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Smart Crack Detection System Using Nanostructured Materials with Integrated Optimization Technology

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Internal crack detection with ultra-sonic sensors in concrete has been suggested as a technique for automatically detecting these types of cracks. In this study, we presented a novel strategy for the design of an ultra-sonic sensor-based crack-detecting technique using nanostructured materials. These ultra-sonic sensors based on nanostructure materials can identify cracks in constructions that are not visible to the human eye, sending an SMS alarm to authorities and identifying the exact location of the cracks utilizing designed GPS and GSM devices. Ultra-sonic sensors can be placed at the interior of concrete cubes to detect interior cracks. We suggested an Adaptive Krill Herd Optimization Algorithm (AKHOA) is then used to process data. We included an optimization algorithm into our novel strategy based on nanostructures, and the results of the experiments reveal that it outperforms the state-of-the-art alternatives. It is clear that this smart system with nanotechnology is highly efficient and may reduce the number of accidents that occur during catastrophes by spreading information via smartphone and buzzing sounds.

Keywords: Crack detection method, Ultra-sonic sensors, Nanostructures, Adaptive Krill Herd Optimization Algorithm AKHOA.

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1. INTRODUCTION

Concrete is the chosen material for the construction of many types of bridges and buildings worldwide. Their structural stability is damaged by several operational environmental factors, despite the fact that they are designed securely by layering the maximum load to the base [1]. Since economic growth relies heavily on civil construction, its stability is of greatest priority, as is the maintenance of a high degree of safe structures and lifespan. A hardware module and a software module comprise the majority of the ultra-sonic sensor that was ultimately selected for its use. In an ultra-sonic sensor with nanostructure materials, the transmitters emit a signal, and the receivers receive it when it has been bounced off of the surfaces or cracks. To operate, an ultra-sonic sensor regularly emits a short burst of ultrahigh frequencies noise [2]. To reduce unwanted noise, ultra-sonic sensors are often utilized. No matter their hue, almost all acoustically reflective materials may be identified. Here, the ultra-sonic sensors are crucial for detecting the crack within the concrete cube. The size and position of surface cracks can be seen using ultra-sonic techniques [3-4]. Implementing GSM (Global System for Mobile Communication), GPS (Global Positioning System), and micro-controller broken bridge tracks detection is an effective way for detecting cracks that are located in the paths. When a stretch is identified, a signal is transmitted to the Arduino UNO board which in turn triggers the GPS module to communicate the data. In this research, we suggest low-power, low-cost nanostructure based embedding technologies to aid and enhance safety requirements for concrete by eliminating cracks and obstructions in construction. The model evaluating cracks' ability to detect structural damage and obstructions in structures is impressive. According to the results, the suggested technique has the potential to increase safety system reliability. Implementing these features into real-time apps has been shown to reduce accidents by as much as seventy percent.

The remaining portion of the research is broken down into parts: part 2, the related review, part 3 the study methods; part 4, the experimental result; and part 5, the conclusion.

2. RELATED REVIEW

In this section, we will explain some ideas that have been suggested by various researchers to design smart crack detection systems in buildings using integrated optimization and internet of things technology

Study [5] established an effective crack detection

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approach for the surface fractures in tunnel linings using infrared images, which can overcome difficult challenges including low contrast, irregular lighting, and extreme noise pollution.

According to research [6], "convolutional neural networks (CNNs)" are potential architectures for high-accuracy and precise crack detection. Moreover, learning allows users to employ CNNs without requiring extensive insight and expertise in methods by adapting pre-trained models network to particular tasks.

Research [7] explored the utilization of combining "geometric and radiometric data" from a point cloud for crack identification. Taking into account the technical features of the scanners and the 'geometric' circumstances of the measurement, the authors were able to design a measuring technique for crack detection in building walls using a "terrestrial laser scanner (TLS)".

To identify cracks in concrete surfaces, research [8-9] presented a TLS-based method that makes use of enhanced image processing and data reduction. Data compression was achieved by building an "octree-based shape information model" using laser scanning information.

3. METHODS

In this part, we investigate the smart crack detection in the building using IoT integrated with the optimization algorithm. The overall approach is depicted in Figure 1. As a first step, we collect data with relevance to the building process and preprocess it. Segmentation is performed with the AKHOA on the preprocessed data. Nanostructure based crack detection method then takes place to identify the cracked area in the building.

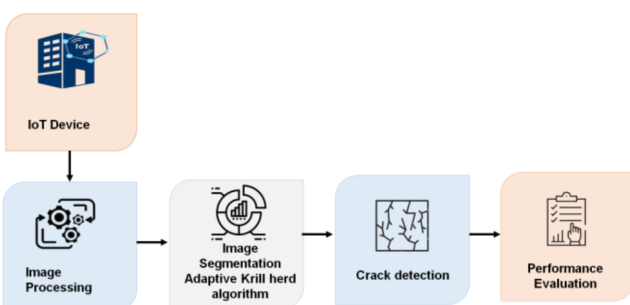

Fig. 1 – Overall approach

3.1 Dataset

Concrete crack photos collected from a variety of Middle East Technical University underground structures are used, together with a publicly available dataset. For the arranging assignment, the remaining 40000 photos of 227 × 227 pixels were generated from 458 complete photographs of 4032 × 3024 pixels and were similarly divided into "crack" and "noncrack" classes. There is a lot of surface finish and illumination condition variation throughout the entire photograph [9-10]. Out of the remaining 20000 cracked photos in the dataset, 600 are selected at random for division. Fig. 2 depicts the Instance of clarified concrete crack images.

3.2 Image Processing

Image datasets can be preprocessed using Otsu's method. This approach is widely used as a thresholding method for images. The aim behind this method is to partition an image's pixel into halves. The ratio between the number of pixels and the average grey level, ω_0 and μ_0, respectively, characterize the separated objects. Similar to the foregoing, the image's background contains two parameters: ω_1 and μ_1. As a result, the image's total average grey level is defined as follows:

$$\mu = \omega_0(d)\mu_0(d) + \omega_1(d)\mu_1(d), \quad (1)$$

where d denotes the image's grey level.

If the following optimization function is maximized, the image has been binarized as efficiently as possible:

$$Arg^{max}_{d} l_g(t) = \omega_0(d)(\mu_0(d) - \mu)^2 + \omega_1(d)(\mu_1(d) - \mu)^2 \quad (2)$$

When deciding on a thresholding value for image binarization, the value of the grey level d_{qb} that corresponds to the highest value of l_g is used. The right-hand side of (2) represents the inter-class variation between the object. The Otsu approach can quickly determine the optimal value of d_{qb} when there are two distinct peaks in the grey-level histogram of the images. A suitable value of d_{qb} may be difficult to find using this technique in the circumstances of uni-modal and almost uni-modal histograms of images.

3.3 Image Segmentation

In KHA, the algorithm's global search capabilities may be enhanced by increasing the inertial factors and u_l of generated movement and hunting movement. To fine-tune the algorithm's capacity for local observations, u_m and u_l can be changed to a lower value.

The results show that selecting reasonable values for u_m and u_l is the most crucial step in enhancing the algorithm's performance. Achieving faster and more accurate integration using KHA is achieved by

$$u_m = u_l = \frac{ygt(j,i) + u_{min} - u_{max}}{R}(R - r) \quad (3)$$

Where r is the current number of iterations, R is the maximum number of iterations, u_{max} is the max value of the induced inertia factor and the hunting inertia factor, and u_{min} is the minimum value of these two factors $ygt(i, j) \in (0, 1)$ denotes the resemblance of individuals j and i, r is the current iteration. This technique can increase the algorithm's global search and local exploration capabilities by adjusting the u_m and u_l values according to various krill populations [11-13].

This method is useful in theory, but in practice, its local exploration ability is low during the first iteration and its global search ability is low at the conclusion of the iteration. It is simple to confuse the algorithm into arriving at a suboptimal value in the first iteration and a global optimum value in the last. Here's a time-variant nonlinear reduction strategy:

$$u_m = u_l = u_{min}.rand + (u_{max} - u_{min})\left(2 - a^{\log(2).r/NJ}\right) \quad (4)$$

Where r is the current iteration time and NJ is the maximum iteration time allowed at this moment. Maximum-induced inertia u_{max} and lowest foraging inertia (u_{min}) are shown for the rand in the range [0, 1]. This equation may be used to alter the present search ability, prevent the local optimum value, and raise the appealing elements of the current global optimal person to the individuals' optimization process by decreasing the value of u_{max} and u_{min}. AKHOA has been optimised as follows.

$$Y_j(r + \Delta r) = Y_j(r) + \Delta r \frac{tY_j}{tr} + k_1\left(Y_{best}(r) - Y_j(r)\right) \quad (5)$$

$Y_{best}(r)$ is the global ideal individual, and k_1 is the attractiveness factor.

3.4 Crack Detection

Arduino is a free and open-source hardware and software platform with a focus on flexibility of use. To illustrate, the Arduino board may receive input from a light sensor, buttons like the one shown in Fig. 2, or tweeting from a user's Twitter account, and then use that information to control other devices, such as motors, LEDs, or a PC [14-16]. Software called the Arduino IDE (Integrated Development Environment) is used to create, build, and upload programs to Arduino boards. The open-source software is easy to set up and use for instant code compilation and support for the vast majority of Arduino boards. An open-source programme called the Arduino IDE is used to programme the Arduino module [17].

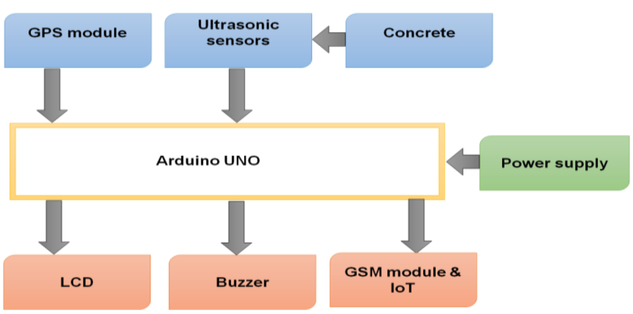

Fig. 2 – Representation of suggested block diagram

A GSM modem sometimes referred to as a GSM module, is a piece of hardware that connects distant networks using GSM technology. They are nearly identical to a standard phone from the perspective of the mobile network, including the necessity of a SIM card to recognize them to the network. In ultra-sonic sensors, compared to regular sound waves, which are the sounds that people can hear, ultra-sonic waves move more quickly. Ultra-sonic sensors emit ultra-sonic pulses into the atmosphere and search for waves that are reflected from things. Ultra-sonic sensors have several applications, including security alarms, automatic door openers, and car backup detectors. Among the many uses for electronic displays; the LCD screen has several applications. A 16 × 2 LCD display module is a common and inexpensive component in many different gadgets and circuits. There are two lines in a 16 × 2 LCD, each of which can show up to 16 characters. Buzzers, sometimes called beepers, are audible signaling devices that can be mechanical, electromechanical, or piezoelectric. Buzzers and beepers are frequently employed in timers and alarm clocks, and they are also used to verify user actions like clicking a mouse or typing a string of characters.

3.5 Experimental Results

In this section, we evaluate the performance of the suggested and current techniques. The parameters are accuracy, precision, recall, f1-score, and MAE, run time. The existing methods are Mask R-CNN [13], DCNN [14], and CedNet [15].
The accuracy is calculated using equation (6).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

The precision is calculated using equation (7).

$$precision = \frac{TP}{TP+FP} \quad (7)$$

The recall is calculated using equation (8).

$$Recall = \frac{FN}{FN+TP} \quad (8)$$

The f1-score is calculated using equation (9).

$$F1 - score = \frac{(precision)\times(recall)\times 2}{precision+recall} \quad (9)$$

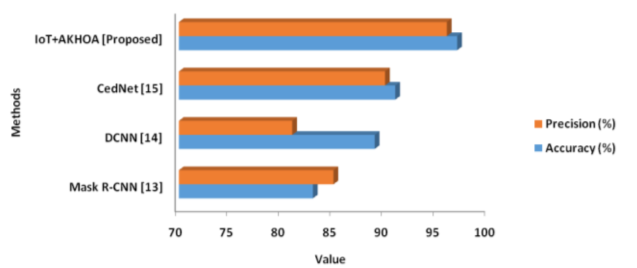

Fig. 3 – Results of accuracy and precision metrics

The system's accuracy is measured using the proportion of samples for which the suggested technique correctly anticipated outcomes as shown in Fig. 3. Mask R-CNN, DCNN, CedNet, and AKHOA have accuracy rates of 83 %, 89 %, 91 %, and 97 % respectively. The recommended method significantly outperformed the alternatives when compared. Precision is one of the most important criteria for accuracy and is well-defined as the proportion of cases that are correctly categorized to all occurrences of data that are predicatively positive. When compared to other methods, Mask R-CNN has an accuracy rate of 85 %, DCNN 81 %, CedNet 90 %, and AKHOA 96 %. It is evident that the suggested strategy outperformed existing strategies that are currently in use.

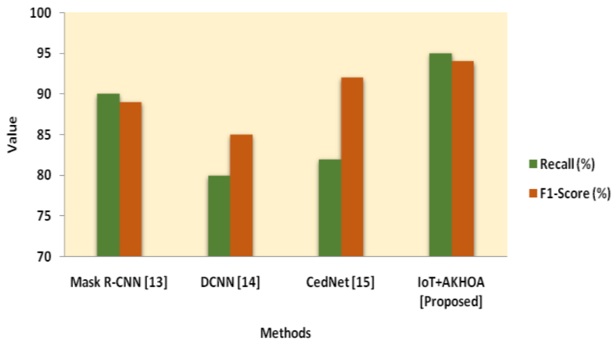

Fig. 4 – Results of Recall and F1-score metrics

Recall, as seen in Fig. 4, is the capacity of a model to recognize each significant sample within a data collection. It is statistically characterized by the ratio of the proportion of TPs to the total of TPs and FNs. Mask R-CNN, DCNN, CedNet, and AKHOA have recall rates that vary from 80 to 95 %. To combine "recall and accuracy" into a single element known as the f1-score, the harmonic mean of the proposed model is calculated. Following Mask R-CNN with an f1-score of 89 % were DCNN (85 %), CedNet (92 %), and AKHOA (94 %).

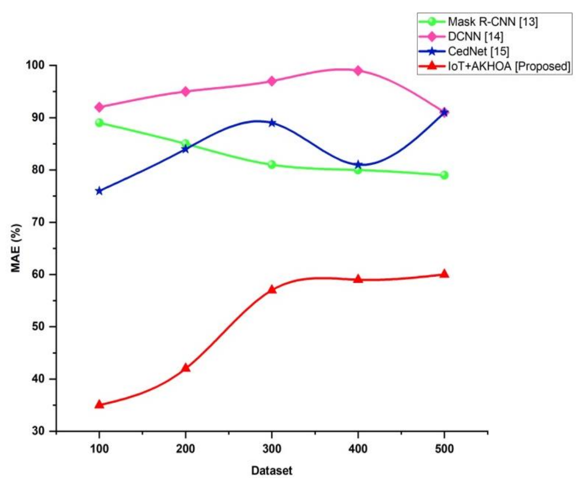

Fig. 5 – Result of MAE in the traditional and suggested method

Fig. 5 and Table 1 depict the Comparison of MAE in the traditional and suggested methods. When compared to currently used approaches like Mask R-CNN, DCNN, and CedNet is high while comparing with the suggested AKHOA. As a result, the suggested method outperforms previous techniques.

MAE is described as the average of the absolute values of the prediction errors.

$$MAE = \sqrt{\frac{\sum_{i=1}^{N}|Predicted_i - Actual|}{N}} \quad (10)$$

Table 1 – Results of MAE

Dataset	MAE (%)			
	Mask R-CNN [13]	DCNN [14]	CedNet	AKHOA [Proposed]
100	89	92	76	35
200	85	95	84	42
300	81	97	89	57
400	80	99	81	59
500	79	91	91	60

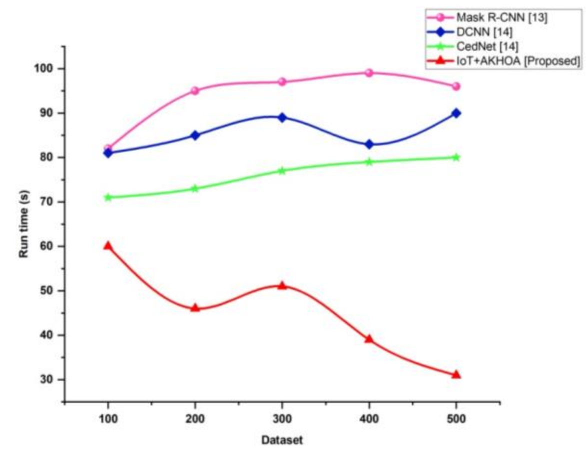

Fig. 6 – Result of run time in the traditional and suggested method

Table 2 - Comparison of Run time

Dataset	Run time (s)			
	Mask R-CNN [13]	DCNN [14]	CedNet	AKHOA [Proposed]
100	82	81	71	60
200	95	85	73	46
300	97	89	77	51
400	99	83	79	39
500	96	90	80	31

Runtime is the amount of time that a task will be performed. It is measured in seconds (s). Fig. 6 and Table 2 depict the Comparison of run time in the traditional and suggested methods. When compared to currently used approaches like Mask R-CNN, DCNN, and CedNet is high while comparing with the suggested AKHOA. As a result, the recommended method shows better performance than conventional approaches.

4. CONCLUSION

In this work, we reveal the innovative technique developed to detect structural flaws in constructing pillars. This approach is not only useful for identifying problems in bridge tracks, but it also reduces costs and increases the certainty of safety measures while bringing down older buildings. This aids in locating the cracks in constructions that aren't readily apparent to our human eyes. It may send an SMS message to the proper authorities and provide their exact position using GSM and GPS modules to identify the specific spots where cracks have appeared. There will be no risk of destruction to surrounding buildings from using this strategy. The layout is really practical and simple to use. This approach using nanostructure materials makes finding surface cracks relatively easy. You can use it with ease, and it doesn't drain your battery quickly. This technique may be used to successfully lessen the occurrence of accidents. In light of these observations, it is clear that this smart system with nanotechnology is highly efficient and may reduce the number of accidents that occur during catastrophes by spreading information via smartphone and buzzing sounds. The absence of feature extraction is a major shortcoming of this study. In the future, feature extraction will be required to raise the system's effectiveness.

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Інтелектуальна система виявлення тріщин із використанням наноструктурованих матеріалів та інтегрованої технології оптимізації

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У роботі запропоновано автоматичний метод виявлення внутрішніх тріщин у бетоні за допомогою ультразвукових датчиків з використанням наноструктурованих матеріалів. Датчики можуть ідентифікувати тріщини в конструкціях, які не видно людському оку, надсилаючи SMS-повідомлення користувачу і визначаючи точне розташування тріщин за допомогою розроблених пристроїв GPS і GSM. Ультразвукові датчики можуть бути розміщені всередині бетонних кубів для виявлення внутрішніх тріщин. Авторами запропоновано використання для обробки даних адаптивного алгоритму оптимізації AKHOA, який був включений в нову стратегію, засновану на наноструктурах. Результати експериментів показують, що він перевершує сучасні альтернативи. Дана інтелектуальна система з нанотехнологіями є більш ефективною та може зменшити кількість нещасних випадків, які трапляються під час катастроф, шляхом поширення інформації через смартфон і звуків дзижчання.

Ключові слова: Метод виявлення тріщин, Ультразвукові датчики, Наноструктури, Адаптивний алгоритм оптимізації AKHOA.