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DETECTION OF ROAD DAMAGES(CRACKS) IN IRAQ BASED ON MACHINE LEARNING

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ABSTRACT: 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). The proposed study will reach a number of results, which are identifying the defect, knowing its type, , and conducting some engineering operations and calculations to determine the state of the roadway, 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, Dataset, Road damage detection, maintenance

1. INTRODUCTION

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 . 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 [2].

2. RELATED WORK

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.

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- 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].
- (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[4].
- (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[5].
- (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[6].
- (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)[7].

3. METHODOLOGY

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. (Figures1,2) show image processing-based technique for crack detection.

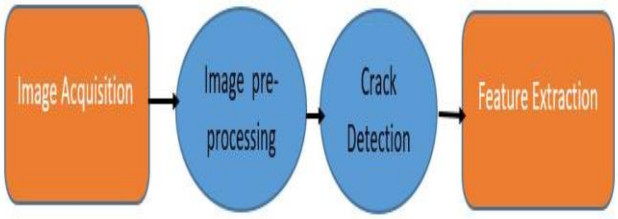

FIGURE 1. -Image processing-based technique for crack detection[8]

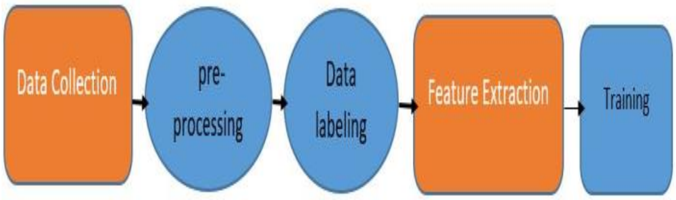

FIGURE 2.- Image processing-based technique for crack detection[8]

That work gives more ideas on how to take advantage of big data to extract important insights for automated decision support[9].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. (Figure3) shows processed image taken with a regular phone camera

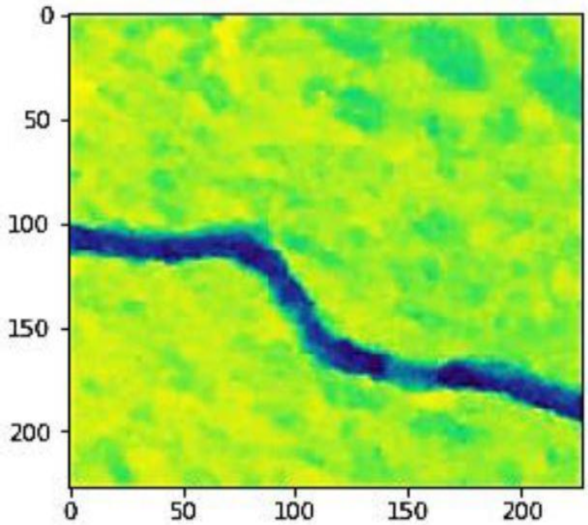

FIGURE 3. -Processed image taken with a regular phone camera

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 sustaining, and it makes it simple for an extensive range of participants 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 provide more environmentally friendly methods of research. In addition, the maintenance of roads late leads to a significant deterioration of the environment and therefore our developed project facilitates sustainable regulatory procedures about the upkeep of roads. 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 urban cities to collect video furthermore image clips through their networks of roads, for instance, public transport vehicles must possess cameras in order to collect the required image data. [9].

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[10], The different types of cracks found are classified for example (transverse cracking, longitudinal cracking, pothole, alligator cracking)[11],[12]. 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[13]. (Figure 4) shows crack ttype classification.

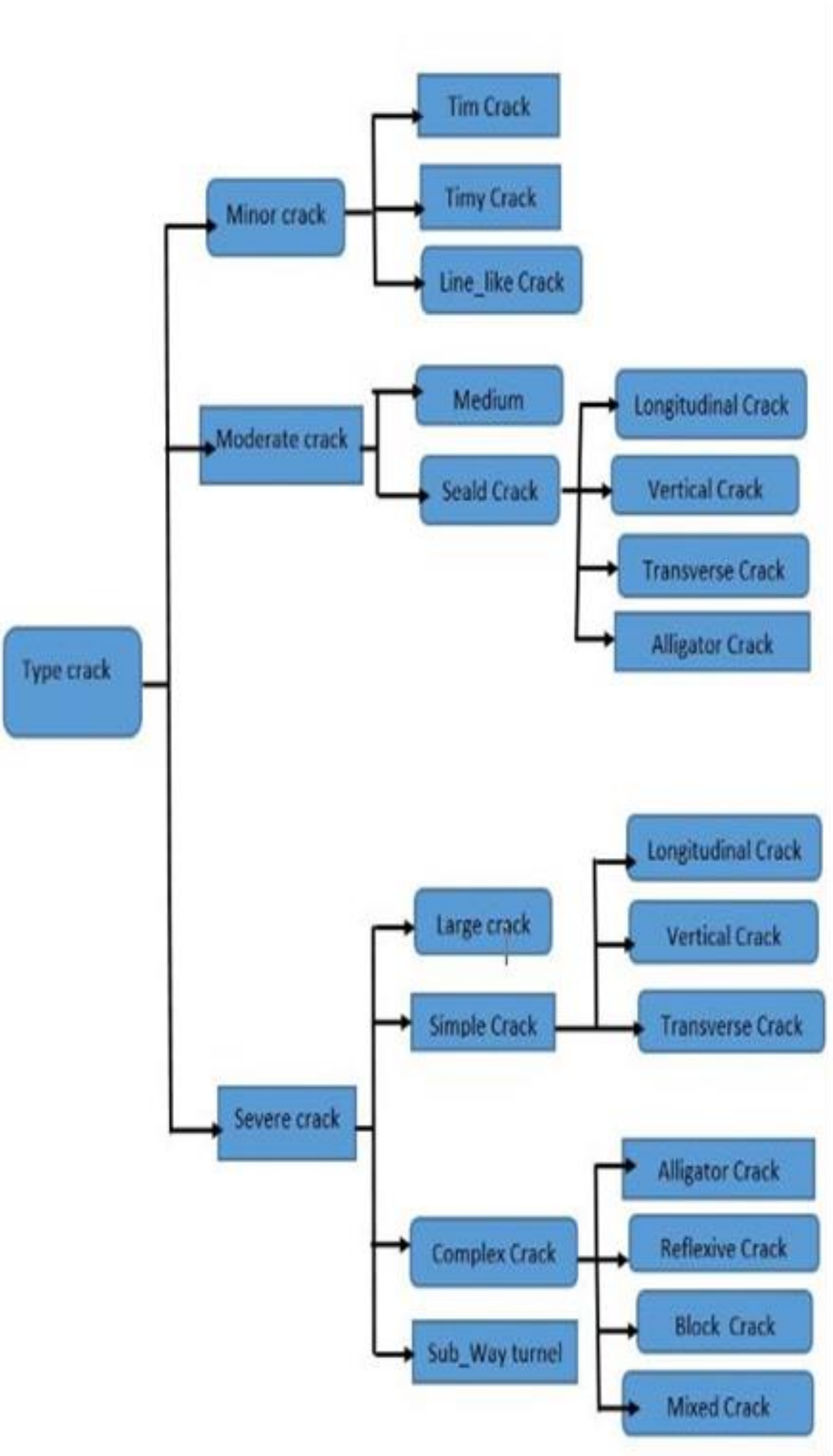

FIGURE 4. - Crack Type Classification

3.2 MECHINE LEARNING

The field of artificial intelligence (AI) has a subfield named machine learning, which concentrates on developing algorithms and models that enabled computers to 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 [14]. ML has recently been used in the discipline of engineering for transportation [15]. 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 based on the severity of the injuries, and the influence of environmental elements, to name just a few [16].

Essentially, machine learning can be applied to detection of cracks in roads in the following ways:

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.

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.

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.

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.

Deployment: After the model was evaluated and trained, it is applicable to evaluate recently 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 5) shows how workflow of machine learning.

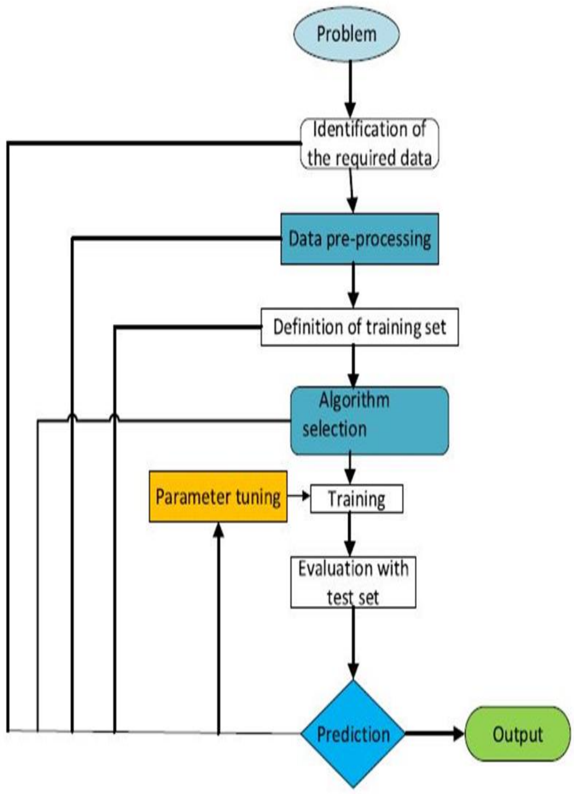

FIGURE 5. - Machine learning workflow[2]

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.

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3.2.1 CNN ALGORITHM

It is 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 divisions originating 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. Convolutional layers are stacked in multiples to let CNNs learn increasingly abstract and complex features. CNNs typically include other types of layers as well, such as pooling layers and fully connected layers. Pooling layers down sample the feature maps to minimize the spatial dimensions and maintain the most crucial information 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. variety of uses for computer vision comprising 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].

3.2.2 CUTOMIZED CNN MODLE

CNNs architecture was constructed entirely from scratch.by fine-tuning numerous architecture hyper parameters such as the quantity of completely linked and convolutional layers, filters, stride, pooling locations, sizes, and the number of units in fully connected layers. Due to the lack of a quantitative process for determining appropriate parameters for some given datasets, The choice of hyper parameters was done through trial and error. (Figure 6) shows the suggested customized CNN's entire computational design. The design includes 5 convolutional layers, three activation layers, 3 max-pooling layers, 2 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. Convolutional layers have been utilized to enhance spatial invariance in blocks, which aids in recognizing essential features in input crack images. For learning, a CNN architecture relies on the spatial or sequential features of the data. If the network's input data is extremely sparse, the network's learning ability suffers greatly. The current literature contains solutions to this problem.

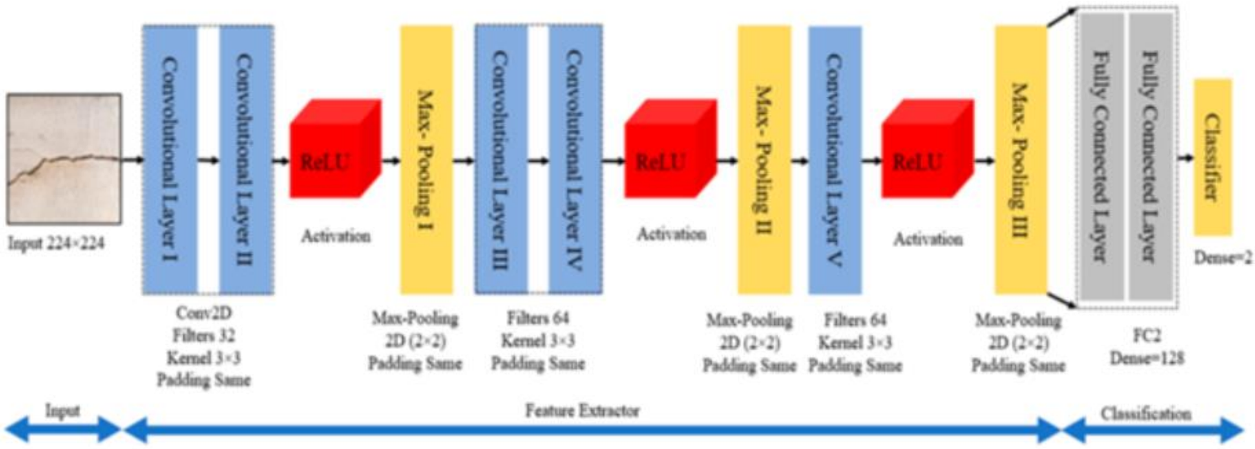

FIGURE 6. - shows the overall computational architecture of the proposed customized CNN

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. RESULT

The results of our study are listed as shown in the following figure (figure7, figure8, figure9). 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 7. - Table 1. metrics for performance for each class of CNN module

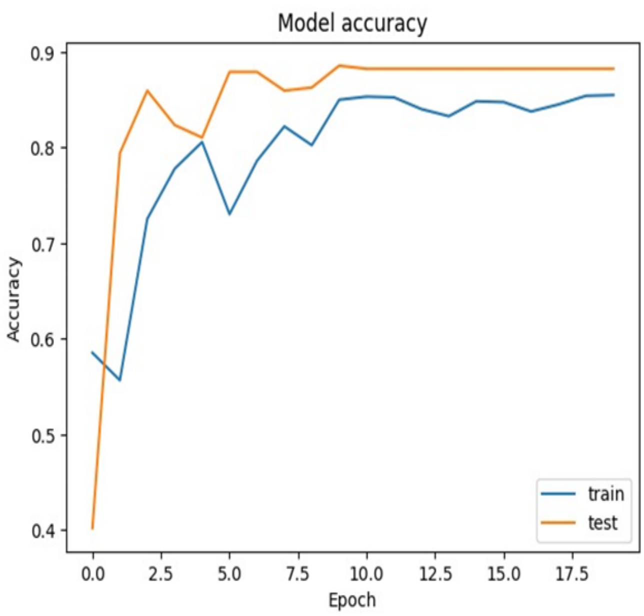

FIGURE 8. - . Plots for training and evaluating the provided CNN model: accuracy graph

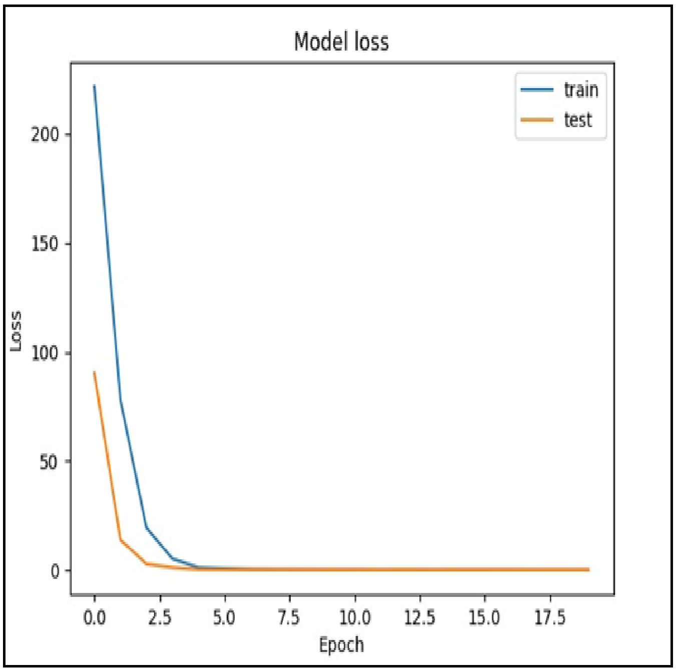

FIGURE 9. - . Plots for training and evaluating the provided CNN model: loss graph

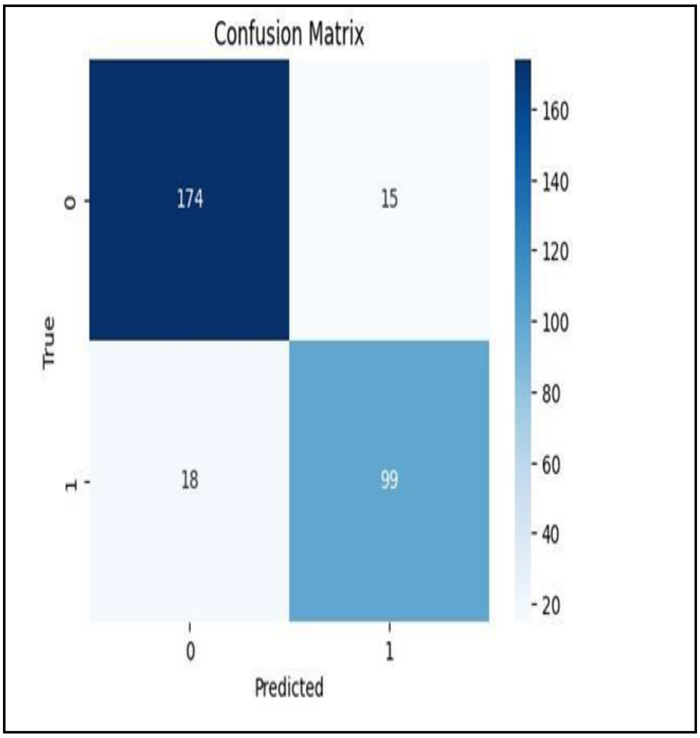

FIGURE 10. - . The test phase confusion matrices

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 positive 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 negative (FN). In our study, four metrics—accuracy, recall, precision, 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.

$$\text{Accuracy} = TP + TN / (TP + FP + TN + FN). \qquad (1)$$

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

$$\text{Recall} = TP + / (TP + FN). \qquad (2)$$

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.

$$\text{Precision} = TP / (TP + FP). \qquad (3)$$

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

$$(\text{F1 score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Recall} + \text{Precision}). \qquad (4)$$

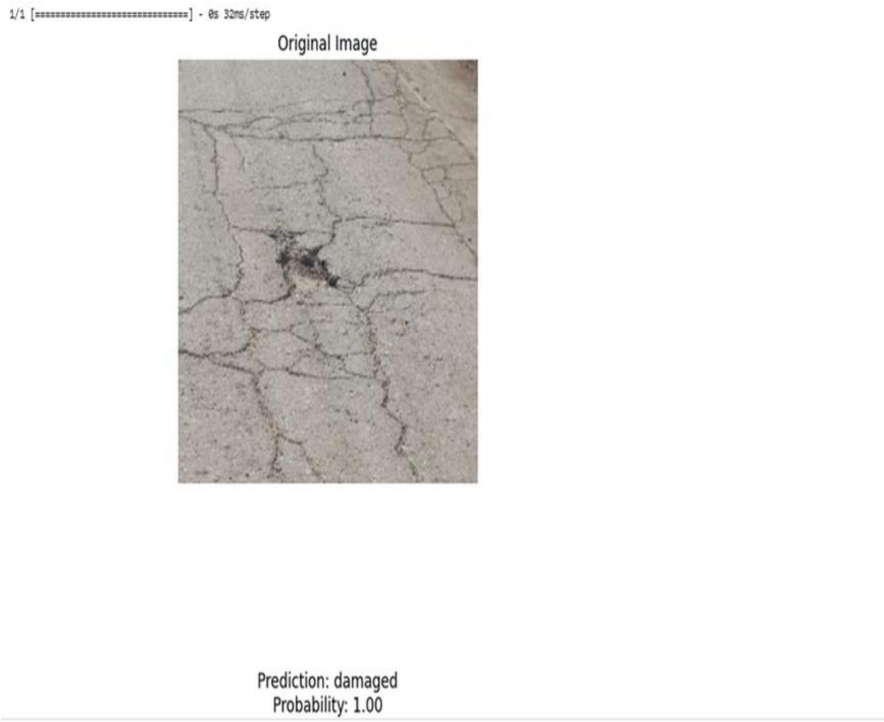

FIGURE 11. - prediction image (damaged)

FIGURE 12. - prediction image (damaged)

4. CONCLUSION

We are keen to develop and rehabilitate the Hila-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:

- Taking a larger number of samples (images) than those we discussed in the subject of our research to increase accuracy in detecting damage.
- Using more accurate cameras to detect damage more accurately.
- 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.
- Installing artificial intelligence-powered cameras to detect road damage in cars and vehicles to avoid traffic accidents that kill lives.
- 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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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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