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Feature Extraction Techniques in Medical Imaging: A Systematic Review

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Abstract:
With the surge in the development of various applications in the field of Computer Vision and Digital Image Processing, a significant amount of medical pictures are being produced. Thus, the patient-specific scan pictures represent the boundless volume of data that requires careful organization and supervision to assist clinical decision support systems. Now that retrieval, classification, segmentation, and other procedures have been completed, these devices assist doctors to uncover serious illnesses including skin conditions, tumors, and cancer. This imaging largely depends on characteristics to detect the afflicted region and perform the diagnosis visually. The authors of this paper present an overview of numerous feature extraction approaches used to extract features from medical images obtained via different modalities, but only used a handful of these techniques for this job and provided the findings.

Keywords: Medical Imaging; Feature Extraction; Imaging Modalities.

I. Introduction:

The newest imaging techniques rely on high-resolution imaging and provide radiologists access to many viewpoints. Furthermore, it provided comprehensive data to support clinical diagnoses and aid radiologists in choosing the best course of action for a patient. Radiology, another name for medical imaging, is the branch of science that involves creating various images of human body components for diagnostic purposes. Nonintrusive tests are used during medical imaging procedures to help doctors to diagnose the patients. Medical imaging techniques[2,14,23] include ultrasound, mammography, computed tomography using x-rays, magnetic resonance imaging (MRI), electrocardiography, endoscopy, Positron Emission Tomography, ultrasound, etc.,

Imaging is a crucial part of clinical medicine and is frequently used for diagnosis, care and treatment planning, and monitoring patient response. Since making diagnostic decisions has always entailed using patient information, the concept of picture similarity has important medical implications. It is extremely challenging for doctors to choose a few reasonably similar photos from a vast collection. It requires considerable amount of time and effort. Thus the creation of a humongous amount of medical data by hospitals and medical institutions in the modern day makes their interpretation a challenging undertaking requiring substantial expertise.

Any image processing system's general design will include elements for data collection, preprocessing, segmentation, feature extraction, classification, and recognition. From data purification through final detection, each of these phases executes a different operation while processing the picture data. The crucial step is feature extraction, which compresses the picture elements to reduce time and storage space. Furthermore, features are essential to any system's performance since they are used as parts of matching and recognition algorithms.

Table 1. Modalities of Medical Imaging

Medical image Modalities	
Ultrasound	A type of imaging that creates pictures of the inside architecture of your body using sound waves.
Mammography	An x-ray imaging technique is used to check the breast to look for early signs of breast cancer and other disorders.
Computed tomography using X-rays	A method that doesn't damage the thing to see what's inside and to get digital data about its 3-D geometry and attributes
MRI	To create precise images of the inside of your body, magnetic resonance imaging (MRI) employs a strong magnetic field, radio waves, and a computer.
Electrocardiography	A quick test that you may perform to examine the electrical activity and rhythm of your heart.
Endoscopy	An examination of the digestive system is performed without surgery.
Positron Emission Tomography	a diagnostic imaging procedure that can assist show how your tissues and organs' metabolism or biochemistry are functioning

The following is a visual representation of a simple medical image processing[27] system:

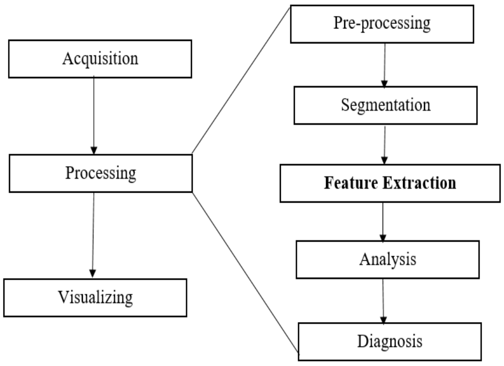

Fig. 1. Basic medical image processing system

The burgeoning field of medical image databases and the medical diagnoses process relies on digital image retrieval techniques that incorporate feature extraction[25], therefore, we authors will provide a brief overview of each technique in this survey paper.

The remaining portion of the essay is structured as a study of medical image processing, including several feature extraction techniques used in medical imaging, results taking into account 2-3 methodologies for performing medical image retrieval tasks, and is then concluded.

II. Feature Extraction Techniques:

The mechanism of reducing the number of dimensions in raw data set is defined as Feature extraction. A new feature value formed by selecting or combining the raw values. An image can have multiple feature values. It is hard to determine the ideal method for feature extraction from the medical image. Many things like data availability, number of dimensions, data labeling methods, etc., play a vital role choosing a significant feature. Based on these key points, one has to choose the optimal feature extraction technique.

2.1.Local Binary Pattern (LBP)

The area around each pixel is considered and after thresholding it and using the result as a binary integer, the Local Binary Pattern [1,9,11,12,13] a straightforward yet very effective texture operator, identifies the pixels in a picture. LBP texture operator has been a well-liked method in many applications because it avoids computational complexity and also it has discriminative capability. It is a technique that unifies the statistical and structural models of texture analysis, which have often been different. The LBP operator's resistance to monotonic gray-scale shifts brought on by, say, changes in lighting may be its most crucial characteristic in practical applications. Its computational simplicity is another significant characteristic that enables picture analysis in demanding real-time environments.

The pixel's LBP code is provided in the following way

$$LBP_{cp} = \sum_{np=0}^{7} s\left(I_{np} - I_{cp}\right)2^{np}$$

$$s(x) = \{1 \quad x \geq 0 \qquad 0 \quad otherwise\ \}$$

Where np is the neighbor pixel, cp is the center pixel

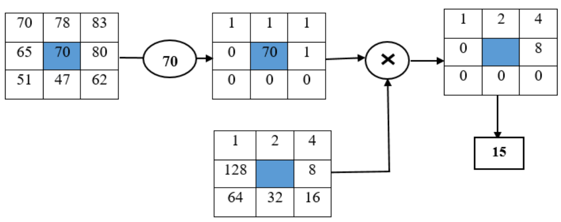

Fig. 2. LBP feature vector construction

2.2. Modified Local Binary Pattern (M-LBP):

In the imroved LBP [36] descriptor, the local difference vector D_p is evaluated for the center pixel X_c which provides significant performance against the lighting situation. The local difference vector is precisely represented as

$$D_p = S_p \times m_p \{S_p = sign(D_p)\ m_p = |D_p|\ \}$$

S_p specifies the sign and $m_p$specifies the magnitude of D_p

2.3.Pyramid histogram of oriented gradients PHOG:

First, the HOG for the entire picture is calculated. For HOG, N bins serve as the standard bin size. By repeatedly doubling the number of divisions along each axis, the image is split into

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a series of spatial grids that are smaller and smaller. It is kept how many points are in each grid cell. This is simply a pyramid representation because amount of points in each cell at each level equals total of the points in the four cells that make up the level below. Each of these levels has its HOG calculated. Cells at a given level of resolution make up the bin count for the histogram that represents that level. Up to a depth of L, this operation is repeated. At level L of the pyramid, there are 2L cells present along each dimension. A weighted mixture of the aforementioned HOG characteristics results in the PHOG features for a picture. To ensure that photos with rich textures are not weighted more heavily than others, the calculation of PHOG values is then added and normalized to unity. In this investigation, the number of pyramid levels at 360 degrees and the number of bins in the histogram were adjusted to 8 and 3, respectively.

2.4. Gray level co-occurrence matrix:

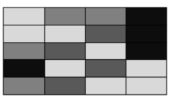
The term "GLCM or Gray Level Co-occurrence Matrix" is mostly used for searching and getting the required texture features. The GLCM[1,16,26,30] depends on the coexistence of matrix and texture characteristics. Any image's GLCM is determined by taking into account the displacement vector and orientation (0^0, 45^0, 90^0, 135^0). A GLCM matrix with a dimension of N x N and N be the number of grey levels in the picture is assumed.

We must extract pixel intensities and bring out the range for the provided picture. And we'll build the k×k matrix based on the greatest value. To obtain GLCM at the end, we must locate occurrences based on the spatial connection. In the illustration above, displacement is taken as 1, and orientation is taken as 0^0.

$$C_M = C_{(D_x, D_y)}(k,k)$$
$$= \sum_{i=1}^{k} \sum_{j=1}^{k} \{ \quad 1 \; if \; I(i,j)$$
$$= k \;\; and \quad I\big(i + D_x, j + D_y\big)$$
$$= k \; 0 \qquad otherwise \qquad \}$$

$$D_x = D.cos\, cos\, (\theta)\,, D_y = D.\, sin\, (\theta)$$

Now, we can utilize GLCM to uncover characteristics that might be used in machine learning, such as homogeneity, contrast, entropy, and others.



1	2	2	4
1	1	3	4
2	3	1	4
4	1	3	1
2	3	1	1

	1	2	3	4
1	2	1	2	1
2	0	1	2	1
3	3	0	0	1
4	1	0	0	0

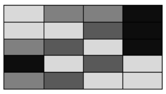
(a)Input image (b)Input size (c)GLCM of size 4×4(0^0)

Fig. 3. Construction of Co-occurrence matrix

2.5. Gray level run length method:

Strings of symbols can be indicated in an image matrix using the GLRLM[1,31,32]. In this instance, a run of collinear, consecutive pixels with the same grey level is referred to as a "grey level run". A run length matrix is utilized for the extraction of texture features in this method. Run length statistics also limit thickness of a texture in a particular direction. The incidence of runs for each grey level and duration in the same direction is counted after defining the direction and length of the GLRM.

Every item of run-length matrix I(x,y) indicates that x is comparable to the no. of runs with pixels having grey level of intensity and y is same as the length of run in a specific orientation. The greatest grey level in the picture and the longest viable run length in the equivalent image, respectively, are used to establish the size of the matrix I as x by y.



1	2	2	4
1	1	3	4
2	3	1	4
4	1	3	1
2	3	1	1

Run Length

Intensity	1	2	3	4
1	2	2	0	0
2	2	1	0	0
3	4	0	0	0
4	4	0	0	0

(a)Input image (b) Input size 5×4 (c)GLRLM of size 4×4(0^0)

Fig. 4. Run length matrix

2.6. Harlicks Features:

In image analysis, Harlick texture characteristics are frequently used as texture descriptors. The quantization procedure, which lowers the image's grey levels, is used to calculate the Harlickfeatures[1,16]. Harlick features cannot be replicated until identical quantization is carried out since the final features largely depend on this phase. The gray level co-occurrence matrix (GLCM) is redefined as a discretized probability density function and is asymptotically quantization invariant.

The co-occurrence matrix created from the pictures centers on the Harlick texture characteristics. The co-occurrence matrices serve as a byproduct to reveal the grey-level spatial dependencies laterally, such as angular relationships, vertical alignments, and horizontal recommendations in images. By manipulating the co-occurrence matrix various modified texture features may be created. 13 features were predicted by Harlick as a result of co-occurrence matrix..

2.7. Gabor feature extraction:

The Gabor filter is the foundation for Gabor feature extraction[1,35]. These filters, which are comparable to Gabor wavelets, were created with the human visual system in mind. In essence, it is a linear filter meant for edge detection. Just a collection of wavelets makes up the Gabor

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texture features. Later, each wavelet began to perceive life at a precise incidence and in a precise manner. The texture feature for the photographs may be extracted after the gathering of energy distributions.

For edge detection, texture categorization, feature extraction, and disparity estimation in image processing, a Gabor filter is a linear filter. It is a bandpass filter, meaning that only frequencies within a specific band are passed through while frequencies outside of that band are attenuated. By adjusting the Gabor parameters during the convolution operation, various low-level features can be retrieved from the original image.

2.8. Harris Corner Detection:

The Harris corner detection algorithm is often broken down into five phases.
1. Color to grayscale
2. The computation of a spatial derivative
3. Setting up a structure tensor
4. Calculating Harris's responses
5. Suppression that is not maximal

2.9. Principal component analysis:

PCA [1,3] is a dimensionality reduction technique that finds important relationships in our data, changes the data based on these relationships, and then quantifies significance of these relationships so we may keep most significant links and discard others. The above definition in the pictorial representation is given below.

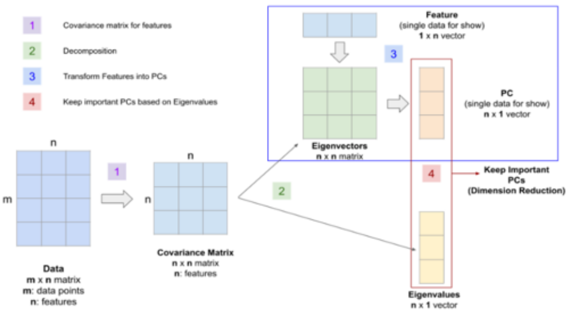

Fig. 5. Working of PCA

2.10. Features from Accelerated Segment Test (FAST)

FAST[17] is a method for locating interest spots in images that were first put out by Rosten and Drummond. Application areas Interest point detection plays a vital role in various area like picture-matching, object- recognition, tracking, etc.,.

Features from the Accelerated Segment Test are referred to as FAST. It is one of the quickest techniques for extracting characteristics from photos. They are the finest from the standpoint of a live, real-time application with effective calculation. In order to find corners, it first circles a pixel (p) from the picture with a circle of 16 pixels known as the Bresenham circle.Each pixel from 1 to 16 will now be labeled as the following phase. Verify N random labels in the circle if the brightness of the tagged pixel is greater than that of the 16 randomly chosen pixels.
For the pixel p to be a corner, the following conditions must be met:
1. It should be the case that the intensity of x exceeds the intensity of the p + threshold.
2. Alternately, x's intensity should be lower than the p-intensity threshold's

2.11. SURF-Speeded Up Robust Features:

A trustable and fast approach for local, similarity-invariant encoding along with comparison of pictures is the SURF[7,8,10,17,20,22,29] method.
The steps followed in locating interest points is as follows:
1. Finding the Integral Image
2. Scale-space representation
3. Orientation assignment
4. Descriptor components:

2.12. BRISK-Based Visual Feature Extraction for Resource-Constrained Robots

Key points that are Binary Robust Invariant Scalable (BRISK)[17,19,24] were recently developed by Leutenegger. Interest spots are discovered by generating features from Accelerated Segment Test (FAST) score for every pixel of the picture. In the event that the pixel's score is above the cutoff, it is classified as an intriguing point. After performing a few simple brightness comparison checks, the data is transformed into a binary feature vector with 512 bits of length. To match interest regions between picture pairs, the Hamming distance between the feature descriptors is then determined. In many instances, this method outperforms SURF in terms of computational performance.

2.13. Oriented FAST and Rotated BRIEF:

The features from the Accelerated Segment Test (FAST) keypoint detector and BRIEF[18] binary descriptor are used in the development of ORB[4,20,24] at "OpenCV labs." The best features from a picture are extracted using ORB, which uses fewer features. Comparing SIFT with SURF, the cost of calculation is likewise lower, but SURF is quicker in terms of magnitude.

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2.14. FIFE: fast and indented feature extractor:

With the aim of quick processing, an appropriate feature extractor is suggested. Another name for this feature extractor is "FIFE: Fast and Indented Feature Extractor"[33]. Indented refers to a multi-level strategy used here that utilizes various features at various levels. Eminent shape descriptors, such as BRISK, SURF, FAST, and ORB, are employed across the levels I throug 4 in this feature extractor. The major goal of this strategy is to extract from pictures all pertinent information in the form of key points and descriptors in order to increase precision of the recognition systems.

2.15. HOG (Histogram of Oriented Gradients)

In image processing, HOG feature descriptor is mostly utilized for detection of objects. A feature descriptor is a representation of an image that simplify the image by drawing out pertinent information.

To describe the appearance and shape of local objects inside an image, the distribution of intensity gradients or edge directions can be used according to the theory behind the histogram of oriented gradients descriptor. This descriptor uses the histograms of gradient direction as features.

2.16. M-HOG (Modified HOG):

It is also referred to as the Manhattan distance-based histogram of oriented gradients or multi-coordinate HOG[5].

Two crucial elements are included in HOG feature descriptor:

The cell image is captured locally, and the cell image is fully independent of the lighting situation. First, the normalized image IN's horizontal and vertical gradients are determined using

Horizontal Gradient =Normalized image × gradient operator

$G_H=I_N \times [-1\ 0\ 1]$

Vertical Gradient =Normalized image × transpose of the gradient operator

$G_V=I_N \times [-1\ 0\ 1]^T$

Where $I_N$is a Normalized image.

The Gradient's magnitude is

$$G_M = \sqrt{G_V{}^2(I_N) + G_H{}^2(I_N)}$$

$$\theta = \left(\frac{G_V(I_N)}{G_H(I_N)}\right)$$

If the procedure has been carefully studied thus far, it is identical to that of HOG. The distinction is that at this stage, however, we are using the Manhattan distance to determine similarity instead of normalized block.

The Manhattan distance measures separation between two points. The total of the discrepancies between the two data points' component values is the Manhattan distance.

Manhattan distance for two points' p(i1,j1) and q(i2,j2)is

$$M_{p,q} = |i1 - i2| + |j1 - j2|$$

2.17. Histogram-based features (HBF):

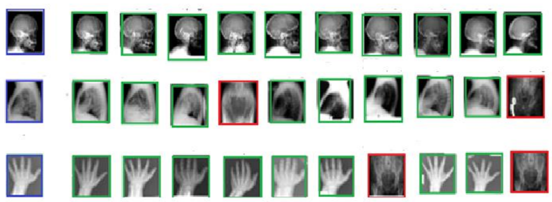
Histogram The histogram of an image area is used to generate features. It employs 10 distinct features, including Mode, Mean, Median, Range, Variance, Standard Deviation, etc., which are all part of the Histogram Based Features (HBF)[26] method.Let I represent the variable representing the image's grey levels and $p(z_i)$ represent histogram where I = 1, 2,…..L, where L represents number of discrete grey levels.Calculating mean, median, range, etc., are thus considered as features.

2.18.Scale Invariant Feature Transform:

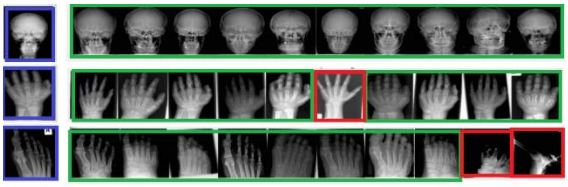
The SIFT [6,9,15,20,21,34] algorithm's step-by-step usage procedure:
1. Selection of a scale-space peak: Potential site for feature discovery.
2. Finding the feature key points with accuracy is known as keypoint localization.
3. Assigning key points with orientation: the orientation assignment.
4. Define the key points as a high-dimensional vector using the keypoint descriptor and Match key points:

III. Results and Conclusion:

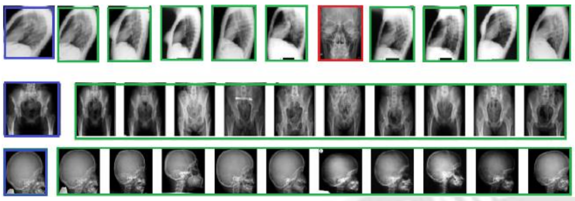
Using a couple of the aforementioned methods for the task of picture retrieval, let's now assess the outcomes.
Consider an IRMA(Image Retrieval in Medical Applications) dataset consisting of 12560 images.
The following findings were obtained using M. Srinivas et al features extraction techniques.



The findings obtained using GLCM, HDSC, HOG, and HOG as a hybrid feature extraction approach are listed below.



The results produced using the feature extraction methods FAST and BRIEF are presented below.



Images with a blue outline need to be looked for (Query images), those with a green highlight have been successfully recovered, and those with red boxes have not. This is true for all the scenarios mentioned above.Now we can use Precision, Recall, F-measure, Accuracy, etc., and can evaluate the performance measure.

The article's collection of feature extraction methods from the literature predicted modified techniques that may be used in various applications. The researchers studying medical imaging feature extraction will benefit from this survey study, according to the authors. Many academics are still putting forward brand-new algorithms as well as hybrid versions of certain already existing ones.

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