with varying receptive field sizes were presented by the authors in [17] to automatically categorize

picture patches clipped from 3D pavement photos into five classes: no cracks, transverse, longitudinal, and alligator with acceptable classification accuracy.

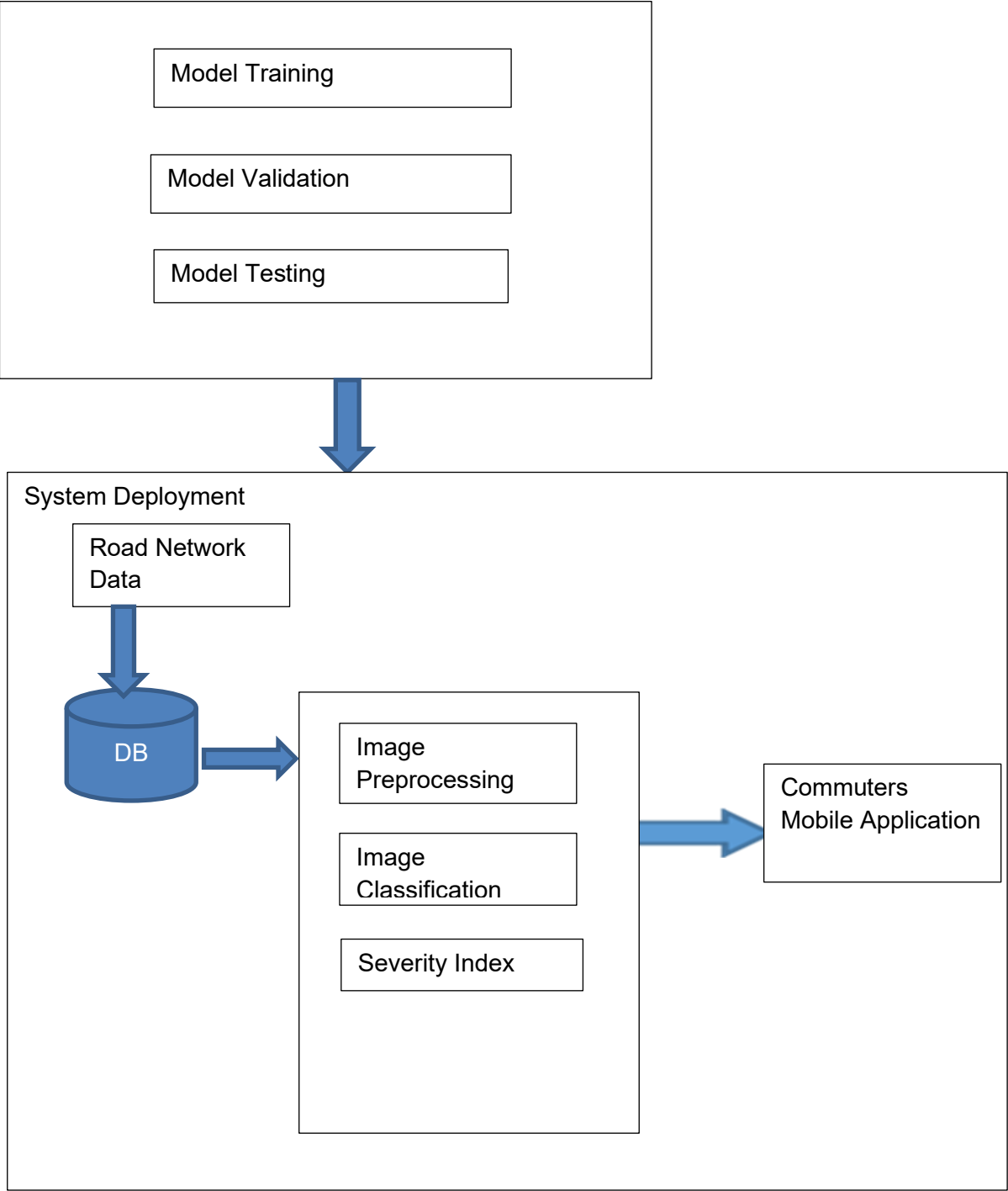


Figure 1: Road Crack Notification System Framework

### 3. System Overview

The proposed method uses cameras installed in a specialized vehicle to gather data about the road surface, and road data from urban management centers' networks. The system database ought to receive this data. This database is utilized by the data processing module to start its services, analyze data, and extract knowledge based on OLAP analysis and the methods employed. The following phases make up the majority of this sophisticated computational module:

1) To ensure that each input image has a similar data distribution and to prevent the influence of high- and extremely low-frequency sounds, the first step in pre-processing the gathered road surface photos is data normalization.

2) Image classification is the process of identifying and categorizing road fractures using a CNN-based module. Alongside longitudinal cracks (of low, medium, and high severity), transverse cracks (of low, medium, and high severity), and alligator cracks (of low, medium, and high severity) are depicted in the photographs. Additionally, the classes of newly acquired images from a sequence of road scans can be predicted using the trained CNN.

3) The transverse crack index (TCI), longitudinal crack index (LCI), and alligator crack index (ACI) are the three indexes that are combined in the severity index computation unit. The counts of each kind of crack seen in the gathered photos are used to calculate these indexes.

Type of Crack	Number of training data	Testing Data	Target Value
Class 1	4225	320	[100000000]T
Class 2	2324	133	[010000000]T
Class 3	2323	136	[001000000]T
Class 4	2326	134	[000100000]T
Class 5	2411	132	[000010000]T
Class 6	2410	134	[000001000]T
Class 7	2420	134	[000000100]T
Class 8	2411	132	[000000010]T
Class 9	2413	131	[000000001]T
Class 10	2423	131	[000000000]T

Table 1: Composition of Data set

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 as less, medium or high.

Image Class	Count
Un cracked	54,253
Less severe alligator cracks	3425
Medium-severe alligatorial cracks	3542
High-severe alligator cracks	3507
Less severe transversality cracks	3987
Medium-severe transversality cracks	4896

High-severe transversality cracks	4656
Less severe longitudinality cracks	7123
Medium severe longitudinality cracks	8967
High-severe longitudinality cracks	6875

Table 2: Classification result of a road scanning

## Result and Discussion

In this section, we present results of the crack detection and its benefits for drivers on the road. Additionally, the road surface condition monitoring service helps make short- and long-term decisions to improve road conditions, as demonstrated by analytical results. Our suggested architecture comprises a CNN-based crack notification and road surface condition monitoring service aimed at road users and authorities. It is recommended to collect road surface data utilizing vehicles equipped with GPS and cameras. This data collection makes the suggested architecture suited for data analytics; however, storing and analyzing increasingly large amounts of data represented a significant barrier in this study. To address this issue, the usage of big data tools was discussed. We chose the Hadoop/MapReduce system as our big data management platform. The contributions of this work include the implementation of a deep CNN-based algorithm for automatic fracture detection that classifies pavement patches into ten categories, as discussed in earlier sections.

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