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Condition assessment of concrete structures using automated crack detection method for different concrete surface types based on image processing

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Received: 20 May 2024 / Accepted: 18 September 2024
Published online: 23 September 2024

Abstract
In the inspection and diagnosis of concrete construction, crack detection is highly recommended in the earliest phases to prevent any potential risks later. However, the flaws in concrete surfaces cannot be reliably and effectively identified using traditional crack detection techniques. The suggested algorithm is a supportive tool for agents or authorities to use in crack detection mechanisms to monitor and assess the current condition of buildings or bridges. The researchers aim to establish an intelligent model for automatic crack detection on different concrete surfaces based on image processing technology. Three different concrete surfaces—bridge decks, walls, and concrete cubes—are used to test the model. A subset of the public dataset of bridge decks and walls from SDNET (2018) and 150*150*150 mm of concrete cubes taken from the material laboratory of the faculty of engineering at Ain Shams University are applied to the model. The model F1-score measures are 98.87%, 97.43%, and 74.11% for detecting cracks in bridges, walls, and concrete cubes, respectively. The validation of the applicability of the suggested novel approach is based on a comparison with recent methods for crack recognition. The contribution of this study is that it could be applied to detect cracks efficiently on three different types of concrete surfaces, including uneven concrete surfaces, random noise, voids, dents, colour changes, and stain marks. The proposed method is transparent in its workflow and has a lower computational cost compared with deep learning frameworks. Thus, the outcomes of this model demonstrate its effectiveness in concrete defect field investigation.

Keywords Image processing · Inspection · Crack detection · Bridge decks · Walls · Concrete cubes

1 Introduction

Structural engineers are responsible for fixing any issues that arise from a specific structure that is defective, deteriorated, or damaged. Condition assessment is essential for selecting the appropriate actions for repairing the structure. It involves a visual examination of exposed concrete, which includes a mapping of the different types of concrete defects that may be visible, such as cracking, spalling, scaling, and other surface problems [1].Crack control is an essential issue for inspectors to understand and diagnose the condition of any type of surface structure. Cracks usually

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occur for several reasons, such as low material quality, environmental factors such as temperature, earthquakes, and others. Regular crack detection plays an important role in the maintenance and operation of existing buildings and infrastructure. The intrinsic damage, deterioration, and possible causes of cracks can be derived from the morphological and positional characteristics of cracks, which gives reasonable guidance on structure assessment [2, 3].

There is a desire to meet the requirement to detect and inspect concrete surfaces due to inaccessible areas of the crack. Manual investigation and automatic investigation are the two methods used for crack detection. Traditional investigation is the manual technique, which is done by skilled inspectors with the use of surveying tools and visual inspection to detect flaws in structures. Nevertheless, this method suffers from some limitations because a troop cannot detect cracks in unreachable areas such as large dams, monuments, buildings, etc. [4]. Superficially, it is simple to make such a decision based on the condition's structure and its ability to meet various structural and functional requirements. However, due to a lack of data and inaccurate theoretical models, it is not always possible to analyse the status of structures [5]. Recently, automatic investigation such as image processing-based inspection has become useful due to its real-time application, precision accuracy, cost-effectiveness, and complete automation. One of the purposes of conducting image analysis is to approach unreachable locations or risky zones, such as high-rise buildings, for investigation for safety assessment and to be able to zoom out and zoom in on the image to inspect the concrete elements. On the other hand, structure monitoring techniques based on acoustic and ultrasonic waves are more expensive, require human intervention, require expertise, and are more challenging to put into practice [6, 7].

Most recent studies are focusing on crack detection and how to solve segmentation problems through image processing or deep learning algorithms. Nevertheless, they are suffering from some limitations, such as the fact that deep learning models require an enormous amount of training data, which consumes a huge computational cost. In addition, the previous studies focused on establishing a model for detecting cracks on one type of concrete surface. These studies neglected that each concrete surface is suffering from its own randomness, unevenness, inherent noise, and dents, which differ from surface to another. Also, the environmental conditions affect the detection efficiency, which is related to illumination, whether it is uniform or nonuniform on the detected surface.

Therefore, it is challenging to find a model that can work on any type of concrete surface to precisely locate fractures and carry out an assessment of the structure under observation because of the uneven concrete surface, random noise on the surface, voids, dents, colour changes, and stain marks. Thus, this study establishes an automated model based on image processing techniques to detect cracks on three different types of concrete surfaces: bridge decks, walls, and concrete cubes, to determine any further actions to be taken once the crack is recognized. The method is validated by comparing it with recent methods for crack detection. This model will be effective and save time in inspection fields for buildings, bridges, and laboratory tests.

2 Literature review

Recently, image processing in crack detection and quantification has become a recommended method in health monitoring systems, and this technique is widely used in the field of civil engineering [8, 9]. Several approaches have been proposed to address this challenge. Talab et al. [10] presented a new approach in image processing for detecting cracks in images of concrete structures. There are three steps in their methodology: First, convert the image to grayscale, use the image's edge, apply Sobel's technique, and create an image filter that uses Sobel's filter to identify cracks. Second, selecting an appropriate threshold in a binary image classifies every pixel into the background and foreground categories. After the images were categorised, any remaining noise was removed using Sobel's filtering. Third, after using Sobel's filtering, cracks were detected using Otsu's method. Noh et al. [11] used image segmentation-based fuzzy c-means clustering to separate crack candidates from the image background for concrete surfaces of bridges. In this step, fuzzy c-means clustering is used to apply image segmentation to the image, leaving only image clusters with cracks. After applying the segmentation, the selection of clusters that contain cracks is based on the average brightness of the pixels belonging to the cluster, and the clusters with the lowest average brightness level are chosen. Then, a morphology dilation operation was applied, followed by three-size mask filtering to eliminate all three kinds of noise, leaving only the cracks. Yu et al. [12] introduced an image processing approach for crack detection in a tunnel lining image. The authors use an anisotropy measure in their crack detection technique. The suggested method considered the low contrast, inconsistent illumination, and severe noise pollution that generally exist in a tunnel-lining image. Their study suggests a three-step process to detect and extract cracks from infrared images of a tunnel's lining. The first step is preprocessing, which includes applying a Gaussian low-pass filter and a canny edge operator. Secondly, the conditional texture anisotropy of each pixel is computed in an image subblock, and an iteration technique is used to determine the ideal threshold. Finally, the cracks in each region are connected. Gopalakrishnan et al. [13] used a deep convolutional neural network (DCNN), especially the VGG-16 model, which was trained on the large-scale ImageNet database, to detect cracks in pavement surface images. However, in order to build a reliable classifier, the DCNN needs an enormous amount of training data, which consumes a huge computational cost.

Hoang [14] developed an automated model based on image processing techniques for detecting and analysing crack defects on the surface of building structures. The model relied on the enhancement of the Otsu method to deliver a satisfying image thresholding outcome, then applied other shape analysis algorithms to extract crack properties. The users were required to tune some parameters to provide a satisfactory output threshold, and they changed from surface to surface, such as asphalt pavement and building surfaces. Quan et al. [15] proposed an improved Otsu threshold crack detection method based on a grey-level histogram. The input images were smoothed, and any remnants of oil stains and spots on the pavement surface were eliminated using a nonlinear median filter. The initial threshold value and its neighbourhood, along with the pixel distribution information of SASBE, were combined in the improved method to improve detection accuracy. Yang et al. [16] have presented an automated technique based on image processing for detecting cracks. They used two artificial marks arranged near both sides of the crack and applied image processing technology to get the number of pixels around the perimeter of the artificial marks in the image. They calculated the actual length of the unit pixel by comparison with the actual perimeter of the artificial marker. Carrasco et al. [17] detected cracks in fibre-reinforced earthen construction materials based on two stages of digital image processing techniques. The two steps are the Perona-Malik filter and binary segmentation. The first step involves a colour change using L*a*b colour space on the original RGB image, and only the L-channel of this transformation was retained. The filtering method suggested by Perona and Malik is employed in the second sub-stage. The second step was binary segmentation, which employed a skeleton algorithm based on the process of distance transformation to determine the centroids of each crack. Safae et al. [18] developed a tile based on an image processing algorithm to detect pavement cracks. It was suggested to use a technique of localised thresholding on each tile to identify cracked ones (tiles with cracks) based on the spatial distribution of crack pixels. The method showed some problems related to detecting low-level cracks in complex patterns. de León et al. [19] presented a methodology for crack segmentation based on the theory of minimal path selection combined with a region-based approach obtained through the segmentation of texture features extracted using Gabor filters. An equalisation of brightness and shadows is a pre-processing step to improve the detection of local minima. To improve the coverage of the cracks, these local minimal are constrained by a minimum distance between adjacent points. Subsequently, two areas are identified using a region-based segmentation technique, which establishes the threshold values for rejection. Lastly, a geometrical thresholding step is presented, which enables the exclusion of small, isolated cracks and rounded areas.

Although a number of automated crack detection models have been established, they have some limitations. For example, while the algorithms of machine and deep learning have shown promise in the previous 10 years, they have some shortcomings: A "black-box" design of neural networks and deep learning leaves the users blind and prevents them from changing any parameters; a significant quantity of labelled data is needed; and lastly, they typically take a long time [19]. On the other hand, the automated models are restricted to detecting cracks on only one type of surface: walls, pavement, bridge decks, pipes, sewers, etc., and can't be generalised to all of them. The crack has several types and propagation patterns based on different factors, such as external loading and the material properties of the structure member. Additionally, the image processing technique required to consider two types of concrete surfaces conditions to get high accuracy and success assessment for crack detection and recognition. The first type is outdoor and general environmental conditions, where acquired images have non-uniform illumination and inconsistent, such as cracked detection on pavement and bridge decks. The second type is an indoor environment that is able to control the illumination to be uniform, such as tunnels, sewer pipes, and concrete samples in the laboratory.Several methods have been developed for crack detection and recognition based on image processing, but their accuracy still needs enhancement if noise is present in the image acquisition environment. In addition, some concrete surfaces are suffering from randomness, unevenness, inherent noise, and dents, which vary from surface to another and affect the ability to measure their crack width.

Therefore, it's a challenge to design an accurate and robust algorithm to be able to detect cracks and measure their widths for any type of concrete surface in different environmental conditions. Thus, the proposed automated method introduces a workflow to detect cracks in a noisy background among three types of concrete surfaces (decks, walls, and concrete cubes) with different crack patterns, colours, and backgrounds, and to consider both outdoor and indoor conditions. The main benefit of the proposed method is the transparency of the workflow compared with deep learning frameworks that require complex training processes and huge amounts of images for successful training. The suggested algorithm is an operational support tool for authorities needing crack detection systems in order to monitor and assess the current state of the infrastructure, such as roads, tunnels, or bridges. This is because the methodology can be directly applied to images obtained at a low cost.

3 Method overview

This paper presents a novel method to detect cracks in three types of concrete elements. The current methodology is based on image processing, which can provide highly precise results and an alternative, cheap approach for structural inspection. The following subsections describe each stage shown in Fig. 1 to produce crack maps for each structural element.

3.1 Image pre-processing

Image pre-processing is the first step that had to be performed before extracting features from complex images. The aim of pre-processing is to enhance important image features and improve their quality for further processing. Image preprocessing includes, but is not limited to, geometric transformations of images (e.g., rotation, scaling, translation), illumination corrections, filtering, noise removal, etc. [20]. In this study, the concrete cube images were taken by an iPhone 7 pulse with 3024×4032 pixels. Thus, the images are resized to not more than half their sizes to reduce the model's running time without affecting its performance.

3.1.1 Bilateral filter pre-processing

A bilateral filter is a combination of smoothing and denoising images while preserving edges. It considers both geometric closeness and photometric similarity of neighbouring pixels while filtering. A bilateral filter works by replacing the intensity of each pixel with a weighted average of intensity values from nearby pixels [21, 22]. The result of the bilateral filter is shown in Fig. 2b, which points out that the edges are clearly preserved and noise is removed. Then, the image in RGB colour is converted to a grayscale image.

3.1.2 Subtraction processing pre-processing

Generally, the visual inspection of any surface structure in a closed area is delivered with uniform light conditions at the same time as the picked image. While the outdoor inspection is suffering from several conditions that may affect the uniformity of illumination, Thus, this step is necessary to overcome the non-uniform illumination in the images. It removes the shadows and converts any non-uniform illumination into an illuminated image. Niblack and Sauvola local thresholds are applied to differentiate cracks from backgrounds. They are highly effective for non-uniform background images [23]. Figure 2c indicates the result of subtracting image processing.

3.2 Image thresholding

Image thresholding is a simple method to highlight an object from its background in an image. It is a type of segmentation that separates the foreground from the background in an image. Thresholding technique is widely used in object tracking, pattern recognition, computer vision, object detection, and so on. This operation leads to a binary image, which can be interpreted as follows: white pixels related to logic 1, while black pixels referred to logic 0 [24, 25]. When the pixel values are greater than the threshold value (T), the output pixel values are turned into 1, and the points are called object points. While the input pixels are less than the threshold value (T), the output values are assigned to 0, and they are reflected as background points, as expressed by Eq. (1) [26].

Fig. 1 The suggested model's procedure

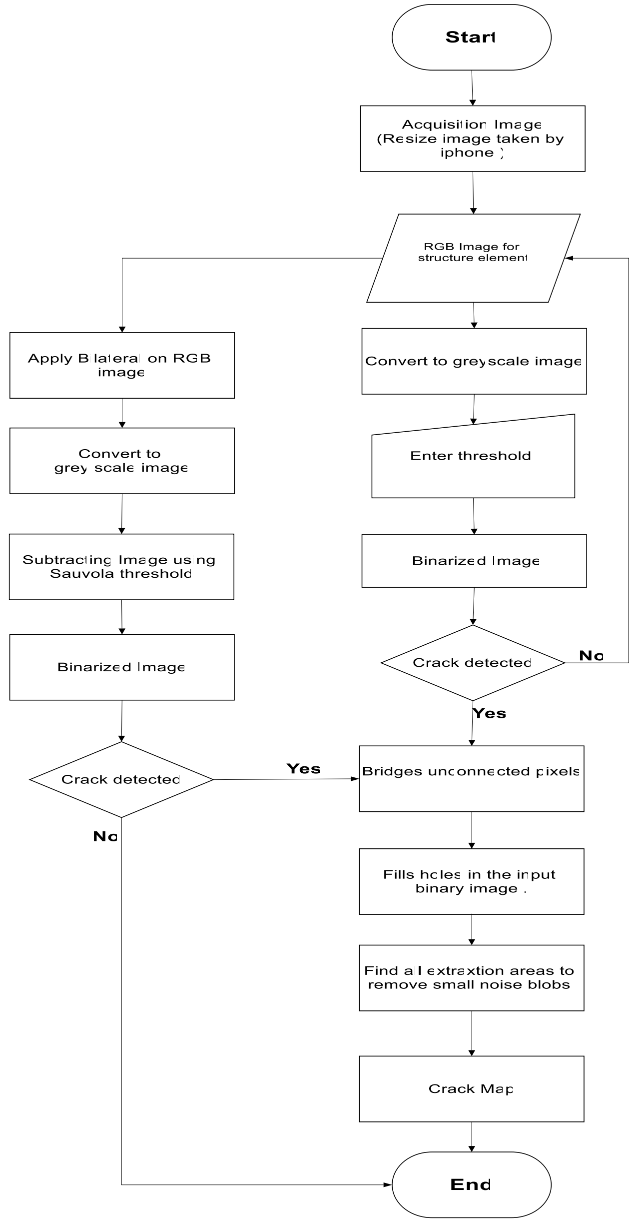
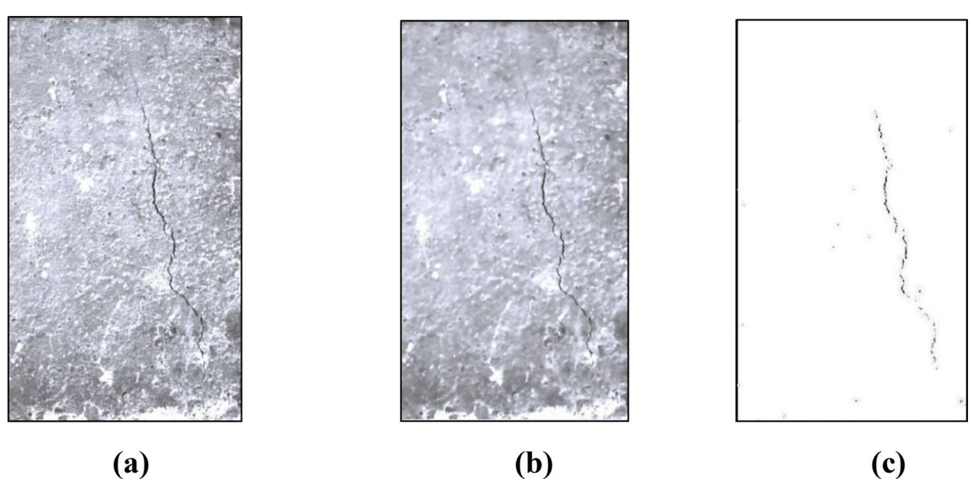


Fig. 2 **a** Original image; **b** after applying a bilateral filter; **c** subtracting processing



$$r(x,y) = \begin{cases} 1 if o(x,y) > T \\ 0 if o(x,y) < T \end{cases} \tag{3.1}$$

where r(x, y) is the thresholded image and o(x, y) is the grey-level image. Global grey thresholding is the fastest and simplest type of image segmentation. It is associated with histogram equalisation to select the best threshold value for the grayscale image [27]. Other methods, such as the otsu and valley-emphasis methods, can be applied to determine the T value. The successful binarization algorithm relied on choosing an appropriate threshold. The binary image can be further improved by using morphological operations such as closing to eliminate small holes and filling thin gaps [28].

3.3 Morphological operation

Morphology is a tool used for extracting features that may be used to characterise and describe an entire image. This operation involves adjusting each pixel in the image based on the value of its neighbouring pixels. A morphological operation that is sensitive to certain shapes in the input image can be created by setting the neighbourhood's size and shape. Examples of morphological operations are dilation, erosion, opening, closing, and filling.

4 Implementation crack detection method

The proposed method was implemented by MATLAB (R2021a) on a desktop PC (Intel(R) Core(TM) i7-8550U CPU @ 1.80 GHz 1.99 GHz, 64-bit operating system) as shown in Fig. 8. The first stage in image preprocessing is to convert the RGB colour image, which consists of three panels: red, green, and blue, into a grayscale image. Each panel has the same size and bit depth and represents a grey-level image. Then, the green plan was selected to be further processed, as it offers less noise. In the model, the T value (threshold) is determined manually, consistent with the trial-and-error method [29]. A histogram is applied to select the best threshold for the grey-level image and to enhance the crack area. If the image is full of dents, noise, and shadows, as shown in Fig. 3, the bilateral filter should be applied to the input image, which is highly effective in removing dents and interference objects. Then, convert the output to a grey image to use the Savoula threshold to binarize the image. Subsequently, a bridge is a type of morphological operation carried out on unconnected pixels. If a pixel has two unconnected nonzero neighbours, it is assigned to 1 instead of 0. It follows the fill holes function and uses the regionprops function to extract crack areas. For a more thorough cleaning process, areas with a less certain number of pixels are cast out.

5 Experimental validation

5.1 Experimental setup and image database

According to the literature review and common practices, there are no specific criteria or formulas to determine the minimum number of images. The proposed model is built based on image processing methods and is less costly and time-consuming than other complicated models based on machine learning. The crack detection model based on machine learning requires a large training sample size, which is not necessary in our model. Thus, the proposed algorithm is tested on 825 images taken randomly from two datasets: our 225 concrete cube samples and 600 images from the open dataset SDNET2018 (bridge decks and walls). The public dataset SDNET2018 includes over 56,000 images of cracked and non-cracked concrete bridge decks, walls, and pavements. The dataset involved 54 images of bridge decks, subdivided into 13,620 cracked and untracked images. The crack size ranges from 0.06 mm (narrow) to 25 mm (wide). The images were taken by a 16-MP Nikon camera at a distance of 500 mm without zoom. Table 1 lists the properties of the camera and taken image discrepancies [30].

The 225 samples of concrete cubes were taken from the material laboratory of the faculty of engineering at Ain Shams University. The size of the cubes is similar: 150 mm*150 mm*150 mm. They were prepared for compression testing and crack propagation investigations. The images have been taken by the camera of the iPhone 7 Plus, which has dual 12-megapixel wide-angle and telephoto cameras. The primary camera is wide-angle with a 56 mm lens and $f/1.8$ aperture, while the secondary camera is telephoto with a 28 mm lens and $f/2.8$ aperture. The image resolution

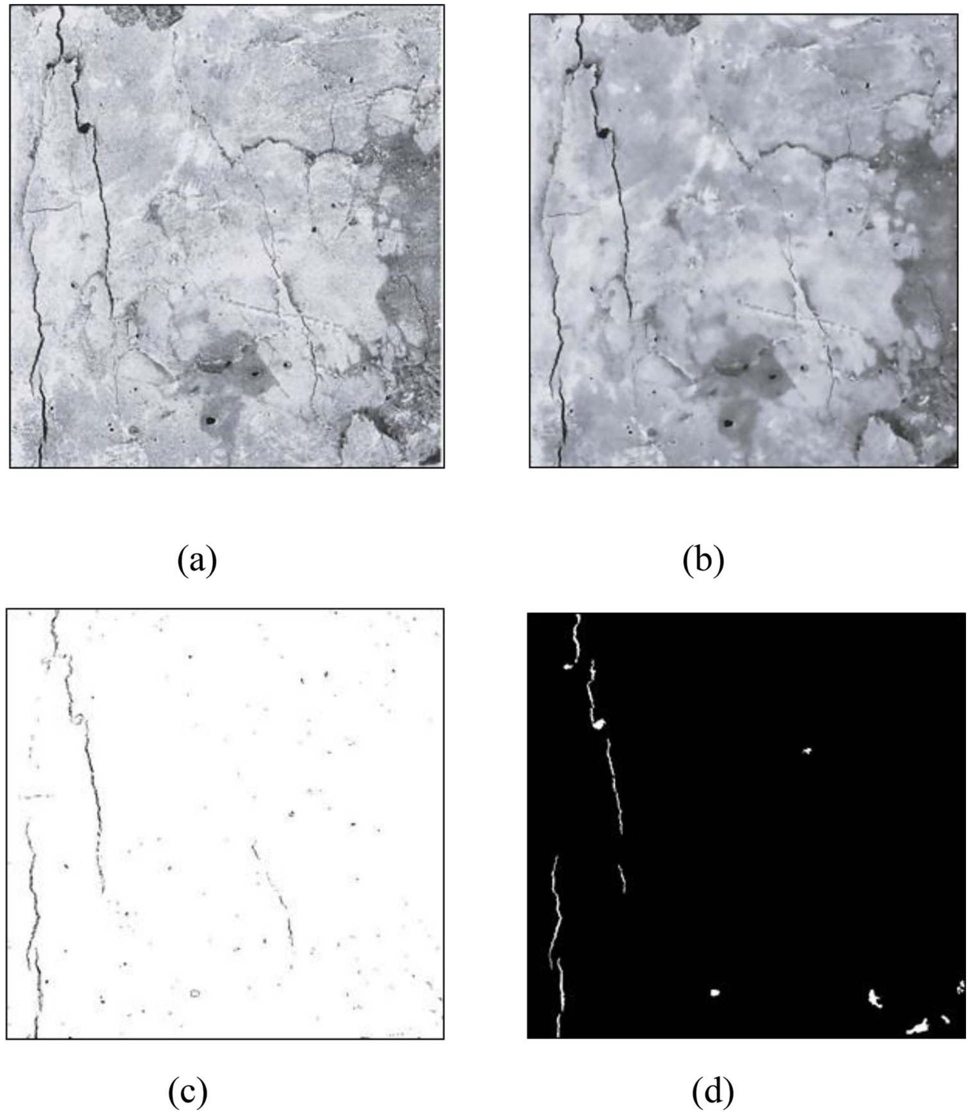


Fig. 3 **a** original image (concert cube); **b** results of bilateral filter; **c** results of subtraction; and **d** crack map

Table 1 Image and camera properties

Camera	16-MP Nikon camera
Type of data	2D-RGB image (.jpg)
The sensitivity	125 ISO
Image resolution	4068 × 3456 px
The surface illumination	(1500–3000 lx)
Subimage size	256 × 256 px
Image physical area	1000 mm × 850 mm
Subimage physical area	60 mm × 60 mm

of the digital camera is 3024 × 4032 pixels. The crack in the screen should be vertical during shooting. We tested the method based on 124 images taken randomly from previous concrete cubes applied to working loads to cause several measures of cracks, as shown in Fig. 4, and the other 101 samples are labelled as un-cracked cubes. The crack size ranges from 0.5 to 4 mm. It is worth mentioning that the ACI 345R-91 and ACI 201.1R [31, 32] classified cracks according to their width into three groups: (a) fine (less than lmm wide); (b) medium (between lmm and 2 mm wide); and (c) wide (over 2 mm wide). But the proposed methodology focuses on crack detection based on visual inspection, not crack width. The concrete cubes in this model are representative concrete samples from any structure element.

Fig. 4 Applying a working load to a concrete cube to cause cracks

5.2 Ground truth definition and image labeling

Cracks from the original images were manually identified, and the region of interest was traced by hand using MATLAB (R2021a). The active contour function was applied to evolve the curves towards object boundaries. The region of interest was then masked with a white layer and placed on a black background, resulting in a ground truth; this process was then repeated for each image in the dataset. Although the user-defined ground truths are not 100% accurate, they provide a reliable approximation of the actual crack location and size because the tracing is done by hand on a pixel-by-pixel level. Figure 5 shows the captured image, model output, and ground truth for one of the dataset images. The concrete cube photos in the current research are labelled manually using visual inspection. While the bridge decks and walls images from the SDNET2018 dataset had already been labelled as either cracks or uncracks [33–35]

5.3 Experimental results

In this article, to evaluate the performance of the current model, a comparison is carried out between detected crack pixels and cracks traced manually. The performance of the proposed method is measured based on the precision and recall of both cracked and uncracked samples for bridge decks, walls, and concrete cubes. Through the experimental results, if the model correctly detected the crack, it is marked as true positive (TP). Similarly, if the sample is uncracked (N) and the model detects it correctly, it is considered to be a true negative (TN). If the model undetected

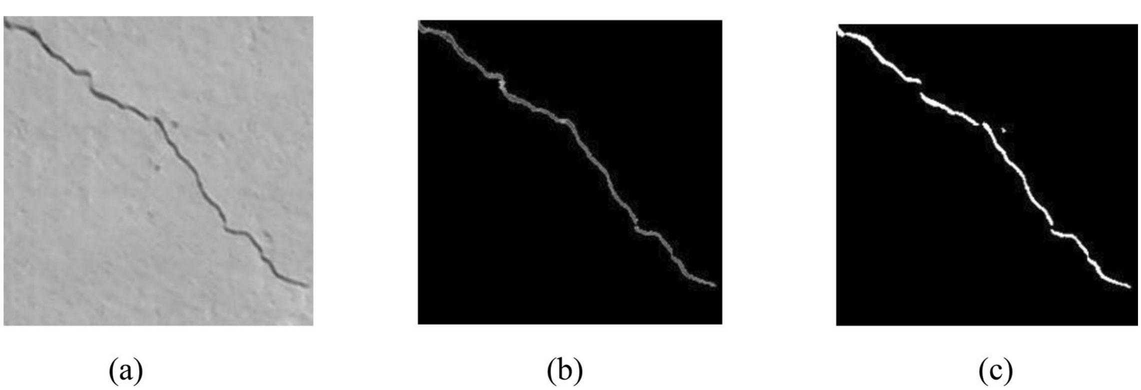


Fig. 5 Dataset image: **a** original image; **b** ground truth of cracked pixels; **c** detected cracked pixels

crack pixels, it's marked as false negative (FN). Finally, if the model incorrectly detects a crack pixel, then it can be marked as false positive (FP).

Accordingly, a number of evaluation factors for binary classification are provided below [36].

Precision is defined as the percentage of correctly recognised positive samples from the detected results, as shown in Eq. (1).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall represents the percentage of correctly recognised pixels among all existing positive samples, as shown in Eq. (2).

$$Recall\ or\ sensitive = \frac{TP}{TP + FN} \tag{2}$$

Specificity: represents the percentage of correctly recognised negative samples from the detected results, as shown in Eq. (3).

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

The accuracy is defined as the ratio of correctly classified images to the total number of images, introducing the overall efficiency of the classifier as shown by Eq. (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{4}$$

F-Score is a comprehensive measure of both precision and recall, and the calculation formula is shown in Eq. (5).

$$Fscore = \frac{\left(1 + \alpha^2\right) Precision \times Recall}{\left(\alpha^2\right) Precision + Recall} \tag{5}$$

When = 1, the F_1 is the common type of F-score, which indicates that a higher F_1 is a more effective performance model.

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

Intersection over Union (IoU): The proportion of the intersection of predictions and ground truth to the total area of predictions and ground truth as shown in Eq. (7)

$$IoU = \frac{TP}{TP + FP + FN} \tag{7}$$

Intersection over Union (IoU) is a performance measure and is also called the Jaccard similarity coefficient. It is widely used to compare the ground truth and predicted segmentation. It measures the amount of overlap between the predicted segmentation and the ground truth. The better the segmentation, the closer the value is to one; the worse the segmentation, the closer it is to zero [37]. An IOU value of 0.5 is used, and the following cases are applied:

- True Positive (TP): A correct detection. Detection with IOU ≥ 0.5.
- False Positive (FP): A wrong detection. Detection with an IOU < 0.5. Also, the prediction is regarded as FP if the object is not in the picture but is nonetheless detected by the model.
- False Negative (FN): A ground truth not detected [if IOU with ground truth = 0, wrong detection].

As such, the metrics of precision, recall, and intersection over union (IoU) belong to positive classes. They depend on TP values, which makes them a more suitable measure for crack detection since poor detection performance will lead to poor model output. High precision implies that the algorithm does not identify many uncracked pixels as cracked pixels. On the other hand, high recall gives an indication that the algorithm can successfully detect cracks. A higher IoU indicates that cracked pixels are accurately identified as belonging to the ground truth. Regardless of the effectiveness of the crack detection performance, all approaches will have a large number of TN.

The other metrics, specificity and accuracy, are highly sensitive to TN, which would represent corrected, uncracked pixels. Since there are simply too many true negatives, 100% accuracy will be achieved. Thus, it will not show significant differences between the different methods.

The average run time of the model is 16 s for a single image size of 667 × 738 pixels and 10.699 s for 256 × 256 pixels. The precision and recall for the cracked sample of bridge decks reached 98.32% and 99.43%, respectively. The model performance for detecting cracks in bridge decks is higher than that of both concrete walls and concrete cubes based on the F1-score measures of 98.87%, 97.43%, and 74.11%, respectively. Other results of performance measures are illustrated in Table 2.

6 Discussion

This article's proposed method verified its ability to detect crack propagation on three surface types (bridge decks, walls, and concrete cubes) with the performance measures shown in Table 2. The application images are collected from different image environment conditions and two types of camera resolution. Figure 6 shows the detection results of the proposed model on bridge decks and walls. It is evident that the combination of applying a bilateral filter and subtraction by using the Sauvola threshold is effective in getting more accurate crack detection on surfaces full of dents and noises, such as concrete cubes, which are the most challenging surfaces, as shown in Fig. 3.

The trade-off between precision and recall is common; typically, high precision results in low recall, and vice versa. This concept is very clear with concrete cube results. The low precision for concrete cubes gives an indication that the algorithm classifies crack pixels as background (uncracked). The low F1-score for concrete cubes is related to the high deviation between precision (59.83%) and recall (97.33%) that leads to a low F1 measure (74.11%). Thus, it gives an indication that the present model has less accuracy to detect cracks for concrete cubes correctly compared with bridge decks and walls. Nevertheless, the model achieved 97.33% for recalling crack pixels and missed only 2.67%, which is acceptable. On the other hand, the ability of the model to detect uncracked samples for concert cubes is better than that of wall samples.

Also, the model results give an indication that, despite the accuracy of the detection techniques, some cracks are always visible to the human eye, even though they are not evident in photographs. The errors and the different results between the three surfaces may be related to many reasons, such as the different resolution between the two cameras used in the proposed study. The resolution of the iPhone 7 Plus camera, which is used with concrete cubes, is less than that of the 16-MP Nikon camera, which is used with bridge decks and walls. Low resolution affects the ability to detect thin cracks with a width less than one pixel or the complex pattern of the crack to distinguish it from the background. In addition, the characteristics of the surface (shape, amount of dents and noises, voids, illumination, size, and width of cracks) affect the detection results. It is worth mentioning that the more dents and noise, the more processing will be required, leading to a longer running time. Also, the size of the image affects the model's running time. Those types of errors may require other sensing devices to be considered.

The proposed method adopted uses a bilateral filter with concrete cubes, which clearly preserves the edges and removes noise. The comparison between median filter, wiener, and bilateral is applied to the proposed method. Then, the Jaccard index metric is applied to measure the similarity between the predicted image and the ground truth. The results show that the bilateral filter outperformed the other two, as shown in Table 3 and Fig. 7.

Although deep learning networks are widely used for concrete defect detection, they are suffering from limitations. Deep learning networks required huge data for training, which is rarely available. Training a large amount of data

Table 2 Performance measure for proposed crack detection model

Surface type	Precision (%)	Recall (%)	Specificity (%)	Accuracy (%)	F1-score (%)	Running time (sec)
Bridge decks	98.32	99.43	95.83	97	98.87	10.69
walls	98.95	95.95	93	94.33	97.43	10.69
Concrete cubes	59.83	97.33	96.03	75.55	74.11	16

Fig. 6 **a** original image for crack (bridge deck); **b** original image for crack (wall); **c**, **d** crack detected for bridge deck and wall respectively

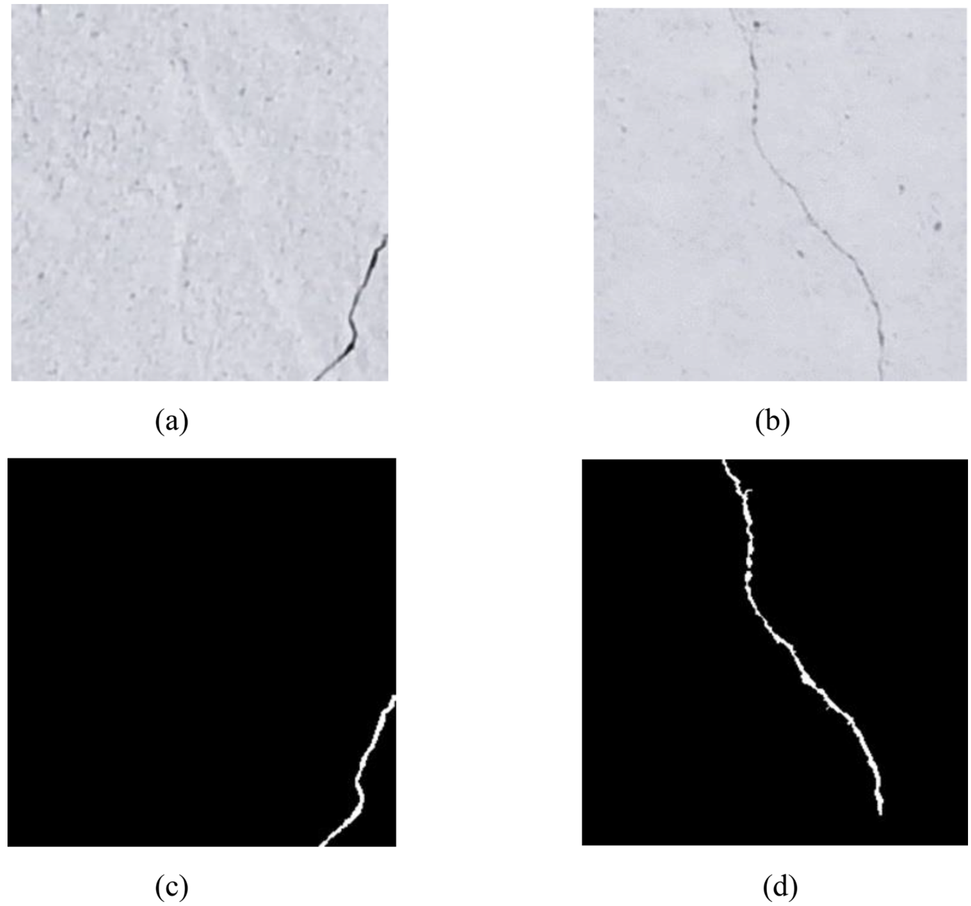


Table 3 Comparison between bilateral, wiener, and median filter

Image no	Jaccard Similarity %		
	Bilateral filter (%)	Wiener filter (%)	Median filter (%)
1	76.56	57.36	73.00
2	80.27	71.12	71.40
3	71.49	61.63	65.01
4	75.73	74.68	71.84
5	80.87	72.19	73.76
6	73.21	68.88	60.28
7	67.41	42.55	58.09
8	59.88	36.13	53.35
9	58.95	57.77	43.27
10	59.77	53.02	53.79

will lead to high computational costs because the training demands computational resources, including a powerful GPU and large memory. In addition, deep learning needs more time for training and can take weeks to completely train from scratch. The "black box" nature is a common disadvantage of the deep learning networks that leaves the users blind and prevents them from changing any parameters. On the other hand, the current study based on image processing required low cost and shorter running time compared with deep learning. Also, the characteristics of the present image processing technique are the transparency of the workflow compared with deep learning. Nevertheless, the output of image processing technology depends on the quality of images used. Thus, the poor image quality leads to inaccurate results.

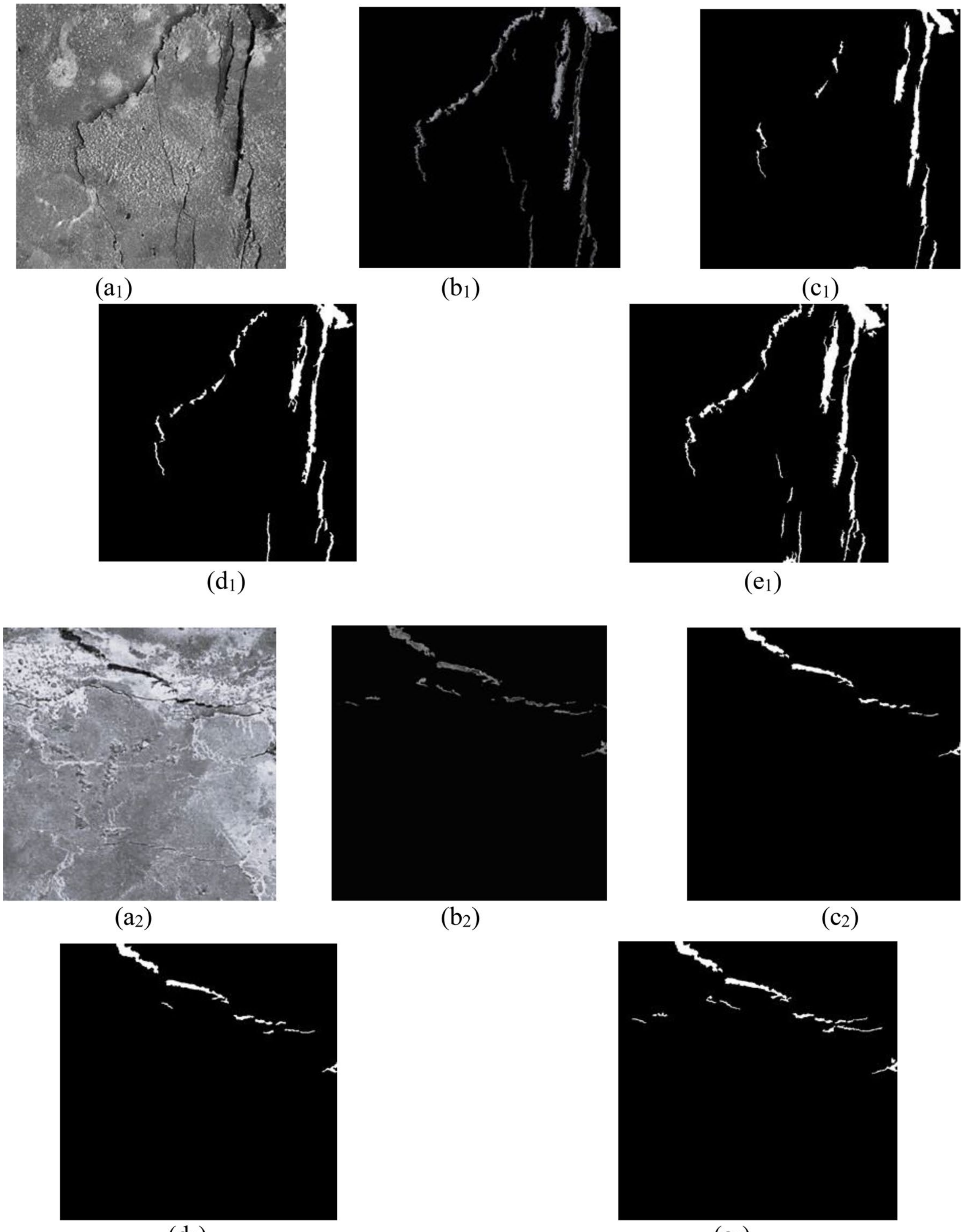


Fig. 7 Comparison of different filters for crack detection on concrete cubes. $\mathbf{a_1}$, $\mathbf{a_2}$Original image; $\mathbf{b_1}$, $\mathbf{b_2}$ Ground Truth; $\mathbf{c_1}$, $\mathbf{c_2}$ applying wiener filter, IoU 57.36%, 71.12%; $\mathbf{d_1}$, $\mathbf{d_2}$ applying median filter, IoU 73%, 71.4%; $\mathbf{e_1}$, $\mathbf{e_2}$ applying bilateral filter, IoU 76.56%,80.27%

The current methodology is compared and analysed with other approaches from the literature. The comparison is performed with the literature, where automated crack detection based on image techniques is used. The comparison is shown in Table 4 for different models that relied on the model's accuracy and running time with other factors such as surface type, type of camera, and the used model. The several models are applied to pavements, building walls,

Table 4 Performance comparison with other techniques from the literature

Author	Year	Surface type	The model	Type of camera	Precision (%)	Recall (%)	Specificity	Accuracy	F_1 score	Running time
Noh et al. [11]	2017	Bridges	Image processing	4 K resolution camera	80	90	NA	NA	NA	NA
Xu et al. [38]	2019	Bridges	convolutional neural network (CNN)	Phantom 4 pro	78.11	100	95.83%	96.37%	87.71$	286 m 33 s
Jang et al. [8]	2021	Bridge pier	Deep learning	Sony dsc hx 99	90.92	97.47	NA	NA	NA	NA
Safaei et al. [18]	2022	Pavement	Image processing	35 mm camera	89	83	NA	NA	86%	27 s
Yin et al. [39]	2023	Tunnel	Image processing	Industerial camera	92.58	93.07	NA	NA	92.82%	18 s
Proposed Model	-	Cubes	Image processing	Smart phone	59.83	97.33	96.03%	75.55%	74.11%	16 s
		Walls		16-MP Nikon camera	98.95	95.95	93%	94.33%	97.43%	10.69 s
		Decks			98.32	99.43	95.83%	97%	98.87%	10.69 s

tunnels, bridges, and concrete cubes. The majority of the work has been carried out on only one type of concrete surface. It is evident from the comparison that the propped model produces the best results.

7 Conclusions

This research implements a novel method of automated crack detection based on an image processing algorithm. The proposed method focused on the binary classification of crack and non-crack contours. This method is proposed to be generalised to different surfaces. All articles discussed crack detection on specific surfaces, such as walls, decks, or others. They are suffering and have limitations regarding whether their model could be applied to other surfaces or not. The current study discussed this point and tried to create a model that could be used on three different surfaces full of different dents and noises and in different environmental conditions. The current approach considers both the outdoor and indoor environmental conditions. In respect to crack detection, the model is applicable to detect cracks on bridge decks, walls, and concrete cubes based on F1-score measures of 98.87%, 97.43%, and 74.11%, respectively. The findings of the performance evaluation and comparison with previously reported work demonstrated that the proposed methodology has improved both the crack detection process and overall performance. The performance of the bilateral filer is higher compared with the median and wiener filters. Additionally, it is clear from the results that a crack detection algorithm created to detect flaws on a bridge's surface will not produce similarly precise results when tested for various concrete surfaces with cracks. The primary advantage of the suggested approach is the transparency of the workflow compared with deep artificial intelligence frameworks. The proposed algorithm can be a supportive tool for authorities to participate in crack detection systems to monitor and assess the current state of the infrastructure, such as bridges, tunnels, and highways. This is because photos acquired at a low cost can be directly subjected to the methodology. The proposed model is restricted to 2D images, and it is recommended that it be improved to be applied to 3D images to be able to measure the crack depth. In future work, the same approach can be adapted for other surface types, such as pavement. Furthermore, besides crack detection, retrieving crack properties such as width is highly needed for condition assessment in future studies. In addition, this method will be used in condition assessment for reinforced concrete bridges to create quantitative damage assessment using a new technique.

Author contributions Yasmin M. Shalaby, Mohamed Badawy, Gamal A. Ebrahim, and Ahmed Mohammed Abdelalimd have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability Any data used during the study can be accessed when requested.

Declarations

Competing interests The authors declare no competing interests.

Appendix

See Fig. 8.

Fig. 8 Coding by Matlab for crack detection

```
% Read in original image, with white lightning on black background.
baseFileName = '7118-162.jpg';
fullFileName = fullfile(pwd, baseFileName);
grayImage = imread(fullFileName);
% Get the dimensions of the image.
% numberOfColorChannels should be = 1 for a gray scale image, and 3 for an RGB color image.
[rows, columns, numberOfColorChannels] = size(grayImage)
if numberOfColorChannels > 1
    % It's not really gray scale like we expected - it's color.
    % Use weighted sum of ALL channels to create a gray scale image.
    % ALTERNATE METHOD: Convert it to gray scale by taking only the green channel,
    % which in a typical snapshot will be the least noisy channel.
    grayImage = grayImage(:, :, 3); % Take Blue channel.
else
    grayImage = grayImage; % It's already gray scale.
end
% Now it's gray scale with range of 0 to 255.
title('Original Image', 'FontSize', fontSize);
% Binarize the image.
lowThreshold = 0;
highThreshold = 180;
% Interactively and visually set a threshold on a gray scale image.
% https://www.mathworks.com/matlabcentral/fileexchange/29372-thresholding-an-image?s_tid=srchtitle
[lowThreshold, highThreshold] = threshold(lowThreshold, highThreshold, grayImage);
mask = grayImage >= lowThreshold & grayImage <= highThreshold;
% Bridges unconnected pixels (morphological operation).
mask = bwmorph(mask, 'bridge');
% Fill holes.
mask = imfill(mask, 'holes');
title('Mask', 'FontSize', fontSize)
```

```
% Find the areas of all the skeletons.
props = regionprops(mask, 'Area');
allAreas = sort([props.Area])
% Extract only skeletons longer than 60 pixels.
mask = bwareaopen(mask, 60);
% subplot(2,3, 3);
imshow(mask)
```

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