Journal of Education and Science (ISSN 1812-125X)

www.edusj.mosuljournals.com

A Review of Road Cracks Detection and Classification Based Image Processing and Intelligent Techniques

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Article information

Article history:
Received: May 06, 2024
Accepted: July 09, 2024
Available online: September 01, 2024

Keywords:
Road defect
Road crack
Moderate cracks
Potholes cracks
Machine learning

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Abstract

Yearly, an amount of funds is spent to achieve defect detection in the principle of infrastructure represented by roads, bridges, and buildings. Urban infrastructure is affected by weather conditions, the natural disasters such as floods and earthquakes. As well as, mistakes during street paving operations and quality of paving materials. Various types of damage may appear in the form of small or vast cracks, which gradually spread, destroying the structure. Therefore, it requires building automatic systems for these inspection operations to guarantee its effectiveness and dependability. Hybrid image processing and machine learning approaches are being applied to guarantee better enhancement outcomes and strength in crack detection. This paper aims to offer a review of road image crack detection techniques that apply image processing with/without machine learning. A total of 32 research articles have been composed and studied for the review which has been issued in publications and conferences in the past years. This research manners a thorough analysis and comparison of various methods to identify the most promising automated methods for crack detection. After analyzing and reviewing previous research using digital image processing methods, it is clear from the results obtained that the best of them is the Franji filter method, whose accuracy is close to 98.7%. While discussing and presenting machine learning techniques and convolutional networks, the deduced results that the best of them is the Support Vector Machine (SVM) technique, whose precision is approximately 98.29%

DOI: 10.33899/edusj.2024.148454.1443,

1. Introduction:

Recently, cracks in roads become very common in buildings, bridges, and tunnels. Their impact on roads has become very large because of the major economic impacts they cause in terms of obstructing the sanctity of passage of vehicles and transport vehicles on the country's economy as well as the ordinary citizen. Therefore, these cracks may occur due to severe pressure that may result from natural disasters such as earthquakes, catastrophic accidents such as explosions, or daily uses. Traditional methods for detecting and classifying cracks include experts who visually inspect the case study and also use specific tools to diagnose any deficiency in the condition under examination. However, these methods are labor-intensive and tedious and are susceptible to human fault [1]. However, automated crack detection and classification techniques can be used to recognize cracks in infrastructure. Therefore, for rapid, effective, confinable crack judgment, the procedure of detection and classification of road cracks have to be automated by dispensing with human testing methods. Currently, researchers increasingly tend to use image processing and machine learning techniques for crack detection and classification. These techniques include capturing an image of the objects and testing them with software applications for detecting and classifying the cracks in the road. Therefore, the techniques are rapid, inexpensive, and strong. These techniques can be classified into two categories they are image processing and intelligent techniques based on machine learning. The first category is image processing techniques that needn't a training model but need morphological analysis, techniques of statistics, algorithms, and enhancement algorithms for operations of crack detection [2]. Figure 1 explains the primitive structure of the techniques of image processing steps for the detection and classification of cracks in roads. Firstly, capturing the images with high resolution by smart imaging devices. These captured images are then preprocessed by image processing techniques such as enhancement techniques and filtering operations. As well as, segmentation and denoising operations. Color conversion operation could be applied to the testing image, where the image could be in a binary or grayscale system. finally, the resulting image is entered into the crack detection and classification operations [3].

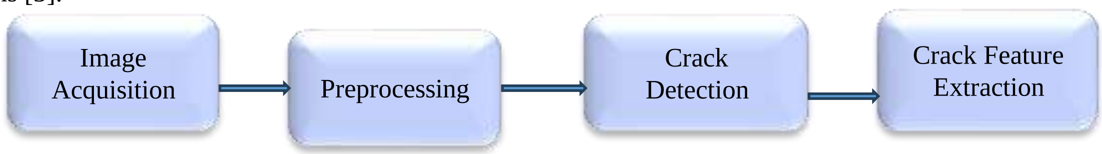

Figure 1. Image Processing Techniques for Road Cracks Detection

The second category is an intelligent technique by Machine Learning that includes visual dataset collection which is used to select a model for training such as CNN, decision trees, and SVM, such techniques could include image preprocessing algorithms. Moreover, a selection of machine learning models is needed for crack detection and classification. The model is constructed from two phases training and testing. The training phase demanded a set of images and annotated of these images that were fetched from the dataset. In the testing phase, the model starts when some new images need to pass to the model to check the suitability of the model for crack detection and classification within the image. Then the testing of the model starts where a new set of images will be applied to the model for crack classification operation [4]. Figure 2 explains the steps for crack detection and classification using machine learning techniques.

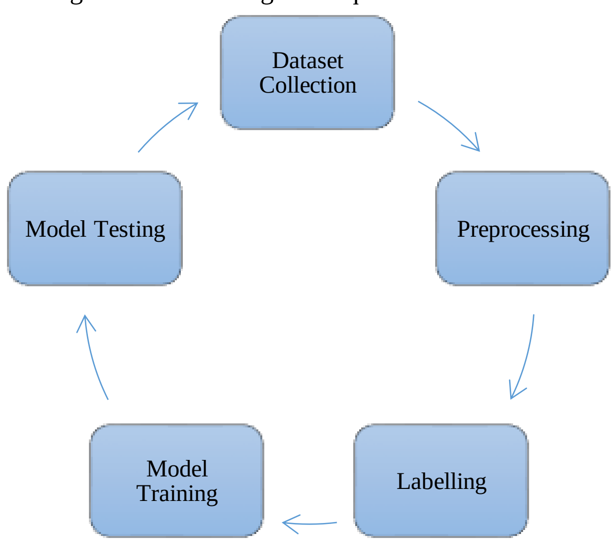

Figure 2. Machine Learning Methods for Road Crack Detection

In this paper, a review of machine learning and image processing techniques will be presented for the detection and classification cracks of in roads which have been proposed over the last decade.

2. Crack Types Classes

The common causes of pavement deterioration and degradation are overloading, improper, or poor road surface drainage, lack of proper road maintenance, lack of proper design, adverse climate conditions, and some other factors. An exhaustive review of crack types is shown in Figure 3 classifying the first-level crack types (minor, moderate, and severe) and further classifying to their subtypes. Minor cracks are very slight or tinny cracks. Moderate cracks are rarely difficult it require measurements but Severe cracks are huge and risky cracks [5].

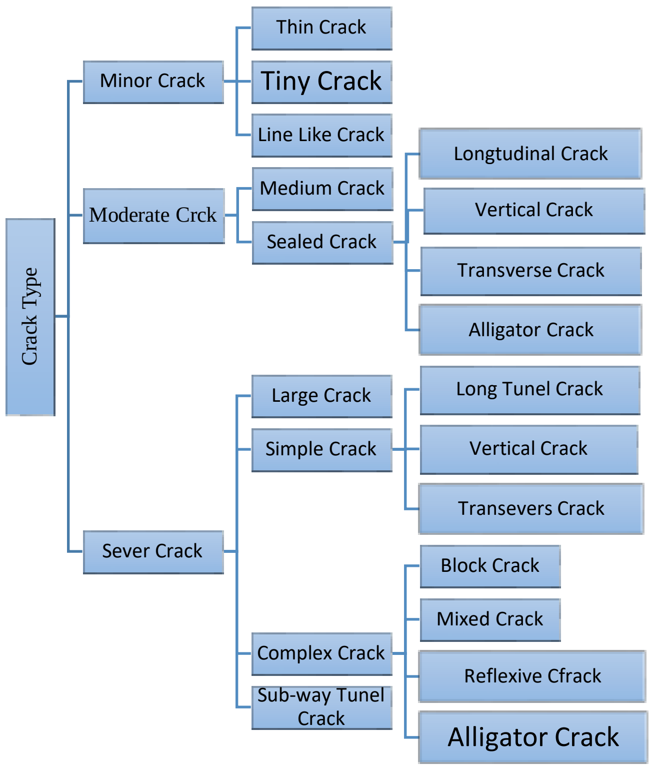

Figure 3. Cracks Type Classes

A sample of these cracks is mentioned in Figure 4.[6].

Distress Name	Sample Image
Longitudinal Crack	
Lateral Crack	
Alligator Crack	
Pothhole	

Figure 4. A Sample of Road Cracks

A crack is defined as a discontinuity in a pavement that generally extends parallel to the centerline of the pavement [7]. A description of these cracks is discussed as follows:

1. Longitudinal crack: it may occur as a result of poorly constructed paving line joints.

2. Lateral crack: it is extending from a side connector and may be caused by the ripping action of the concentrated load on the slab.
3. Alligator crack: it appears as a series of interconnecting fatigue failures of the surface. Fatigue failure is often the result of repeated traffic loading.
4. Potholes: it is the areas of road surface where the surface layer, usually asphalt, has developed cracks and then broken away under the repeated load of traffic passing over, forming a hole with rough vertical sides.

3. Related Works

Traditional detection algorithms generally use the framework of the sliding window. It mainly includes three steps:
1) extract the candidate area of the research.
2) extract the relevant visual features of the candidate area.
3) use the classifier to identify.

Whereas, a classification algorithm is a function that weights the input features so that the output separates one class into positive values and the other into negative values [1].

3.1 Image Processing Techniques Related Works

Image processing is a way of controlling image properties to analyze and extract intended distinctive attributes from the images. Some set of rules or processes followed to extract the attributes from an image are known as image processing algorithms. Therefore, there are many image processing techniques available to manipulate the image for crack detection and classification. Some of these techniques are mentioned below [8].

3.1.1 Tree Structures

Zou et al. presented a new technique that minimizes shadows or noise from the corrupted images to make the cracks in the road extra conspicuous for identification. A scheme of tensor voting was prepared to build a probability map for cracks that demand using visual clues of vicinity and connectivity. The edges are undesirable and can be ignorant to win the curves of crack. The model that is being validated on the dataset which is consisted of 206 road images for pavement roads. The metrics like F-measure, precision, and recall have values registered as 0.85, 0.79, and 0.92 respectively which signify a great correctness and connotation for the techniques [9].

3.1.2 Gabor Filter

It is a linear filter that dissects the characteristics of the surface in a region to detect the existence of fulfilled that have specific repetitiveness in any orientation. Therefore, this technique can be very useful for recognizing the cracks in roads that the rich textures. The expletory results explain accuracy of precision detection is 95% which is applied for multidirectional crack detection [5].

3.1.3 Particle Filter

Particle filters could be used as a consequence of the detection of cracks in civil structures. It is initially created for monitoring objects in clutter. The error range could be registered between 7.51% to 8.59%. An entire pixel number of cracks could be detected by the technique detection of cracks that could multiply with a resolution of the pixel [10].

3.1.4 Beam Let Transformation

Salari and Ying introduced a Beam Let transformation in consequence for the image of pavement road crack detection and classification. Beam Let is a m management of lines segmented into different locations, angles, and scales. The linear features such as edges and lines are recovered by using this method. Therefore, it appeared like effectiveness for cracks detecting that the features are curvilinear outside of the images of pavement noisy textures [11].

3.1.5 Frangi Filter

Yeum and Dyke concentrated on bridge images for detecting cracks. Particularly, they target crack detection. Images that are captured, each have the region of interest (ROI) like a bolt. Operators of dilate, detector of canny edge, and median filter were utilized for extracting the parts within images and then applying a Hessian matrix technique which is called Frangi filter for crack detecting. The precision detection of the system was 98.7% [12].

3.1.6 Shi-Tomasi technique

Li and Kong focused on crack detection. A snapshot video is cached from the structure of the bridge. Some features are detected by using the Shi-Tomasi technique. Exploratory results show the efficiency and robustness of this technique until in diverse conditions of illumination. The resolution of a camera is increasingly dependent on the limitation [13].

3.1.7 Genetic Programming

This paper employed image processing methods for automatic crack detection from concrete images. Major cracks are detected via genetic programming (GP). Genetic programming has been employed to optimize important structures by applying the fuzzy genetic algorithm. Introducing a floating-point genetic algorithm helped address system issues. Noisy images were minimized through the use of filters, followed by the detection of minor cracks through the iterative application of an image filter. This approach achieved an 80% accuracy rate on a dataset consisting of 18 test images [14].

Table 1. Image Processing Techniques for Road Cracks Detection and Classification

Techniques	Features	Dataset	Results(accuracy)
Recursive Tree Edge Pruning [9]	Crack Detection and Classification	206 image, 800x600 pixel	F-measure=85%, Precision=79% Recall=92%
Advantage / Disadvantage	High Accurateness and Implication of the Methods /Amplified Runtime (up to 30 s)		
Gabor Filter [5]	Crack Detection	5 images, 336x339 pixel	Precision Up to 95%
Advantage / Disadvantage	Effective to Detect Cracks Having Good Textures/ Computational Complexity, Parameter Change and Sensitivity to Noise		
Particle Filter [10]	Crack Detection & Measurement	14 Images, 12 MP	Error Range 7.51-8.59%
Advantage / Disadvantage	Flexibility and Robustness / Computational Complexity and Sensitivity		
Beam Let Transformation [11]	Crack Detection, Measurement & Classification	256x256 Pixel	Robust to Noise, Fast and High Accuracy
Advantage / Disadvantage	Effective in Detecting Cracks/ Computational Complexity, Storage Usage, and Sensitivity to Noise		
Frangi Filter, Canny Edge Detector, Dilate Operators [12]	Crack Detection	72 Images 4288 x 2848 Pixel	Detection Rate= 98.7%
Advantage / Disadvantage	Robust and effective/ Parameter Sensitivity, Require Additional Preprocessing		
Shi_Tomasi Feature Point Detection [13]	Crack Detection	Real-time Crack Detection	The Strongest System with Variety Conditions of Lights and Complicated Textures
Advantage / Disadvantage	Robust and Reliable Method /The Accuracy Is Influenced by The Restricted Resolution of The Camera, Which Is Limited by Noise		
GP and Image Filtering [14]	Crack detection	17 (varying resolution)	Accuracy=80%
Advantage / Disadvantage	Powerful and Flexible for Search Problems Via Succeeding Generations/ Limit Its Capability to Huge Dataset		

3.1.8 Road Cracks based-Image Processing Techniques Discussion

From table 1 it is shown that the First paper in the table adapted 206 various road crack images. These images have been resized to 800 x 600 pixels. They addressed problems of noise in edge cracks. Low intensity lengthwise of the cracks.

Shadows and occlusions. The algorithm processed and addressed these problems while retaining and clarifying the cracks. The Second discussed many crack detection and classification techniques, The work is entitled Gabor filter as best filter for texture and edge detection. Third research hybrid techniques of statistical filtering (particle filters) and machine vision techniques. The first technique recognized cracks automatically while the second measured the crack dimensions. The Forth work extracts the road cracks from the images and subdivides them into small tiles then, a beamlet transformation algorithm is applied to each tile. In the last work after the image capturing, a preprocessing operation is applied in order to extract the features for accenting the cracks by Genetic programming. From Table 1 it is clear that the Fifth research that applied the Frangi filter is the best with a detection rate of approximate 99%.

3.2 Machine Learning Related Works

Road crack detection utilizes machine learning or deep learning algorithms to generate meaningful results. Just like humans can quickly recognize and identify cracks in images, computers aim to replicate this intelligence through crack detection. Crack detection involves two main tasks: crack localization, which determines the location of cracks in an image, and crack classification, which assigns cracks into different categories. In recent years, the field of computer vision, particularly crack detection has undergone significant advancements. The use of machine learning and deep learning techniques has greatly improved the field of crack detection, allowing for more accurate and efficient identification and categorization of cracks in images and videos. Machine learning is a science of artificial intelligence that uses computers to simulate the way humans learn. A variety of algorithms included in machine learning can achieve data prediction, clustering, pattern recognition, and other functions by learning from data or previous experience. There are many methods of machine learning, which can be divided into two categories, supervised learning and unsupervised learning, depending on the learning approach [15].

3.2.1 CNN-model

The CNN (Convolution Neural Network) model is found commonly in the literature on the detection and classification cracks of in roads. As shown in Figure 5 it has three layers of neurons such as:

1. Convolution layer,
2. Pooling layer
3. Fully connected layer.

The first one is catted out the features from images. It is capable of learning and distinguishing between cracks and non-cracks in the image. The second one is using cutting out and downsizing the image. The third layer is considered the output of the previous layer and the input then mapped as the labels.

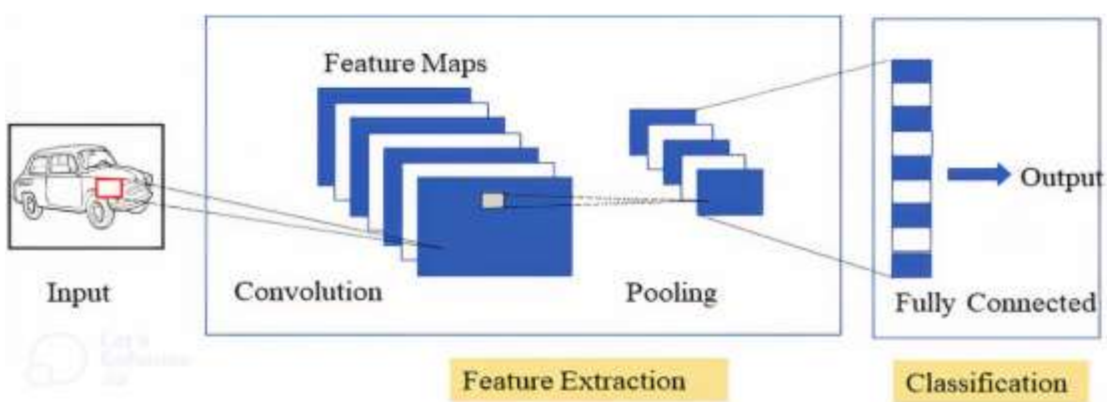

Figure 5. Convolution Neural Network (CNN) as Feature Extractor

The description of cracks demands identification and segmentation. Ni-et-al., computerized it by using pixel classification and feature map fusion techniques [16].

- GoogleNet CNN was applied for crack classification on dataset 600 images. The feature pyramid network (FPN) is used to produce the output. It is composed of a fusion layer and a consecutive convolution layer that absolutely performs the crack description. Therefore, the result appears to prove that the network enables description crack with a precision of about 80.13% [17].

- Deep-Crack Net builds upon the structure of Seg-Net that is manufactured from encoder, and decoder structures. The characteristics that are contrived from a convolution of the encoder and decoder networks steps melded within a pair-wise approach. Therefore, four regular datasets of cracks which are Crack-Tree, CRK-WH100, Crack-LS315, and Stone-331 are employed for evaluation, three of them are utilized for testing and the other one for training. The exploratory results showed an F-measure above 0.87[10].

- The FCN (fully-convolution network) model is used at the pixel level for crack segmentation in the image of pavement roads and walls. It is training on 500 images by utilizing different types of cracks. The precision that is performed by the system of crack segmentation is 97.96% [18].

3.2.2 K-Means Cluster

The technique of crack features deals with classifying the detection cracks by their types. Correia and Oliveira released a crack detection and classification manner, which did not need human labeling of the dataset of images. Images of roads were cached by utilizing a digital camera, some of them are used for training the system. Some images from the training dataset are used for the unsupervised training of the system. Mixtures of two Gaussian models and a technique of K-Means clustering were tested for detecting cracks within an image. The mixture of Gaussian models exposed the highest f-measure 93.5% and the lowest rate of errors 0.6% [19].

3.2.3 Logistic Regression

Thurley and Sandstorm released a system of crack detection and measurement that utilizes morphological image processing on about 500 images as a dataset. Firstly, during the segmentation and the slight defects, 80% of a crack's length in an image is catted out or cracks are neglected. Then, the statistical classification is achieved by utilizing the logistic-regression above this segmentation of an image that detects all of the main cracks. The precision that is registered by the system is above 80%[20].

3.2.4 FPHBN-Technique

Yang. Et, al. [21] released Feature-Pyramid and Hierarchical-Boosting Network for detecting cracks. The performance assessment for the detection of cracks in the images is the average intersection over union (AIU) which is a new measurement technique. It is evaluated upon five stander datasets of cracks. AIU is obtained by utilizing the technique which is 0.081 and 0.241 is the time that is taken to present the output of a single image, the results appear the precision is 80.11%.

3.2.5 SVM technique

Gavilan-et-al. [22] released a technique for road crack detection. Therefore, hundreds of images are cached by a line-scan camera mounted on a vehicle with laser beams. Then the images applied the MDNMS (multiple directional non-minimum suppression) technique for the detection of cracks. A linear classifier S.V.M. was utilized to distinguish variation between pavement roads over the track to bounding the optimum parameter for crack detection. The achieved crack detection techniques were developed by adjusting the parameters that are précised to the pavements. The precision of this technique is 98.29% and the recall of 93.86%.

3.2.6 SVM and Random Forest

Finding cracks in bridges is crucial to maintaining their structural integrity and ensuring the safety of those who use them. Using robotic imaging, Prasanna et al. were able to locate cracks in 600 bridge images. They published a technique for fracture identification known as spatial-tuned robust multi-feature (STRUM). To complete the classification of the cracks and non-cracks pixels, machine learning techniques like SVM, AdaBoost, and random forest are applied. Despite the noise in the photos, the potential region of cracks is bound by robust curve fitting. The STRUM classification method has a 95% accuracy rate [23].

3.2.7 SVM and ANN

There has been a proposal for a fracture detection system for civil structures that segments data based on depth characteristics. Reconstructing 3-D scenes accepted for the determination of crack depths. This technique is unique in that it extracts all of the cracks from the 500 input images, whereas other techniques rely on the detection of edges just by segmenting the cracked regions. Morphological techniques are utilized to remove and segment cracks. The accuracy of the crack detection and classification utilizing NN and SVM classifiers is 79.5% [24].

3.2.8 Artificial Neural Network (ANN)

Many issues that researchers may deal with are the summarization of cracks in roads in the images. Wu et al. exposed that the "Morph-Link-C" cracks summarization techniques such as a solving of this problem. This technique joins the many fracture segments that appear in an image [16-11]. Group pieces of cracks are submitted to a dilation transform. A transformation of thinning is employed to join these parts. This technique is also utilized to determine the width of cracks. The technique was created to detect cracks in images of roads and pavements. The last stage of the classification is assigning the images of the label’s "crack" or "no-crack," which is carried out by ANN. It has appeared that the Morph-Link-C manner shortens the classifier's training period while increasing classification accuracy [25].

3.2.9. Random-Structured Forests (RSF)

Crack-Forests are a random structured forest-based crack detection method for roadways, similar to Shi et al. This model aims to address the problem of the intensity of fractures in road photographs not being uniformly distributed on typical datasets. Integral channel characteristics are used to obtain a better representation of cracks in order to detect them in such images. Crack detection is done using a random structured forests method after this. With this technology, complicated and arbitrary cracks in photos may be accurately detected. 96.73%is the total accuracy attained for the classification of cracks [26].

3.2.10 Decision-Tree Technique

Fernandez et al. employed a variety of image processing and machine learning techniques to identify cracks. A filter based on morphology, a canny edge detector, a bilateral filter, and a logarithmic transformation are among the processes. Ultimately, the fracture was categorized by the types using a decision tree classifier. There are three different types of cracks: alligator, longitudinal, and transverse. 88% of cracks were detected successfully, and 80% of cracks were classified correctly. Crack detection has benefited from the application of a decision tree technique [27].

3.2.11 Machine Learning Algorithms

The proposed system utilizes vehicles, smartphones, and onboard diagnostic (OBD) devices to get the private dataset, and machine learning algorithms (K-means, Fuzzy, GMM). development of a cost-efficient smart city-based assessment system that evaluates roadway pavement roughness conditions more frequently than current systems, with an accuracy rate of about 79.40% [28].

3.2.12 YOLOv7

In order to train deep learning for autonomous road damage detection and classification, this work proposes to gather and classify photographs of damage using Google Street View and the YOLOv7 (You Only Look Once version 7) technique together with coordinate attention and associated accuracy fine-tuning technique. This method is used in the IEEE BigData-2022 Crowdsensing-based Road Damage Detection Challenge (CRDDC2022). The results of the experiment demonstrate the effectiveness of the data collected from Google Street View. The Deep Learning technique yielded a result of 81.7, while the road damage data obtained from the United States using Google Street View on all test photos in this dataset was 74.1 [29].

3.2.13 State-of-the-Arts Solutions (YOLO)

In this instance, the data consists of 26336 road images that were gathered from the Czech Republic, Japan, and India in order to suggest techniques for automatically identifying road damage in these nations. A total of 121 teams from various nations signed up for this competition. Examining the provided answers, two datasets (test1 and test2) of 2631 and 2664 photos each were used. The best 12 answers that these teams came up with are summarized in this publication. YOLO-based ensemble learning is employed by the top-performing model, which yields an F1 score of 0.67 on test 1 and o.66 on test [30].

3.2.14 Deep Neural Network (CNN)

The dataset consists of 9053 photographs of road damage that were taken using a smartphone mounted in a vehicle. 15435 of these images show occurrences of damage to the road surface. We trained the damage detection model using our dataset using a state-of-the-art object detection method utilizing convolution networks, and we compared the accuracy and runtime speed using a GPU, server, and smartphone. The accuracy performance is approximately 79% [3].

3.2.15 Deep Learning Approach

This paper proposed a deep learning method for automatic road pavement crack detection, inspired by deep learning in computer vision problems. A dataset of 500 images was collected as a visual database and segmented to a number of tails. A supervised deep convolutional neural network is trained to classify each image patch in the collected images. This approach demonstrates that the learned deep features outperform hand-crafted methods in crack detection performance. According to what was mentioned, Table 2 represents a summary of the related works with techniques of machine learning-based detection and classification of cracks [31].

3.2.16 YOLO v2 Deep Learning Framework

YOLO is an object detection algorithm that uses a classifier to detect objects in an image, testing them at different locations and scales. It reframes object detection by looking at the image once and correctly performing object detections. Using a single CNN, it can predict multiple bounding boxes and class probabilities, making it fast and easily applicable to various scenarios [32].

Table 2. Machine Learning Techniques for Road Cracks Detection and Classification

Techniques	Characteristics	Dataset	Accuracy
Google-Net, FPN, CNN [17]	Crack Detection	64000 non-Crack Images 6000 Images	Precision = 80.13% Recall = 86.09% F-Measure = 81.55%
Deepcrack Network [10]	CrackTree, CRKWH100, CrackLS315, Stone331	260 Training Images 512 x512 pixels	F-Measure = 87%
FCN [18]	Crack Detection	Various Resolution	Accuracy = 97.96%
K-means Clustering and Gaussian Models [19]	Crack Detection and Classification	84 Images 1536 x 2048 Pixels	F-Measure = 97%
Logistic Regression [20]	Crack Detection	500 Images	Accuracy > 80%
FPHBN [21]	Crack Detection	5 Standard Crack Datasets	80.11%
SVM [22]	Crack Detection and Classification	7250 Images 4000 x 1000 Pixels	Precision = 98.29% Recall = 93.86%
SVM, Random Forest [23]	Crack detection and and Thickness Evaluation	100 Images 1920 x 1280 Pixels	Accuracy = 95%
SVM, ANN [24]	Crack Detection and Classification	38,000 Images 6144 × 1024 Pixels	Accuracy NN = 79.5%, SVM = 78.3%
RSF [26]	Crack Detection and Classification	38 + 118 Images 480 x320 Pixels	96.73%
Decision Tree [27]	Crack Detection and Classification	400 images	Crack Detection = 88% Classification rate =80%
Machine Learning Algorithms [28]	Crack Detection and Classification	Special Dataset	Accuracy Rate =78.40%
YOLOv7 [29]	Crack Detection and Classification	CRDDR2022 Custom Dataset	RDD2022 Precision = 95.23%, Recall = 95.45% Custom dataset precision = 93%, Recall = 91.58%
State-of-the-art Solutions [30]	Crack Detection	2631Images 2664Images	67% 66%
Deep Learning Approach [31]	Crack Detection And Classification	500 Images 3264 x 2448	Precision= 0.8696% Recall= 0.9251% F1-Measure =0.8965%
YOLO v2 Deep Learning Framework [32]	Crack Detection	9,053 Images	Precision = 88.51% Recall = 87.10% IoU = 87.80%

3.2.17 Road Cracks Based-Machine Learning Techniques Discussion

The previous papers focused on detecting road cracks using deep learning that aids in facilitating road monitoring activity without the help of human operators. To recover the problems of road cracks detection and classification there exists a need to automatically predict road recently. Researcher hybrid their work for detecting road cracks using deep learning and computer vision techniques. A number of these works were recorded in at table. 2. The most common traditional ML methods are Support Vector Machines (SVM), Artificial Neural Networks (ANN), random forest, and clustering. Old ML methods use a feature extraction stage before model training. The most common method of Deep Learning for crack detection is CNN. It is clear from the outcomes shown in Table 2 that SVM gains a superior precision result equal to 98.29% which reflects that this is the best technique among all other techniques. Also, the hybrid SVM with Random Forest and ANN evaluate optimal results. The outcome from techniques FCN (fully-convolution network), K-means clustering and Gaussian Models, Random-Structured Forest (RSF), YOLOv7s, and Deep learning approach varied throughout the nineties. But the rest methods change within the eighties. Machine learning approaches for road crack detection face limitations like processing time, manual parameter setting, large datasets, extensive labeling, and poor real-time performance. Decomposing networks into low-bias sub-networks reduces these issues.

4. Analysis and Recommendations:

Road crack Detection and classification using the branch of artificially intelligent machine learning and image processing is an appreciated task for preserving road safety and structure. The analysis and recommendation stages will be discussed below:

4.1 Analysis Stage

The research presents an inclusive analysis of image processing and machine learning-based techniques for crack detection. The image processing-based methods contain the use of filters, statistical methods, and categorization techniques for crack detection. These methods typically include preprocessing phases like noise removal and image color conversion, followed by crack detection procedure techniques like edge detection and segmentation. The machine learning-based methods require collecting a visual dataset, which is then used to train the selected machine learning models for the crack detection task. These models may also hybrid image processing steps for preprocessing. This work used image processing and machine learning techniques for crack detection at a 39% rate while reviewed 60% for cracks detection and classification while the rest articles have discussed the issue of road cracks in general. The paper also discusses research focused on crack classification and measurement. For instance, the K-means clustering and Gaussian mix models were used to classify cracks into various types such as pothole, longitudinal, minor cracks, and miscellaneous. Another method, Crack Forest, used random structured forests to detect arbitrary and complex cracks, and an SVM model to classify the cracks.

The most ten studies focused on crack detection and classification, while four of them dealt with both crack detection and measurement. The rest discussed crack detection only. The paper also discussed the field of crack detection, noting that a large mainstream of papers focused on detecting cracks in pavements and roads. Research in both fields illustrates that the obtained results regardless of the technique used that the machine learning approach achieves better results than the image processing approach. Despite the Machine learning limitations that include complex calculations, the need for huge datasets, and cost considerations.

4.2 Recommendation Stage

After reviewing this literature, the researchers suggest implementing these recommendations practically when constructing an automated system for identifying and classifying road crack defects on paved roads. This will aid in developing robust, exact, and efficient systems-based machine learning and image processing techniques:

1- The authors recommend the need to focus on enhancing methods for crack detection that can be useful to other materials like leather, wood, steel, textiles, and other manufacturing products, besides the current focus on road pavement and building structures.

2- Image Acquisition the crack road data must be collected under various situations like different intensities and various weather conditions. Also, choosing the best image equipment for capturing photos is important. Data augmentation to **enhance dataset size progresses** the model's robustness.

3- The recommendation for Image Processing Techniques such as preprocessing based on denoising filters and image enhancement techniques. Feature extraction to extract crack features after detection by traditional techniques like SIFT (Scale-Invariant Feature Transform), Gabor filter Beamlet transformation, and many other approaches.

4- Recommendation on model selection via Convolutional Neural Networks (CNNs) architectures like U-Net, VGG16, and ResNet for their efficiency in image classification and segmentation. Also, choosing the best Transfer Learning considering the amount of the dataset to save time and computational resources.

5. Conclusion

This article focused on scopes of image processing and machine-learning as a consequence of the detection and classification cracks of in roads. It previewed the state-of-the-art techniques of detection and classification of cracks that have been developed in the last years with its results that are published in usual conferences and journals. Different articles were inspected and the applied criteria were and performed testing of their details. The papers were evaluated these techniques have been utilized, the details of datasets, imaging techniques, achieving results, limitations, and features. By analyzing that it can be inherited an expansive extent of papers focused on the detection and classification of crack. Therefore, a majority of techniques appeared to an excellent achieving results such as the accuracy values for the detection of cracks domain from 75% to 100%. Other observations push the scientists to utilize their datasets which desired to utilize the particular necessities for the techniques that the system utilized. The greatest reviews of techniques for the detection and classification of cracks are applied to concrete components and civil infrastructure. In the last few years especially between (2016 to 2020), the greatest studies are focused on utilizing the techniques for crack detection and classification on machine learning in place of image processing. During all of the previous techniques mentioned in this article, CNN and YOLO have got the highest utilization by the specialists and researchers in their interest to solve all the problems that faced them. The article could be extended in the future to consolidate valuation criteria to examine the performance, for instance, the runtime algorithms, consumption of resources, and resistance to real-time settings.

6. Acknowledgment

The author would like to thank his supervisor, lecturer at the Department of Computer Science, College of Education for Pure Science, University of Mosul for her support and ideas in writing this paper. Also, the authors are grateful to the University of Mosul for associating this scientific paper and their provided facilities to improve the superiority of this work. The authors express thanks to the Journal of Education and Science Management for allowing them to submit a paper for publication, thereby providing valuable knowledge to readers.

7. References

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EDUSJ, Vol, 33, No: 3, 2024 (45-57)

مراجعة للكشف عن تشققات الطرق وتصنيفها باستخدام معالجة الصور والتقنيات الذكية

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المستخلص

يتم إنفاق مبالغ مالية سنويًا لتحقيق الكشف عن العيوب في البنية التحتية التي تمثلها الطرق والجسور والمباني. تتأثر البنية التحتية الحضرية بالظروف الجوية والكوارث الطبيعية مثل الفيضانات والزلازل، وكذلك بالأخطاء أثناء عمليات تمهيد الشوارع وجودة مواد التمهيد. قد يظهر أنواع مختلفة من الأضرار على شكل شقوق صغيرة أو واسعة، والتي تنتشر تدريجيًا وتؤدي إلى تدمير الهيكل. لذلك، يتطلب بناء أنظمة آلية لهذه العمليات التفتيشية لضمان فعاليتها واعتماديتها. يتم تطبيق تقنيات معالجة الصور الهجينة وتعلم الآلة لضمان نتائج تحسين أفضل وقوة في الكشف عن الشقوق. يهدف هذا البحث إلى تقديم مراجعة لتقنيات الكشف عن شقوق الصور في الطرق التي تطبق معالجة الصور مع أو بدون تعلم الآلة. تم تجميع ودراسة 32 مقالة بحثية للمراجعة التي تم إصدارها في المنشورات والمؤتمرات في السنوات الماضية. يجري هذا البحث تحليلًا شاملاً ومقارنة لطرق مختلفة لتحديد أكثر الطرق الواعدة للكشف الآلي عن الشقوق. بعد تحليل ومراجعة الأبحاث السابقة باستخدام طرق معالجة الصور الرقمية، يتضح من النتائج التي تم الحصول عليها أن أفضلها هو طريقة فلتر فراني، والتي تصل دقتها إلى حوالي 98.7%. بينما، عند مناقشة وتقديم تقنيات تعلم الآلة والشبكات العصبية التلافيفية، تُستنتج النتائج أن أفضلها هو تقنية آلة الدعم المتجه (SVM)، التي تصل دقتها إلى حوالي 98.29%.