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ROAD DAMAGES(CRACKS) DETECTION IN IRAQ By USING ML

Noor Hamzah Nwelle AL-BUJASIM

Master's Thesis

Supervisor
Asst. Prof. Dr. Oğuz KARAN

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This thesis title ROAD DAMAGE (CRACKS) DETECTION IN IRAQ BY USING AI prepared by NOOR HAMZAH NWELEE JAWAD AL-BUJASIM and submitted on 29/12/2023 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

Asst. Prof. Dr. Oğuz KARAN
Supervisor

Thesis Defense Committee Members:

Asst. Prof. Dr. Oğuz KARAN	Department of Software Engineering, Altınbaş University	_________________
Assoc. Prof. Dr. Sefer Kurnaz	Department of Computer Engineering, Altınbaş University	_________________
Asst. Prof. Dr. Zeynep ALTAN	Department of Software Engineering, Istanbul Aral University	_________________

I hereby declare that this thesis meets all format and submission requirements of a Master's thesis

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Noor Hamzah Nwelle AL-BUJASIM

Signature

DEDICATION

Thank God first and last. I dedicate that humble work to the icon of truth and justice in this land. This work is dedicated to my parents who have continually put my feet on the first step in the journey of life, to everyone who illuminated my mind and taught me a letter, to my brother and all sisters who are proud of my success and they wish me progress, to all my friends and colleagues who stood with me and helped me in my studies, and to all my family, friends, acquaintances who wish me well and happiness, and are happy to see a smile on my face.

ABSTRACT

ROAD DAMAGES(CRACKS) DETECTION IN IRAQ By USING AI

NWELEE, Noor Hamzah,
M.Sc., Electrical and Computer Engineering, Altınbaş University,
Supervisor: Asst. Prof. Oğuz KARAN
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That research aims to develop road maintenance operations that include the road survey process to determine types of defects, knowing the type of proposed maintenance, solving the problem of reporting road problems, and also seeks to facilitate the process of road maintenance at the lowest possible costs To achieve these goals, a project is being designed that automates road maintenance and uses artificial intelligence to determine kind of defect in the way by using the libraries (tensorflow with Detection Object), (sklearn is considered one of the most famous libraries for the Python programming language, which specializes in The related fields of data science and machine learning. This library includes a set of algorithms, methods and techniques that are used in the machine learning field, and among these Methods are the concept of classification, and this library was built based on various Python libraries such as: Scipy, Numpy, Matplotlib, and many other libraries.). The proposed study will reach a number of results, which are identifying the defect, knowing its type, measuring the area of the defect, and conducting some engineering operations and calculations to determine the state of the roadway, and the type of maintenance proposed as a final output. This study will use a deep learning-based object detection method to identify road cracks under different shooting, weather, and illumination scenarios. This makes it possible to identify any cracks in a very short amount of time and at a low cost. Images will take in different weather conditions, such as the intensity of brightness being high, medium or very low. They will also be taken in foggy, rainy and dark conditions. Pictures are also taken at different distances (such as one meter, half a meter, one and a half meters) to study the behavior of the pictures and the possibility of extracting defects from them in different circumstances.

Keywords: AI, ML, CNN Algorithm, Data Set, Road Damage Detection, Maintenance.

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1. INTRODUCTION

1.1 BACKROUND

In this research, we will discuss the discovery of road cracks in the international highway in Iraq, (The part of the road that extends from Baghdad to Hila, which has a length of 550 km.2), Which in turn is part of the external Road No. 8 in Iraq reaches from Baghdad, Baghdad International Airport to Safwan, passing through Mahmudiyah, Hila, Diwaniyah, Rumaitha, Samawah, Nasiriyah and Zubayr, then to Safwan and the Safwan border crossing with Kuwait [1], This road is one of the important traffic roads, which in turn connects part of the governorates of central and southern Iraq, which in turn connects Iraq with the State of Kuwait through the Safwan border crossing. The entry of this road into service was in 1989, and the project at that time ranked third in the Middle East [2].

Figure 1.1: Highway No. 8 [2].

Among the negative influences that diminish the efficiency and performance of the road is that this road is becoming obsolete, in addition to the damages caused to it as a result of heavy traffic, human errors, paving structure, climate, and natural calamities like hurricanes, sun, earthquakes, dust storms, erosion, rain, and natural weather factors, temperature and humidity, in addition to the age of the road, paving materials, construction quality, and maintenance used to maintain the road are the most frequent reasons for damage to roads, and These elements affect the road's performance to varying degrees [3].

1.2 STUDY AREA BOUNDARIES

Iraq is an extremely recent country within the domain of construction, implementation, operation and maintenance of highways Whereas, the total lengths of highways in Iraq before the opening of parts of Highway No. 1 for the period from 1986-1990 of the last century do not exceed tens of kilometers only, all of which are in the governorate of Baghdad, the capital. Then came Highway No. 1, which is the first project of its kind in Iraq in terms of linking the countries of the eastern Mediterranean with the Arab Gulf countries, in addition to linking the western and central governorates of the country with the southern ones. Its length is approximately 1,200 kilometers, starting from the Iraqi-Syrian and Iraqi-Jordanian borders to the border Al-Iraqi Al-Kuwaiti, in addition to a branch to the center of Basra Governorate, and because of the enormity of this project, because of which Iraq was considered the largest highway workshop in the world, it was divided for implementation purposes into ten parts [4] .In this research, we will take the database that we will adopt from a part of the international highway (which connects Hila with Baghdad (Part One / 4 Baghdad - Hila)).

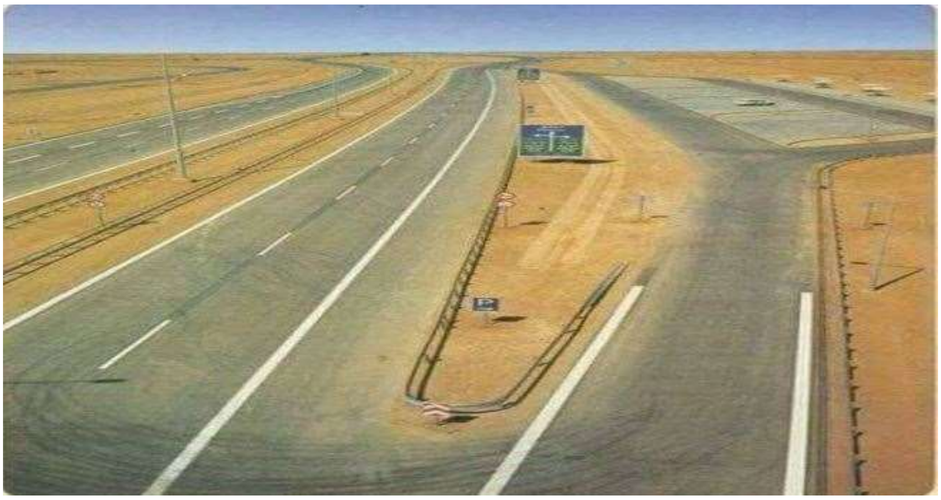


Figure 1.2: Part of The International Road In Iraq.

1.3 PROPLEM STATEMENT

The damage of the roads is the largest concern for users of roads in the past few years, and the damage of the roads leads to a significant slowdown in traffic, which causes an increase in the number of road accidents that kill human lives, and this negatively affects in all respects the economic and urban growth of the country. we have forced the follow-up of this problem by directing the enormous technological development to serve this important edifice. Technical maintenance of roads using modern software methods is no less important than their implementation and creation, as maintenance is a continuous work aimed at maintaining the condition of roads and the quality of its performance, in order to ensure safe and comfortable traffic operations. Before the operation ,Maintenance it is necessary to conduct a comprehensive assessment of the road to find out the defects present in the road, their intensity and severity In order to assess a condition of the road and then determine the best available means of maintenance and estimate the cost of the maintenance process .Due to the huge technological development in addition to the importance of the maintenance process, the use of technology and techniques it is more accurate to determine the types of defects, their density and severity, and therefore suggest guaranteed means of maintenances. In this research, Techniques for pattern recognition and image processing are used to find defects, Therefore, it is necessary to assess the state of the roadway and suggest a appropriate type of maintenance. The maintenance of roads is no less important than its implementation and construction, because maintenance is a continuous work that aims to maintain the condition of the road and the quality of its performance, in order to secure safe and comfortable traffic operations. Before carrying out the maintenance process, a comprehensive evaluation of the road must be conducted to find out the defects in the road and their density and severity in order to assess the road's condition. Due to the tremendous technological development in addition to the importance of the maintenance process, the use of technology and modern techniques leads to facilitating this process and saving a lot of effort, time and money, and may lead to more accurate results in determining the types of defects, their density and severity, and thus suggesting guaranteed means of maintenance. In this research, modern software techniques are used based on image processing techniques and artificial intelligence algorithms (convolutional neural networks) in order to identify a patterns of defects in the road, their area and density, and thus correct the state of the roadway and suggest an appropriate type of maintenances.

Figure 1.3: Crack in the Road.

1.4 THESIS OBJECTIVES

In grow thing countries, road damage is detected manually. Although this task is difficult to execute, its numerous disadvantages include the need for additional labor., Reducing the security of the inspector, obtaining correct section values and it is based on the judgment of human experience. These searches can result in traffic jams in addition to other things. and take a long time, There are human factors that can distort damage detection results [5][6][7]. The discovery of road cracks is necessary before creating a maintenance plan to ascertain the circumstances surrounding the maintenance procedure. The arranging of road maintenance procedures is determined by the level of distress. [8]. Table 1.1 shows an example of a road cracks maintenances work based upon the degree of damage.

Table 1.1: Program for Road Maintenance [9].

Damages levels %	Conditions	Program for maintenances
<6	well	Standard Maintaining
6.0-11.0	modest	Small-scale Rehabilitating
11.0-15.0	Slight Damages	Significant Rehabilitating
>15	Huge Damages	Reconstructing

Concerned engineers have been paying more attention to road maintenance lately. One of the most crucial elements in efficient and cost-effective road network maintenance that can extend service life is the evaluation of maintenance conditions. We can summarize the desired objectives of the research with the following points:

a. Directing modern technology to improve the reality of roads that commensurate with the digital revolution taking place in order to reduce the time, effort and financial cost resulting from the old traditional methods.

b. Design a project that recognizes defects and their area.

c. The project should evaluate the road condition.

d. The project should also suggest the appropriate type of maintenance.

e. Studying the behavior of road images in different weather conditions and the possibility of extracting defects from those images in those conditions.

f. The possibility of detecting the state of the road and evaluating its condition before deterioration, which provides the sustainability of the road and traffic infrastructure.

1.5 RESEARCH CONTRIBUTION

This study set out to address a significant research question: "How can two-dimensional front view images be used to automatically detect road surface cracks?", we address this matter by combining ml algorithms and their applications [10], this study includes a contribution to the following research domain as shown in Next, The development process that is being presented helps to solve the issue of visual crack detection. We assume that one relatively recent issue is that of automating road monitoring that is formed by the latest technologies, whether it is manual or specific to road monitoring, and then the front view image analysis to identify road cracks represent the new field and so it is considered using, generation and developing machine learning algorithms to identify image cracks can be viewed as a novel strategy.

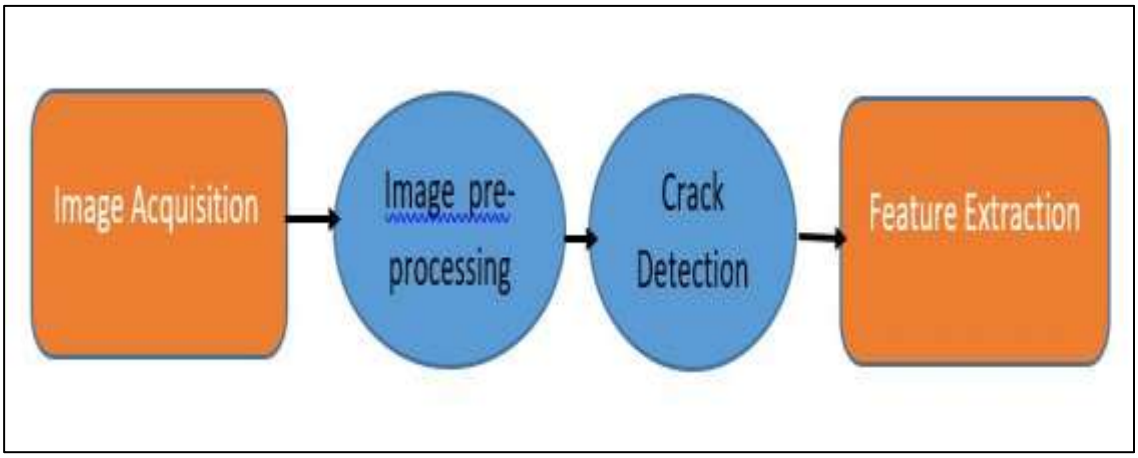


Figure 1.4: A Method for Detecting Cracks Using Image Processing [11].

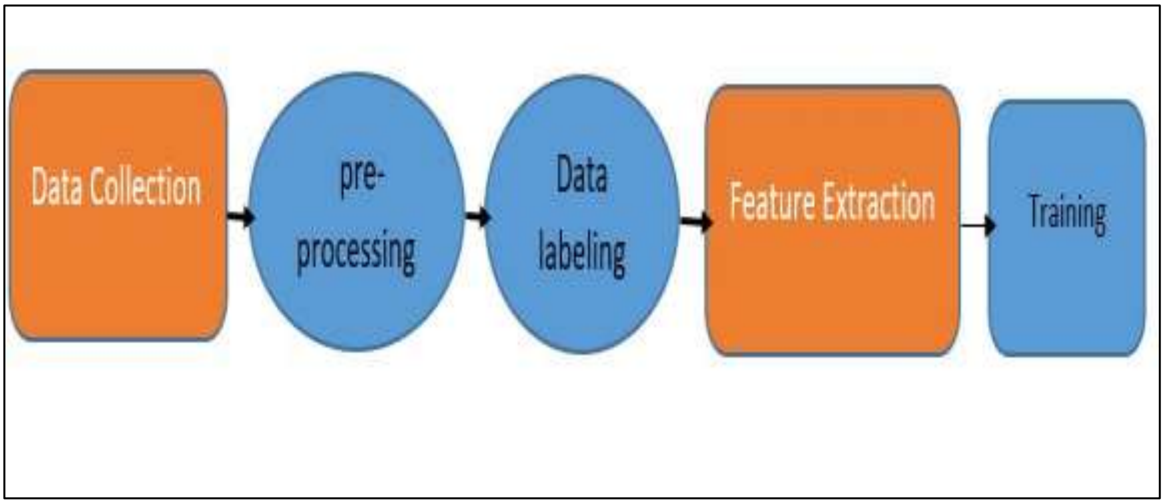


Figure 1.5: A Method For Detecting Cracks Using Image Processing [11].

That work gives more ideas on how to take advantage of big data to extract important insights for automated decision support [10].ML is used To find any road problems in images used using super pixel way and ML and. The ability in our developed project to accept images with two dimensions increases its value. because of the simplicity of data collection and the low cost using frequently used equipment, like the cameras on smartphones, so avoiding the requirement for pricey specialized tools and thus we can combine the mechanical nature for techniques for machine learning and a wide range of common equipment that are inexpensive to implement.

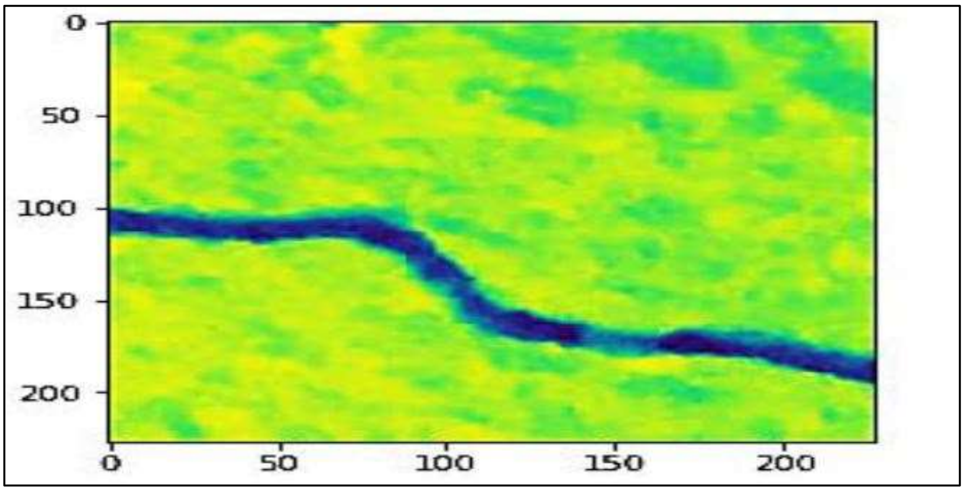


Figure 1.6: Processed Image Taken With A Regular Phone Camera.

This developed project offers an affordable and scalable tool for monitoring infrastructure in a timely manner. Hence, this study opens up opportunities for crowdsourcing and efficient management of transportation infrastructure maintenance, and it makes it simple for a wide range of contributors from government agencies to service providers, citizens, and individuals to participate in road condition monitoring, it is also possible to expand the project and crowdsourcing and integrate them within the framework of the service map to present more data, intelligent services or analysis. Applications for smart city services like navigation or traffic control can also notify residents of hazardous road conditions .This project makes it possible to maintain roads more properly and evaluate their conditions more quickly. Long-term maintenance tasks, for instance, can be avoided through discovering cracks in their initial stages. Fuel consumption is also reduced by maintaining a better road condition, thus reducing emissions that pollute the city. The IS Green research community calls for concrete research findings that enable more sustainable research practices. In addition, the maintenance of roads late leads to a significant deterioration of the environment and therefore our developed project facilitates sustainable regulatory procedures in the context of road maintenance. Besides contributing to information systems and decision support systems research in the above ways, this study also provides important implications for practice. First, this study systematically describes how a vision-based crack detection project should be designed enabling its adaptation and implementation to practice. Then practitioners can use the advanced knowledge to enhance their ability to observe paving. This study encourages cities to collect video and image clips from their road networks, for example public transport vehicles must be equipped with cameras to obtain the necessary image data [10].

1.6 REEARCH STRUCTURE

There are five chapters in the current study. The second chapter reviews the related works that following the first chapter's introduction. The proposed study method will be discussed in the third chapter. The method is tested and simulated in the fourth chapter. A future work and summary are included in the fifth chapter. In conclusion, the study's questions are:

a. What is the relationship of advanced technology and learning machine language in particular to detecting road damage and maintaining it?

b. What is the definition of artificial intelligence and machine language, and the types of algorithms used in learning machine language?

c. What are the types and types of damage to roads that can be detected and maintained by machine learning?

d. What are the types of libraries in the Python language that can be used in this study, which enable us to improve the quality of the images used and detect damages in them?

e. How can citizens, civil society organizations, and those responsible for road maintenance contribute to collecting data for damaged roads by taking images with their regular phones or any other camera of the damaged road and sending them to the competent authorities for the purpose of treating those damages?

f. How can this study contribute to reducing traffic accidents that claim the lives of thousands of people every day by early discovering the damage that causes accidents before they deteriorate and then maintaining them?

2. RELATED WORKS

There are many previous studies that dealt with the issue of roads, their development, and the use of the software aspect for their benefit.

In this proposal, we try to develop the results of previous studies using modern and advanced digital technology.

We refer to some previous studies related to the subject of our research:

a. (Automatic pavement damage predictions using various machine learning algorithms: Evaluation and comparison):This study employs eight distinct machine learning algorithm to predict the deterioration of the road pavement. The system for predicting pavement damage is illustrated visually with four steps: features engineering, dataset separation, anticipated result, and metrics for evaluation [3].

b. (Intelligent Road Inspection with Advanced Machine Learning; Hybrid Prediction Models for Smart Mobility and Transportation Maintenance Systems):

To execute the proposed theory, 236 sections of pavement from Tehran-Qom motorway in the State of Iran were used in this work. The artery includes the understudy route that connecting Tehran to southern Iran, which runs through provinces of Qom and Tehran. The motorway contains three paths in every direction, each having a three.65-meter width. The pavement on this roadway is pliable. This freeway's pavement condition index was calculated using 236 pavement segments, as specified within the pavement condition index subsection. Following the calculation of PCI, a load was delivered to a pavement with a FWD outfitted including seven sensors that record pavement deflection. The average deviation across every segment of pavement was measured using these sensors segments [8].

a. (Development of the Road Pavement Deterioration Model Based on the Deep Learning Method):

In Korea, social infrastructure that was developed extensively during the 1980s rapid growth period is aging; When it comes to roads pavement, it is anticipated that in the next ten years, the service life of 85% of all roads will surpass 20 years. A pavement management system (PMS) is a systematic approach to a care and management of road the pavement that is aimed at preventing these paved roads' aging. A pavement management system (PMS) is an instrument that methodically regulates every aspect of road pavement, encompassing fundamental planning, design, construction, upkeep, and assessment, with the ultimate goal of preserving optimal pavement quality at the most economical cost [12].

b. (Road Severity Distance Calculation Technique Using Deep Learning Predictions in 3-D Space):
   When several things on the side of the road are too close to the road, they represent a significant risk to people and motorists. Trees, poles, and fences are a few examples. Their closeness to a road able to fluctuate over time as a result of natural or actions of humans. Earliest detection of potentially dangerous roadside conditions can help avert collisions and contributes to saving human lives. However, given to a vastness and complexity of the road network, detecting roadside severity objects necessitates a large number of resources and novel methodologies. To meet this requirement, Techniques for image processing and deep learning can be applied to create an autonomous roadside severity detection system[13].
c. (Implementing Machine Learning With Highway Datasets):
   An engineering property of materials or pavement can be estimable early in the project. Furthermore, sophisticated decision-making aid afforded by such machine learning models helps maximize scheduling and construction. This project improved current models for machine learning with additional data and created and tested novel machine learning models for relevant datasets, including those pertaining to drilling and pavement, project duration, and datasets of images of highway rights-of-way (ROW) [14].

d. Using Supervised Machine Learning to Predict the Status of Road Signs:
   The purpose of this research is to be used supervised machine learning to forecast the state of the traffic signs installed on Swedish roads. The prediction's accuracy is assessed in this research in relation to the use of analysis of principal components (PCA) and data scaling. Before using, the data were prepared, and two methods—normalization and standardization—were used to scale the data. In this study, Random Forest, Artificial Neural Networks (ANN), and Support Vector Machine (SVM) was investigated. They are using for forecast the condition of a traffic signs[15].

e. Road Maintenance Management System Using Artificial Intelligence:

The study produced numbers of conclusions., including the definition of the defect, identification of its type, measurement of the defect area, execution of some operations and engineering calculations to ascertain the state of the road, and the type of maintenance recommended as the system's ultimate exit [16].

f. Performance Evaluation of Deep CNN-Based Crack Detection and Localization Techniques for Concrete Structures:

In that study, a tailored convolutional neural network has been proposed for the detection of cracks in concrete structures. Based on the size, the numbers of epochs of training data heterogeneity and network complexity, the suggested technique will be compared with four different deep learning techniques. The suggested The performance of the convolutional neural network (CNN) model is assessed and compared with that of the Inception V3 models, VGG-19, VGG-16 and ResNet-50, which are pertained networks, on eight datasets of various sizes that were produced from 2 open-source datasets. An evaluation took into account the calculation time, classification measures for each model and crack localization outputs [17].

g. Cost Prediction for Roads Construction using Machine Learning Models:

That study provides brand-new datasets that incorporates aspects of a road building and financial benefits in the construction of the project year. From 2012 until 2021, a high-accuracy predictive model for rural roads in the State of Iraq / Diyala Governorate was constructed using machine learning (ML) techniques. Models that use actual data to estimate the cost of building roads have been developed using techniques such as the Ridge and Least Absolute Shrinkage, Selection Operator (LASSO), Random Forest (RF), K Nearest Neighbors and (k-NN) Regressions [18].

h. Crack Detection and Classification in Moroccan Pavement Using Convolutional Neural Network:

Since 2011, an inspection vehicle (SMAC) outfitted with GPS/DGPS receivers and high resolution cameras has been used to periodically assess about 57,500 kilometers of Moroccan roads. To ensure that find damages on the surfaces of roads and categorize them based on their kind, the groups at the National Center for Road Study and Research

(CNER) previously visualized images of the pavement surface that were taken by the Multifunctional Pavement Assessment System (SMAC). But this approach requires manual processing, is difficult, takes a long time, and is subjective. In that study, it is suggesting a Convolutional Neural Networks (CNN)-based automated technique for cracking identification and the classification of Moroccan Flexible Pavements. Testing a model of the Visual Geometry Group 19 (VGG-19) that has already been trained is another way to apply transfer learning. The result shows that both models are capable of detecting and classifying cracks in the dataset utilized in this work [19].

3. PROPOSED METHOD

3.1 CRACK CLASSIFICATION

Detection of road cracks and classification of crack types are required to guarantee the reliability of the road, traffic and driver safety [19], The different types of cracks found are classified for example (transverse cracking, longitudinal cracking, pothole, alligator cracking)[20],[21]. Classifying cracks is a process for finding a specific crack through the use of algorithms for machine learning, it determines the detection of the crack or a recognition of the existence of the crack, whereas the classification of the crack can be classified based to the feature that was taken out of it. Artificial intelligence includes machine learning as a subdomain that is beneficial for performing clustering, prediction, and classification on application-driven datasets. Prediction and classification are done applying algorithms for supervised learning in contrast, clustering is performed with the use of an unsupervised algorithm. The various kinds of algorithms for supervised learning adopted for decision classifications are:(Convolutional Neural Network(CNN), K Nearest Neighbors or (KNN), Extreme Learning Machine or (ELM), a daboost and random forest[22] .

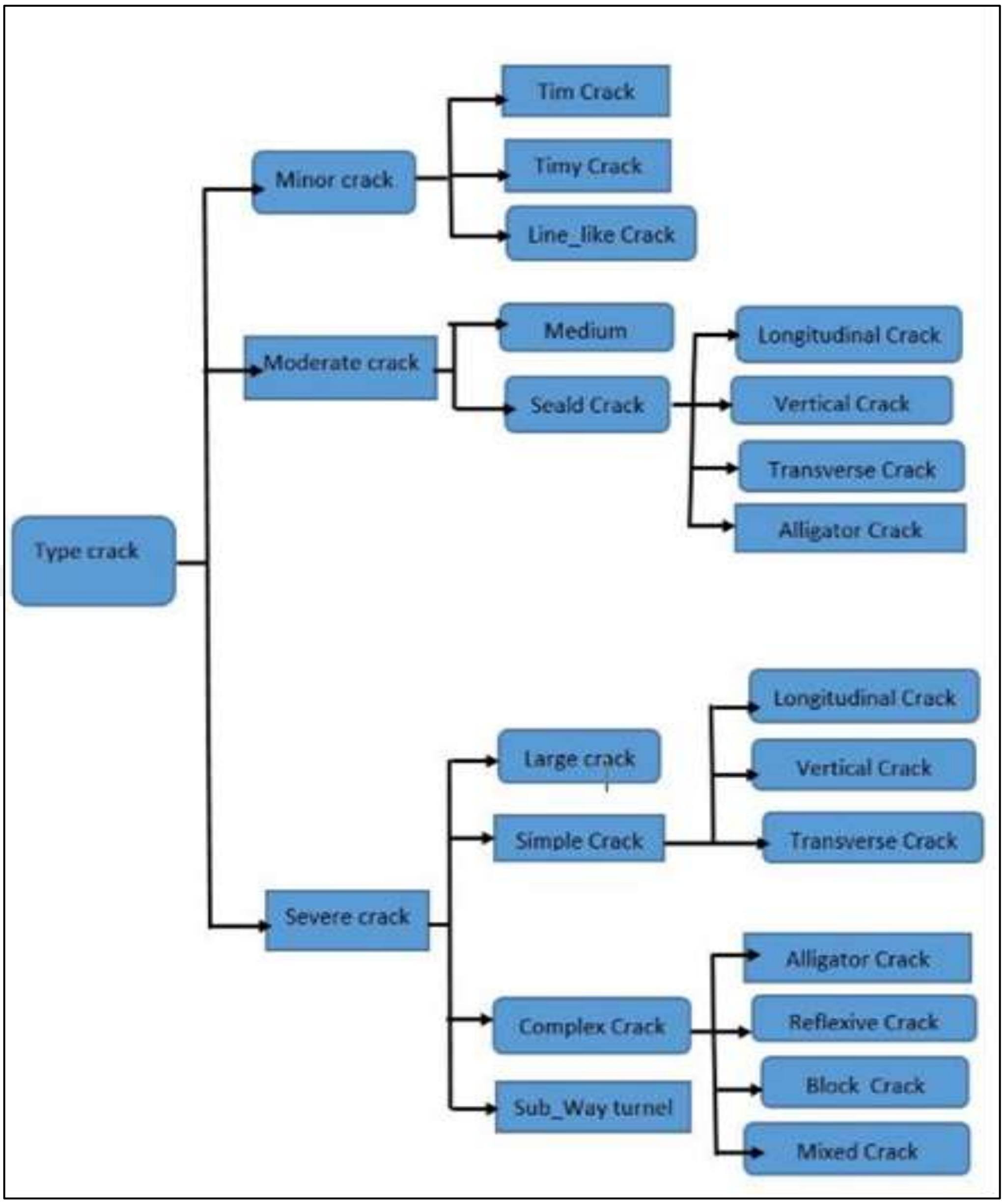


Figure 3.1: Crack Type Classification.

3.1.1 Minor Cracks

Minor crack is tiny and that cracks and include 3 sub-kinds: small, thin, streak-like cracks. That crack often occurs in RC bridges, roads, plastics, submerged dams, aircraft and cars. In RC bridges, thin cracks are frequently seen and detectable with stereotactic technique of triangulation, the optical flow analysis method and the least squares method, that techniques have the capacity to capture cracks in the surface of concrete that are 0.2 pixels in width using control point and region of interest (RIO). It is challenging to find cracks and classify them up into small, big and medium crack. Therefore, sun images are used Line-like cracks are common in roads and plastic surfaces. A series of methods are used to detect cracks in roads, Reduction method to remove jamming, Image gradation to reconstruct the crack of an image, Shape-based visual model for crack identification and circularity for shape finding. The proposed methods are better than the clustering method and the Otsu's method, while quantitative analysis and discontinuities are not discussed. From an analysis, it was noted that the minor crack need long time to discover and classify crack, given that the cracks are discontinuities and small, and the accuracy ranges between 80% and 87% [22].

Figure 3.2: Sample of Minor Crack.

3.1.2 Moderate Cracks

Moderate crack does not represent a severe crack, and therefore measures can be taken to treat those cracks. In general, this crack occurs in concrete roads and underwater dams. It is of the types (severe, sealed, and medium cracks). It’s very hard to detect the crack and classify it into a small, large, and medium crack. Thus, a solar image is being used. Common on concrete roads are sealed cracks., with kinds like transverse, vertical, longitudinal, and alligator cracks [22]. Morphological processes and segmentation can be used to detect it, thresholding method, with a high standard of consistency and accuracy. We would like to note that the observed metric values, we would like to note that the observed metric values of rendering, accuracy and check are respectively 87%,93.3 and 98%. Based on the analysis, it is concluded that a size of the moderate crack is larger than the minor crack and thus the discontinuities can be dealt with easily. It is worth noting that the classification accuracy of moderate crack range about 93.3 to 93.3 percent.

Figure 3.3: Sample of Moderate Crack.

3.1.3 Severe Cracks

Severe crack is very dangerous and large therefore very prompt corrective measure is necessary. That crack occurs frequently. in concrete roads, civil structures, sub-tunnels, bridges and underwater dams. It is important to remember that sever cracks can be readily identified [22] , There are several methods for detecting these cracks (K-means collection, minimum spanning tree, and adaptive tensor voting), we will use CNN algorithm to detect these cracks. From the analysis. The level of accuracy for detecting large cracks reaches more than 95%.

Figure 3.4: Sample of Sever Crack.

3.1.3.1 Simple cracks

Simple crack is less complex and include transverse, longitudinal, and vertical cracks. Longitudinal cracks are often found in bridges, sidewalks, concrete roads, and civil structures.

They can be detected by using KD tree, wavelet transform, EMD method, morphological process, binary coding, fractal threshold, and area cultivation method. It is also classified using Adaboost, Random Forest, and SVM [22] and CNN. Concrete roads often have vertical cracks., bridges and civil structures and can be detected using wavelet transform, morphological process, particle filtering, Sobel edge detection method, least square method, random forest, SVM, adaboost, and CNN classification. Transverse cracks are frequently seen in concrete pavement, roads, and buildings and it is detectable by threshold method, fragmentation, morphological process, Particle filtering, least squares, fractal threshold, Sobel edge detection, color feature extraction, and radon transform. While the classification is done using random forest, SVM, adaboost and CNN. With wavelet transform and KD tree, simple cracks from low-resolution images and discontinuities in the image can also be noted. [22].

Figure 3.5: Sample of Simple Crack.

3.1.3.2 Complex cracks

Complex crack is complex in terms of direction and shape, and therefore More information is needed to classify. Complex crack is frequently seen in concrete roads, bridges, sidewalks, and civil structures. There are different types of complex cracks: alligator, block, reflective, and mixed cracks. Alligator cracks frequently occur in concrete roads and bridges and able to be found by fragmentation method, threshold, morphological process, EMD method, binary, radon transform, area cultivation method and least square method as classified by SVM, adaboost, forest random and CNN. Commonly, reflection cracks occur in roads and bridges and can be found by using morphologic process, KD tree, SVM, and wavelet transform. In concrete pavement, block cracks are frequent and can be found by using radon transform and fractal threshold and can be classified utilizing a ran Asphalt pavement frequently has mixed cracks, which can be determined using the Gabor filter method, Dom forest, SVM, adaboost and CNN. Mixed crack is common in asphalt pavement and can be detected using Gabor filter method [22].

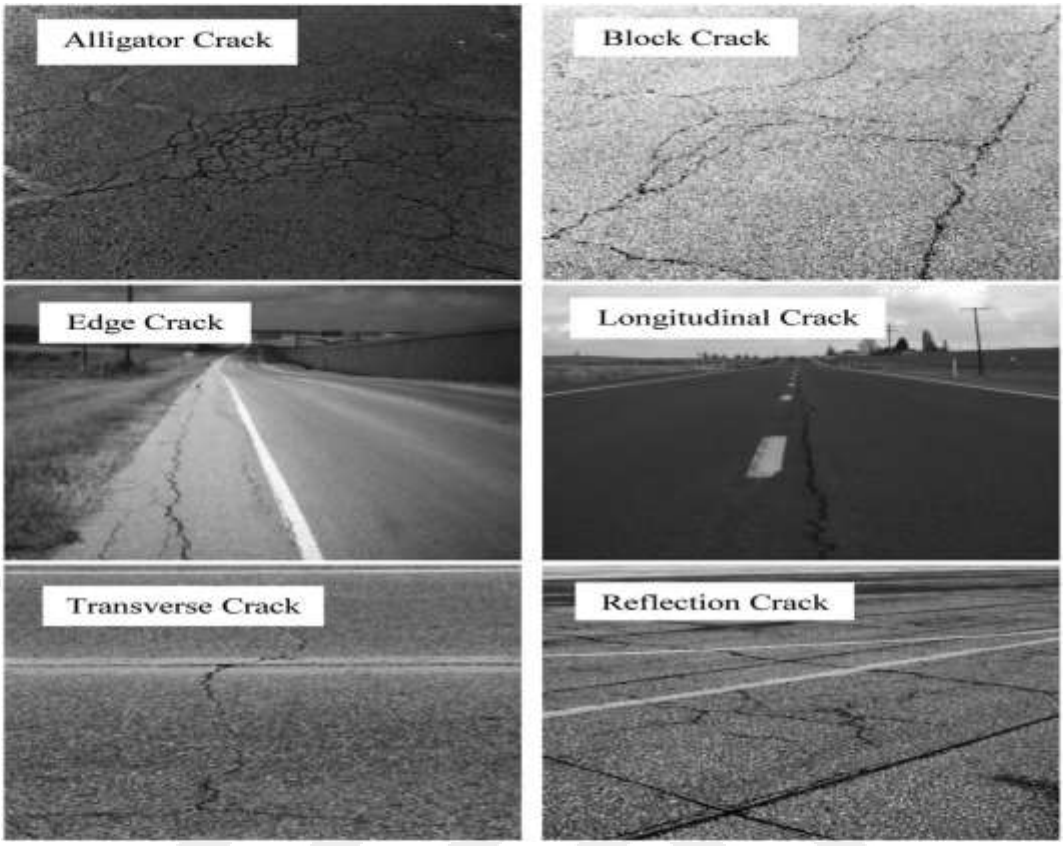


Figure 3.6: Examples of Asphalt Pavement Crack.

3.2 TYPES OF DIGITAL IMAGE

The two most significant digital image formats for photography are color and black & white. Black and white images are formed of grayscale pixels, while color images are composed of colored pixels[23].

3.2.1 Black and Wihte Image

Each pixel in a black-and-white image is made up of a single number that represents the gray level of the image at that specific position. These gray scales, which typically come in 256 different shades, cover the whole spectrum from black to white in a succession of incredibly small increments. Since the eye can only tell the difference between 200 different shades of gray, This is sufficient to provide the impression of a step less tonal scale, as shown below [23].

Figure 3.7: Gray Level of the Image [23].

Each black and white pixel can be kept in a single byte (8 bits) of memory, assuming 256 gray levels.

3.2.1.1 Binary or bi: level images

Each pixel in binary images is represented by a single bit. Every pixel in a binary image must be one of just two colors, typically black or white, because a bit can only have one of these two states: on or off. This incapability to depict varying tones of gray what makes them less effective for handling photographic images.

3.2.2 Color Image

Each pixel in a color image contains three numbers that represent the red, green, and blue levels of the image at that specific position. The main colors for combining light are red, green, and blue (often referred to as RGB); these so-called additive primary colors differ from the subtractive primary colors (Cyan, magenta, and yellow) Colors used to mix paint. Red, green, and blue light can be combined in the right ratios to produce any color. Each color pixel can be stored in three bytes (24 bits) of memory, assuming 256 levels for each primary. This is equivalent to a total of around 16.7 million distinct color combinations. Be aware that a black-and-white version will use three times less memory than a color one for images of the same size [23].

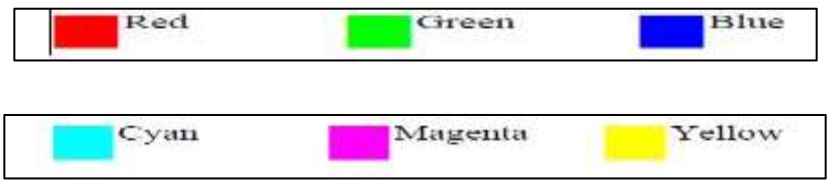


Figure 3.8: Primary and Secondary Colors [23].

3.3 EDGE DETECTION TECHNIQUES

Since physical edges correlate to discontinuities in the physical, photometrical, and geometrical characteristics of scene objects, they give significant visual information. Significant differences in scene surfaces' reflectance, light, direction, and depth are reflected in the primary physical edges. Since variations in the intensity function serve to depict physical edges in an image, image intensity is frequently proportional to scene radiance. Steps, lines, and junctions are the three most typical types of visual intensity fluctuations. The majority of the time, steps are the sort of edge encountered. This kind of edge is caused by a variety of occurrences, such as when an object hides another or when a surface has a shadow. It typically happens between two areas with different gray levels but nearly constant. Where the grey level discontinuity appears is at the step edge. Step edges are localized at the image's in lection points in actual images. In actuality, the convolution of the camera point-spread function with the edge pro le damaged by noise generates a smooth function during the image generation process (see Figure 3.9 a and b). The first-order derivative's positive maxima or negative minima, respectively, or the second-order derivative's zero-crossings, respectively, are the results of this localization, which is shown in Figures (3.9 c and 3.9 d). In two dimensions, the gradient operator determines the first derivative, and the Laplacian or the second derivative in the gradient direction approaches the second derivative. The geographical distribution of edges is not included in this step's definition of edges. Consider a step edge as a collection of various intersection sites for a more practical perspective. The double step edge (two intersection sites close to one another) is the most widely used edge model [24]. The pulse (Fig. 3.9. e) and the staircase (Fig. 3.9 f) are two examples of double edges.

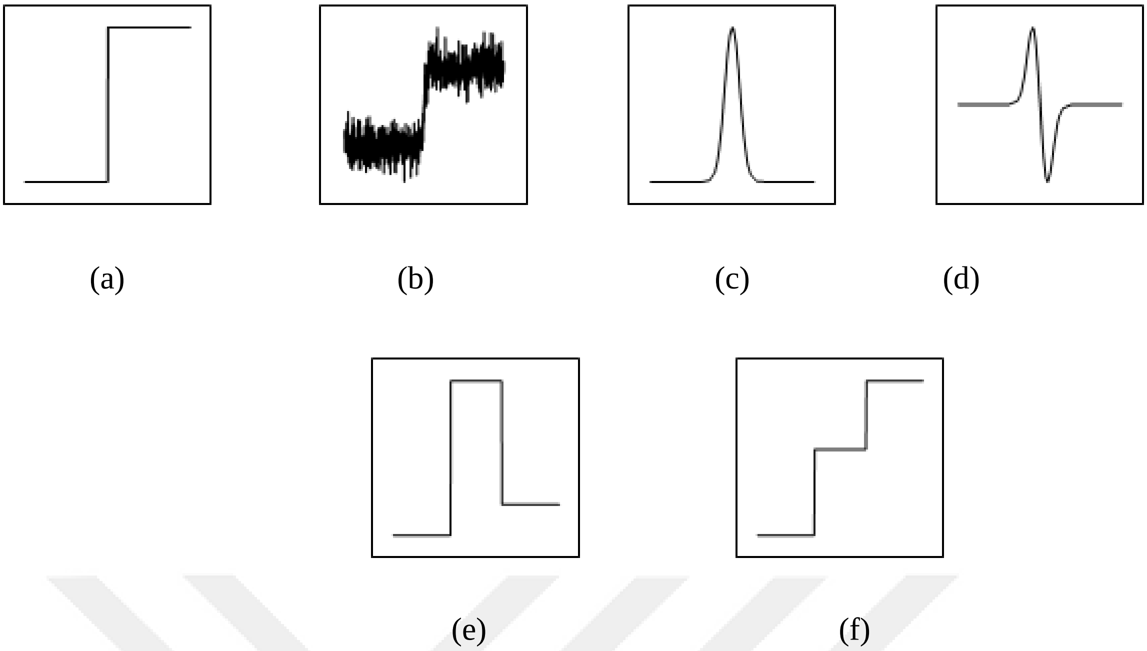


Figure 3.9: The Step Edge Pro Le. A) Optimal Step Edge, B) Noise-Contaminated Smoothed Step Edge, C) and D) The Smoothed Step Edge's First and Second Order (Noise-Free) Derivatives, E) The Pulse, F) Stairs [24].

Mutual lighting between in-contact items or thin items positioned against a backdrop cause the initial derivative zero-crossings, local Laplacian maxima, or the local maximum of the smoothed image's grey level variance are examples of how to localize them. Roads and rivers can be detected using this kind of edge in remote sensing images [25], for example (Figure 3.10.a) displays the pro le of lines. Lines are related to the image's local extreme. When at least two physical edges collide in the scene, the junction the physical corner is created. Additional factors, such as lighting effects or the existence of occlusions, can also result in the creation of corners in an image; for example, a T-junction is formed when one physical edge covers another (see Figure3.10 b). In the sentences that follow, the terms "junction" and "corner" will be used interchangeably. A junction is a 2D element in the image. It will be pointy and designated as the intersection of two or more edges (which may have different types). T, L, Y, and X are a few junction models. The junction can be located in a number of different places, such as a point with high curvature, a position with significant gradient direction change, a site where the Laplacian zero-crosses with high curvature, or a location close to an elliptic extremum. The term "edge" as it is frequently used, refers to all forms of edges, although step edges, which are the most prevalent, are the focus of the bulk of edge detection algorithms currently in use. There are additional edge types listed in [26].

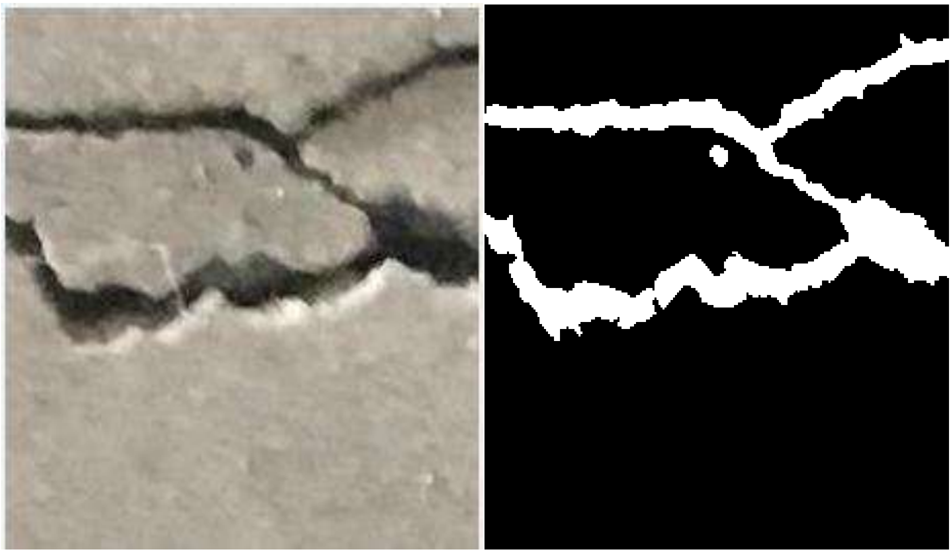
(a) (b)

Figure 3.10: a) LPne pro le, b) T-Junction Pro le

[25].

3.3.1 Properties of Edge Detectors

An edge detector generates an edge map as an output from the input of discrete, digitalized images. Some detectors explicitly contain details about the issue scale, orientation, and force of the edges in their edge maps. Only positional information is included in the example in (Figure 3.10). Many edge detectors have must developed during a development of image processing, varying in their function (the edge's geometrical and photometric properties) and in their algorithmic and mathematical characteristics. There are two sorts of edge detectors from the perspective of integrating of an edge detector within a computer vision system. The first detectors comprises those that do not rely on prior information of the edge to be detected and the scene[25].



(a) (b)

Figure 3.11: a) Initial Image, b) Position of the Information Obtained Using an Edge Detector.

neither contextual information nor the other parts of the vision system influence the class of autonomous" detectors. That detectors are versatile because they aren't constrained to particular types of images. Even so, they're dependent on localization of processing, as an only pixel in close proximity to an edge are used to name it. Contextual detectors are the 2nd kind, meaning that they are influenced by the outcomes of a different system elements or by prior knowledge of the edge or the scene's structure. They therefore only function in a specific setting. A small number of Contextual detectors have suggested. Given a knowledge that a detectors are using, it’s obvious that the independent detectors are suitable for all types of vision systems. Contextual detectors, on the other hand, are tailored to certain applications where processed images always contain the same items. In terms of concept, differentiation, smoothing, and labeling are the three operations included in the most frequently proposed edge detection techniques (For contextual as well as autonomous detectors). Differentiation involves assessing the intended image derivatives. Image noise is reduced and the numerical differentiation is regularized by smoothing. identifying edges locally and boosting the edge image's signal-to-noise ratio are key components of labeling. The last procedure to be performed is labeling. Nevertheless, as it will be demonstrated further on, the arrangement of smoothing and differentiation is determined by their properties. Only by altering the image using the smoothing filter's differentiation can an image be made smooth and distinct. The terms later and detector are frequently used interchangeably in this context [27-31].

This three operations' effectiveness are connected. The specification of the false edge suppression step based up on an effectiveness of other 2 procedures, thus smoothing really regularizes the differentiation. False edge suppression is simple to do if the smoothing step decreases noise without sacrificing information. Three processes make up an incomplete specification for an edge detector. In actuality, a scale calculation and the exact context in which it might be employed are not included in an edge detector. It is required to develop an edge detection methodology to make explicit [32].

3.4 IMAGE PROCESSING TECHNIQUES

Techniques for image processing can be used to detect cracks in a road. Using an edge detection technique is one popular way, which includes determining an image's object edges. Regarding the detection of road cracks, edges line up with the boundaries between the cracks and the road surface. Below are some actions you could take to use techniques for image processing to detect road cracks:

a. Gather images of the surface of the road: You need to gather images of the road surface in order to find cracks. Numerous techniques, including drones, stationary cameras, and cameras mounted on cars, can be used to gather these images.

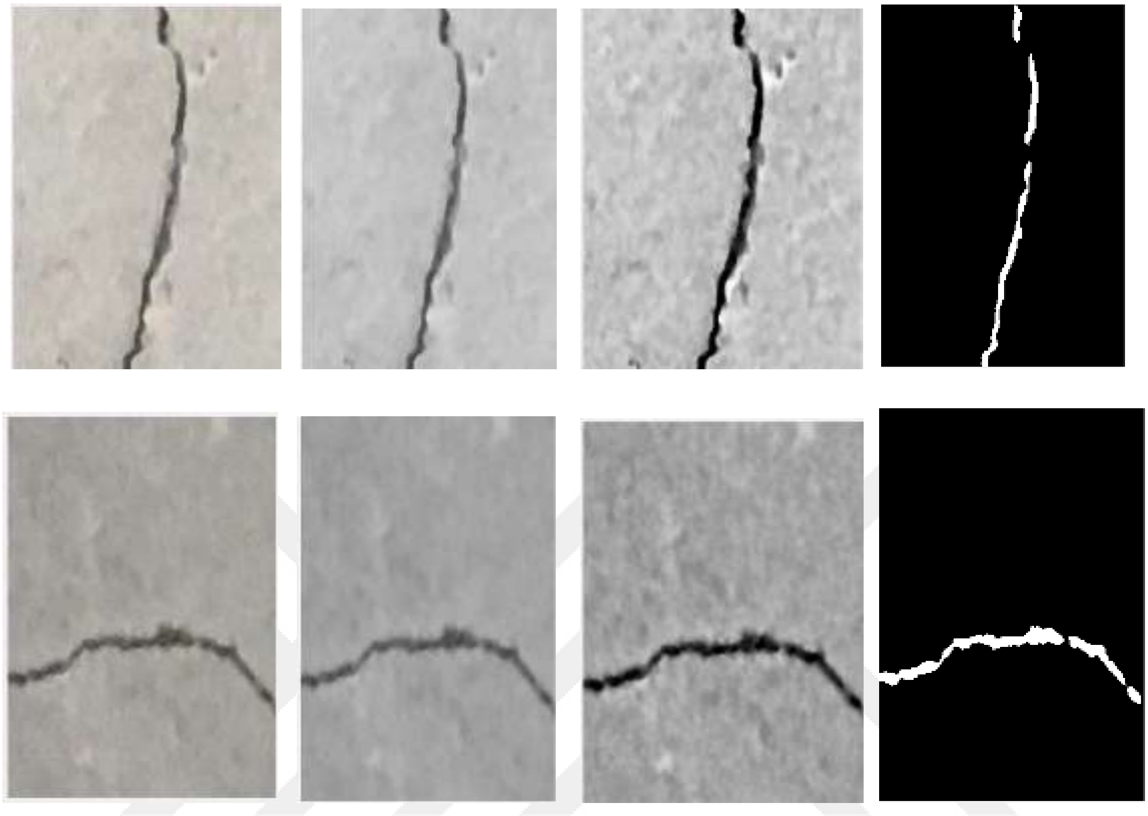
b. Image preprocessing: After having gathered images, for the purpose of enhance a quality and facilitate a detection for cracks, preprocessing is required. This may entail ways like image normalization, contrast enhancement, and noise reduction.

c. Implement edge detection: After preprocessing of the images, algorithm of an edge detection must be used to determine the cracks' edges. We can select from a variety of edge detection algorithms.

d. After processing the edges: Next to the detection of the edges, to get rid of any noise or false positives, you can post-process them. This may entail techniques like thresholding, filtering, and morphological operations.

e. Display results: As soon as the cracks are determined, we can see them in the initial image or make a different one that just displays the cracks.

All things considered, utilizing image processing techniques to find cracks in a road can be a challenging process that calls for knowledge of both image processing and computer vision. Nonetheless, it is an effective technique that can enhance traffic efficiency and safety.



(a) (b) (c) (d)

Figure 3.12: a) Initial Images, B) Image That Has Been Smoothed, C) Improvement of Contrast, D) Segmented Image.

Road-related applications like road safety analysis, autonomous driving and traffic monitoring frequently use image processing techniques. Overall, image processing techniques can be very useful in road-related applications as they can offer useful details about a traffic and road conditions, which can be used to improve safety and efficiency on the roads. An efficient filter is applied at processing stage to smooth the initial images. For a smoothing procedure, an average filter should be employed because a tiny filter will correctly smooth the original images while a large filter will obliterate the details of the cracks. The alligator, block, transverse, and longitudinal cracks are the four primary types of cracks that the image processing technique finds [33]. The authors claim that calculating a shape factor will reveal the nature and shape of the crack. The spread is subtracted from the average of the sub-blocks to determine the form factor. On the other hand, the spread is the quantity of pixels above the mean of the sub-blocks around the mean. The shape of the cracks is then determined using the shape factors obtained from the computations [34].

3.4.1 Why Image Processing Techniques is Used

The image processing technique is employed for a number of reasons, one of which is that it enables a dense acquisition of the road surface. Unlike other approaches, such as the laser method, where measurements of the condition of the highway surfaces are accessible every four millimeters, the authors contend that the imaging process method has the capacity to acquire the conditions for the full road service. Each millimeter of a measurement can be given by the image processing technique. An image processing method permits the observation of the road surface conditions that are not viewable by other means, making it particularly valuable for the traffic information system[35]. The acquisition methods used to process the photographs of the road surface are more user-friendly than other systems, which is another factor contributing to the widespread use of the image processing technique. Compared to other techniques, the systems are less susceptible to movement and vibration of the road surface. The faults found on the road surfaces can also be precisely measured using image processing techniques[36]. The images are sufficient for measuring purposes and enable for the acquisition of the road conditions down to the millimeter. Finally, the image processing technique also produces images with greater contrast. Images with great contrast can be produced by the devices' optical sensors since they have a higher signal-to-noise ratio. An image processing algorithm is able to find many cracks in the road surfaces and provide numerical statistics for each crack [37]. The capacity of the image processing technology to detect noises that are not prioritized by the human eye is another factor that makes it superior to other methods. The method's algorithm is able to recognize the slight noise provided on by the markings on the roadway surfaces. The best method for keeping track of the state of road surfaces is image processing. Since the technique enables a dense acquisition of the road surface, it is employed. Unlike other methods, such as the laser method, where measurements of the highway surface conditions are accessible every four millimeters, imaging process method has the capacity to acquire the conditions for the full road service. The image processing technique can produce measurements down to the millimeter. The traffic information system can observe conditions of the road surface that are not visible using other techniques thanks to the image processing technology. The image processing technique can identify several cracks in the surface of the roads as well as provide numerical information for each crack[34] .

3.4.2 Filtering Techniques

Digital images can be improved and modified using filtering technique. Additionally, image filters are used for edge detection, sharpening, and noise reduction. Image filters are primarily used to suppress frequencies that are low (edge detection, image enhancement) and high frequencies (smoothing techniques). Here is a list of classifications for image filters [38].

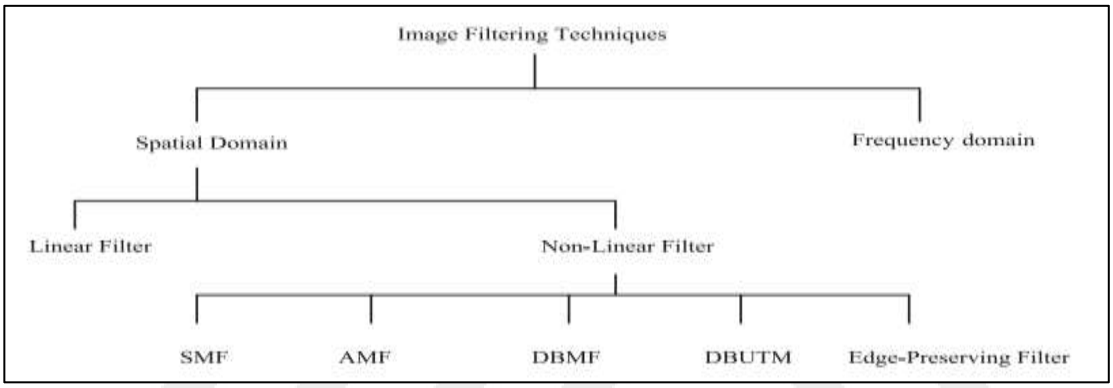


Figure 3.13: Classification of Images Filters[38].

To detect edges, non-linear filters are used. These filtering methods outperform linear filters in terms of efficiency. Details and edges in images tend to get blurry when using a linear filter. Examples of linear filters include the Gaussian, Laplacian, and Neighborhood Average (Mean) filters. Non-linear filters include median filters. The topic of various linear and non-linear filters is covered in the next section.

3.4.2.1 Median filter

One type of non-linear filter is the median filter. Each pixel's values are swapped out for their neighbors' median values. This is the most effective method of removing pepper and salt noise. Below is a summary of how the median value was determined [38].

Table 3.1: How Median Filter Do[38].

30.0	35.0	40.0	42.0	42.0
35.0	42.0	37.0	37.0	40.0
38.0	39.0	40.0	41.0	42.0
40.0	41.0	42.0	43.0	43.0
42.0	43.0	45.0	44.0	46.0

		41.0		

37.0,37.0,39.0,40.0,41.0,42.0,42.0,43.0b

(a) **(b)**

Figure 3.14: a) Initial Image, b) Image processing by Median filter.

3.4.2.2 Laplace smoothing

Laplace smoothing is a technique that is mostly used to find edges in images. Discontinuities at the gray level are highlighted. It’s based up on an image's secondary spatial derivation. Using the equation below, the Laplacian operator has been defined. One kernel is used by the Laplace edge detector. This kernel uses a single pass to detect the Second-order derivatives of the intensity levels of an image at its edges. "Kernel 2" can be used to find edges with diagonals. It will provide a more accurate estimate. Laplace method also produces results more quickly than other methods[38].

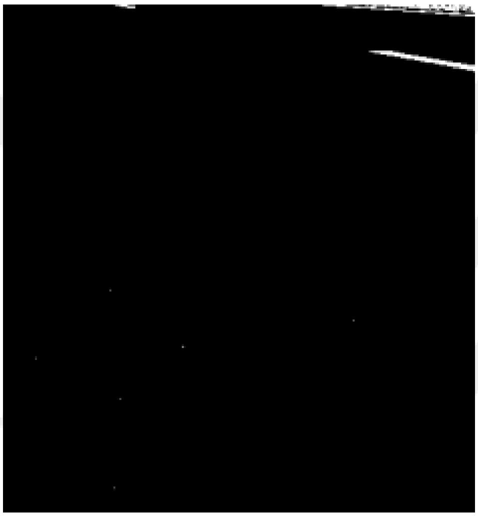
Table 3.2: a) Kernel 1, b) Kernel2.

(a)

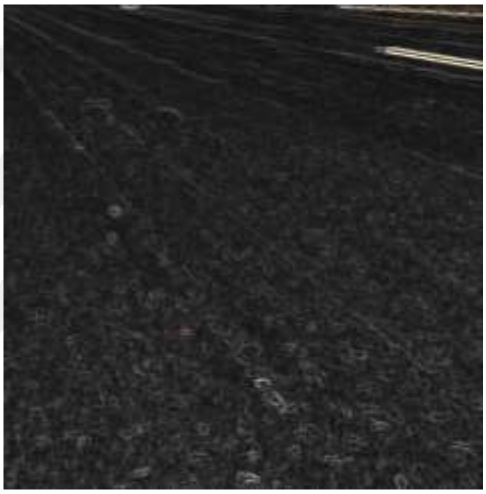
0.0	-1.0	0
-1	4	-1
0	-1	0

(b)

-1.0	-1.0	-1.0
-1.0	8.0	-1.0
-1.0	-1.0	-1.0



(a)



(b)

Figure 3.15: (a) Image with kernel 1, (b) Image with kernel 2

3.4.2.3 Gaussian filter

A 2-D convolutional operator is used in this filter. Images used to be blurry. It also eliminates noises and details. Mean filter and the Gaussian filter are comparable. The primary distinction is that the Gaussian filter employs the kernel. The kernel is shaped like a Gaussian hump. The center of the Gaussian kernel is given a substantially higher weight than its edges. Different Gaussian kernels exist. The resulting image will vary based on kernel size [38].

Table 3.3: a) 3*3 Kernel, b) 5*5 Kernel.

(a)

1/16

1.0	2.0	1.0
2.0	4.0	2.0
1.0	2.0	1.0

(b)

1/173

1.0	4.0	7.0	4.0	1.0
4.0	16.0	26.0	16.0	4.0
7.0	26.0	41.0	26.0	7.0
4.0	16.0	26.0	16.0	4.0
1.0	4.0	7.0	4.0	1.0

(a) (b)

Figure 3.16: a) Image with 3*3 Kernel, b) Image with 5*5 Kernel.

3.4.2.4 Neighborhood average filter

Mean filter is another name for this filter. With average filtering, neighboring pixels' average values take the place of the original pixel values. The average value is determined as follows [38].

Table 3.4: Average Value.

23.0	25.0	30.0	35.0	30.0
25.0	30.0	35.0	37.0	40.0
45.0	40.0	37.0	43.0	45.0
38.0	40.0	43.0	42.0	46.0
35.0	40.0	42.0	45.0	47.0

		39.0		

Value = (30.0+35.0+37.0+40.0+37.0+43.0+40.0+43.0+42.0)/9=38.55=39.0.

3.4.2.5 Box filter

A linear image filter in the spatial domain is the box filter. This box filter also functions as a low-pass filter. Its operations are comparable to those of a standard filtering approach[38].

3.4.3 Image Segmentation

One technique used in computer vision is image segmentation that entails segmenting an image into several areas or segments, every one of which represents a distinct object or area within the image. That are numerous techniques for performing image segmentation, comprising:

a. Thresholding: With this technique, a threshold value is s segmentation of images et, and every pixel in the image is classified according to whether its intensity value is above or below the threshold.

b. Segmentation based on edges: Using this technique, the edges in the image are found and used for separating various areas. It is possible to identify the borders between regions by using edge detection algorithms.

c. Segmentation based upon regions: With this technique, areas of the image are identified according to attributes like color, texture, or intensity, and neighboring pixels that share the same attribute are grouped together. The techniques like watershed segmentation and region growth can be used to accomplish this.

d. Segmentation based on clustering: Using this technique, pixels are grouped together according to similarities in feature space, like texture and color. The techniques like mean shift clustering and k-means clustering can be used to accomplish this.

e. Segmentation using deep learning: Using this technique, a deep neural network is trained to detect limits among various image regions in order to perform segmentation. That can be achieved with techniques like Mask R-CNN or U-Net. One common segmentation architecture based on CNN is U-Net. The U-Net architecture can create extremely accurate segmentation masks and is built to handle features at both the high and low levels in images. Deep Lab, Fully Convolutional Network (FCN), Mask R-CNN, and FCN are some additional CNN-based segmentation architectures. These architectures differ in their advantages and disadvantages and might be more appropriate for specific purposes.

These techniques can be used individually or in combination to perform image segmentation, depending on the particular application and the image's features being segmented. Image segmentation has many applications in computer vision, including object recognition, image editing, and medical imaging [39].

3.4.3.1 Semantic segmentation

Self-driving systems and image understanding both heavily rely on semantic segmentation, which seeks to logically categorize each and every pixel in images. Recent developments in deep convolutional neural network (CNN) models have been made it possible to make significant advancements in tasks involving pixel-wise segmentation with semantics [40],[41],[42] as a result of an end to end trainable framework and rich hierarchical characteristics [43],[44] ,[45],[46],[47],[48]. Modern semantic segmentation systems often consist of these three essential elements:1) a fully convolutional network or as it is called in short (FCN), which was 1st described in [43], replaces a final fewest fully interconnected layers with convolutional layers to inference that can handle any input size and to make effective end to end learning. 2) Conditional Random Fields or as it is called in short (CRFs), which can be used to better the prediction map by capturing both local and long-range dependencies inside (Figure 3.16) Dilated convolution (Also called Atrous convolution), which raises a resolution of intermediate feature maps to produce predictions with a higher degree of accuracy while keeping the computational cost constant. Fully-supervised semantic segmentation system improvements have primarily been centered on 2 aspects since the initial introduction of FCN in [43]. 1st Applying deeper FCN models. When a VGG-16 (16-layer) model [41] was substituted with a 101 ResNet-101 layers [44] model, significant improvements in mean Intersection-over Union (mIoU) scores on the PASCAL VOC2012 dataset The PASCAL VOC2012 dataset's Intersection-over Union (mIoU) scores [49] were found. Using a 152-layer ResNet-152 model results in even greater improvements [50]. Deeper networks are typically able to model more complicated representations and acquire more features with discrimination to improve category separation, so this tendency is consistent with how well these models perform on ILSVRC [51] tasks involving object classification. The second is to strengthen CRFs. In order to enable end-to-end training, this entails applying fully connected pairwise CRFs [52] as a post-processing step [53], integrating CRFs into the network by simulating its mean-field inference steps [44],[45],[47], and adding extra information to CRFs like edges[54], and object detections.

more enhancements to semantic segmentation from a different angle: the opposing convolutional operations for encoding (from input picture to feature map) and decoding (from intermediate feature map to output label map). Modern semantic segmentation methods simply use bilinear up sampling to obtain the output label map during decoding (before the CRF stage) [46],[47],[48]. Bilinear up sampling might lose fine features and is not teachable. We recommend a technique termed dense up sampling convolution (DUC), which is incredibly simple to use and can reach pixel-level accuracy and was inspired by work in image super-resolution [55] instead of attempting to immediately retrieve the full-resolution label map. To upscale the reduced feature maps into the final dense feature map of the necessary size, we learn a variety of upscaling filters. By enabling end-to-end training, DUC naturally fits the FCN framework and greatly improves the mIOU of pixel-level semantic segmentation on the Cityscapes dataset [56], notably on items that are relative. Dilated convolution has lately gained popularity for the encoding portion, as it preserves the network's resolution and receptive field by introducing "holes" in the convolution kernels, negating the requirement for down sampling (using stride convolution or max-pooling). The current dilated convolution framework does, however, have a disadvantage that we refer to as "gridding": because zeros are padding pixels in a convolutional kernel, the receptive field of this kernel only covers an area with checkerboard patterns - only locations with non-zero values are sampled, losing some neighboring information. When the receptive field is big and the rate of dilation increases, the issue becomes worse because the convolutional kernel is too sparse to adequately cover any local information since the non-zero values are spaced out too widely. A large percentage of the information is lost because each fixed pixel's contribution always comes from its predetermined gridding pattern. As a first step in solving this issue, we present a straightforward hybrid dilation convolution (HDC) framework here: rather than using the same rate of dilation for the same spatial resolution, we employ a range of dilation rates and concatenate them serially in the same manner as "blocks" in ResNet-101[57].

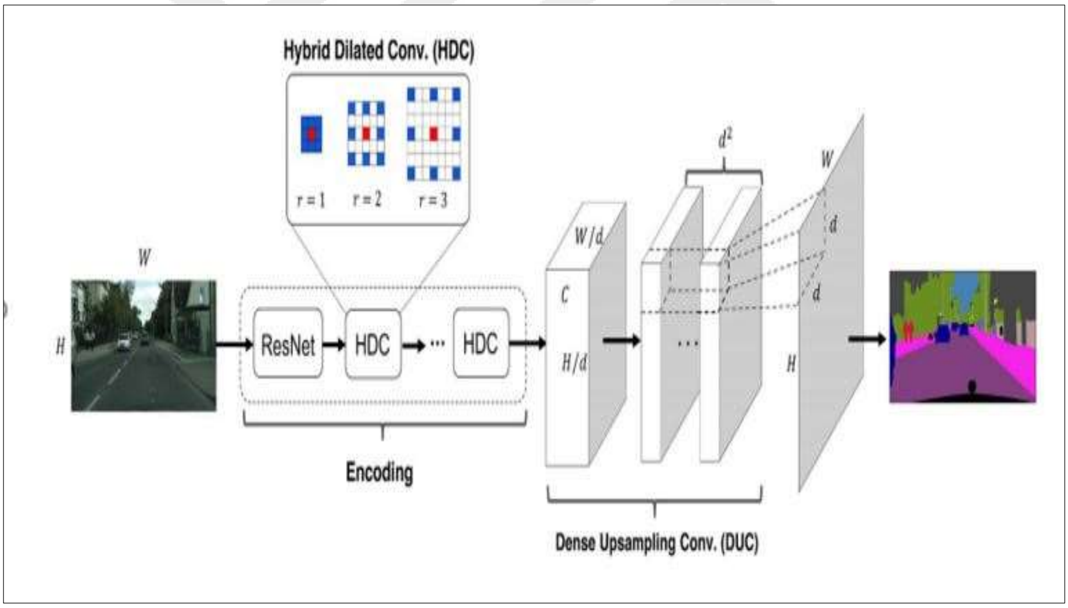


Figure 3.17: An Illustration of the Resnet-101 Network's Architecture Showing the Dense Up Sampling Convolution (DUS) and Hybrid Dilated Convolution (HDS) Layers.DUC Is Applied on Top of the Network and Is Used For Decoding, While HDC is Applied Within The Resnet Block.

3.5 MACHINE LEARNING

Artificial intelligence (AI) has a subfield called machine learning that focuses on creating models and algorithms that let computers learn from data and make predictions or judgments based on it. Rather than being specifically programmed, machine learning algorithms are trained on large datasets and learn patterns or relationships within the data to make accurate predictions or take appropriate actions. It is a data-driven technique that has applications in numerous academic and real-world application sectors[58],[59],[60],[61]. ML has recently been used in the discipline of engineering for transportation [58],[59],[60],[61],[62]. It has been investigated in the following areas of traffic engineering: identifying high-accident road locations, assessing accident-related damage and injuries, determining a role of other road users in accidents, an effect of drunk driving on injury severity, and the influence of environmental elements, to name just a few[63].

There are several different kinds of machine learning algorithms, including:

a. Supervised Learning: With this type of learning, the labeled data is used to train the algorithm, where matching output labels are paired with the input data. Maps inputs to outputs are learned by the algorithm by generalizing from the training examples. Support vector machines, decision trees, random forests, and linear regression are examples of common supervised learning algorithms.

b. Unsupervised Learning: In unsupervised learning, the algorithm is trained using unlabeled data, where, in the absence of explicit guidance, an algorithm discovers structures or patterns within the data. In unsupervised learning, clustering and dimensionality reduction are frequent tasks. Principal component analysis (PCA), hierarchical clustering, and k-means clustering are a few examples of unsupervised learning algorithms.

c. Reinforcement Learning: Through reinforcement learning, an agent gains the ability to maximize a reward signal by making decisions in its surroundings. Through trial and error and interaction with the surroundings, the agent learns and gains feedback, either positive or negative, depending on its actions. Applications like autonomous driving, gaming, and robotics frequently use reinforcement learning.

It is possible to use machine learning for road damage detection. This application falls within the computer vision domain., where road images and videos can be analyzed by machine learning algorithms to detect damage or other sorts of deterioration. Essentially, machine learning can be applied to detection of cracks in roads in the following ways:

a. Data collection: You'll need a labeled dataset, which is made up of videos or images of cracked road surfaces with identifies indicating the presence and location of cracks, in order to train A model for machine learning. The cracks in the videos or images can be manually annotated to produce this dataset.

b. Preprocessing: To improve image quality and extract important features, preprocessing of the collected data might be necessary. Preprocessing techniques to increase the model's accuracy can include resizing, normalizing, and filtering the images.

c. Model Training: After preprocessing the data, a machine learning model can be trained. Crack detection and other image-related tasks are often performed by Convolutional Neural Networks (CNNs). From the input images, the model learns to extract features and categorize them as either cracked or non-cracked. During training, For the purpose of increasing its crack prediction accuracy, the model updates its internal parameters depending on to the labeled data.

d. Model Evaluation: It's essential for evaluating the model's performance using an independent, previously untested set of test data, this is done after training. It helps in evaluating how well the model applies to new and invisible images. Evaluation metrics that can be utilized to measure the model's accuracy in crack detection include precision, recall, and F1 score.

e. Deployment: After the model was evaluated and trained, it can be used to evaluate new videos and images of a road. It has the ability to automatically analyze the data, find cracks, and possibly even provide details about the size or severity of the cracks.

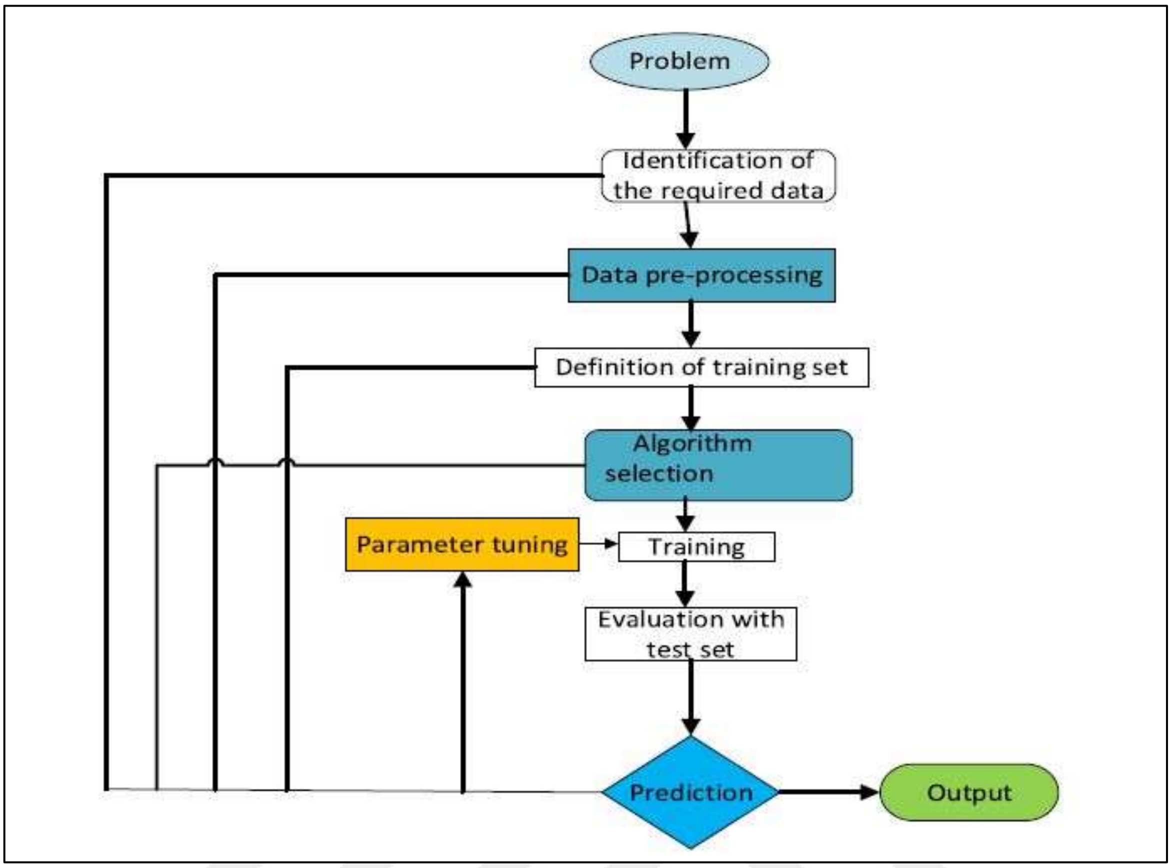


Figure 3.18: Workflow for Machine Learning [3].

It's important to remember that the quality and variety of the training data determine how well machine learning crack detection works, in addition to the model's hyper parameters and construction. In addition, external influences like lighting and camera angles might have an impact on the model's performance.

Overall, machine learning can significantly aid in automating crack detection in roads, enabling timely repairs and maintenance to ensure road safety.

3.5.1 Deep Learning

The "deep learning" section of machine learning, Concentrates on teaching artificial neural networks to make decisions and obtain learning without the need for definite programming. It draws inspiration from the composition and operations of the human brain, particularly from the intricate network of neurons. [64]. We would like to point out that in deep learning, Neural networks are arranged into layers of connected nodes, or "artificial neurons", The input layer receives data input, and it spreads through various hidden layers, as the data is transformed by each layer, more complex features are extracted. The desired classifications or predictions are generated by the final output layer. In deep learning, "deep" refers to the neural network's depth, which represents the quantity of hidden layers it has. Hierarchical data representations can be learned by deep neural networks, giving them the ability to record intricate relationships and patterns. Deep learning's capacity to automatically extract features from raw data is one of its main advantages. Handcrafted features were often required for traditional machine learning methods, Deep learning algorithms, on the other hand, can automatically extract pertinent features from the data, lowering the necessity of manual feature engineering. In many fields, deep learning has shown impressive results, including speech recognition, natural language processing, computer vision, and recommendation systems. It led to in advances in a variety of fields, including sentiment analysis, machine translation, object detection, and image classification. Some popular deep learning architectures include Convolutional Neural Networks (CNNs) for image-related tasks, Recurrent Neural Networks (RNNs) for sequential data processing, and Transformers for natural language processing tasks. These architectures, along with advancements in optimization algorithms and increasing computational power, have contributed to the rapid progress of deep learning in recent years. However, deep learning also has some challenges, such as the need for large amounts of labeled data, computational resource requirements, and potential overfitting. Ongoing research aims to address these challenges and further advance the field of deep learning[65].

There is some a branch of machine learning algorithm such as:

3.5.1.1 ANN algorithm

ANN stands for Artificial Neural Network, that is a foundational concept in the deep learning. It’s a mathematical model that is inspired by the design and functionality of the human brain's neural networks. (ANNs) are composed of layers of interconnected artificial neurons, also referred to as units or nodes [66].

Here's a general synopsis of the algorithmic stages there are involved in training an Artificial Neural Network:

a. Initialization: Set the neural network's weights and biases at random or with a particular initialization technique.

b. Forward Propagation: Feed the input data through the network. Every neuron gets data from the layer before it, gives each input a weight, blends them, and sends results via an activation function. Layer by layer, that process is repeated up until the final result is achieved.

c. Compute Loss: Compute the mistake or loss by comparing network's outputs to intended outputs. Depending on the task, the loss function selection such as, cross-entropy for classification or mean squared error for regression.

d. Reverse propagation: Spread the errors backward across the network. Based on each neuron's contribution to the total error, update the biases and weights of the neurons in every layer. To do this, use optimization of gradient descent or its variants, in which the loss function's gradients with regard to the biases and weights are calculated.

e. Update the weights: Utilizing the selected optimization algorithm and the computed gradients, update the network's weights and biases such as, Adam or stochastic gradient descent (SGD). The objective of that step is to enhance network performance and reduce a loss function.

f. Repetition: For a certain number of iterations or until convergence, repeat the process of weight updates, loss computation, forward propagation, and backpropagation. The network can learn from this iterative process and adjust its parameters to more closely resemble the intended output.

g. Prediction: By utilizing forward propagation, the trained network can be utilized for predicting a new and unseen data. The classes or predicted values for the input are represented by the network's output.

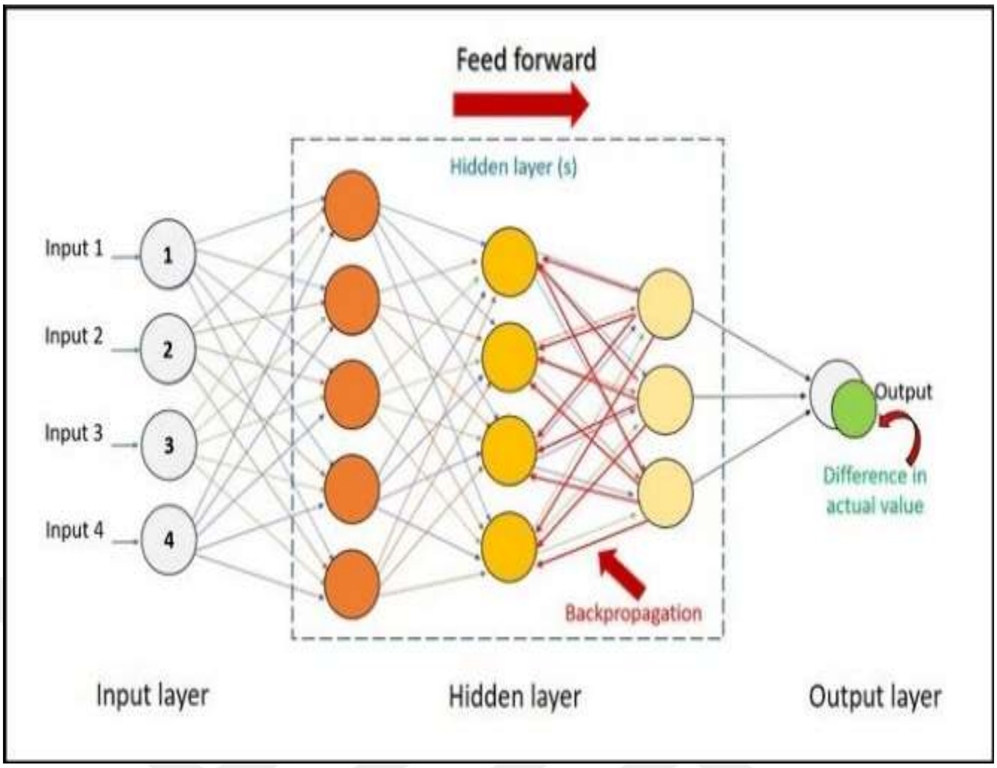


Figure 3.19: The Algorithm of an Artificial Neural Network (ANN).

Remember that artificial neural networks (ANNs) can have a variety of architectures, which include feedforward neural networks, recurrent neural networks, and convolutional neural networks (CNNs). Every architecture is unique and best suited for a particular set of tasks.

Optimization algorithms, Activation functions, iterative learning, and mathematical calculations are all used in a training of artificial neural networks (ANNs). A number of elements, including the initialization, architecture, hyper parameters, and the quantity and quality of training data, affect the network's performance. [67].

3.5.1.2 CNN algorithm

Convolutional neural networks, or CNNs for short, are deep learning algorithms, which are usually applied to tasks involving the processing of videos and images. It’s a specialized kind of neural network, which is developed to automatically and adaptably learn feature spatial hierarchies from input data. A key feature of CNNs is the convolutional layer, which it’s a specific kind of neural network that was designed to learn spatial feature hierarchies from input data adaptively and automatically applies a group of learnable filters to the input data. These filters pick up on a variety of features, including edges, corners, and textures at different spatial locations in the input. Multiple convolutional layers are stacked to enable

CNNs to learn progressively abstract and complex features. CNNs typically include other types of layers as well, such as pooling layers and fully connected layers. In order to reduce the spatial dimensions and preserve the most important information, pooling layers down sample the feature maps that were acquired from the convolutional layers. Fully connected layers, also known as dense layers, apply regression or classification to the high-level features extracted by the convolutional layers. During the training process, CNNs learn to optimize the values of their filters and weights by backpropagation and gradient descent. Training is done on huge data sets with labeled examples., wherein the network updates the parameters to lessen differences among the true and predicted labels. In a range of computer vision applications, including object recognition, segmentation, image generation, and image classification, CNNs have achieved remarkable success. They are useful for obtaining both global and local structures in visual data because of their capacity to automatically learn hierarchical representations [17].

Data Set Preparation:

The dataset in the proposed system was built from openly accessible datasets. The size and volatility of a dataset have a substantial impact on deep learning model generalization [48]. As a result, datasets were pooled to generate heterogeneity or variance among data samples, and a base image classification dataset 1525 was created. The data samples from the datasets were chosen at 625 as un damage and 900 as damage, and the variance was calculated using the kind of concrete surface, lighting shadowing, and fracture patterns. The patches were chosen at random from the datasets, and the split ratio for training an validation was determined and the testing sets were 60:20:20. Manual labeling was done for both the crack and non-crack classes,

The goal of creating numerous datasets was to see how model performance changes as dataset size changes.

Customized CNN Modle:

In the proposed study, a CNN architecture was built from the ground up by fine-tuning several architecture hyper parameters such as the number of convolutional and fully connected layers, filters, stride, pooling locations, sizes, and the number of units in fully connected layers. Because there is no quantitative procedure for calculating acceptable parameters for a specific dataset, the selection of hyper parameters was done through trial and error. Figure 3.18 shows the overall computational architecture of the proposed customized CNN. The design includes five convolutional layers, three activation layers, three max-pooling layers, two fully linked layers, and a soft max layer. These layers' primary function is to improve model performance by extracting valuable features, lowering data dimensionality, and introducing nonlinear it [68]. Convolutional layers have been used in blocks to improve spatial invariance, which aids in recognizing essential features in input crack images. A CNN architecture depends on the spatial or sequential aspects of the data to learn. If the network's input data is extremely sparse, the network's learning ability suffers greatly. The current literature contains solutions to this problem [69],[70].

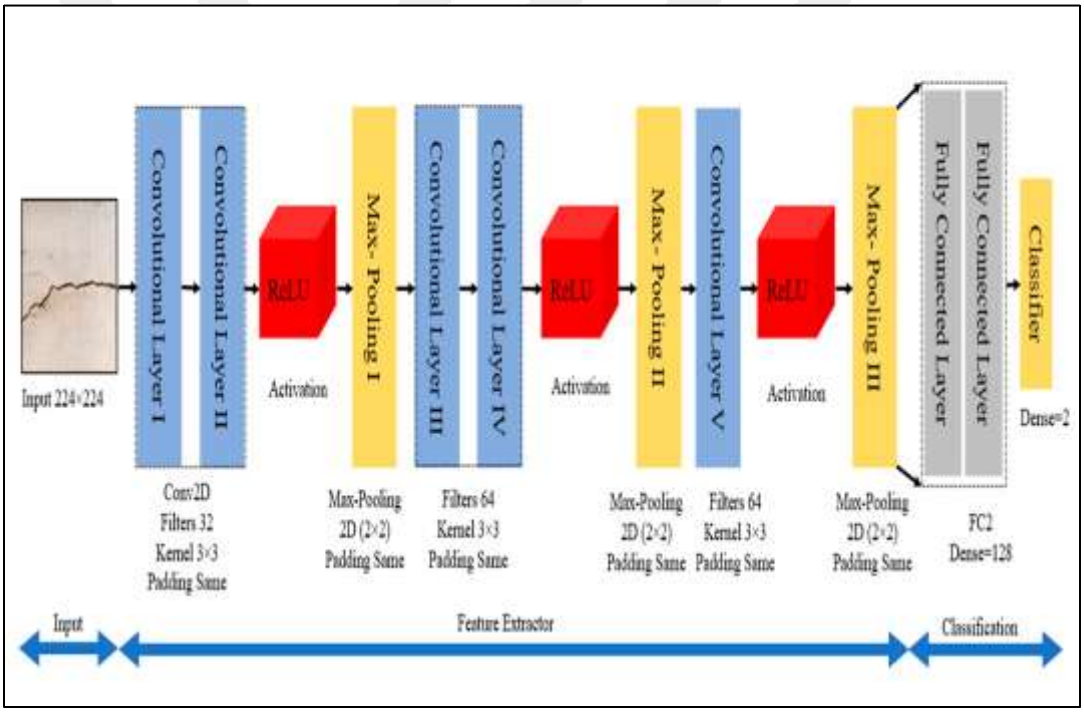


Figure 3.20: Convolutional Neural Network (CNN) Architecture [70].

The first layer here accepts an image of (h* w* c) pixels as input and reduces its spatial size by passing it through multiple convolutional and max pooling layers. Where (h, w, and c) represent the picture height, width and channel count). The final feature vector is obtained at the end of numerous convolutional and max-pooling layers.

4. PROPOSED METHOD

This section presents details of the proposed approach to predict road damage detection on a vital Iraqi road using machine learning methods.

Here, I go over methods of predicting damage detection on the mentioned road using actual data that I gathered. Such procedures take several steps, from gathering preliminary data to evaluating and optimizing the models. The suggested methodology considers the challenges posed by data collection circumstances and leverages the capabilities of contemporary machine learning algorithms to produce reliable predictions.

Applying machine learning (ML) to detect damage to roads, models are trained to identify components of images or groups of images as damaged or undamaged. This is a suggested plan for damage road detection with machine learning:

a. Collection of Datasets: Build a dataset of images showing both undamaged and damaged road surfaces. A range of road types, conditions, and damage types (such as cracks and potholes) should be included in these images. To train a reliable machine learning model, a varied and representative dataset is essential.

b. Preprocessing of Data: To get the dataset ready for training, preprocess it. To increase the diversity of the training data, this may entail resizing the images to a uniform size, augmenting the dataset and normalizing pixel values, using methods like flipping ,rotation and scaling.

c. Annotation: By manually classifying the images or components of images as damaged or undamaged, you can annotate the dataset. The ML model will be trained using these annotations as the ground truth labels.

d. The Extraction of Features: To represent the road surface, obtain informative features from the image segments or images. Conventional computer vision methods or pre-trained deep learning models, like feature extraction from a convolutional neural network (CNN) trained on a sizable dataset like ImageNet, can be used for this.

e. Model Choice: Select a suitable machine learning (ML) model, such as a CNN, SVM, random forest, decision tree, or deep learning model, for damage road detection. The desired performance and the intricacy of the data determine which model is best.we choose cnn modle in our study

f. Training: Divide the annotation dataset into sets for validation and training. Feed the extracted features and associated labels into the training set to train the machine learning model. The model picks up patterns and characteristics that distinguish between damaged and undamaged road surfaces during training.

g. Tuning of Hyperparameters: To enhance the performance of the ML model, optimize its hyperparameters. Techniques like random or grid search can be used for this, where the validation set is used to test and assess various combinations of hyperparameters.

h. Evaluation and Testing: Using a different testing set that the model has not seen during training, evaluate the performance of the trained model. Analyze performance metrics like recall, accuracy, precision, and F1-score to evaluate how well the model detects damage on roads.

i. Deployment: The model can be deployed to identify damage in new road stream video or images after it has been trained and assessed. The model takes an input image or segment, extracts features, and predicts whether it is damaged or undamaged.

It's worth noting that the success of ML-based damage road detection depends on the quality and representativeness of the dataset, the choice of features, the model architecture, and the availability of labeled data for training. This proposed method provides a general framework, and you may need to adapt it based on your specific requirements and dataset characteristics.

4.1 SYSTEM SETUP

It is crucial to set up the system and environment in which the research project was conducted before delving deeper into the application of the suggested technique. Prior to implementing the method, this must be completed. The software tools, programming languages, and hardware resources that were utilized to complete the various steps of the approach, The system configuration includes all of the steps involved in pre-processing the data, training the model, and evaluating it.

4.1.1 Software Tools and Libraries

A collection of necessary libraries and tools that are vital to data facilitation, the success of their learning models and strategic application. Because Python offers a flexible and complete environment for data analysis, machine learning, and scientific computing, that is why we will be using it. It is a good fit for this research project because of its extensive library ecosystem. The following libraries and software programs have been intended for use:

a. Pandas: With the Python programming language, the "pandas" library is a well-liked open-source data manipulation and analysis tool. It offers strong and adaptable data structures for working with structured data as time series, tabular data and more—efficiently.

b. NumPy: A key open-source library for numerical computing for the language of programming, Python, is called NumPy. It represents "Numerical Python". NumPy offers a robust and effective method for manipulating and executing mathematical operations on large multidimensional arrays.

c. Scikit-Learn: There is a popular open-source machine learning library for the Python programming language is called Scikit-Learn, or sklearn. For a wide range of machine learning tasks, such as model selection, regression, dimensionality reduction, clustering and classification, it offers an extensive collection of tools and algorithms.

d. TensorFlow and Keras: Two well-known open-source Python libraries for deep learning and artificial intelligence are Keras and TensorFlow.

   i. TensorFlow: It is an open-source, end-to-end machine learning platform. It offers a vast ecosystem of resources, libraries, and tools for deploying and building machine learning models.

ii. Keras: Operating on top of TensorFlow (as well as other deep learning frameworks like Microsoft Cognitive Toolkit and Theano) is Keras, an advanced neural network API. It offers an easy-to-use interface for creating deep learning models.

e. Matplotlib and Seaborn: Two well-known Python data visualization libraries, Matplotlib and Seaborn, offer tools for making visually appealing and informative plots, charts, and graphs.

i. Matplotlib: Matplotlib is a flexible plotting library with many different plotting options. You can use Matplotlib to create interactive, animated, and static visualizations in Python.

ii. Seaborn: Built on top of Matplotlib, the Seaborn is a library for statistical data visualization. It offers extra statistical functionalities and a higher-level interface to produce statistical graphics that are both aesthetically pleasing and educational.

4.1.2 Hardware Resources

The suggested method can be implemented on a standard home computer, however using hardware resources with more computing power can significantly speed up the training process. This is particularly true when utilizing challenging methods or huge datasets. The efficiency of the study project can therefore be increased by having access to a computer with enough RAM, a strong CPU, and ideally a GPU that is fully dedicated to the machine.

4.1.3 Data Storage and Management

A secure and controllable data storage and management system was designed in light of the sensitive nature of data related to road use as well as the need to maintain both privacy and security. Smart meter data was recorded in a database that was well-organized and restricted access to those who were authorized. An sufficient data backup plan was implemented to prevent any data loss.

4.2 DATASET

The dataset in the proposed system was built from openly accessible datasets. The size and volatility of a dataset have a substantial impact on deep learning model generalization [48]. As a result, datasets were pooled to generate heterogeneity or variance among data samples, and a base image classification dataset 1529 was created. The data samples from the datasets were chosen at (629 image represent images with damage and 900 image represent images with undamaged), and the variance was calculated using the kind of concrete surface, lighting shadowing, and fracture patterns. The patches were chosen at random from the datasets.

4.2.1 Data Pre-processing

The collected datasets underwent extensive pre-processing before model training to guarantee their quality, correctness, and compatibility. Steps in data pre-processing included:

Handling Missing Data: Depending on how many values were missing, any missing readings or partial data were handled using interpolation, imputation, or elimination.

Outlier Detection: Outliers that might affect the performance of the models were found and either eliminated or rectified.

Data Integration: To produce a comprehensive dataset for model training, the smart data and auxiliary datasets were combined and harmonized.

4.3 PROPOSED ALGORITHM

CNN, short for Convolutional Neural Network, is a type of deep learning neural network that is particularly effective for image recognition and computer vision tasks. CNNs are designed to automatically and adaptively learn hierarchical representations from image data.

Here are some key concepts and components of CNNs:

a. Convolutional Layers: Convolutional layers are the core building blocks of CNNs. They are made up of a collection of kernels or filters that conduct convolution operations by swiping over the input image. Convolution creates a feature map by multiplying the filter element-by-element with the input image patch and then adding the results. Visual features and local patterns in the input image are captured by these feature maps.

b. Layers of Pooling: CNNs often use pooling layers to decrease the feature maps' spatial dimensions while keeping crucial information. Selecting the maximum value from a local neighborhood of the feature map is a commonly used pooling technique called max pooling. Through pooling, we can capture spatial invariance in the input data, reduce the number of parameters, and manage overfitting.

c. Functions of Activation: Activation functions give the CNN non-linearity, which helps the network to learn complicated patterns. Sigmoid, tanh, and ReLU (Rectified Linear Unit) are common activation functions utilized in CNNs. ReLU's popularity comes from its ease of use and ability to prevent the vanishing gradient issue.

d. Completely Connected Layers: Dense layers, or fully connected layers, link each neuron in one layer to every other layer's neuron. They are added at the end of the CNN and are in charge of predicting things based on the features that the convolutional layers have learned. [Depending on the learned features as a basis, the fully connected layers carry out regression or classification tasks.

e. Training and reverse propagation: Backpropagation is a technique used to train CNNs. The weights and biases are updated by computing the gradients of the loss function with respect to the network's parameters. During the training phase, the network is fed labeled training examples, the loss is calculated, and the network is optimized using optimization algorithms like stochastic gradient descent (SGD) or its variants.

f. Transfer of Learning: With CNNs, transfer learning is a popular technique. It is based on starting a new task with a pre-trained CNN model, usually trained on a large-scale dataset such as ImageNet. Transfer learning shortens training times, increases generalization, and facilitates efficient training on smaller datasets by utilizing the learned features from the pre-trained model.

In a variety of computer vision tasks, such as object detection, image segmentation, image generation, and image classification, CNNs have shown to be incredibly efficient. Deep learning and computer vision have made extensive use of them because of their capacity to learn hierarchical representations from raw image data.

5. RESULTS

The results of our study are listed as shown in the following figure. To demonstrate the performance of the CNN model, a variety of evaluation calculations are calculated, such as the F1-score, accuracy, precision, recall.

10/10 [==============================] - 2s 54ms/step

	precision	recall	f1-score	support
0	0.91	0.92	0.91	189
1	0.87	0.85	0.86	117
accuracy			0.89	306
macro avg	0.89	0.88	0.89	306
weighted avg	0.89	0.89	0.89	306

Figure 5.1: Metrics for Performance for Each Class of CNN Module.

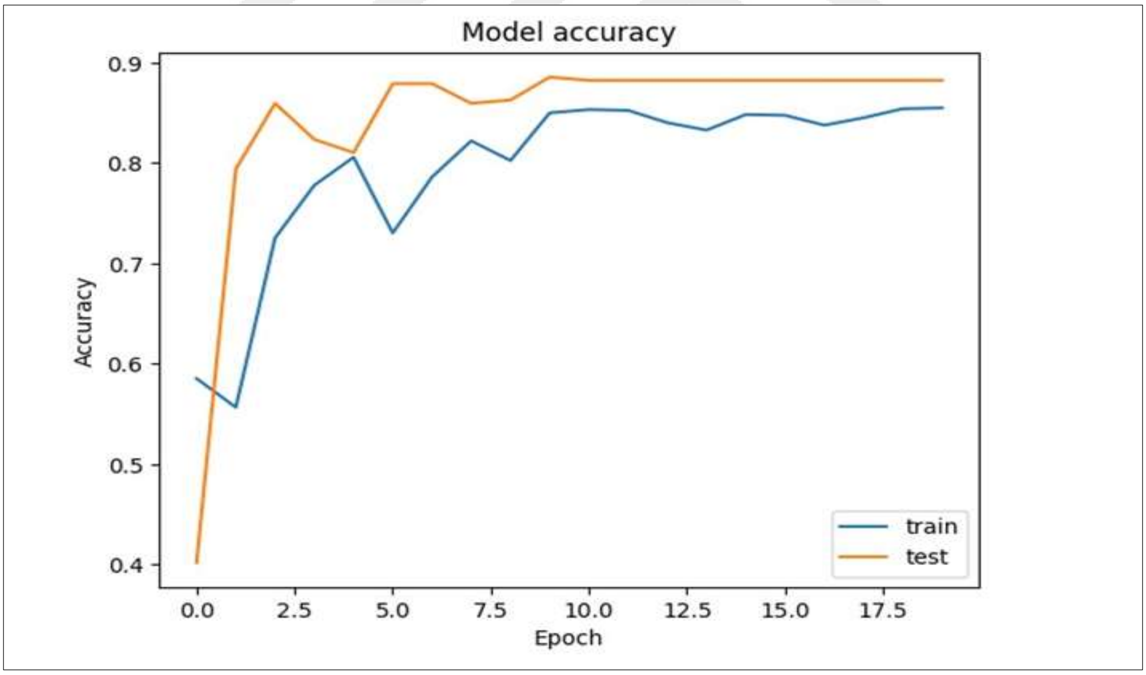


Figure 5.2: Plots for Training and Evaluating the Provided CNN Model: Accuracy Graph.

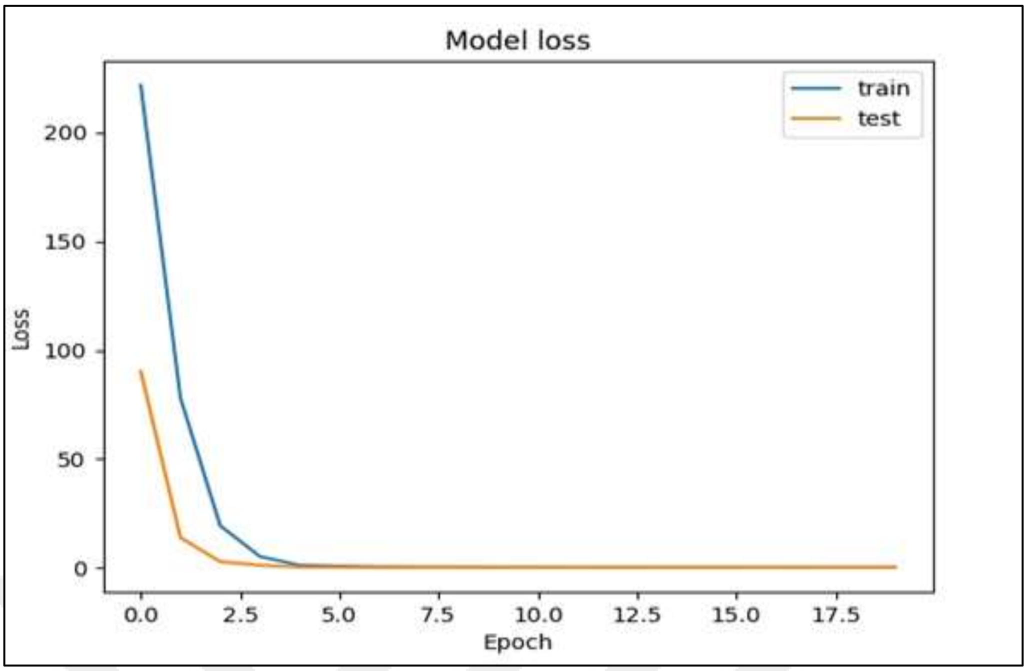


Figure 5.3: Plots for Training and Evaluating the Pro-Vided CNN Model: Loss Graph.

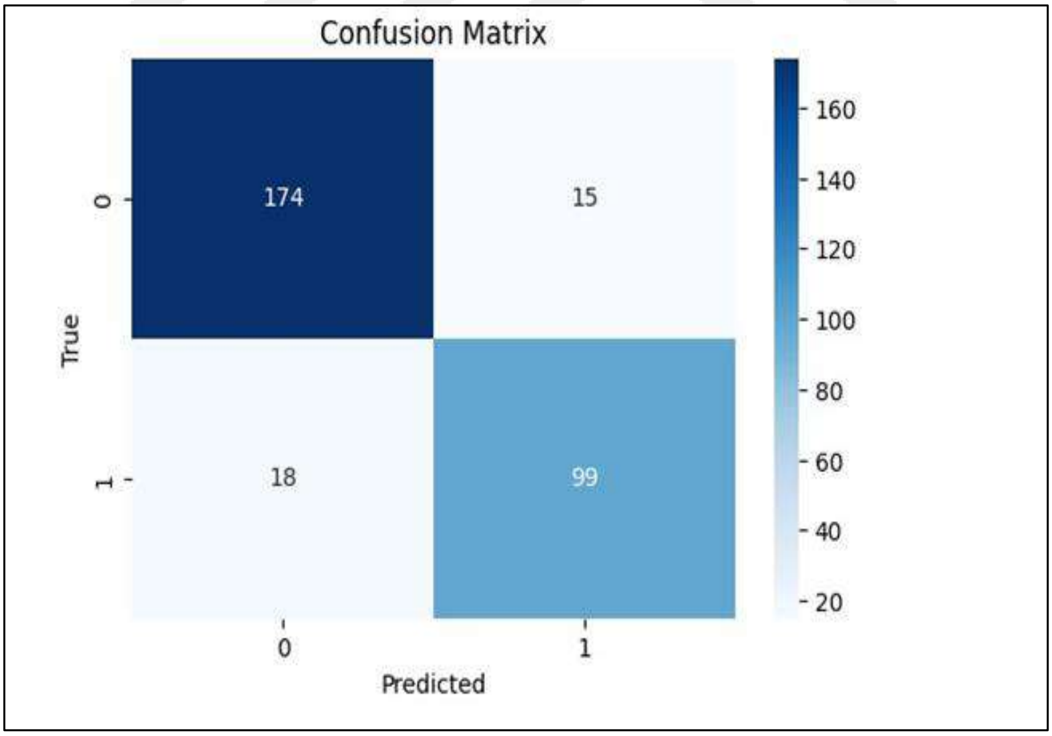


Figure 5.4: The Test Phase Confusion Matrices.

Considering a positive class, The number of testing images that are successfully classified is known as true positive (TP). The number of negative testing images that were correctly identified as negatives is known as the true negative (TN). The number of negative images that are tested and labeled as posi-tive is known as the false positive (FP) rate. The number of positive pictures that were categorized as negative following the test is known as a false neg-ative (FN).

In our study, four metrics—accuracy, recall, preci-sion, and F1-score—are employed to evaluate pro-posed networks. Equation (5.1) says the accuracy is defined as the proportion of successfully identified images to all images tested.

$$\text{Accuracy} = TP + TN / (TP + FP + TN + FN). \qquad (5.1)$$

According to the following Equation (5.2), recall is defined as the proportion of positive images cor-rectly classified as positive to the total number of True positive and False negative images.

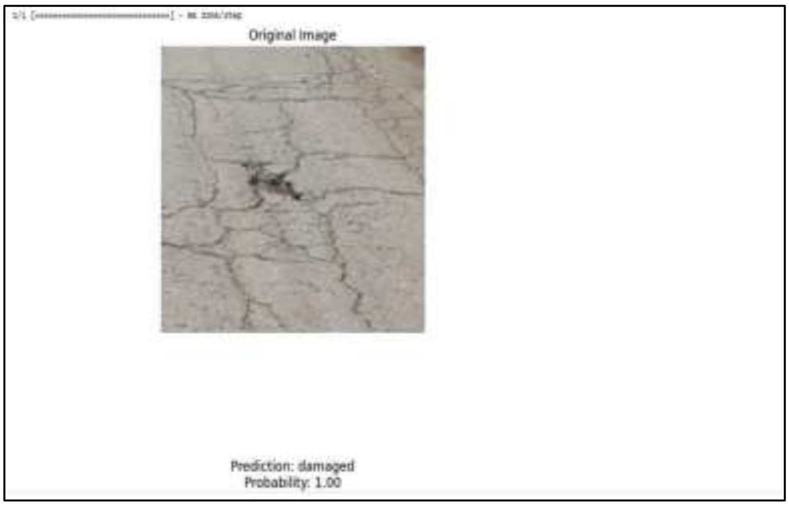
$$\text{Recall} = TP + / (TP + FN). \qquad (5.2)$$

According to the following relation, precision is the ratio of positive images that have been correctly classified as positive to the total number of true positive and false positive.

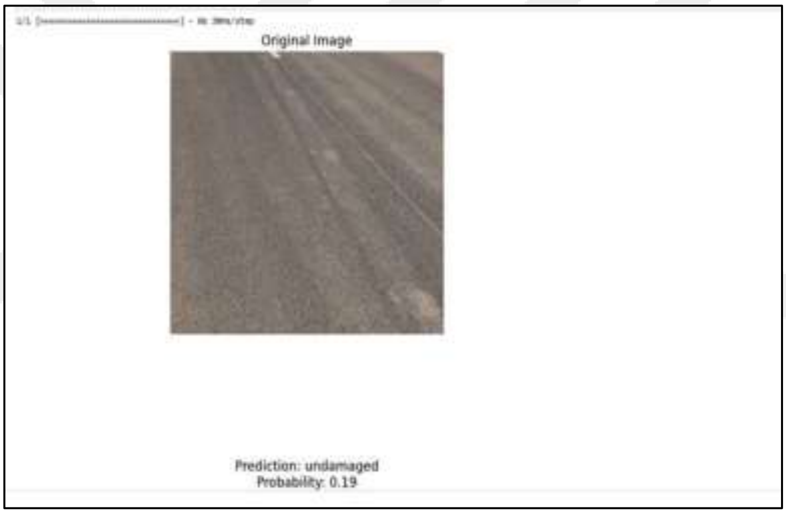
$$\text{Precision} = TP/(TP + FP). \qquad (5.3)$$

Last but not least, the F1-score evaluates accuracy based on the precision and recall values based on the following relation.

$$(\text{F1 score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Recall} + \text{Preci-sion}). \qquad (5.4)$$



(a)



(b)

Figure 5.5: Prediction Image: A) Damaged, B) Un-Damaged.

6. CONCLUSION AND FUTURE WORK

Our study focused on the international highway linking Baghdad to Hilla, which was established in 1989. It is an important vital road linking Baghdad, the capital of Iraq, with the central and southern governorates. We can shorten the search steps with the following steps:

a. The data was collected in the form of two-dimensional images (where we went out in the field to the geographical location and took images with a regular phone camera) and at different distances between the phone and the ground (one meter, one and a half meters, two meters), in addition to the images that we obtained related to the subject of the research from Ministry of Construction, Housing and Municipalities/Department of Roads and Bridges in Iraq. The images were collected in different weather conditions (sunny weather, cloudy weather, rainy weather, foggy weather) as well as during different periods of the day (morning, noon, and evening) to obtain images with different lighting intensities .To study the behavior of damage detecting in images in different weather conditions and the effect of lighting intensity and image capture distance and their effect on the accuracy of damage detecting.

b. 1,526 samples of images were collected and classified into two main groups. The first group represents samples of images that do not contain damage and their number is (900 samples). The second group represents samples of images that contain damage and their number is (625 samples).

c. Artificial intelligence technology was used to classify these images and detect damages in them using machine learning, where the CNN algorithm was used (using the Python language) and calling some of the libraries in it prepared for this purpose (for example, sklearn). The following steps are followed:

   i. Load the two folders to google drive to execute the project global.

   ii. Combined them into a list

   iii. Shuffled, and randomized the image to reduce bias when training

iv. Augemented the data

v. Then using Sklearn library for Model training split the data into 80% for training and 20% for validation.

d. The appearance of the final results in our data set indicates the following:

i. The accuracy of detecting damages is 89%.

ii. The first group, which represents image samples in which there are no damages, The following results appear in it (precision ,recall,f1_score) as follows in sequence (91%,92%,91).

iii. The second group, which represents image samples in which there are damages, The following results appear in it (precision ,recall,f1_score) as follows in sequence (87%,85%,86).

After the results appeared, we found that the intensity of lighting affects the accuracy of detecting damage to roads, The stronger the lighting intensity, the stronger the probability of detecting damage.

The benefits of our research can be summarized as follows:

a. This project allows any person in the community, groups and civil society organizations to monitor roads and their performance by taking an image of the damage using a regular phone camera or any other camera and sending it to the competent authorities so that they can treat and maintain it in a timely manner before it deteriorates.

b. This project allows for reducing the financial costs of discovering and maintaining damage. The traditional method used to discover damage is for the civil engineer responsible for road maintenance to go in the field to conduct surveys and discover whether there is damage or not Which results in financial costs, represented by transportation costs, fuel, and other costs.

However, at the present time, it is possible to by pass this process by taking an image of the road and sending it to the relevant departments without any financial costs.

c. Reducing congestion, noise, and air pollution resulting from vehicle traffic used by people responsible for conducting road surveys to discover damage.

d. Reducing the number of traffic accidents that claim human lives and occur as a result of damage to roads by detecting them early and maintaining them before they deteriorate.

e. Dispensing with the old traditional procedures used to detect road damage and adopting modern technological methods to discover these damages, which allows keeping pace with the rapid technological development occurring in the world.

f. We are keen to develop and rehabilitate the Hilla-Baghdad road using modern, advanced technological methods, as we chose it as the subject of our study in the field of artificial intelligence, as it is a vital, important and effective road, as it connects the capital of Iraq, Baghdad, to the central and southern governorates.

We suggest to researchers interested in the same field as our work or related to it, and who are interested in directing technological development and linking it to the development of methods, the following things:

a. Taking a larger number of samples (images) than those we discussed in the subject of our research to increase accuracy in detecting damage.

b. Using more accurate cameras to detect damage more accurately

c. Installing surveillance cameras on the road that operate with an artificial intelligence system to detect damage to be able to monitor roads periodically, detect damage in its initial stages, and treat it before it deteriorates.

d. Installing artificial intelligence-powered cameras to detect road damage in cars and vehicles to avoid traffic accidents that kill lives.

e. Installing artificial intelligence-powered cameras to detect road damage in drones and directing those drones to conduct road surveys at different altitudes between the plane and the ground.

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