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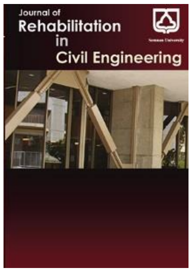

Evaluation of Different Methods of Machine Vision in Health Monitoring and Damage Detection of Structures

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ABSTRACT

The application of Digital Image Processing (DIP) and computer vision is increasing in civil engineering branches nowadays. By implementing DIP methods, analyzation, and detection of intended objects and elements on the images will be done. So, these methods can be used for automatic inspection and decreasing manpower's direct controls on structures and infrastructures. This paper will study the application of DIP such as health monitoring and damage detection in structures. After reviewing various researches in this field, a classification including five classes was done. These classes including 1-identification and evaluation of the crack, 2-identification and evaluation of defects in steel structures, 3-identification and evaluation of other imperfections and defects, 4-deflection, deformation, and vibration assessment, and 5-identification of texture, dimensions, elements, and components. The researches also are classified based on various aspects such as the implemented methods, specification of images, the performance of the method, and so on. Finally, after investigating the shortage of researches, the future suggestion for researchers was made.

1. Introduction

The monitoring process of structures and infrastructure to assess their physical condition and status is conducted by a group of trained supervisors, by which the level of risk or existing deficiencies is detected. This process, that performed periodically and regularly, to ensure proper operation during and after construction or natural disasters, is always faced with challenges. Individual judgments and sometimes human errors in

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measurements reduce accuracy [1]. Also, some dangers can lead to irreparable casualties. Examples of this are the incidents and casualties that occur every year around the world. One of the other issues in this regard is the considerable amount of time and money spent on this, which should be sought after.

Due to the increasing of DIP application in various sciences as well as the development of its tools, such as digital cameras and scanners, this science has also entered the field of civil engineering and has been used by engineers in this section. For example, in the health monitoring of structures, the problem of machine vision and image processing is one of the inseparable tools of this field [2]. Implementation of DIP methods gives us the advantage of taking pictures of different parts of a structure and processing them using a computer and making the right decision about the status of a structure without incorrect engineering judgments. In addition to having the appropriate precision, this will save us time and money too.

DIP and Computer vision constitute many methods and tools which selecting and using the correct tools in this area, require special knowledge and experience. Fig. 1 shows the overall picture of the computer vision from the preliminary to the most advanced stage schematically [2]. There are also methods of DIP based on 3-D processing of data, known as 3D point clouds. Here, the approach is to first capture images from different angles with the help of the camera from the subject, then combine the images with the help of some tools and form the 3D model of the subject, and finally process the model [3-6].

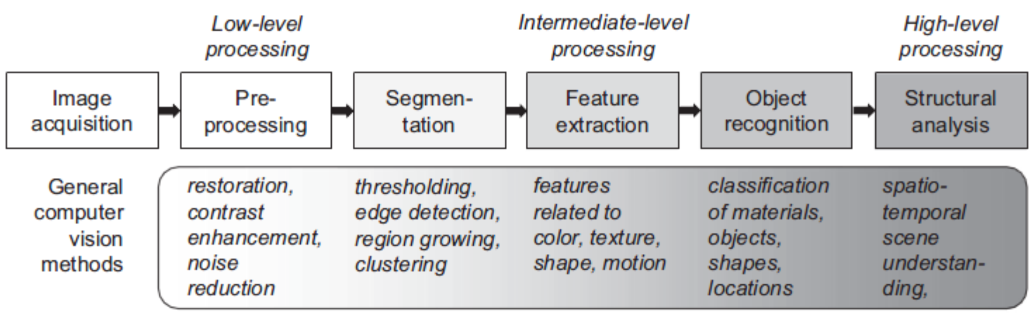

Fig. 1. Categorizing general computer vision methods [2].

The researchers in DIP fields for determining the performance of their works, measure some factors such as accuracy, precision, recall, F-measure, or error. Precision refers to the concept of consistency, or the ability to group well, while accuracy refers to how close we are to the target, and accuracy refers to how close we are to a specific target on average [7]. Recall (also known as sensitivity) is the fraction of the total amount of relevant instances that were retrieved and evaluated the rate of completeness of detection [8]. In the term of image processing, there are other parameters for calculating performance as F-measure that sometimes known as F-score or F1, that is a weighted harmonic mean of Recall & Precision [9]. These parameters are calculated by Eq. 1 to 4.

$$precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{1}$$

$$Accuracy = \frac{true\ positive + true\ negative}{true\ positive + true\ negative + false\ positive + false\ negative} \tag{2}$$

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \tag{3}$$

$$F-measure=\frac{2*precision*recall}{precision+recall} \quad (4)$$

True positive means cracks detected correctly, True negative means the ones that truly are not detected, False positive means cracks detected mistakenly, and False-negative cracks that are not detected [7].

In this paper, the studies which have been carried out on the application of DIP in civil engineering are introduced and classified in separate sections. In each section, to clarify the discussion, a table is presented to compare various researches. This table demonstrates the subject, method, accuracy, image, or video specification and implemented tools in each article and research. At the end of the article, a series of results and conclusions have been carried out, and finally, suggestions are provided for future works by the DIP.

2. State of research on various application of DIP

In structures and infrastructure, there are various defects such as cracking, rotting, rusting, settling, layering, wear, erosion, and other damages which are occurred depending on the type of structure and infrastructure and the material components of them. On the other hand, some of the damages are identifiable by the processing of the image and some are not. In this research, after reviewing various types of studies, to organize them, classification based on their topics is done which its result is the formation of five categories with the following titles: 1-identification and evaluation of the crack, 2-identification and evaluation of defects in steel structures, 3-identification and evaluation of other imperfections and defects, 4-deflection, deformation, and vibration assessment and 5-identification of texture, dimensions, elements, and components.

In each section, a table is presented to compare various researches. This table consists of six columns that are reference, subject, method, image or video resolution, performance, and implemented tools in each article. The accuracy column identified the percentage of Accuracy, Precision, Recall, F-measure or Error in each research that is demonstrated respectively by “A”, “P”, “R”, “Fm” and “E”. Image or video specification expresses the resolution of the image in terms of megapixel, and the video rate in terms of frame per second (fps). Tools column demonstrates the methods such as supervised or unsupervised learning methods like Artificial Neural Network (ANN), Convolutional neural networks (CNN), Support Vector Machine (SVM), Self-Organizing Map (SOM), Kohonen map, etc. if there is in every article.

One of the recent developments in the field of image processing is the use of deep learning tools, especially convolutional neural networks (CNN) in identifying the desired parameters. In this way, between the inputs, which are image; And network output, complex relationships are established using nonlinear parametric functions and nodes [10]. CNN usually consists of convolutional layers, a Max-pooling layer, and fully-connected layers [11]. The application of deep learning in each area will be discussed separately in the relevant sections. Some columns in each table are identified by the (-) sign. It means that the research has not addressed that issue.

2.1. Identification and evaluation of the crack

The studies carried out in this section have the largest share of articles in the field of DIP in civil engineering, which are divided into two general categories. The first group only identifies and detects cracks in the images, and the second one evaluates its characteristics and derives parameters such as length, width, and depth of the cracks. Each of these two categories can be distinguished, depending on what kind of structure or infrastructure it is. For example, some articles have identified and evaluated cracking on the road and road pavement, and others on concrete surfaces such as columns or some on the soil. The following are categorized into separate sections.

2.1.1. Detecting and evaluating cracks on the road surface

One of the usages of DIP techniques is the detection and evaluation of cracks on road surfaces and pavements. In these researches, the factors such as width and length of cracks or deteriorations are evaluated. Table (1) is a brief summary of the DIP application in this field. For more review on the researches in the field of crack identification in asphalt pavements, Zakeri et al [25] is referred.

Table 1. Detection and evaluating cracks on the road surface.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[12]	Road crack detection	The focus was more on images that were difficult to detect because of their massive texture. The way was to first divide the images of the road into smaller rectangular parts, then a collection of data is collected as a sample of these pieces and analyzed in terms of texture and color properties. To extract region from background Kohonen map is used. Combining these two categories prevents the identification of some edges and cracks in the images. The images used in this article were made on a sunny day and the camera was located at a steady distance, perpendicular to the road surface. The applied method is independent of the capturing condition. The results showed that the proposed algorithm reduces the false positives in crack detection.	2448*3264	P=77 R=73	Self organization map (SOM)
[13]	Road crack detection	an image enhancement was initially carried out. This operation involves removing all types of noise. After the image enhancement operation, image segmentation is done to extract the crack information. To do this, there are two methods of threshold and edge detection. After completing these two steps, information on cracks as much as possible comes from the background. Then photos are ready to be detected for cracks. For this purpose, an artificial neural network will be used. In the preprocessing phase, problems caused by environmental conditions in images, such as ambient light, are eliminated. After this step, each image is split into several units, and in a screening operation, the units are classified according to whether there are cracks or not. Only the units with cracks are transmitted to the next stage where graphical information is converted into data for understanding the existing cracks. Results showed that the proposed method is a suitable tool for pavement crack identification and is effective for all kinds of cracks and are acceptable for engineering application.	832*576	A=94	Artificial Neural Network

[11]	Pavement crack detection	A deep learning approach was presented that can implement road pavement with different conditions. To learn the structure of the cracks, a Convolutional Neural Network (CNN) is applied to a collection of raw photos without the need for preprocessing. For this purpose, a small fraction of the cracks were extracted from the images and introduced as input to the network to prepare a large set of data for learning. Then CNN was trained and crack identification was modeled to classify the problem. It should be noted that the network is trained according to two categories of RGB images and gray-level images. The presented method is compared with five existing methods and experimental results showed that it outperforms the other methods. Fig. 2 shows the structure of CNN.	320*480	P=92 R=88 F=90	Deep learning-Convolutional Neural Network (CNN)
[14]	Pavement crack detection	An approach for automatically detecting cracks in digital images using the Gabor filter is presented. Using the Gabor Filter, the cracks can be distinguished in different directions. The proposed method concentrated on pavement images with high levels of surface texture and the detection precision up to 95% has been reported.	1070*1080	P=97 R=78	-
[15]	Road crack detection	A system for automatic identifying cracks is devised. This identification is based on a sample and a template. In this way, a subset of the photographs is automatically selected and used for non-supervised learning. Then, based on the identification of the cracked blocks, the width of the crack is estimated.	1536*2048	P=91.6 R=95.5 F=93.5	Non supervised learning
[16]	Crack identification in bridge	For identifying cracks on the deck surface of concrete bridges a histogram-based classification algorithm along with the SVM technique is used. After collecting and analyzing high-resolution images, feature extraction using the training set images, and statistical inference algorithms are employed for crack identification. The results demonstrated sufficient feasibility of this method.	-	A=76	Support Vector Machine
[17]	Pavement crack detection	A preliminary study on the modeling of the formation of cracks in concrete pavements on digital images is done. particularly on short and longitudinal cracks as well as the profile of the fittings and discontinuities of concrete pavements using reflection changes. The model reveals that a clear and explicit relationship between the width and depth of the crack as well as the highest intensity of the pixel's contrast is visible in the images. The presented method has definitive potential to evaluate shallow cracks and can differ cracks from other defects.	-	-	-
[18]	Pavement crack detection	A system is presented which uses image processing to extract road pavement characteristics and features. A Neural network approach is used for the detection of regions of images with defects and classifying them into separate types. The results showed great potential for using the proposed method as an automatic road pavement survey instrument.	3648x2736 pixels	A=89.2	ANN
[19]	Road crack detection	A neural network-based approach for classifying road images into two general categories is proposed and divided them into crack and without crack. At first, the density and histogram of the images are extracted. These attributes are then used as inputs in a back-propagation neural network and divide the images into two non-cracked and cracked categories. After this classification, the cracked images are again passed from another neural network to determine the type of cracks in the images. The results confirmed that the proposed method is an appropriate crack detection tool.	-	A=91	ANN

[20]	Classification of asphalt pavement crack	A smart model presented for automatic detection and classification of asphalt pavement crack. Using image processing techniques, the noises in the image eliminated and cracks were identified. After establishing cracks map, using Projective Integral, different types of crack such as longitudinal, transverse, and alligator characterized. The properties of cracks are determined by the Otsu thresholding algorithm and Min-Max Gray Level Discrimination. The results indicated that using the projective integral better classification of cracks can be done.	150*150	A=96	SVM – Artificial Bee Colony
[21]	Pavement crack quantification	A model presented for measuring the length and width of pavement crack based on the AASHTO PP67-10 protocol. For accurate measuring of crack width, an orthogonal projection method is developed based on the cracking skeleton and contour and the width of the crack in each pixel along the skeleton calculated. Results showed that the presented method can be used to investigate the spalling distress in concrete cracking or joints.	-	-	-
[22]	Road crack detection	For classifying images a CNN is trained in this paper. A low-cost smartphone is used for collecting 500 images and quantitative evaluation was conducted on them. The proposed method provides very good crack detection performance when compared with features extracted with the existing hand-craft method	3264*2448	P=87 R=92 F=89	CNN
[23]	Pavement crack detection	A CrackNet one of the architectures of CNN is used on asphalt images. This method isn't dependent on width and height through all layers. The feature maps are input and predicted class scores are output data. 1800 asphalt images are used for training and 200 images for testing the CrackNet. This method had better performance than traditional machine learning techniques.	-	P=90 R=87 F=88	CNN
[24]	Asphalt texture recognition	The authors employed three different algorithms to extract the feature vector and statistically analyzing the texture of six types of defects in asphalt pavement. At first 2nd order textural statics using GLCM in the spatial domain, and then, the 2nd descriptors of images local binary patterns were extracted in spatial and wavelet transform domain. The defects classified using a combination of the K-nearest neighbor method and Mahalanobis distance. The results demonstrated that two stages arranging of the gray levels of the defected images edges by applying wavelet transform and the local binary pattern had a very good performance in comparison with other algorithms.	14 Mp	A=61 A=75 A=97 respectively.	K-nearest neighbor

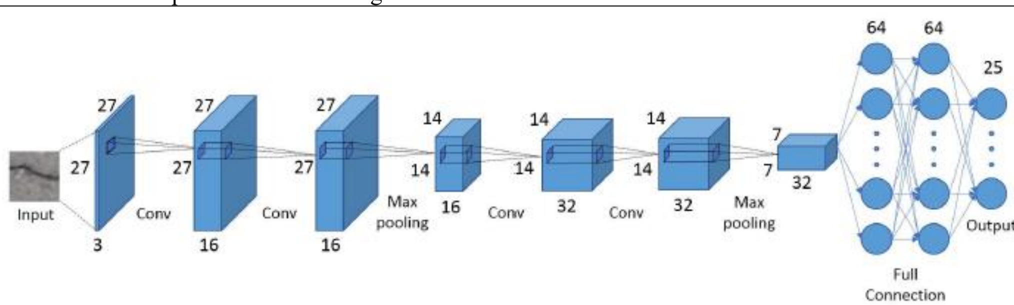

Fig. 2. The structure of CNN [11].

2.1.2. Identification and evaluation of cracks in bridges

Crack identification in bridges is another usage of DIP method that are expressed in Table (2). The mean of “Stereo” in Table (2) is using 2 cameras in different locations for taking pictures of an element as shown in Fig. 3 [26].

Table 2. Identification and evaluation of cracks in bridges.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[26]	Thin crack detection in bridge pier	A method is presented for analyzing images in which they can identify small cracks in reinforced concrete specimens. The proposed method consists of two processes including the operational process and photo analysis process. The operational stage involves level processing, installation of two fixed cameras (stereo), image capture and adjustment, and eventually capturing the desired photos. Level processing is meant to process surface, paint, or mark on concrete surfaces to easily monitor and observe surfaces. Also, to analyze deformations, an image of the initial state of the element is needed. For this reason, due to the constraints mentioned above, this method is more suitable for lab work. The proposed method was implemented on the piers of a bridge and was able to detect cracks width less than 0.2 pixel. The results of the proposed method showed that this method can capture surface cracks before dark crack lines visible to the naked eye appear.	5184*3456 4752*3168	-	-
[27]	Crack properties in bridge	This paper by employing a 3D visualization of crack patterns presents a process for image capturing and projection, crack segmentation, change detection, and data fittings. To divide cracks and gain their specifications some functions, such as crack identification and quantification were designed. By comparing the images at various times this method can follow the crack trends. Also, an artificial neural network model was developed to relate the crack depth to its width. The model could be implemented in a bridge management system to decide for the condition assessment of concrete bridges.	-	E=12.44	ANN
[28]	Bridge crack extraction	An image-based methodology for identifying and extracting crack characteristics on bridges is presented. three basic trends to overcome the problems of light interference, inappropriate shape, and fluctuation is expressed. Initially, the images obtained from the bridges were processed and after removing noise from them, the crack properties were extracted. In the second step, suspicious cracks were extracted using a pixel gray value comparison technique. Finally, incorrect cracks were extracted using the Pixel Gray-Value Comparison technique. The results showed that the proposed methodology has sufficient robustness and efficiency for crack detection.	-	-	-
[29]	Bridge inspection	A method is presented that consisted of two stages. First, the crack detection and tracking algorithm in a way that can measure crack characteristics, such as its width and length, and secondly, testing an algorithm conducted on a real bridge. A ground robot is used to collect images and using the average filter, the smoothing operation was carried out in its preprocessing stage. Then morphological operations, such as expansion and thinning, were performed on the crack points to identify the crack elements. The method was compared with 3 methods of Fujita, Sobel, and canny that were consistent with the results of these three methods. Results indicated that the suggested method has good preformation and also is effective for searching crack lines and measurable properties of bridge structures.	640*480	A=94.1	Robot
[30]	Crack Identification in Bridges	The performance of four crack detection methods are compared. These methods are fast Haar transform, fast Fourier transform, Sobel, and Canny. The results indicated that the fast Haar transform is more accurate than the other.	640*480	A=86	-

2.1.3. Identification and evaluation of crack and automatic monitoring after the accident

The efforts made after an incident for recovery and reconstruction are slow and laborious and may be at risk. A system that can detect injuries and defects in critical members such as columns before people enter a damaged structure can be very helpful and can save lives from potential hazards [5]. So, in some cases, a robot shooting method is also proposed to reduce the potential risks faced by individuals. Table (3) demonstrates the researches in this field.

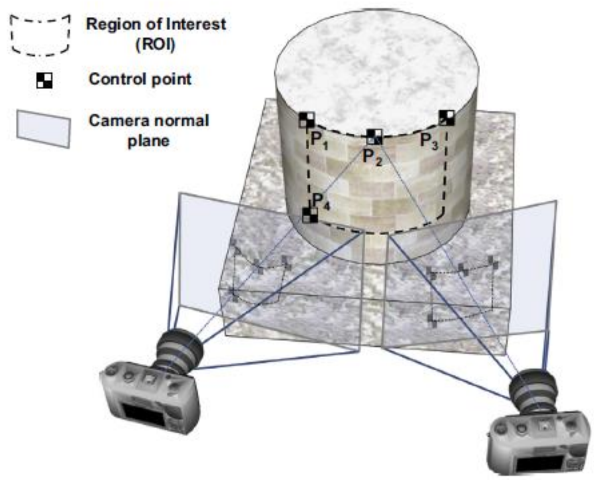

Fig. 3. Stereo photography model using two cameras [26].

Table 3. Identification and evaluation of crack and automatic monitoring after the accident.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[٥]	Post-disaster building assessment	In this paper, a system that identifies and analyzes three-dimensional images, cracks, and injuries on a 3D basis is proposed. At first, images are collected around the target object to reconstruct. These images will be used in a structure-from-motion algorithm for detecting feature points. After isolating the building elements, a colored mesh model is created and trimming is performed on it. Then the crack detection begins. A robot shooting method is also proposed to reduce the potential risks faced by individuals. Results showed that the presented algorithm performed well and identified cracks successfully. Of course, this method is not capable of detecting vertical cracks less than 5 mm wide, because the three-dimensional model of these cracks is not constructed.	1600*2900	Crack measurement: E=2.2 Column detection: E=4	Robot
[31]	Post-earthquake inspection	A framework for the automatic rapid post-earthquake assessment of buildings is provided. In the presented method, only the columns in the concrete bare frame are examined and visible damage such as cracks and openings are identified in the columns by machine vision. Then, the damage index is measured concerning the dimensions and direction of the column, and so the status of the column is determined with the help of the Damage Index. So far seven parts of the framework have been implemented, tested, and validated. The success of all pieces of the proposed framework with high accuracy shows that the whole framework will be successful too.	-	column recognition: P=89.7 R=84.3 Crack recognition: P=64.2 R=91.8 Spalling recognition: P=81.1 R=80.2	-

2.1.4. Identification and evaluation of cracks in concrete surfaces

The big part of researches in DIP usage is about crack evaluation in concrete surfaces. Table (4) expresses these researches. Various methods such as preprocessing for noise elimination, light and brightness correction, and also different edge detection methods like Sobel, Canny, Otsu, and Kittler are used.

Some research used three-dimensional scene reconstruction techniques. To create depth perception, the 3D structure of a scene has to be recovered. First, several overlapping images of the object are captured from different views. The Structure from Motion (SfM) approach aims to optimize a 3D sparse point cloud and viewing parameters simultaneously from a set of geometrically matched key points taken from multiple views [32].

Table 4. Identification and evaluation of cracks in concrete surfaces.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[33]	Crack detection	A new approach is presented to detect cracks in the photos of concrete members. This method consists of 3 steps. In the first step, the RGB image is converted to a gray-scale image, and the edge of the image and the Sobel filter are used to identify the cracks. In the second step, a proper threshold is used in binary images, and all of the pixels of the image are divided into two background and foreground categories. Then a region is specified, its area is calculated and the surface filters are applied to it, and then the next area is examined. In the third step, the Otsu method will be used to identify the main cracks. This method detects the cracks with high accuracy.	5184*3456	-	'
[34]	Concrete damage detection	An automated classification method developed to more accurately identify crack, in different environmental conditions, using a class based on Canny edge detector and K-Means methods. The results demonstrated that the presented method can classify accurately and is more robust than established edge-based approaches.	-	A=93.3	'
[35]	Crack detection in reinforced concrete	An identification method, combining digital image correlations and Acoustic Emission is created. This method identifies, based on a very accurate measurement of surface displacement, debris, and cavities associated with the cracks. In addition to this method, to investigate the mechanism of failure, the acoustic emission that resulted from internal damage was used for analysis. The results showed that the measured values more or less agree with the calculated values at low strains and for the smallest beam size.	1000*1000	-	'
[36]	Crack detection	A crack detection algorithm is presented based on DIP. By preprocessing the components of the image and extracting the profile, the information about the crack photo is obtained. In this paper, the segmentation threshold method was used after smoothing the input images.	4752*3168	-	'
[37]	Crack detection in noisy concrete surfaces	A system for automatically detecting cracks in images of noisy concrete surfaces is devised. The system consists of two stages of preprocessing and two identification stages. The shadows were removed with the help of the median filter. Then, using a multi-scale linear filter and Hessian matrix, the cracks are determined. The combination of probabilistic relaxation and adaptive thresholding obtains higher sensitivity or specificity than the global thresholding. The proposed method presents a high accuracy.	3872*2592	-	'

[38]	Crack detection in concrete structures	A picture-based system devised for crack identification. Crack detection images are categorized into four categories: Integration Algorithm, Morphological Approach, Percolation Approach, and Practical Technique. Shadow correction operations in photographs are done using an integrated algorithm, indeterminate prediction of cracks by penetration method, detection of fine cracks by morphological approach, and finally extraction of precise specification of cracks by practical technique. The result indicated that the presented algorithm is appropriate for pre-processing and the morphological approach performs better than Otsu's method. It must be mentioned that some micro-cracks in images will not be detected. The percolation-based method is suitable for unclear crack detection.	-	-	-
[39]	Crack detection and measurement	A system based on the concept of machine vision is developed to automatically measure the cracking process. The algorithm receives the image as an input and outputs a photo of several red components representing the cracks. The pixel position of the red components is stored inside a vector and passed through a crack measurement algorithm. Depending on the position of the pixels, the algorithm estimates the number of pixels and ultimately gains the dimensions of the crack. The analysis demonstrated that the error is small and compared with other methods, the presented methodology fares very well.	3872*2592	Crack length: E=8.59 Crack width: E=7.51	Robot
[40]	Cracks detection using depth perception	A crack identification system was proposed for extracting a complete crack map using three-dimensional scene reconstruction techniques, morphological operators, and machine learning. Results showed that the presented method is suitable for using mobile systems, such as unmanned aerial vehicles, for crack inspection in inaccessible regions.	-	A=79.5 P=78.4	ANN- SVM
[41]	Flexural cracking behavior	A laboratory work was performed on the flexural behavior of three types of concrete. They performed three types of conventional-strength concrete, high-strength concrete and high-strength reinforced concrete, using a Digital Image Correlation technique, detecting, expanding, and measuring crack widths and strain measurements. strain measurement and analysis using strain gauge (LVDT strain gauges and sensors) and DIC method are performed. Results showed that the DIC method is an effective tool for measuring displacement and strain because there is rather good agreement between the LVDT and the DIC technique. [42, 43].	-	-	-
[44]	Crack detection in concrete surface	A model extracted for evaluating crack width based on Stereo Vision. In this approach, unlike other methods, two cameras are used. Using the two cameras, they use the Canny-Zernike algorithm to get the profile of the crack margins. Then, the width of the crack was measured by using the Minimal crack edge detection technique, which measured the accuracy of the curvilinear curve precision. Results indicated that the presented approach compared with the crack width gauge or the vernier caliper can measure the crack width accurately.	2048*2048	E=5.4	-
[3]	Concrete crack assessment	With the 3D scene reconstruction, identify the three-dimensional position of the crack margins. First, using image processing techniques, the precise specifications of the cracks were taken from two-dimensional images, after the removal of the noise. Then, using a series of crack images, a 3D reconstruction was performed and evaluated using a 3D cloud point method. The results indicated that the proposed method can offer a new way for the health monitoring of concrete structures.	-	E=2-32	-

[45]	Automatic crack monitoring	An integrated approach presented for auto-crack monitoring using photogrammetric and image processing methods. In the first case, using photogrammetry, the crack map is set and then the image processing is implemented on it. Verification and calibration are done using an empirical sample made. This article defines the pattern of the crack and its characteristics, including the width, length, and area of the crack at each stage of loading to complete failure of the sample. The presented method can be used for monitoring the whole surface of the concrete from crack starting to fail.	5184*3456	-	-
[32]	Crack detection for condition assessment	Two-dimensional images are processed in consideration of their geometric characteristics, and the details of the crack are determined automatically. This system extracts the crack from the background. The feature that distinguishes this article from others is the ability to identify cracks in any image taken at different distances with each focal length. In this way, many pictures are taken from the location, from different directions and views. Then, with the help of methods, the scatter plot structure, as well as the location of the camera, its orientation, and other internal features of each perspective are determined. By calculating the reconstructed 3D model, the depth value is determined. The classification is then identified and performed using a trained model to identify the true cracks. The results indicated that this system, as opposed to the edge-base technique, extracts the entire crack and the obtained map can be used for crack thickness quantification.	-	A=79.5 P=78.4	ANN- SVM- Nearest neighbor
[46]	Characterization of concrete cracking	An innovative method called MCRACK introduced, whose purpose is to determine the abstract features automatically, using digital image processing. The steps of this method, which is only applicable to laboratory samples, are to prepare the sample first and install a crack width ruler on it to obtain precision. Then, in the process of loading with a camera perpendicular to the surface of the sample, it is photographed and for the clarity of most discontinuities, the images are converted in binary form. After the failure of the sample, all images are analyzed using different edge detection algorithms. The crack characteristics including length, width, and surface are calculated, and finally, the crack profile is plotted. It is concluded that 'MCRACK' reduced working time and has high reliability.	1000*1000	-	-
[47]	Crack detection in buried concrete pipe	A search was performed about the crack in a two-step approach. The first step involves preprocessing and combining images, and the second step defines the cracks through the components of the image using a clean-up and linking technique. The overall performance of the proposed method is good for underground pipe images with minor, major, and multiple cracks.	4752*3168	A=96	-
[48]	Crack detection in underground pipeline	A three-step method was developed for detecting cracks in high-contrast images. The curvature assessment and computational morphology to identify cracks in a noisy environment are used. Using linear filtration, after evaluating the curvature, cracks can be detected from the background. The results compared to other detection methods, showed that the presented method under varying background and color performs quite well.	3872*2592	A=94.3	-
[49]	Damage assessment In masonry structures	A new digital image correlation based approach was proposed to assess damage to building structures at the junctions. To this end, a large laboratory specimen was created that represents the soil conditions and structure, as well as the building structure. An injury index was developed concerning the total length of the crack, to complete the evaluation of the crack. The uncertainty and accuracy of the proposed index were evaluated using Monte Carlo simulation. Results indicated that the proposed indicator is capable to evaluate the local damage of structure so it is more useful compared to the conventional methods.	-	E=3	-

[50]	Determining crack intensity of soil	Using MATLAB software, an image-based program developed for identifying and analyzing soil layers on a laboratory scale and detecting the cracks and determining the severity index of compacted clayey soil.	3872*2592	E=10	-
[51]	Concrete crack detection	A method using AlexNet and CNN is designed using 60000 images for training and testing. The adaptability of the method is tested on 205 images. Also, a smartphone application is designed for crack detection. The results indicated a high accuracy in crack detection.	3120*4160	A=99	CNN
[52]	Crack detection	For detecting cracks on concrete, a method is proposed using CNN without calculating the features of the defect. 40000 images are used for training and 55 images of 5,888 × 3,584 pixels are used for testing. The results indicated that this method has better performances than the Canny and Sobel methods.	256*256	A=98	CNN
[53]	Crack classification	A method based on CNN is presented for crack detection. This method classifies cracks and non-crack noise patterns. For extracting cracks image binarization is used in the training stage and then speeded-up robust features CNN is used for classifying. The results showed high accuracy for crack detection.	227*227	P=94 R=96 F=95 A=98	CNN
[54]	Damage detection	A method is proposed using CNN for detecting 6 various types of defects such as cracks and spalling on concrete and asphalt, exposed rebars, steel corrosion, fracture, and fatigue cracks. The output of this method is a segmented image that shows the location of damages. The results indicated high accuracy for the presented method.	600*600	A=87	CNN
[55]	Crack detection	In this research, image binarization is studied for crack detection focusing on optimal parameters. Also, the performance of 5 various binarization methods is compared. A comparative analysis is done with various conditions based on the crack length and width measurement and computation time. The results showed that the determined optimal parameters for each method were accurate enough for crack detection. This method has been used before evaluating cracks in bridges [27, 56]and tunnel cover[57].	18.1 MP	E=11	-

2.2. Identification and evaluation of defects in steel structures

Articles that identify and evaluate defects in steel structures can be classified into two categories. The first category seeks to identify common defects in welding. The most evaluated welding is Friction Stir Welding (FSW) which is a solid-state joining process that uses a non-consumable tool to join two facing workpieces without melting the workpiece material[58]. Also, an assessment of welding in the gas pipeline is done in some research. characteristics of different areas in welding such as the mixing region, the region affected by the heat, the base metal, and the weld line are determined by DIP. The second group seeks to identify other damage on steel members such as cracking and corrosion, each of which will be discussed below. Table (5) shows the researches in this field.

Table 5. Identification and evaluation of welding defects.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[58]	Classification and identification of surface defects in FSW	Various surface defects in the FSW, identified, studied, and categorized using image processing. Detection of defects is done using image pyramid algorithms and image reconstruction. Also, using the same algorithms, due to the unique feature of each of these defects, the defects are classified into different types of void, groove, cracks, key-hole, etc. The vertical diagram of intensity and area of defects are presented to them to correctly identify the location and analyze them. To identify the void, groove, cracks, key-hole, rapid, and simple convolutional transformation is used and for identifying other defects, other methods such as the Sobel edge detection method are applied. The proposed method will be suitable for increasing weld quality, online feedback of welding parameters, monitoring, and controlling the weld.	2231*500	-	-
[59]	FSW classification	An attempt was made to monitor the friction-driven opacity welding process using welding surface images. In this regard, the discrete wavelet transform has been used on images of this type of welding to extract useful features that can be used to describe good and defective welding. Also, the obtained characteristics are used as inputs in a supported vector machine-based classification model for classifying a good and defective welding classifier. In this research, on the surface of the weld images, using the histogram equalization method, a pre-processing operation was performed to remove the non-uniformly illumination effect of images. Then, pre-processing images of the welded areas were divided into several sub-regions of uniformity. Subsequently, the images of each sub-area were evaluated and three attributes, called energy, variance, and entropy, were obtained. Results showed that the Gaussian kernel performs more accurately compared to the polynomial kernel. Also, the presented method is flexible and can be used for online monitoring.	280*840	Gaussian: A=99 polynomial kernels: A=97	SVM
[60]	Zone wise local characterization of weld	Characteristics of different areas in welding such as the mixing region, the region affected by the heat, and the base metal determined using the digital image correlation method. A method of micrographic observation and image processing is used to identify different weld regions and compare the behavior of welded regions in the plastic and elastic region with the intact area. The stress-strain diagram for all regions was also obtained. Parameters such as Young's modulus, Poisson coefficient, yield stress, strain hardening, and resistivity coefficient have been investigated. The proposed methodology was found to be effective in the prediction of local constitutive properties over the weld zone.	2448*2048	-	-
[61]	Assessment of FSW	The surface-level images of the friction-induced brittle disturbances were evaluated by image processing techniques. By defining a suitable area for high-quality welding as well as defective welding, X-ray images are processed digitally. The welding line profile and the bootstrap contour map are plotted. Changes in the slope of the weld line profile as well as the contour display along with a defective welding point and weld area help to assess the quality of the weld. The obtained results verified by Acoustic Emission data were acquired during FSW.	4288*2848	-	-
[62]	Monitoring of high-power laser welding	An effective way to monitor high-power laser welding is provided. By combining a high-speed camera with an ultraviolet and visible filter, an image of laser welding can be achieved in three different welding conditions. The results revealed that the parameters such as plume size and growing direction, spatter radius, velocity, ejected direction, and gray value, were related to the quality of welding. The proposed method also can be used for monitoring the stability of the laser welding process.	512*512 200fps	-	-

[63]	Assessment of heat affected zone	The affected zone for Submerged Arc Welding was evaluated. Concerns about this type of welding are the existence of uncertainty about the heat-affected zone in the regions around the parts because the fatigue failure may occur as a result of the warming and cooling cycle of that zone.	-	-	-
[64]	Welding defects detection	An automated system is presented for detecting and categorizing the classification of weld defects in radiographic images. The performance of two classification methods, one based on an artificial neural network and another based on an adaptive network-based fuzzy (ANFIS) inference system, has been evaluated. In the first step, image processing methods, including noise reduction, contrast enhancement, and threshold making, were used to identify the areas of welds and imperfections. In the next step, a set of 12 geometric characteristics that determine the shape and direction of defects is extracted from the imperfections mentioned. In the third stage, a competition between neural network and ANFIS methods was used to classify the welding defects. The results indicated that the presented methods have good performance. But the ANFIS technique achieved better results than an artificial neural network when the input feature vector is presented as input combination.	2900*950	Neural network method: P=78.9 ANFIS method: P=82.6	ANN - Adaptive Network-Based Fuzzy (ANFIS)
[65]	Welding defects classification	This paper focused on a model of gray-level radiography images to interpret and review these images by identifying and classifying the defects. Results showed that the developed model is 20% better than the statistical approach and 30% better than the neural approach with respect to their performance.	-	A=95.64	ANN - K-mean
[66]	Welding defects on gas pipeline	An automated vision system for detecting and evaluating defects presented in gas pipes using radiographic images. The proposed system is capable of detecting defects in welding by applying different methods of image processing on radiographic images and calculating information such as width, length, environment, and area of defect. For analysis, a software written in the C programming language called AutoWDA. The AutoWDA software uses various image processing algorithms for detecting welding defects on radiographic images. The proposed system is cheaper than commercial automatic inspection systems and there is no need for a skilled inspector for image interoperation.	760*570	-	-
[67]	Welding monitoring	In this research, the application of the Acoustic Emission (AE) technique combining with image parameters is studied for analyzing the FSW. The results indicated that both the AE and Image parameters have a similar trend.	-	-	-
[68]	Crack detection	To identify cracks near the bolts of steel structures a method is presented. In this method, too many images were processed and analyzed without controlling the positions and angle of cameras while shooting.	1716*1149	A=98	
[69]	Corrosion detection	In this research, some parameters that affect the performance of color wavelet-based texture analysis algorithms were studied for corrosion detection and a method for utilizing depth perception is presented.	128*128	A=83	-
[70]	Determination of rusted surface	Researchers presented a three steps method for determining rusted surface regions on a steel bridge that should be blasted, due to the current standards. These steps consist of color space conversion, using J48 decision tree algorithm to classify the rusted area, and determination of the blasting area. 119 images were used to evaluate the presented method.	256*256	A=97	-
[71]	Fatigue crack detection in box girder	A method for crack identification in steel box girders of bridges images is proposed. These images contain various textures such as handwriting scripts, and background. 350 different scaled images were used as input data in a CNN that were taken by a consumer-grade camera. To evaluate the performance of CNN, a confusion matrix is defined and six images are used to determine feasibility and robustness. Results indicated that the proposed method can detect the cracks, handwriting, and background automatically.	64*64	-	CNN

[72]	Crack detection on steel structure	A method is proposed to identify cracks in steel box girders of bridges from images containing complicated backgrounds that are taken by a consumer-grade camera. A deep learning model is constructed consisting of multiple processing RBM layers for learning the features. For obtaining and updating the optimal biases and weights a contrastive divergence learning algorithm is employed.	3264*4928	A=91	Restricted Boltzmann machine (RBM)
[73]	Detection of corrosion damage in power transmission lattice	A combination of supervised and uncontrolled collation methods is used to identify corrosion areas in images of power transmission towers using color attributes. The image is split into smaller pieces by using the K-means clustering algorithm. To detect corrosion in the images, the hue obtained in these parts is compared with the color of a series of corrosion-proof images. Therefore, the corrosion identification process has been implemented in two stages in the application software. In the first step, images are plotted based on color. In the second step, the identification of corrosion-bearing parts is based on the properties of the value of the shades in the images. Results indicated that the presented method, except for some false positives, can identify corrosion successfully. It should be mentioned that by preprocessing, optimizing the cluster numbers, and acquiring images at suitable conditions this error can be eliminated too.	-	-	K-mean

2.3. Identification and evaluation of other imperfections and defects

This section will refer to researches that use the DIP methods to identify and evaluate defects other than cracks, such as corrosion, humidity, and other failures. In some cases, for evaluating defects, quantitative results should be converted to qualitative results. So, some professionals and experts will be needed. In this way, a photograph of an element is first shown to an expert, and he is asked to determine its quality concerning defects. This scoring for example is based on numbers 1 (best quality) to 5 (lowest quality) [74]. Table (6) demonstrates the summary of the researches.

Table 6. Identification and evaluation of other imperfections and defects.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[75]	Moisture marks detection	An integrated model developed and created based on image processing and artificial intelligence techniques to automatically identify points of humidity and their number. This integrated model uses a succession process that automatically detects moisture-related symptoms on concrete surfaces, as well as artificial neural networks to detect and measure their value. Initially, the RGB image is filtered and pre-processed by spatial filters to improve the properties and characteristics of the wet points. In the second step, a moisture detector, with a set of morphological algorithms, is used to identify wet areas. In the next step, the percentage of the area and its moisture content are measured using artificial neural networks. The results showed that the neural network model quantifies the moisture marks area with acceptable accuracy. This model can evaluate the extent of damage automatically and also can be used to assess the generic condition of subway networks.	10.1 Mega Pixel	A=91.5 P=96.1 R=93.2	ANN

[76]	Tracking of defects in reinforced concrete bridges	A new approach presented to the intermittent estimation of deformation in concrete bridges is based on a set of dimensionless criteria for fractal analysis of digital images. The method presented in this paper, using fractal analysis of digital images, estimates surface imperfections with fractal dimensions. The proposed method overcomes the limitation of other methods and generates unique metrics necessary for change quantification successfully.	5.1 Mega Pixel	-	Fractal analysis
[77]	Determination of seal coat deterioration	A reliable method of image processing is provided to determine bleeding deterioration in seal coats. The proposed method was implemented on 140 images taken from 4 highways. Each image is in one of the two categories with "satisfactory" and "faulty" labels. The edge-detection algorithm was implemented to identify the edge of aggregates in the overlay. The results showed that the presented algorithm can determine bleeding deterioration on the seal coat successfully.	3782*2592	-	-
[74]	Concrete surface quality assessment	A novel approach is presented for automatically evaluating air pockets and discoloration. These defects must first be identified then, their characteristics, such as the number of air pockets and the color of the discoloration, are obtained, and an index is calculated as the defects Visual Impact Ratios (VIRs). Then, the appropriate value as the threshold is determined for VIRs to be specified automatically by comparing the VIR value of each air pocket or the cavity with the threshold value, quality, and conditions of the fault. The results of this model are quantified quantitatively by consulting with some professionals. Results showed that the presented method can identify air pockets, and discoloration successfully. Also, the calculated VIRs can evaluate the amount of air pockets and discoloration successfully.	1024*768	P=85.8	-
[78]	Damage detection	The application of the Grey level co-occurrence matrix (GLCM) in texture analysis, as well as the application of the ANN, is expressed to obtain information such as the total amount of surface cracks and their width and length. The method was implemented on the photos of the thermographic, colored, and gray levels of concrete blocks, such as slabs that had been laid out for 10 years. Each of these samples was partially damaged by the alkali reaction of aggregates. Ranking classification results indicated the highest degree of precision in the identification of damaged textures. However, all three types of photos have an acceptable precision in identifying the characteristics of crack damage but the infrared thermography produced more accurate results.	512*512	A=75.2	ANN
[79]	Patches detection in road pavement	image processing used to create an efficient and low-cost system for removing the number, size, and density of existing patches on the pavement surface using a camera mounted on a riding car.	-	-	-
[80]	Detect pavement distresses	A 3D structure obtained of the pavement surface using Kinect sensor and image processing technology, and SURF and MSAC algorithms, and used it to investigate faults with depth dimensions at the surface of the pavement.	-	-	-
[81]	Evaluation of asphalt pavement	Details of the image processing method provided and its history, embedded machines for this purpose, and a summary of how to analyze information in existing software.	-	-	-
[82]	Damage index estimation of concrete column	A method is presented for damage state detection of concrete columns. This method is combined with all of the methods developed by the authors before. The performance of the method was good and effective.	1600*1200	P=70 R=64 A=79	-

2.4. Deflection, deformation, and vibration assessment

The diagnosis of a structural system is one of the key points in the health monitoring strategy. The current system identification methods, based on the measurements of displacement, accelerations, and strains, estimate the structural model with the help of wired or wireless sensors [83-85]. The installation of wired or wireless sensors in a physical manner may result in additional load on light structures, and installing them on large structures may increase the costs and the required time. On the other hand, these sensors can only be installed at limited points in the structure. Non-contact measuring methods, such as laser seismographs, have high accuracy and do not apply any additional loads to the structure. However, this method also requires follow-up measurements that will take a long time [86]. The use of machine vision methods provides the advantage of using non-contact tools [87]. In this section, research has been carried out to calculate the deflection, deformation, or vibration of different elements of a structure. Some of these parameters have static effects and some such as vibration and acceleration have dynamic effects that are used in modal analysis of structures[87]. It should be noted that Ye et al. [88] and Feng and Feng [89] studied the application of image processing in the dynamics of structures.

Digital Image Correlation (DIC) is a technique that is used in this field. DIC is a versatile non-contact optical technique that is used as a reliable tool in experimental mechanics to obtain whole field displacement and strain fields [42, 43, 90, 91]. It is based on an image comparison of the specimens coated with a random speckle pattern[60]. For further studies on the DIC method, the articles of Satin et al. [92] and Penn et al. [93] are referred. Table (7) expresses a summary of these researches.

Table 7. Deflection, deformation, and vibration assessment.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[94]	Identification of full-field vibration modes	A computer vision and advanced video processing algorithm presented that can measure video-based metering as well as applied modal analysis. Measurement using fixed motion cameras, in combination with machine vision algorithms, has been successfully applied to measure vibrational measurements and subsequently modal analysis, using techniques such as digital image correlation and point tracking. A multi-level image processing method is first implemented on the video frames of the vibrational construction, to extract the phase of the local pixel representing the local structures of the structure to form the spatial matrix of motion. The proposed method can automatically obtain the modal frequency, the damping ratio, and the shape of the modalities by measuring the measurement of the video. Results showed that the proposed method can blindly extract modal frequencies, damping ratios, and full-field mode shapes from video frames.	1920*1080 240 fps	-	'

[95]	Structural system identification	A method consists of four steps: Selecting a region of interest, identifying and selecting a feature to control the movement (such as corner points), tracking and controlling the selected feature, removing non-consistent displacements, and out of range areas. To validate the proposed approach, a model of a 6-story structure on the seismic table was selected and the results of the proposed method were compared with the results of an accelerometer. The experimental results indicated that the presented method with reasonable accuracy can identify the natural frequency and the mode shape of the structure.	1280*720 120 fps 1920*1080 30 fps	E=0.2	-
[96]	Displacement measurement	A vision-based system is provided that can measure the displacement in large vibrational structures, such as bridges. To do this, one or more cameras that need to be placed at a fixed point is needed. The displacement of the structure can be calculated altogether through the processing of images. Measurement of displacement is done by tracking some of the features on the structure and therefore no need to use mark point and target points. The verification of this model was done by a sample on the laboratory seismic table as well as a long-span bridge.	-	-	-
[86]	Bridge column drift estimation	The ability to use the computer vision method to estimate the most experienced displacement of the affected seismic column related to the damaged bridge was examined. The main goal is to determine if there is a definite relationship between the most seismic displacement and the damage observed in the photographs obtained after the accident. For this purpose, some experiments were carried out on the concrete columns of the bridges and exposed to lateral loads. The computer vision algorithm based on the segmentation of image digitization, extraction of features, and nonlinear regression, estimates the maximum displacement. In this way, the images were first processed to be converted to binary format. The results indicated a high dependence between the crack pattern and the displacements. Also, the accuracy of the estimates is heavily dependent on ambient light during photographic shooting.	50 pixel per inch	E=25.4	Regression model
[97]	Measurement of vertical deflection of bridges	A model presented for measuring the vertical displacement of railway bridges in a real-time, non-contact manner, without the need for point and goal points using digital image correlation. Measurements are performed in pixels, which are converted by a conversion function into millimeters. Easy installation and live measurement and monitoring of railway bridges that are subject to train passage reflect the accuracy and applicability of the proposed model.	1024*768 117 fps	-	-
[98]	Remote sensing of bridge displacement	For measuring the dynamic displacement of bridges as live and remote measurements a system based on IP is presented that can measure. A camcorder captures the motion of the target points mounted on the measuring location of the meter. The displacement rate is determined using the image processing technique and the number of pixels displaced. For verification, a test specimen was evaluated on a seismic table in the laboratory and a real bridge sample. The results indicated that the presented method can be used for measuring the displacement of a bridge with high resolution.	720*480 30 fps	E=3	-
[99]	Deformations under fluid load	DIC is used to measure the structural deformation in the wind tunnel. The presented methods can capture the variation in deflection and twist for small changes over a large distance.	2452*2056	E=1	-

[100]	Measuring displacements and strains on concrete surfaces	A method presented for measuring strain and concrete deformations that track targets on the surface of the concrete using a photographic camera and image processing technique. Two different trends have been expressed for this purpose. In the first process, a series of circles are plotted on the concrete surfaces and the location of the center of their surface is determined. In the second process, there is no need to draw on concrete surfaces, but small traces such as air bubbles are tracked. By examining the relative displacement of these two surface centers, the strain of a measurable sample is obtained. This method was tested on several concrete samples in several stages of loading and unloading, and the results were successfully compared with the results of the strain gauge.	16 Mega Pixel	E=14	'
[101]	Normal strain measurement	A method for measuring the normal strain measurement with high precision was presented. At first planar projection is modeled for enabling the measurement without the need to imaging coplanarity and measured plane. By translational displacement of known values, some parameters are determined. The results indicated that the proposed method is rational, succinct, and accurate for measuring normal strain.	640*480	-	'
[102]	Monitoring of deformations in building structures	Digital image processing has been used to develop and design a simple, distinctive, and economical system for detecting deformation in building structures. Selected points of the structure are photographed by the camera, at regular intervals, and their location is measured. For points to be independent of ambient light, the selected points are equipped with several LED lamps. This system was implemented on the roof of a building. A laboratory test method showed that tracking and controlling target points at distances with a precision of one millimeter can be done.	1280*1024 30 fps	1mm	'
[103]	Condition assessment of structures	A visual-based method was used to measure the in-plane deflection curve in constructional structures, which was done by the digital image correlation coefficient. Homography mapping can calculate the deformation value using two images of a structure that has been taken from two different points. These two images are related to the state before and after loading. A filter and a corner finder were also used to map the homography between the two views. The system monitors the status of the structure and informs whenever a critical situation occurs in the measurements. By implicating the presented method, it is possible to measure the dynamic processes of the structures using a binocular system. The mode shape is obtained by calculating the displacements of the selected points.	4272*2848 4368*2912	E=1.5	'
[104]	Measuring displacement of concrete samples	Considered the new method of digital image processing to measure the displacement of concrete cylindrical samples. The results of analyzing and processing images using GEOPIV software are verified using the results of the traditional method of using the mechanical gauge for measuring displacement.	-	-	'
[105]	Determine the mechanical properties of bending members	The amount of deformation in bending members in laboratory samples was discussed. In this way, instead of using the usual LVDT methods, image processing techniques are used for this purpose.	-	E=2.99	'
[106]	Identification dynamic characters	A method for identifying the structural modal parameters is presented using fast Fourier transform and measured multi-point dynamic displacements. A steel beam with simple supports constructed to test and compare the presented method and accelerometer. The effect of the measurement distance and various types of targets (LED lamp and black spot) on the accuracy of the method is studied. The results indicated that this method is accurate and effective for modal parameter identification and structural dynamic response monitoring.	-	-	'

[107]	Displacement measurement	A method is presented for measuring displacement in laboratory and field experiments with enhanced robustness of sunlight. The results showed high accuracy for both laboratory and field experiments.	640*480 30 fps	E= 0.77 mm	'
[108]	Displacement measurement	The authors proposed a method for data fusion with acceleration measurement to improve the dynamic range of displacements while lowering signal noise. Complementary filters and a time synchronization method between two different sources are proposed for achieving fusion between vision-based displacement and acceleration. Several tests were conducted to evaluate the presented method.		A=83.5 E=10.43	'
[109]	Dynamic displacement measurement	The authors studied the effects of key parameters of the system in selecting an appropriate sensor for structural dynamic applications. Some of these are amplitude range, the spectral content of the dynamic displacements, location and orientation of sensors, fusing of measurements from several sensors, rolling shutter, and sensor noise effects, and so on. The results indicated that the subject sensors are accurate enough for transnational motion when the frequency range of the evolving field is about ten Hz; if the displacement field generates discrete sensor measurements with enough resolution.	640*480 30 fps	E=6	'
[110]	Displacement measurement	A system for displacement measurement has developed using DIP and the results compared with the magneto strictive displacement sensor (MDS) to evaluate the performance of this method. Conducted tests and experiments on a shaking table indicated that illumination and vapor have a significant effect on the results.	-	-	'
[111]	Displacement measurement	A three-story model on the shaking table is designed to evaluate the performance in both time and frequency domains by measuring the displacement of each floor. For measuring the displacement one camera and both natural and artificial targets such as nuts and bolts are used. The results showed high agreements between the presented method and high-performance laser displacement sensors. The identified modal parameters are used to update the finite element model and demonstrate that this method has good potential for structural health monitoring applications.	1280*1027	E=0.72	
[112]	Displacement monitoring	A method is presented for measuring multipoint displacement using a consumer-grade camcorder for video capturing and processing. This low-cost method is tested on a cable-stayed footbridge for measuring deck deformation and cable vibration. The results showed an accurate estimation of modal frequencies that could be used for studying different modal frequencies under various pedestrian loads.	-	A=95	'
[113]	Frequency measurement	The vibration frequency of all vibration targets in the sequence is obtained simultaneously through local neighborhood analysis. This study is performed by short-term Fourier analysis to calculate changes in motor frequencies. This data can be displayed as a color frequency map that can be mounted on a video sequence to provide a complete description of the analyzed sequence. Hence it can be used to analyze complex structures because at a glance different vibrating components are visible.	Fps=120	-	'
[114]	Distribution of vehicle load	The authors presented a method for identifying the Spatio-temporal distribution of vehicle loads for long-span bridges using a camera at a cross-section. The camcorder sampled pattern images for moving vehicles at the weigh-in-motion system (WIM) location. The captured vehicle weight information was extracted from the WIM output data sheet based on the passing time. Pattern technique and particle filters have been used to track the moving loads of the vehicle on the bridge. An experiment was conducted to evaluate the accuracy and effectiveness of this method.	70*110	-	'

[115]	Modal survey	An unmanned aerial vehicle (UAV) is used to present a method to extract the frequency and mode shape of infrastructure using video analysis. A model on the shaking table and a pedestrian suspension bridge are used to evaluate the presented method.	3840*2160 Fps=30	E=0.5	'
[83]	Monitoring displacement	A system developed using one or some video cameras for monitoring the vibration of large structures such as buildings and bridges. The displacement is accurately measured by tracking some existing features on the structure using a robust object search algorithm. Experiments were conducted on a shaking table and also on a long-span bridge to evaluate the efficiency of the presented method.	640*480	E=0.27mm	'
[116]	Vibration measurement	Some data that were used to test, analyze, and correlate of DIC method is compared with traditional accelerometers and laser scanning vibrometers in constructing the finite element model. The results demonstrated that all approaches have a good correlation with the finite element model and the DIC method is accurate for full-field vibration measurement.	1024*1024	-	'
[117]	Evaluate fatigue behavior	During fatigue test for specific load cycles displacement fields were analyzed to determine some parameters such as crack width, beam deflection, curvature, and major strains. The results were compared with data collected using conventional sensors and indicated that the DIC method provided detailed and accurate information.	2024*2024	-	'
[118]	Deformation measurement	The authors researched to evaluate the usage of 3D-DIC for measuring surface deformation on masonry walls and producing crack maps of it. The experiment consists of 3 confined masonry walls under horizontal in-plane reverse-cycle loads. The evaluation of 3D-DIC measurements of drift, diagonal deformations, and interface slip between the RC tie columns and the masonry infill showed high accuracy of this method.	3072*2048	E=10	'
[119]	Damage assessment	In this research images collected from Hurricane Sandy are used to explore image-based 3D reconstruction for post-hurricane residential building damage assessment. To reconstruct several impacted residential buildings to evaluate their performances two common image reconstruction pipelines are employed. To evaluate the performance ground truth damage data recorded by a light detection and ranging (LIDAR) system. The results proposed that image-based 3D reconstruction can be used for hurricane damage assessment.	-	-	'
[120]	Bridge deflection measurement	To correct the effect of camera movement for measuring bridge deflection a method is presented using DIC. An equation of perspective transformation is used to describe the relationship among images before and after the camera movement. The proposed method applied to the rigid body rotation and translation measurement of a planar specimen, measurement of a bridge, and a wide-flange beam deflection to evaluate the accuracy of the method.	1280*1024	E=0.6mm	'
[121]	Deflection measurement	Image processing techniques are used to detect the location of maximum deflection and measure its value. At first, the perspective of color images is eliminated, and then they are pre-processed using spatial domain filters. Afterward, image segmentation, in combination with nonlinear regression, is used to calculate the equation of the deflection curve of an element. Finally, the location of maximum deflection and the amount of it are determined by calculating the derivative of the deflection curve. The proposed method is validated through two experiments.	16 MP	E=0.2mm	'

2.5. Identification of texture, dimensions, elements, and components

In this section, studies will be introduced to identify the dimensions of an element or structure on images, such as the dimensions of a column, bridge, or geometric dimensions of the road. Some studies in this section also identify a particular element in the images. This means, for example, that a column or a wall can be identified in the image.

2.5.1. Identification of elements and components

DIP in some cases is used for the identification of elements and members in images of the structure. This procedure will help to assess the condition of a structure automatically. It means that in the first step the specified element and member such as column, beam, and so on will be identified in images. Then in the second step, the defects on the element or member will be evaluated. Some automatic identification of members of the structure is based on the color and texture information, in which this method makes the identifying of members in the connected elements that are also of the same material impossible [73]. So, it is necessary to introduce a new way to identify members in the researches. Table (8) demonstrates information about this problem.

Table 8. Identification of elements and components.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[122]	Concrete column recognition	A new way to identify concrete columns identified. The first step in this method is to detect long vertical lines in the image or video, using the Edge detection and Huff Transform method. Then the rectangle is bounded between each pair of lines. When the rectangles are similar to the shape of a column, their color and texture match with one example of concrete columns in the database. This method is based on two assumptions. First, a line is assumed long when the number of its constituent parts exceeds a third of the height of the photo, and second, the ratio of the column width to height is less than one. The results indicated that if at least one surfaces of a column are visible, concrete columns in images can be detected and if there are multiple columns in an image, the concrete columns near to a viewer can be recognized easily.	3264*2448 25 fps	P=84.4 R=74.5	-
[123]	Detecting construction materials	A comparative study on various techniques of machine learning was conducted to identify building materials in digital images. The performance of the artificial neural network, radial basis function (RBF), and SVM investigated in the recognition of the three most common categories of building materials, namely concrete, red brick, and OSB sheets, which results showed better performance of the SVM method than others for all three types of materials.	-	P=94 R=96	ANN- Radial Basis Function (RBS)- SVM
[124]	Visual inspection	The authors presented a method based on Faster Region-based Convolutional Neural Network (Faster R-CNN) for visual inspection of structures and identify five types of damages such as concrete crack, steel corrosion, bolt corrosion, and steel delamination. For modifying, training, validating, and testing 2366 labeled images were collected.	500*375	P=87.8	CNN

[125]	Automatic inspection	A method for automating and enhancing the level of inspection decisions is proposed to generate vision-based condition-aware models. The condition-aware models are generated by projecting the inference of trained deep-learning models on a set of images of a structure onto a 3D mesh model generated through multi-view stereo from the same image set. For semantic segmentation of images of buildings to provide damage information such as cracks and spalling, contextual information such as the presence of a building, and visually identifiable components like windows and doors deep fully convolutional residual networks are used. Results indicated that the proposed method has the potential for automating post-earthquake inspections.	288*288	A=90	CNN
[126]	Detection of structural components	A method for detecting slab, pier, pier cap, and girder components in the RC bridge is presented in this paper. This method first separates the deck assembly from pier assemblies. Then using surface normal pier caps is detected and using oriented bounding boxes and density histograms girders are detected. The detection performance of ten bridge point clouds indicated that this method has very high accuracy.	-	P=100 R=98.5 F=99.2	-
[127]	Damage detection	Inspired by CNN the concept of Structural ImageNet is proposed herein with 4 naive baseline recognition tasks: component type identification, spalling condition check, damage level evaluation, and damage type determination. A small number of images are selected from the Structural ImageNet and labeled manually 4 recognition tasks. To avoid overfitting, Transfer Learning based on VGGNet is introduced and applied using two different strategies, namely feature extractor and fine-tuning. Two experiments are conducted to find the relative optimal model parameters and scope of application. Results indicated the accurate recognition and various application potentials where feature extractor and fine-tuning can be used respectively for preliminary analysis and more improvement.	448*448	A=93	CNN
[128]	Automatic inspection	A new training method in deep learning is proposed for post-disaster inspection of the RC bridge in three stages. Image classification, object detection, and semantic segmentation are respectively, proposed using CNN to conduct system-level failure classification, component-level bridge detection of the column, and damage-level localization. The results indicated high accuracy and performance.	430*400	A=90	CNN
[129]	Bridge component recognition	In this article for recognizing bridge components, semantic segmentation algorithms are used. So, three approaches are studied for combining 10-class scene classification and 5-class bridge component classification to obtain a high-level scene consistency. These approaches are naïve configuration, a parallel configuration, and a sequential configuration of classifiers. The results showed that the presented method is effective in recognizing bridge components in complex scenes.	320*320	E=1	CNN

2.5.2. Identification of texture

Identification and evaluation of pavement's texture in roads and highways, such as asphalt or concrete, is one of the proposes of these researches that are shown in Table (9).

Table 9. Identification of texture.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[130]	Evaluation of the texture of concrete pavers	A method provided for evaluating and classification of pavement texture using standard deviation. To quantify the texture of the surface proved to correlate to the visual classification performed by production experts, the standard deviation of a frequency histogram of grayscale paver images was used. The standard deviation was obtained by the use of a scanner. The results obtained from this method were compared with the results of monitoring by individuals, which indicates the high accuracy of the method.	400dpi	-	-
[131]	Highway condition assessment	A new approach is presented to 3D image reconstruction, as well as integrated color, shape, and texture identification for highways. The presented method consists of the following steps: 3D image-based reconstruction of all objects; Segmentize each image by Semantic Texton Forrest algorithm; Integrate camera parameters recognized with the segmented areas; Project and visualize the results into a common 3D environment. The advantage of the proposed method is no requirement to implement filter-bank responses or local descriptors which are expensive.	-	P=93 R=98	-
[132]	Determination of the parameters of hot stone asphalt aggregates	The parameters of rock massive mixing of asphalt were analyzed and determined with image processing. The method is based on the fact that by using the edge detection in the input images and determining the boundary of different aggregates, using the edge-detection, the numbering of the aggregates was done accordingly and by taking the number of these aggregates from the user and calculating the distance of pixels (at the edges found) from each other, the distance is detected.	-	-	-
[133]	Evaluate the skid resistance of asphalt pavement	An image processing intelligence system was introduced that was able to analyze the pavement texture and provide a new index for slip resistance of the pavement, taking into account the effect of the horizontal, vertical, and diagonal components of the pavement. The final results of the proposed system and the result of the British Pendulum Test with them were compared.	-	-	-
[134]	Improving the result of asphalt mixtures density	A new method of nonlinear fuzzy thresholding was proposed using a digital image scanning process to study the volumetric properties and density of the asphalt mix. This algorithm uses a fuzzy threshold for image scanning to separate the asphalt mixture into three parts: air, bitumen, and aggregate.	-	-	
[135]	Achieve the properties of asphalt concrete mixtures	A new approach introduced using image processing technology to predict the properties of asphalt mixes, as well as to isolate and identify each of its three phases (aggregate, bitumen, air). Modeling of asphalt specimens is done based on two-dimensional CT-scan images of specimens. By using an advanced algorithm based on image processing, tried to extract the laboratory characteristics of asphalt specimens based on a non-destructive test, and finally, laboratory values and values obtained from image processing were compared.	-	-	-

[136]	Evaluate the static separation of self-compacting concrete	A new method used for image processing of the concrete cross-section to evaluate the dispersion of aggregates, and compared their results using a standard detachable split method.	-	-	'
[137]	Evaluate internal specification of asphalt	The microstructural characteristics of asphalt cores are evaluated in this paper. Also, the internal structure features in the laboratory and the field samples were compared. The results showed high accuracy and effectiveness of the image processing method.	-	-	'

2.5.3. Calculation of geometric dimensions

In some cases, it needs to calculate the geometric dimensions of the member such as column, wall, or an element in a roadway like a sign or bridge. Researches introduced in Table (10) are a summary of this field.

Table 10. Calculation of geometric dimensions.

Reference	Subject	Method and Result	Image Resolution or Video Rate	Performance (%)	Tools
[138]	Dimensional analysis of bridges	A scientific approach is pointed out to analyze the dimensions of a bridge, which uses a picture to calculate the geometric dimensions. The most important step in this method is to identify the components in the images. This method was evaluated on several bridges. Of course, this method is not responsive to bridges with unconventional and complex shapes such as convex, concave, and curved. The results showed a high level of automation.	-	10cm	'
[139]	Roadway geometry computation	An algorithm is provided for calculating geometric dimensions of the path, such as the length of the road, the width of the road, and the size of the road signs, from the images. The paper consists of two parts. In the first section, a general algorithm for calculating the geometric dimensions of the road, based on the two-dimensional and three-dimensional reconstruction of images, is provided. This algorithm involves the steps for setting up a camera, Roadway vanishing line computation, homography, two-dimensional and three-dimensional reconstruction, and ultimately calculating the geometric dimensions of the road. In the second part, this paper presents an error calculation model, called the Roadway geometry error model (RGEM), for measuring the quality of the measurement. The results indicated that, when the computation locations approach the roadway vanishing line, the errors increase. The experiments demonstrated that the proposed model for error computation evaluates the roadway geometry computation errors with good accuracy.	1300*1060	-	'
[140]	Estimation of the particle-size in the gravel-bed river	Using watershed algorithm methods and image reconstruction algorithms a model proposed to estimate the distribution of Armor layer aggregates in the substrate of alluvial sandy bed rivers.	-	A=93.6	'

3. Result and discussion

The study of articles and researches on the application of DIP techniques in civil engineering has resulted in a diverse range of topics in this section.

The first result: Research in this area can be classified into five categories. These categories are the identification and evaluation of cracking; identification and evaluation of defects in steel structures; identification and evaluation of other imperfections and defects; evaluation of deflection, deformation, and vibration; identification of texture, dimensions, elements, and components.

The second result: It can be argued that these types of researches often have been limited to identifying and analyzing only one parameter. As an example, they only examine the cracks in a concrete column or road pavement. According to Koch et al. [2], no work has been done to identify several defects in one location for construction projects. Perhaps because there is no standardization in the clear definition of the parameters that are generally available defect description. Therefore, it can be said that one of the challenges in the field of image processing is to find a way to comprehensively analyze and evaluate an image so that it can be extracted from a different set of information that can be extracted from a photo; Made a comprehensive decision about its general conditions.

Result III: Table (11) demonstrates a general view of the research on automatic detection of defects and the assessment of conditions in structures, facilities, and infrastructure, with the help of DIP methods. The cases that have been fully investigated have been marked with the "+" sign. Some studies that have been carried out but not yet completed, with the "~" sign and those that have not been investigated so far, with the "-" sign are marked. Some part of Table (11) is extracted from Koch et al. [2] and the other is the author's findings.

Finally, after studying the various researches that carried out in this area, it can be said that the issues of identification, location, and evaluation of the characteristics of the cracks (type, width, and length) and deterioration in concrete have been studied to a large extent in such a way that these defects are automatically identifiable from images including concrete and asphaltic pavement, tunnels and pipes and concrete connections [5, 11, 12, 14, 15, 31, 33, 35, 37, 38, 141-149]. Also, computer vision-based methods have had an acceptable success in identifying defects in joints and deformation in the members of the structures [83, 86, 97-102].

Result Fourth: An important issue in using machine vision methods is to collect accurate information. This information, which is the images, should have a series of minimalistic features, and the better the image quality is, the more accurate the data will be processed and the more accurate results are obtained. For example, the higher resolution of the image will lead to more accurate processing and identification of the defects. In general, performance and work precision depend on parameters such as the quality and clarity of the images and the amount of noise in them, environmental conditions such as the amount of light and brightness in the shooting area, the placement of the subject in shadow or light, wind blowing, camera location, camera spacing to the desired subject and position of the camera. What comes out of the papers and researches is that the best positioning of the camera relative to the subject and scene to be captured is a situation in which the camera is positioned parallel and perpendicular to eliminate the perspective problem or minimize it [12]. Also, for preventing camera shaking, in some cases, it is better to use a tripod [59, 77, 94].

Table 11. General view of the research on automatic detection of defects and the assessment of conditions in structures, facilities, and infrastructure: (+) achieved, (~) partially achieved, (-) not achieved yet ([2] & Paper findings).

Infrastructure	Defect type	Defect detection		Defect properties (type, width, length, etc.)	Condition assessment
		Presence	Location		
Reinforced concrete bridges	Crack	+	+	~	-
	Spalling	+	+	~	
	Other defects	~	~	~	
	Vibrations	~	~	~	
	Deflections	~	~	~	
Precast concrete tunnels	Cracks	+	+	~	-
	Spalling	+	+	~	
Underground concrete piped	Cracks	+	+	~	-
	Holes	+	+	~	
	Joint damages	+	+	~	
Asphalt and concrete pavements	Cracks	+	+	+	-
	Holes	+	+	~	
	Patches	+	+	~	
Buildings	Crack in elements	~	~	~	-
	Spalling in elements	~	~	~	
	Deflection	-	-	-	
	Settlement	-	-	-	
	Other defects	~	~	~	
Power transmission lattice tower	Cracks	-	-	-	-
	Corrosions	+	+	-	
Gas pipes	Cracks	-	-	-	-
	Corrosions	-	-	-	
	Welding defects	+	+	+	
Water pipes	Cracks	-	-	-	-
	Corrosions	-	-	-	
	Joint damages	-	-	-	

In the machine vision study, there is a key statement that "you can process what you can see" [2]. This sentence means that the scenes under observation should be bright enough to be processed by machine vision methods. For example, the existence of a shadow in the images will cause the border between the shadow and the brightness and it can be mistakenly identified as an edge, which will cause negative effects and reduce the accuracy of the results.

Fifth result: Imaging of subjects and scenes can be done by a person or as well as mentioned in some researches, by ground robots [5, 29, 39] and unmanned aerial vehicles such as a quadcopter or drone [115, 150-156]. Using these devices will have a significant role in reducing the risks of shooting for a photographer. In some cases, taking images should be done at altitude, or the need to enter damaged structures after an earthquake, which will increase the safety considerably with the use of this instrument and auxiliary equipment.

Sixth result: For taking and collecting images, various tools such as professional digital camera [3, 32, 46, 72], amateur digital cameras [95, 138], camcorders [83, 94, 98, 157], scanners [130] and CT-Scan devices [134, 158] can be used. The images can also be colored (RGB) [11, 72, 86, 94, 98, 99, 159-161], HSV [162], gray [11, 72, 77, 163], radiography[59, 62-64], thermography [77] and ultraviolet light [60]. Also, in some studies, more than one camera was used for imaging, which is named stereo photography[26, 44, 96, 99]. It should be noted that video processing is one of the applied topics in civil engineering, especially in the field of the modal analysis of structures, which, given that the purpose of this article is the only study in the field of image processing; It has been avoided in detail, and in some cases has only been mentioned [94, 106, 112, 164-166].

Seventh result: From the review of various papers, it was concluded that image processing can be performed in two dimensional or three-dimensional model, which parameters such as cracks and surface damage in 3D models can be identified with high precision [3, 5, 27, 46, 131, 133, 167-170]. For constructing a 3D model, it is necessary to take multiple images in different directions from the subject, then the different points called "point clouds" are extracted from the images that are used to compile them for the 3D scene model. After making this model, the processing is done on it, which is referred to as acceptable results in the articles. Other methods in producing the point clouds are using laser scanners[171-174] and photogrammetry[45, 175, 176] that have been avoided in detail, according to the purpose of this research.

Result Eight: As seen in some researches, besides DIP methods, machine learning tools such as ANN [11, 19, 23, 27, 51, 53, 54, 57, 62, 70, 71, 77, 124, 128, 177] and SVMs [40, 46, 56, 123] for pre-processing or processing data can be used.

Result Nine: In all studies that calculated the deformation and displacement of elements and members of buildings and structures such as beams; this was done in cases where the images of that element before and after applying the load, exist and the discrepancy was determined by comparing the images in these two stages[86, 97, 101, 178]. For this reason, the studies carried out in this field have had more experimental aspects, so that they can obtain the amount of deformation by constructing a beam in the laboratory and applying the required load to it. So, it's possible to say that there has been no research on measuring the deflection and deformation of a roof or a beam in existing buildings because often there are no images that represent the initial state of a structure.

Result ten: Among the studies carried out in this area, some cases are only laboratory aspects and they cannot be implemented in practice [30, 32, 41, 86, 94, 98, 100, 105, 179, 180]. This discussion may have several causes, including the fact that in some cases, as expressed in the ninth conclusion, the image of the initial state of the structure is not at hand. Some cases require special markings on the subject, which cannot be done in practice and on actual structures. In some cases, the purpose is measuring the vibration or displacement of a structure under earthquake force so it must be carried out in a laboratory and on a shaking table. In contrast, many cases can be fully implemented in practice, as mentioned in the previous sections[12, 28, 32, 45, 46, 58, 97, 103, 131, 136, 181-183].

As a final discussion, to be aware of the performance of the various methods presented in the articles, depending on what parameter is used to measure performance in each article; The average of all these parameters is calculated and given in Fig. 4. As this chart shows; The horizontal axis represents the ten general categories expressed in this article, for each category, 5 performance evaluation indicators, which are accuracy, precision, recall, F-measure, and error, respectively, are shown in percentage. Items marked with a zero in the chart mean that the index was not used to evaluate the performance of those articles.

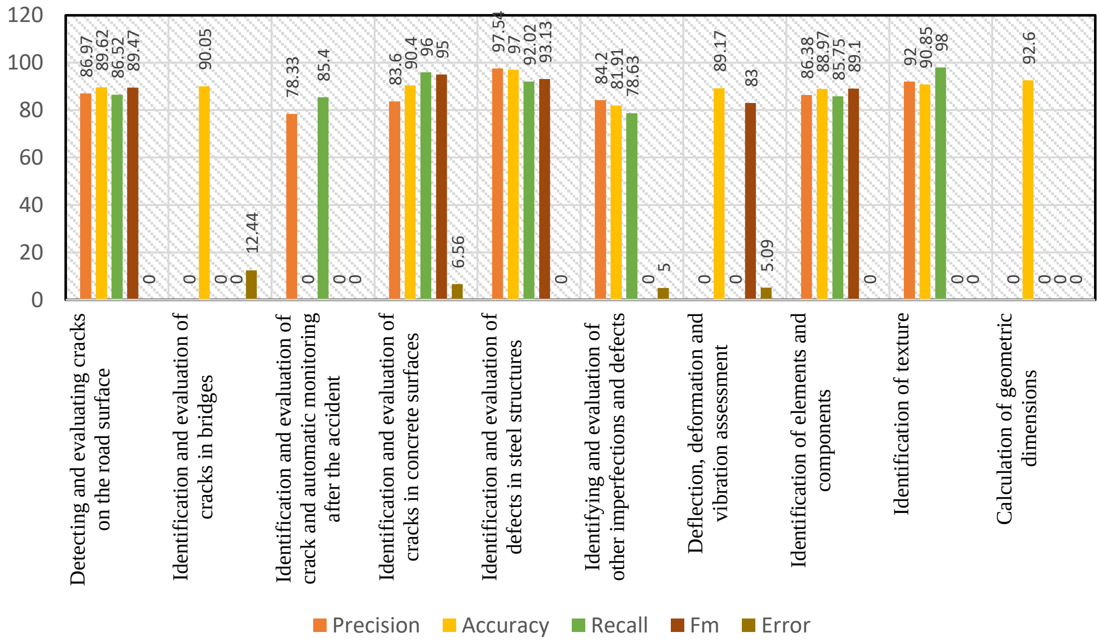

Fig. 4. Comparison of researches performance in various category.

It should be mentioned that other methods can be used for damage detection such as wavelet analysis [184-190], modal data [191-194], contourlet transform[195] and so on that were not explained in this paper due to their lack of direct connection with the DIP.

4. Conclusion

The investigated studies indicated that the DIP techniques will increasingly find their place in monitoring and controlling structures and infrastructures. Because with the help of DIP methods and implementing ground and aerial robots in shooting, it is possible to automate the monitoring, controlling, and evaluating the structures and infrastructures. To achieve this goal, the deficiencies and shortcomings that currently exist in this area need to be addressed by further research. Therefore, it is suggested for future researches, including providing a solution for examining a set of imperfections in a structure and a location simultaneously and evaluating the conditions of a structure concerning those defects, conducting research on the detection and measurement of the deflection of a beam or roof in existing buildings, providing a solution for the detection and measurement the settlement of building and foundation, identification and evaluation of welding conditions in connections and steel members of buildings and other structures, identification and evaluation of defects such as cracks and corrosions in water and gas pipes. It is expected that by carrying out these studies, the automation of the process of monitoring and controlling structures and infrastructures will be achieved in the future.

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