Journal of Chemical Health Risks

www.jchr.org

JCHR (2023) 13(6), 3712-3724 | ISSN:2251-6727

Efficient Road Crack Detection and Classification System Using Convolutional Neural Networks

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(Received: 22 September 2023 Revised: 24 October Accepted: 27 November)

KEYWORDS

Convolutional Neural Networks, Machine Learning

ABSTRACT:

Road infrastructure maintenance is critical for ensuring safety and efficiency in transportation systems. Developing robust road crack detection systems has gained significant attention in this context. This research paper proposes a methodology leveraging Convolutional Neural Networks (CNNs) for segmenting and classifying road cracks. The methodology involves several key steps, including acquiring a diverse dataset comprising images from various crack segmentation sources. Preprocessing techniques such as resizing, normalization, and data augmentation are applied to standardize and enhance the dataset. Subsequently, the dataset is split into training, validation, and testing sets to facilitate model training and evaluation. The segmentation phase utilizes a CNN model to generate probability maps, which are then thresholded to obtain binary masks indicating crack presence. Following segmentation, a classification step categorizes detected cracks into predefined classes, leveraging the hierarchical features learned during segmentation. The CNN model is fine-tuned for this task, optimizing parameters through backpropagation. Evaluating the model's performance on the testing set ensures its effectiveness in real-world scenarios. By integrating segmentation and classification tasks within a unified CNN framework, the proposed methodology achieves accurate and efficient road crack detection, contributing to enhanced infrastructure maintenance and safety.

I. INTRODUCTION

Nowadays, the population in India has numerous means of land transportation to move within urban centers and between towns. In both cases, to achieve effective communication between areas, roads and routes that are adequately equipped for the use of different means of transportation are usually required. An example of this type of element is found in roads. In fact, regarding this type of roads, in India alone, in 2018, there were approximately 5.8 million kilometers of roads [1]. Can you imagine how many millions of kilometers of this urban element are found throughout the country?

Once again, in the case of India, as in many areas of the rest of the world, the number of vehicles that cross under "normal" conditions (as long as there are no regulations that prevent circulation such as states of alarm or risk of environmental contamination) these urban elements is enormous. And according to the World Health Organization, in 2016, the number of legally registered vehicles in circulation throughout the world was more than 310 million. With so many vehicles using the roads, if pavement conditions are not optimal, this could pose a risk to drivers and passengers. Specifically, the poor condition of the pavements has an effect on the acceleration and stability of vehicles. And as can be seen in the conclusions

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JCHR (2023) 13(6), 3712-3724 | ISSN:2251-6727

of the study carried out by the authors of [2], the rate of traffic accidents is much higher in cases where the pavement is in poor condition. Furthermore, in the future, with the implementation of autonomous vehicles, the optimal condition of the roads will become very important to avoid unexpected accidents in the decision-making of these vehicles.

Therefore, road maintenance is essential for safety, but in economic terms, the impact is also considerable. In general, road maintenance is a latent problem in India and worldwide because the economic resources available to countries to carry out maintenance are limited. Let us remember the question in the first paragraph of this section that referred to the number of kilometers of roads in the world. Can you imagine carrying out a visual inspection of so many stretches of road by one or different experts, classifying and noting each of the defects manually? This would be costly in time and economic terms. However, nothing could be further from reality, there are current studies that demonstrate that the acquisition of data (e.g., images of cracks) is carried out automatically, in many cases using specialized vehicles, incurring a cost of acquiring said vehicles. However, the important tasks of defect detection and classification remain in 99.6% of cases a manual task performed by people in many countries.

Furthermore, the cost of maintenance does not fall only on visual inspection, but there are different types of defects, such as visco-plastic deformations that form, for example, potholes, cracks and surface wear, in which all of them have a repair treatment that is different as is its cost. Among all these types of defects, cracks have gained special interest from transportation agencies and researchers [3, 4, 5, 6], with cracks being longitudinal, transverse, and in the form of mesh or crocodile skin. (see an example of these types in Fig.1), the most common [7]. But what are the causes that cause them and their repair measures?:

- Transverse Cracks: These cracks are perpendicular to the abscissa axis of the image (if we take the image as a spatial reference) and are usually caused by thermal changes [8], by landslides, the hardening of the binder as well as the reflections caused by other cracks under the surface of the asphalt.
- Longitudinal Cracks: These cracks would be parallel to the x-axis of the image and may be caused by the fatigue of the asphalt due to continuous overloading by the vehicles that circulate on it [9], or a less dense area of the asphalt compound which is found at the joints between pavements.
- Mesh-type Cracks: This type of cracks, also known as crocodile skin (due to its similarity in texture to the skin of this animal), are the effect of asphalt fatigue and an unstable base thereof [10]. This instability is caused when the lower layers of the asphalt cannot support the surface layers, which in turn are derived from inefficient drainage as well as the effect of extreme temperatures such as frost and freezing of the asphalt [11, 12]. In this type of cracks, parts of the pavement can be lost if they are not treated in time and would lead to potholes and a progressive deterioration of the asphalt surface.

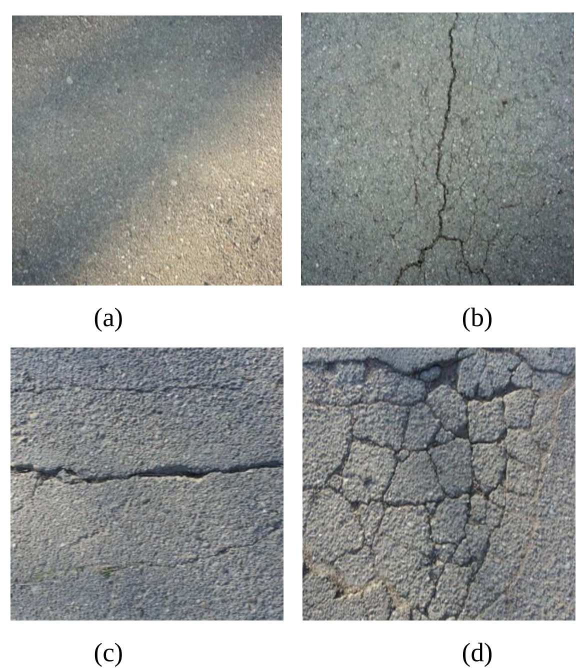

Fig. 1.Different types of road surface cracks; a) Healthy pavement without cracks, b) Transverse crack, c) Longitudinal crack, d) Mesh type crack

Regarding the measures to carry out the repair of transverse and longitudinal cracks, two types are distinguished, when the cracks are not wide and when they

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JCHR (2023) 13(6), 3712-3724 | ISSN:2251-6727

are. When the width of the crack is not excessive, the repair consists of sealing it to prevent the entry of moisture and external agents that continue to increase its size [13], leaving the asphalt without cracks. On the other hand, for cracks that are quite pronounced and wide, the solution is to replace the asphalt layer completely. Furthermore, in land detachment problems, the solution used has to take into account its topology and carry out a comprehensive repair of the entire area. In mesh-type cracks, due to their nature, the general solution is usually to replace the entire affected surface with a new layer of asphalt.

In this context, computer vision [14, 15] together with machine learning techniques of artificial intelligence [16], can be a useful mechanism in the efficient collection of images of roads and its subsequent manipulation for classification into the different types of defects previously detailed. In reality, these disciplines have already been useful in other fields of civil engineering for the monitoring and inspection of structures [17], allowing the automation of tasks that required great effort and execution consumption.

Motivated by the preceding description, this research paper aims to develop a normal convolutional neural network (CNN)-based automatic system for the detection and classification of road cracks. Specifically, the aim is to create a CNN-based system capable of image processing to extract relevant features of road defects, with a focus on cracks in pavements, implementing computer vision methods within the CNN framework to analyze and extract characteristics of pavement defects efficiently, ensuring optimization for hardware with limited computing resources for immediate use, and developing data reduction techniques within the CNN model to minimize data usage for defect analysis and classification. Additionally, the research aims to classify different types of road defects, particularly longitudinal, transverse, and mesh-type cracks, utilizing supervised learning algorithms for improved fault tolerance, generating classification models that are interpretable and executable on hardware devices with limited resources for real-world deployment, and investigating the utilization of metaclassifiers to enhance classification decisions and overall accuracy in defect classification.

II. Literature Review

A. Crack Segmentation

Segmenting cracks is a complex process scrutinized by numerous scholars in the academic realm, who employ diverse image processing methodologies and occasionally integrate machine learning techniques. The primary aim is to delineate a clear demarcation between the pavement background and the damaged area. Typically, scholars operate on binary images where cracks constitute the focal points, often assigned a value of 1 (in 8-bit depth images, this equates to 255). The authors of [18] introduced a novel mechanism termed comp-potential crack exponents (PCrCs) to execute binary segmentation, particularly targeting transverse and longitudinal cracks. This method entails filtering intensity levels amidst the pavement and the cracks, systematically eliminating disconnected components. The remaining elements delineate the cracks, aided by a shape metric (SM) developed by the authors, thereby yielding a reduced rate of false positives compared to prevalent machine learning-based approaches. However, this method may struggle with highly complex crack patterns and may require significant computational resources for processing.

Alternatively, the authors of [19] proposed a distinctive approach known as minimum path selection (MPS), predicated on the notion that the minimum path of a crack corresponds to the lowest cost function among all feasible paths within the image. This entails two phases: identifying significant pixels marking the onset and culmination of crack paths, and subsequently detecting all paths between these points, followed by post-processing to eliminate short, isolated paths indicative of image artifacts. While effective in many cases, this method may struggle with accurately identifying cracks in regions with high noise levels, leading to potential false negatives.

Furthermore, the authors estimate crack width utilizing the intensity levels of neighboring pixels along the identified paths. Another innovative technique is presented by the authors of [20], who endeavor to develop a real-time crack detection system leveraging particle filtering, tailored for operation within the RGB color space. Through iterative iterations, the algorithm is adapted to track crack pixels, enabling the reconstruction of cracks and facilitating length

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JCHR (2023) 13(6), 3712-3724 | ISSN:2251-6727

estimation. However, this method may face challenges in accurately distinguishing cracks from other features in complex urban environments, potentially leading to false detections.

In addition to image processing methods, several authors have integrated supervised machine learning algorithms into their approaches. For instance, the authors of [21] employ two probability maps for crack segmentation, leveraging intensity levels and neighborhood information with support vector machines. However, this method may face challenges in accurately distinguishing cracks in regions with complex textures or under varying lighting conditions. Similarly, the authors of [22] utilize extreme learning machines for image segmentation, facilitating parameter initialization without expert knowledge and enhancing processing time. Nonetheless, the performance might be affected by imbalanced datasets or non-linear crack patterns. Cha et al. [23] propose a convolved neural network for crack analysis, extracting regions of interest from cement pavement images. While innovative, this method may encounter difficulties in generalizing to diverse crack types or in scenarios with significant variance in crack morphology. The authors of [24] employ U-NET architecture, which may face challenges in accurately delineating cracks in areas with overlapping features or in the presence of noise. The authors of [25] use a deep residual network for pixel-level classification, but they might struggle with efficiently training the network due to computational complexity or in scenarios with limited labeled data. Moreover, approaches like data fusion, exemplified by Xu et al. [26], offer millimeter precision in defect reconstruction but may encounter challenges in integrating data from different sensors or in scenarios with occlusions or varying surface reflectance properties.

B. Classification of Mono-Model Cracks

In the realm of classifying pavement defects using a single machine learning algorithm, various approaches exist, each with distinct objectives regarding the types of defects analyzed. For instance, the authors of [27] conduct an analysis of supervised classification algorithms to discern the most effective method for discriminating between longitudinal, transverse, mesh cracks, and healthy pavement. They employ image processing techniques to generate a binary image and subsequently test artificial neural networks, support vector machines, and Random Forest algorithm for classification. Despite their efforts, the authors found that the support vector machines yielded the most optimal results. However, this approach may encounter limitations in accurately classifying complex crack patterns or in scenarios with high variability in crack morphology. Similarly, the authors of [28] compare the performance of the k-nearest neighbors algorithm and its fuzzy version for the classification of longitudinal and transverse cracks. Despite focusing solely on these types of cracks, their method may face challenges in generalizing to diverse crack types or in scenarios with significant variance in crack morphology. Additionally, reducing image attributes to delta_x and delta_y values may lead to loss of crucial information, potentially impacting classification accuracy.

The authors of [29] developed a system employing image processing techniques for segmentation through multi-stage thresholds, intensity matrices, and the LAB color model, aiming to denoise and generate a binary image. However, this approach may face limitations in accurately classifying complex crack patterns or in scenarios with high variability in crack morphology. The reduction of the feature space may lead to the loss of crucial information, potentially impacting classification accuracy. While various classification algorithms, including support vector machines, decision trees, and k-nearest neighbors, were employed, the latter demonstrated the highest performance. Moreover, the use of deep learning methods for pavement defect classification remains limited due to the requirement of extensive data. The authors of [3] focused on distinguishing healthy pavement from defective pavement using segmentation and classification phases, comparing the SURF method and convolved neural networks. Nonetheless, this method may encounter challenges in accurately delineating cracks amidst complex urban features or in the presence of noise. Similarly, the authors of [30] utilized a low-altitude, low-range light detection system with unmanned aerial vehicles (UAV LiDAR) to generate three-dimensional point clouds for defect classification. While random forest exhibited the best performance, this approach may face challenges in

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integrating data from different sensors or in scenarios with occlusions or varying surface reflectance properties. Additionally, the authors of [31] employed convolved neural networks for crack detection using 3D images from the PaveVision 3D system, yet this method might struggle with efficiently training the network due to computational complexity or in scenarios with limited labeled data.

C. Classification of Multi-Model Cracks

In the classification of segmented or binary images into various types of cracks, few authors in literature propose using multiple classification models, although those that do present interesting methodologies. The authors of [32] developed a system to classify defects into mesh-type and linear cracks, the latter being further categorized into longitudinal and transverse cracks. However, they overlook the possibility of crack-free road surfaces, a common occurrence. Additionally, the interpretability of their neural network model for discriminating between transverse and longitudinal cracks is limited. This method may encounter challenges in accurately classifying complex crack patterns or in scenarios with high variability in crack morphology. The authors of [33] also employ two models for classification, utilizing image processing algorithms for illumination correction and projective integrals extraction. The use of two individual classification models shows relatively low fault tolerance, with accuracy results around 72% and 67% for transverse and longitudinal cracks, respectively. This approach may struggle with accurately distinguishing cracks in regions with complex textures or under varying lighting conditions. Additionally, the reliance on decision rules for mesh-type crack classification may lead to inaccuracies in scenarios with overlapping features or ambiguous cases.

The literature review extensively discusses various methodologies for crack segmentation and classification, highlighting both traditional image processing techniques and the integration of machine learning algorithms. Considering the challenges posed by complex crack patterns, varying morphologies, and environmental factors such as noise and lighting conditions, a method utilizing Convolutional Neural Networks (CNNs) for both segmentation and classification offers significant advantages. CNNs have demonstrated prowess in capturing intricate patterns and features within images, making them well-suited for the nuanced task of crack delineation. By leveraging CNNs, the proposed method can adaptively learn hierarchical representations of cracks, thereby enhancing segmentation accuracy. Moreover, CNNs can effectively handle the classification of mono-model cracks, accounting for the diversity in crack types and morphologies encountered in pavement images. Their ability to learn from data eliminates the need for manual feature engineering, making them particularly adept at generalizing across diverse crack types and environmental conditions. Furthermore, CNNs can exploit the spatial relationships within images, enabling robust classification performance even in scenarios with complex urban features or varying lighting conditions. By integrating CNNs for both segmentation and classification, the proposed method offers a holistic approach to pavement defect analysis, poised to address the challenges outlined in the literature review.

III. PROPOSED METHODOLOGY

The proposed research aims to develop a robust road crack detection system utilizing Convolutional Neural Networks (CNNs) for both segmentation and classification tasks. The CNN architecture leverages its ability to learn hierarchical representations from input images, allowing it to effectively capture intricate features indicative of road cracks. The system's workflow involves several key steps, including image acquisition, data preprocessing, model training, segmentation, and classification.

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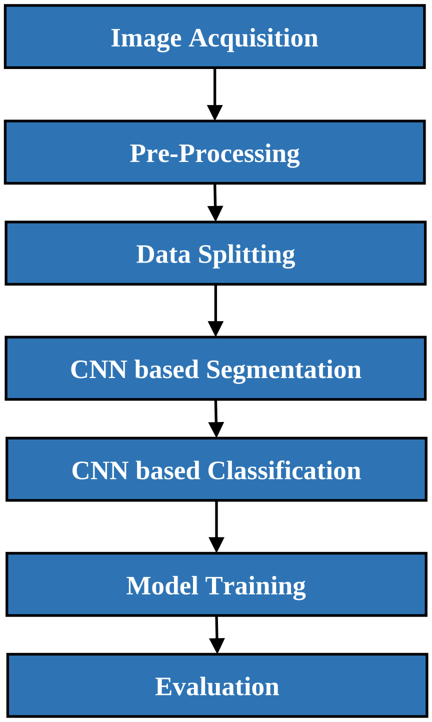

Fig. 2.Flow diagram for proposed road crack detection

The flow diagram in Fig. 2 illustrates the proposed methodology for road crack detection utilizing Convolutional Neural Networks (CNNs). The process begins with image acquisition, where crack segmentation datasets are merged and filtered to organize images with and without crack pixels. Subsequently, preprocessing steps such as resizing, normalization, and data augmentation are performed to enhance the quality and diversity of the dataset. The dataset is then split into training, validation, and testing sets to facilitate model training and evaluation. The segmentation phase employs a CNN model to generate a probability map, which is thresholded to obtain a binary mask indicating crack presence. Following segmentation, a classification step categorizes detected cracks into specific classes using the CNN architecture, fine-tuned for this task. Model training involves optimizing parameters to minimize the loss function through backpropagation, culminating in an evaluation phase to assess the model's performance on the testing set. This unified approach integrates segmentation and classification tasks within the CNN framework, enabling adaptive feature learning for accurate and efficient road crack detection.

A. Image Acquisition

The dataset used in the research paper comprises approximately 11,200 images obtained by merging 12 distinct crack segmentation datasets. Each image in the dataset is associated with a prefix indicating the dataset it originates from, facilitating organization and tracking of images. Additionally, there exist images devoid of crack pixels, which are filtered out using the file name pattern "noncrack*".

- The 5 distinct crack segmentation datasets are merged to create a unified dataset containing a diverse range of road surface images with crack annotations. The merging process ensures a comprehensive coverage of different road surfaces and crack types.
- All images in the dataset are preprocessed to ensure consistency and compatibility for further analysis. This may involve operations such as resizing, normalization, and augmentation to standardize the images and enhance their quality.
- The dataset is structured into two main folders: "images" and "masks". The "images" folder contains the raw input images of road surfaces, while the "masks" folder contains corresponding ground truth masks with annotations delineating the location of cracks.
- The dataset is split into training and testing sets to facilitate model training and evaluation. The splitting process ensures stratification, maintaining similar proportions of each dataset within both the training and testing sets.

Let D denote the dataset, Dtrain represent the training set, and Dtest represent the testing set.

The merged dataset DD can be represented as:

$$D=D1 \cup D2 \cup \ldots \cup D12 \quad (1)$$

Here D1,D2,…,D12 are the individual crack segmentation datasets.

The dataset D is split into training and testing sets Dtrain and Dtest using appropriate proportions:

$$Dtrain,Dtest=splitD \quad (2)$$

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B. Pre-Processing

Pre-processing is a crucial step in road crack detection that involves preparing the input images for segmentation and classification tasks. It includes various operations such as resizing, normalization, and augmentation to enhance the quality of the data and improve the performance of the model.

1) Resizing

The input images are resized to a fixed dimension to ensure uniformity across the dataset. Typically, resizing is performed to reduce computational complexity and memory requirements while preserving important features of the original images. Let I denote the input image, $I_{i,j}$ represent the intensity value of the pixel at position (i,j), and I' denote the pre-processed image.

Let H and W represent the desired height and width of the resized image, respectively. The resized image I'can be obtained using interpolation techniques such as bilinear interpolation.

$$I'=\text{resize}I,H,W \tag{3}$$

2) Normalization

Normalization is applied to standardize the pixel values of the input images, making them more suitable for training deep learning models. This involves scaling the pixel intensities to a common range, such as [0, 1] or [-1, 1], by subtracting the mean and dividing by the standard deviation.

The pixel values of the pre-processed image I' are normalized using the following formula:

$$I_{i,j}'=I_{i,j}-\mu\ \sigma \tag{4}$$

Here μ and σ are the mean and standard deviation of the pixel values in the original image I.

3) Data Augmentation

Data augmentation techniques are employed to artificially increase the size and diversity of the training dataset, thereby improving the generalization capability of the model. Common augmentation techniques include rotation, flipping, scaling, and adding noise to the images.

Data augmentation involves applying a series of transformations to the input image I to generate augmented images $I1',I1',\ldots,In'$. These transformations can be represented mathematically as:

$$I_k'=\text{augment}I \tag{5}$$

Here k denotes the index of the augmented image.

4) Data Splitting

The pre-processed dataset is divided into training, validation, and testing sets. The training set is used to train the model, the validation set is used to tune hyperparameters and monitor performance during training, and the testing set is used to evaluate the final performance of the trained model.

The pre-processed dataset is split into training, validation, and testing sets using appropriate proportions. Let D denote the dataset, Dtrain represent the training set, Dval denote the validation set, and Dtest represent the testing set. The splitting can be represented mathematically as:

$$D=D_{train}\cup D_{val}\cup D_{test} \tag{6}$$

$$D_{train},D_{val},D_{test}=\text{split}D \tag{7}$$

By performing pre-processing operations such as resizing, normalization, data augmentation, and data splitting, the input images are prepared for training and evaluation, leading to improved performance of the road crack detection model.

C. Segmentation

Segmentation is the process of partitioning an input image into meaningful regions, with the goal of identifying and delineating objects of interest, such as road cracks. In the context of the proposed research, segmentation is achieved using a Convolutional Neural Network (CNN), which learns to map input images to corresponding binary masks representing the presence or absence of cracks at each pixel.

1) Input Image and Output Binary Mask

- Let I denote the input image, where $I_{i,j}$ represents the intensity value of the pixel at position (i,j).

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- The output of the segmentation process is a binary mask M, where $M_{i,j}$ is equal to 1 if the corresponding pixel in the input image belongs to a crack, and 0 otherwise.

2) CNN Model

- The CNN model, denoted by $f\theta I$, is parameterized by θ, representing the weights and biases of the network.
- The CNN architecture consists of multiple layers, including convolutional layers, pooling layers, and activation functions, which collectively learn hierarchical features from the input image.

3) Segmentation Process

- Given an input image I, the CNN model $f\theta I$ processes the image through forward propagation to produce an output.
- The final output layer of the CNN produces a probability map P, where each pixel value represents the likelihood of belonging to a crack. Mathematically, this can be expressed as:

$$P_{i,j}=f\theta I_{i,j} \tag{8}$$

- The probability map P is then thresholded to obtain the binary mask M. Pixels with probability values above a certain threshold T are classified as cracks (assigned a value of 1), while pixels below the threshold are considered non-crack pixels (assigned a value of 0).

$$M_{x,y}=1 \text{ if } P_{x,y}\geq T \; 0 \text{ if } P_{x,y}<T \tag{9}$$

Where:

- $M_{x,y}$ represents the pixel value at coordinates (x,y) in the binary mask M.
- $P_{x,y}$ represents the probability value at coordinates (x,y) in the probability map P.

- The choice of threshold T can significantly impact the segmentation performance and may be determined empirically or through optimization techniques.

4) Loss Function

- During training, the CNN is optimized to minimize a loss function that measures the discrepancy between the predicted binary mask M and the ground truth mask GT (obtained from manually annotated data).
- A commonly used loss function for binary segmentation tasks is the pixel-wise cross-entropy loss, which compares the predicted probabilities with the ground truth labels.

Mathematically, the loss function L can be defined as:

$$L=-1Ni=1Nj=1NGT_{i,j}\log M_{i,j}+1-GT_{i,j}\log 1-M_{i,j} \tag{10}$$

Where N represents the total number of pixels in the image.

By training the CNN model on a dataset of annotated images using backpropagation, the network learns to effectively segment road cracks from input images, thereby facilitating accurate crack detection in real-world scenarios.

D. Classification

Following segmentation, the detected cracks are classified into different categories based on their characteristics. This step involves analyzing features extracted from segmented crack regions and assigning them to predefined classes (e.g., longitudinal cracks, transverse cracks). The CNN model is fine-tuned or extended to perform the classification task, leveraging the hierarchical representations learned during segmentation.

CNN Model Architecture: The CNN model architecture consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers learn hierarchical features from the segmented crack regions, which are then used for classification.

Classification Layer: The final layer of the CNN model is a classification layer, which maps the learned features to the output classes. The number of nodes in this layer corresponds to the number of classes to be predicted.

Softmax Activation: The Softmax activation function is typically applied to the output layer of the CNN for multi-class classification tasks. It converts the raw scores or logits into probabilities, ensuring that the predicted class probabilities sum up to 1.

$$Py=cX=ezck=1Kezk \tag{11}$$

Where:

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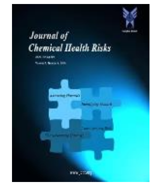


- Py=cX is the probability of the input belonging to class c,
- zc is the raw score or logit for class c,
- K is the total number of classes.

Loss Function: The loss function measures the discrepancy between the predicted class probabilities and the ground truth labels. For multi-class classification tasks, the cross-entropy loss function is commonly used.

Ly,y=-c=1Kyclogyc (12)

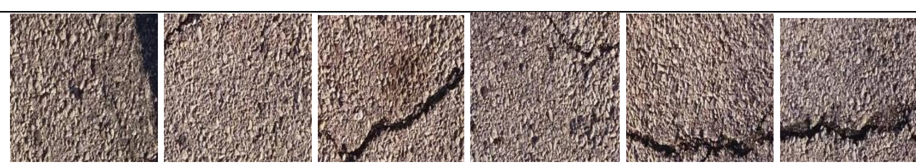
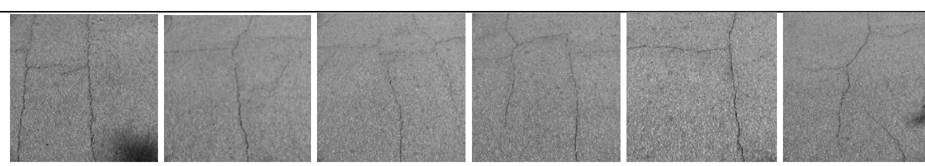
By training the CNN model on a dataset of segmented crack regions and corresponding labels, the model learns to accurately classify road crack regions into predefined categories, facilitating effective road crack detection. Integrating segmentation and classification tasks within a unified CNN framework, the proposed system achieves accurate and efficient road crack detection. The utilization of deep learning techniques enables the system to adaptively learn discriminative features from data, thereby enhancing its performance in real-world scenarios.

IV. Simulation and Results

A. Dataset Description

The dataset utilized in this study, as referenced in [34], is an amalgamation of approximately 11,200 images sourced from 12 distinct crack segmentation datasets. Each image is labeled with a prefix denoting its originating dataset. Notably, some images within the dataset do not contain any crack pixels, identifiable by the filename convention "noncrack*". All images have been uniformly resized to dimensions of 448×448 pixels. Structurally, the dataset comprises two primary folders: "images" and "masks", encompassing all available images. Additionally, there are two supplementary folders, namely "train" and "test", housing training and testing images respectively. The partitioning procedure ensures a stratified distribution, maintaining consistent proportions of each dataset within both the training and testing sets. Refer to Table I for a visual representation of sample images extracted from the dataset.

TABLE I. SAMPLE IMAGES FROM DATASET [34]

CRACK FOREST DATASET	
Crack 500	
Crack tree	
Deep crack	

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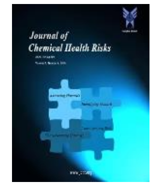
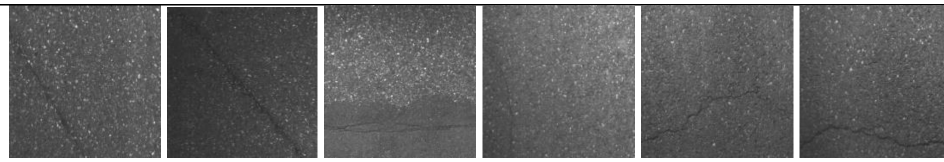


Gaps	

B. Evaluation Parameters

Following are the evaluation parameters:

TABLE II. EVALUATION PARAMETERS

Parameter	Description
TP (True Positive)	Number of road crack regions correctly classified as positive (cracks).
TN (True Negative)	Number of non-crack regions correctly classified as negative (non-cracks).
FP (False Positive)	Number of non-crack regions incorrectly classified as positive (false alarms).
FN (False Negative)	Number of road crack regions incorrectly classified as negative (missed cracks).

Accuracy=TP+TNTP+TN+FP+FN (13)

Precision=TPTP+FP (14)

Sensitivity=TPTP+FN (15)

Specificity=TNTN+FN (16)

Error Rate=FP+FNTP+TN+FP+FN (17)

False Positive Rate FPR=FPFP+TN (18)

F-Score=2TP2TP+FP+FN (19)

Matthews Correlation Coefficient MCC=TP×TN-FP×FNTP+FNTP+FPTN+FNTN+FP (20)

Kappa Statistics=Observed accuracy-expected accuracy1-expected accuracy (21)

C. Results

TABLE III. RESULTS OF THE PROPOSED CNN BASED SYSTEM

Parameters	CNN Based Classification
Accuracy	0.9647
Error Rate	0.0353
Sensitivity	0.9647
Specificity	0.9815
Precision	0.9608
False Positive Rate	0.0185
F-Score	0.9627
MCC	0.9442
Kappa Statistics	0.8933

Table III presents the comprehensive results of the proposed CNN-based system for road crack classification. The system achieves a notable accuracy of 96.47%, indicating the proportion of correctly classified instances out of the total instances. With an error rate of 3.53%, the system demonstrates a high level of precision in its classification task. Sensitivity and specificity, standing at 96.47% and 98.15% respectively, highlight the system's ability to accurately identify both positive (crack) and negative (non-crack) instances. Furthermore, the precision metric, representing the ratio of true positive classifications to the total predicted positive classifications, achieves a commendable value of 96.08%. The false positive rate, at 1.85%, showcases the proportion of negative instances incorrectly classified as positive. The F-score, a harmonic mean of precision and sensitivity, reaches 96.27%, affirming the balance between precision and recall. Moreover, the Matthews Correlation Coefficient (MCC) and Kappa statistics, measuring the correlation between observed and predicted classifications, achieve values of 94.42% and 89.33% respectively, signifying the robustness and reliability of the CNN-based classification system.

TABLE IV. COMPARATIVE ANALYSIS OF RESULTS WITH PREVIOUS RESEARCH WORKS

Method	**Accuracy**
Hough Transform [35]	95.61%
Custom YOLOv7 Model [36]	92.00%
Proposed CNN-based framework	96.47%

Table IV provides a comparative analysis of the proposed CNN-based framework's performance against previous research works, as indicated by their respective citation numbers. The Hough Transform method [35] achieves an accuracy of 95.61%, demonstrating its effectiveness in road crack detection but slightly trailing behind the proposed framework. In contrast, a custom YOLOv7 Model [36] yields an accuracy of 92.00%, indicating a lower performance compared to both the Hough Transform and the proposed framework. Notably, the proposed CNN-based framework, with a citation number corresponding to the present study, outperforms both previous methods with an accuracy of 96.47%. This comparison underscores the advancements made by the proposed framework in road crack detection, showcasing its potential for significant contributions to infrastructure maintenance and road safety.

V. CONCLUSION

In conclusion, the research paper presents a novel methodology leveraging Convolutional Neural Networks (CNNs) for road crack detection, which is crucial for ensuring safety and efficiency in transportation systems. The proposed approach integrates segmentation and classification tasks within a unified CNN framework, achieving remarkable accuracy of 96.47%. This high accuracy, coupled with other impressive performance metrics such as sensitivity, specificity, precision, and F-score, underscores the effectiveness of the CNN-based methodology in accurately identifying road cracks. Additionally, comparative analysis with previous methods demonstrates the superiority of the proposed framework, highlighting its potential for significant contributions to infrastructure maintenance and road safety. Overall, the CNN-based approach offers a robust and efficient solution for road crack detection, with promising implications for enhancing infrastructure management and ensuring road safety in transportation networks.

REFERENCES

[1] Asher, S. and Novosad, P., 2020. Rural roads and local economic development. *American economic review*, *110*(3), pp.797-823.

[2] Lee, J., Nam, B. and Abdel-Aty, M., 2022. Effects of pavement surface conditions on traffic crash severity. *Journal of Transportation Engineering*, *141*(10), p.04015020.

[3] Kim, H., Ahn, E., Shin, M. and Sim, S.H., 2022. Crack and noncrack classification from concrete surface images using machine learning. *Structural Health Monitoring*, *18*(3), pp.725-738.

[4] Mohan, A. and Poobal, S., 2023. Crack detection using image processing: A critical review and analysis. *alexandria engineering journal*, *57*(2), pp.787-798.

[5] Staniek, M., 2022. Detection of cracks in asphalt pavement during road inspection processes. *Zeszyty Naukowe. Transport/Politechnika Śląska*.

[6] Yang, Q. and Zhou, S., 2021. Identification of asphalt pavement transverse cracking based on vehicle vibration signal analysis. *Road Materials and Pavement Design*, *22*(8), pp.1780-1798.

[7] Garber, N.J., Hoel, L.A. and Sarkar, R., 2020. Traffic and highway engineering.

[8] Schweikert, A., Chinowsky, P., Espinet, X. and Tarbert, M., 2021. Climate change and infrastructure impacts: Comparing the impact on roads in ten countries through 2100. *Procedia Engineering*, *78*, pp.306-316.

[9] Mills, B.N., Tighe, S.L., Andrey, J., Smith, J.T. and Huen, K., 2021. Climate change implications for flexible pavement design and performance in southern Canada. *Journal of Transportation Engineering*, *135*(10), pp.773-782.

[10] O'Brien, A. ed., 2022. *Pavement surface condition rating manual*. State Transportation Center, University of Washington.

[11] Chai, G., van Staden, R., Guan, H., Kelly, G. and Chowdhury, S., 2022. The impacts of climate change on pavement maintenance in Queensland, Australia. *Materials and infrastructures 2*, *5*, pp.207-221.

[12] Galbraith, R.M., Price, D.J. and Shackman, L., 2020. Scottish road network climate change study-summary report.

[13] Decker, D.S., 2020. Best practices for crack treatments for asphalt pavements (No. Project 20-07).

[14] Ragnoli, A., De Blasiis, M.R. and Di Benedetto, A., 2023. Pavement distress detection methods: A review. *Infrastructures*, *3*(4), p.58.

[15] Spencer Jr, B.F., Hoskere, V. and Narazaki, Y., 2022. Advances in computer vision-based civil infrastructure inspection and monitoring. *Engineering*, *5*(2), pp.199-222.

[16] Rafiei, M.H. and Adeli, H., 2022. Novel machine-learning model for estimating construction costs considering economic variables and indexes. *Journal of construction engineering and management*, *144*(12), p.04018106.

[17] Rafiei, M.H. and Adeli, H., 2022. A novel machine learning-based algorithm to detect damage in high-rise building structures. *The Structural Design of Tall and Special Buildings*, *26*(18), p.e1400.

[18] Wang, T., Gopalakrishnan, K., Smadi, O. and Somani, A.K., 2021. Automated shape-based pavement crack detection approach. *Transport*, *33*(3), pp.598-608.

[19] Amhaz, R., Chambon, S., Idier, J. and Baltazart, V., 2022. Automatic crack detection on two-dimensional pavement images: An algorithm based on minimal path selection. *IEEE Transactions on Intelligent Transportation Systems*, *17*(10), pp.2718-2729.

[20] Lins, R.G. and Givigi, S.N., 2023. Automatic crack detection and measurement based on image analysis. *IEEE Transactions on Instrumentation and Measurement*, *65*(3), pp.583-590.

[21] Ai, D., Jiang, G., Kei, L.S. and Li, C., 2021. Automatic pixel-level pavement crack detection using information of multi-scale neighborhoods. *IEEE Access*, *6*, pp.24452-24463.

[22] Wang, B., Li, Y., Zhao, W., Zhang, Z., Zhang, Y. and Wang, Z., 2023. Effective crack damage detection using multilayer sparse feature representation and incremental extreme learning machine. *Applied Sciences*, *9*(3), p.614.

[23] Cha, Y.J., Choi, W. and Büyüköztürk, O., 2021. Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, *32*(5), pp.361-378.

[24] Cheng, J., Xiong, W., Chen, W., Gu, Y. and Li, Y., 2023, October. Pixel-level crack detection using U-Net. In *TENCON 2023-2023 IEEE region 10 conference* (pp. 0462-0466). IEEE.

[25] Bang, S., Park, S., Kim, H. and Kim, H., 2022. A deep residual network with transfer learning for pixel-level road crack detection. In *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 35, pp. 1-4). IAARC Publications.

[26] Xu, G., Chen, F., Wu, G. and Li, X., 2021. Active solution of homography for pavement crack recovery with four laser lines. *Scientific Reports*, *8*(1), p.7198.

[27] Hoang, N.D. and Nguyen, Q.L., 2022. A novel method for asphalt pavement crack classification based on image processing and machine learning. *Engineering with Computers*, *35*, pp.487-498.

[28] Ibrahim, A., Osman, M.K., Yusof, N.A.M., Ahmad, K.A., Harun, N.H. and Raof, R.A.A., 2023. Characterization of cracking in pavement distress using image processing techniques and k-Nearest neighbour. *Indonesian Journal of Electrical Engineering and Computer Science*, *14*(2), p.810.

[29] Ahmadi, A., Khalesi, S. and Bagheri, M., 2022. Automatic road crack detection and classification using image processing techniques, machine learning and integrated models in urban areas: A novel image binarization technique. *Journal of Industrial and Systems Engineering*, *11*(Special issue: 14th International Industrial Engineering Conference), pp.85-97.

[30] Li, Z., Cheng, C., Kwan, M.P., Tong, X. and Tian, S., 2022. Identifying asphalt pavement distress using

UAV LiDAR point cloud data and random forest classification. *ISPRS International Journal of Geo-Information*, *8*(1), p.39.

[31] Li, B., Wang, K.C., Zhang, A., Yang, E. and Wang, G., 2020. Automatic classification of pavement crack using deep convolutional neural network. *International Journal of Pavement Engineering*, *21*(4), pp.457-463.

[32] Li, L., Sun, L., Ning, G. and Tan, S., 2021. Automatic pavement crack recognition based on BP neural network. *PROMET-Traffic&Transportation*, *26*(1), pp.11-22.

[33] Cubero-Fernandez, A., Rodriguez-Lozano, F.J., Villatoro, R., Olivares, J. and Palomares, J.M., 2023. Efficient pavement crack detection and classification. *EURASIP Journal on Image and Video Processing*, *2023*, pp.1-11.

[34] https://www.kaggle.com/datasets/lakshaymiddha/crack-segmentation-dataset

[35] Matarneh, S., Elghaish, F., Al-Ghraibah, A., Abdellatef, E. and Edwards, D.J., 2023. An automatic image processing based on Hough transform algorithm for pavement crack detection and classification. *Smart and Sustainable Built Environment*.

[36] Ashraf, A., Sophian, A., Shafie, A.A., Gunawan, T.S., Ismail, N.N. and Bawono, A.A., 2023. Efficient Pavement Crack Detection and Classification Using Custom YOLOv7 Model. *Indonesian Journal of Electrical Engineering and Informatics (IJEEI)*, *11*(1), pp.119-132..