Survey Of Image Processing Techniques In Medical Image Analysis And Identification

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Abstract
A detailed analysis of the medical image is an important step in radiation preparation. The image processing is mostly radiological, medical and treatment planning techniques. Image processing is a major part of real-time applications in the modern world. This technique of image processing enables better digital image solutions to be found. The image processing tools have different techniques, most of them including abstractions of the compressed image data in order to reduce the quality of the image, noise-free image processors and saving space. This paper helps users to investigate the different technologies used by medical imaging to diagnose human body detection as well as to develop new techniques to improve the detection accuracy. This paper also presents technologies that apply image processing techniques to the classification of medical images with advantages and disadvantages.

Keywords: Medical Image, Image Processing, Deep Learning Convolutional Neural Network (DCNN).

1.IMAGE PROCESSING

Image processing involves any type of signal processing in which the input is provided as an image, such as a photo or video frame; An image processing output is an image or set of features or parameters associated with that image.

Image processing requires the desired processing or modification of an existing image and it also helps to get the image as readable. Most image processing techniques include the treatment of the image as a 2-dimensional signal and the execution of standard signal processing techniques

2. MEDICAL IMAGE PROCESSING

Medical images play an important role in the medical field. The main purpose of medical image analysis is to gain knowledge from images obtained from devices such as X-Ray, CT scan, MRI, PET-CT [1]. Structured, unstructured data emerges in large numbers. Huge amounts of data and unstructured data pose huge challenges for healthcare systems, over the years, more and more countries have been actively involved in medical information reform. Applying image processing technology to the medical and health field, using classification and analysis technology to analyze medical data and combining it with traditional medical data could achieve accurate and personalized health care services. In clinical applications, image processing technology can be used to achieve disease pattern analysis, clinical effect comparison, susceptibility population analysis, personalized treatment, clinical decision support, remote patient monitoring. Making full use of medical data is an important way to promote medical information and develop the efficiency and quality of the medical industry. Thereare four imaging modalities [2].

2.1 Protentional Imaging

X-rays are a form of electromagnetic radiation (EM), which has a wavelength range between 0.1-10 nm. They are translated into photons with energy levels, 12-125 keV. The X-ray imaging projection used almost at the same time with the need to use laboratory testing as a medical diagnostic tool. Image formation process is divided into three main steps: Image pre read, Image main read, Image processing [3].

2.2 Computed Tomography (CT)

The classic x-ray imagery projection often fails because of the small attenuation differences (less than 5%). By distinguishing under 1%, the CT increases the subject contrast. CT is also used in cancer screening applications such as lung and virtual colonoscopy. CT imaging is different: Positrone emission tomography (PET)/CT, CT perfusion, CT angiography, dual source and dual CT electricity[4][3].

2.3 Magnetic Resonance (MR)

A powerful magnetic field is used in Magnetic ResonanceImaging method (MR) for the nuclear magnetizationalignment of hydrogen atoms in water molecules. MR becamethe standard of cross-sectional imaging modalities that usefulto visualize soft tissues (such as muscle, brain), fat and bone(especially marrow bone)[5][3].

2.4 Ultrasound Imaging

The high- sound waves with the frequency range from 1-20 MHz that can be applied to produce cross-sectional imagesof the human body. The strength of the echo ultrasound returndepends on the characteristics of biological tissue which theypass through[6].

3.IMAGE PREPROCESSING

Preprocessing is one of the easiest and most important image processing methods and helps to explain diagnostic data. It is an important and diverse image preparation kit for the next image processing process. The techniques involved in pre-processing are important in ensuring that applications for post-processing are accurate and productive[7]. Pre-processing requires noise reduction and the removal of unwanted and invisible data. Additional pre-processing steps can include grey level and/or spatial quantification (lowering the pixel bits or image size)[8].

3.1NOISE

Noise is any distortion in the digital image that occurs and can damage the quality of the image. So, it is important to delete the noise until the picture is closer to the scene of the photographer's real goals. The noise in the images is a serious problem or is caused by any noise added to the data by the electrical device used for storage, transmission and processing[9][10][11].

Types of noise existing in the images used in the research are following:

3..1 1. Salt-and-pepper noise:

Darker pixels in light areas and brighter pixels in dark areas appear in the image with salt and pepper noise [12]. This type of noise is a stimulus, also called intensity spikes, and it occurs as a result of data transmission errors[13].

3.1.2. Shot noise (Poisson noise):

Due to statistical differences, this noise appears in lighter areas of the film. Noise appears at different pixels and is unrelated to each other. Shot noise is also known as poison noise, and is very similar to Gaussian noise.

3.1.3. Speckle noise:

This type of noise is double noise because the random interference between obstacles is coherent. It's usually occurs inimaging systems. It follows the gamma distribution

3.1.4. Gaussian noise (Amplifier noise):

Gaussian noise is a kind of statistical noise. It is a essential part of reading image sensor noise. The probability densityfunction for Gaussian noise is equal to the normal distribution function, also known as the Gaussian distribution.

3.2. FEATURE EXTRACTION

Features are information extracted from Medical image that are most representative of the data than can befed into machine learning models[14]. The use of characteristics eliminates redundancies and decreases the dimensionality where the model's computational cost is high. The algorithms which extract characteristics are also known as descriptors of images. Features may be selected using conventional (statistical) or biology-based approaches in medical image analysis[15].

The method should be selected according for each specific application. Measured characteristics can include: importance, energy, phase, amplitude, moments. Generally, the algorithms of the image descriptor may rely on strength, shape or texture. Transformation functions can be used to extract the relevant information when there is a high correlation in images (e.g. between voxels in each area). Some examples of these transformation functions include the main component analysis and discrete Fourier transformation.

3.2.1. Principal Component Analysis (PCA):

In PCA, the data is linearly transformed to a new coordinate system. This projection of the data into the framework of the lower dimension is performed in such a way that the greater variances are emphasized. The first main component has the greatest data uncertainty and is the most insightful component[15]. Due to reduced dimensionality, PCA is also a type of data compression. The linear combination of these orthogonal components displays all data with minimal knowledge loss[16][17][18].

3.2.2 Fourier Transform:

The Fourier Transform is suitable for image processing including filtering, compression, and reconstruction, todecompose the image into sine and cosine components which represent the image. The Discrete Fourier Transform (DFT) offers an example of each image frequency, which is large enough to fully represent a spatial domain image’s geometric characteristic[19].DFT can provide a good representation of signal changes and behaviorfor discrete time signals. The characteristics that change with time cannot be represented using DFT since itcan only be used for slices (windows) of the signals that have a fixed time duration[20].

3.3. IMAGE SEGMENTATION

The most important component of image processing is the image segmentation, which is used almost everywhere to process images so that our model can identify what is inside the image. The segmentation divides the image into different parts or items. The size of the problem was solved depending on the isolation of the image [21].

There are two main types of image separation techniques or methods. Layer based partition methods and block based partition methods are two types of partition methods.

Methods of L**ayer-based segmentation** The object detection and image segment using a layered model integrates the bank's performance of object findings to define form masks, describe appearance, and evaluate both class and event segment [22]. And B**lock-based Segmentation Methods** which is based on various features found in the image. This might becolor information that is used to create histograms, or information about the pixels that indicate edges orboundaries or texture information [23].

Table I. Compilation of Medical Image Classification Techniques

Author Name Year	**Method**	**Image Modalities**	**Performance Metrics**	**Advantage and Disadvantages**
Cheng et al. [30] 2019	CNN	radiographs	Accuracy of 91%, a sensitivity of 98%	increased the accuracy from 79% to 91%., upside-down X-rays are rare.

Chung et al. [26] 2018	deep CNN model	radiographs	Top-1 accuracy (96%)	JPEG compression mayinfluence the image quality., Not to use healthy images for fracture classification
D.P. Yadav et al. [24] 2020	Deep Neural Network (DNN)	X-ray image	92.44% Accuracy. The accuracy on 10% and 20% of the test data is more than 95% and 93% respectively.	The classification accuracy of themodel is 92.44%, Large dataset not used.
Dimililer[33] 2017	three-layer neural network	X-ray image	-	accuracy has been obtained, the number of images in the dataset is low.
Faiyaz Mohammad Saif et al. [46] 2018	Artificial Neural Network (ANN) with back engendering	X-Ray Images	Accuracy is 92.24%	precision is 92.24%., Notaccurately distinguish if break exists if or not.
Feng Yang et al. [44] 2020	convolutional neural network (CNN), SVM, ELM, RF	radiographic	Accuracy reach 78.63%.	best and the average accuracy of classification, different types of cracks not classified
J. Gregory et al. [45] 2019	deep convolutional neural networks (DCNN),	X-Ray image	-	improve classification and localization performance, Not improve network performance.
J.S. Yu et al [42] 2019	deep convolutional neural network (CNN)	radiographs	Mean sensitivity and specificity for fracture detection was 97.1% (81.5/84) and 96.7% (118/122).	good concordance with saliency maps for lesion identification, but sensitivity waslower for characterizing location.
Jiménez-Sánchez et al. [27] 2019	CAD tool	X-ray image	x-ray images into types "A", "B is precision 89%, Normal 84%.	improving classification accuracy, unbalanced data must be defined.
K. Seetharaman and S. Sathiamoorthy [40] 2016	Adaptive Binary Tree BasedSupport Vector Machine(ABTSVM)	CT, MRI, Microscopy, Mammogram, Ultrasound, X-ray and Endoscopy images	Average retrieval rate = 84.87%.	Low computational and storage cost. The ground reality and the subjectivity of the particular consumer are used to make significance decisions.
K. Sirinukunwattana etal. [39] 2016	Neighboring Ensemble Predictor (NEP) + Convolutional Neural Network (CNN)	Histopathology images	Weighted Average F1 score=0.784 Multiclass AUC= 0.917	Accurately predict. The Weighted Average F1 score and Multiclass AUCresult not considerably different with softmax CNN +SSPP
Kamil Dimilileret al. [41] 2017	backpropagation neural network	X-Ray images	Accuracy of 94.3%.	great efficiency and an outperforming rate.Notimprove the percentage ratios
Kim and MacKinnon [35] 2018	pre-trained CNNs	radiographs.	Sensitivity and Specificity resulted in values of 0.9 and 0.88, respectively.	Apply the same enlarged images for the entire calculation with a modest dataset size
Leonardo Tanzi et al. [48] 2020	convolution neural network (CNN)	X-ray images	Maximum accuracy 94%	achieved results comparable to those of humans in bone fracture classification.,number of wrong diagnoses
Lindsey et al. [25] 2018	deep CNN	radiographs	The average clinician's sensitivity was 80.8% (95% CI, 76.7–84.1%) unaided and	specialists' evaluations may be improved, Not use in different data sets.

			91.5% (95% CI, 89.3–92.9%) aided, and specificity was 87.5% (95 CI, 85.3–89.5%) unaided and 93.9% (95% CI, 92.9–94.9%) aided.	
M. Anthimopoulos etal. [38] 2016	ConvolutionalNeural Network (CNN).	Lung CT Scan Drawback	Accuracy 85.5%	High classification accuracy. The training time becomes slower due to very large number of parameters.
M. J. J. P. Van Grinsven et al. [37] 2018	Convolutional neural networks (CNNs) + Selective Sampling (SeS)	Color fundus image	-	Good performance. Uses the orientation guide from a single expert.
Marcus A. et al. [47] 2019	Convolutional Neural Networks (CNNs)	radiographic	Accuracy 95%	helping radiologists detect fractures,it is unclear how radiologists should interpret theirpredictions.
Nisha V M et al. [43] 2019	Radius Boundary Cellular Automata	X-Ray images	-	constant time complexity, Algorithm not used.
Olczak et al. [34] 2017	deep learning networks	radiographs.	The finalaccuracy at 83%	High accuracy, Huge amount data cannot candle manually.
Q. Dou et al [36] 2016	3D Convolutional NeuralNetwork(CNN)	Cerebral micro-bleeds (CMBs) MRI	High sensitivity of 93.16%	High accuracy 93:16%. The accuracy and detection speed are not stability.
Rajpurkar et al[32] 2018	169-layer convolutional neural network	radiographic	-	improve the performance of the model, only on a small dataset.
S. Yazdani, R. Yusof, A. Riazi, and A. Karimian [49] . 2014	SVM	Resonance Images (MRI)	Accuracy 95%	Magnetic Desirable performance. Not consider sub-cortical structures and 3 T images. Reduce error rate from 30% down to less than 10%.
Satoru Masubuch[28] 2020	deep neural network	optical microscope images	-	A great amount of 2D materials simply through automatic searching exfoliation and .
Thurston et al. [31] 2018	The network used is the InceptionV3 network.	radiographs	Image appropriately in92.4% of cases.	Improve accuracy,semi-automated only used.
Yahalomi et al. [29] 2019	rained Faster R-CNN		Accuracy of 96% in identifying fractures and mean Average Precisionof 0.866.	The images have been labelled by just one specialist; however, it would have been better to have a second opinion

4.FEATURE EXTRACTION AND IMAGE CLASSIFICATION

4.1. FEATURE TYPES

Types of features depend on the type of system in whichthey are going to be implemented. In image processing, spectral, geometrical and texture characteristics can be divided into types used most often.

4.1.1. Spectral features:

The image is processed as a matrix of pixels when using spectral features. Each one represents the level of brightness and color at the respective place in the image. For this area, all ties between pixels are meaningless, as we are not interested in shapes and contours. One of the advantages of processes with this function is that it is independent of image size and deformation coding[50].

4.1.2.Shape Features:

Form recognition is one of the most fundamental problems in image processing. While finding forms on an image current system is very simple for a person, a lot of work is required to achieve the same result. Consequently, several different form-based functions have been built for this method. These characteristics have been shown to be very necessary to be divided into two groups, first features invariant to translation, rotation and scaling, while in the other group features are not divided. The first community features are typically easier to extract and require simpler procedures.

4.1.3. Texture features:

Texture characteristics mean visual patterns that have homogeneity, which are not a single-color or intensity product. These features provide essential information on the surface structure and the relationship to the environment around them[51].

4.2. IMAGE CLASSIFICATION TECHNIQUES

This section delineates the supervised image classificationtechniques that are used recently.

4.2.1. Artificial Neural Network (ANN)

Artificial neural networks are non-parametric classifiers. Thestructure of the artificial neural networks is inspired fromthe human nervous system. The basic unit of this type ofnetwork is unified processing rudiment known as neuron.Each neuron has two stages- training and using phase[52][56]. Inthe training phase, the neuron learns to perform an operationwhile in the testing phase, they use the training informationto predict the output. Generally, these neural networks areused in order to detect specific trends or patterns in thegiven data.

4.2.2. Support Vector Machine (SVM)

Support Vector Machine, also known as SVM is a nonparametric classifier. Support Vector Machine is a binaryclassifier and separates the classes using a linear boundary.This classifier assumes that there is no prior information onhow to classify the data. This optimizes the use of trainingdata, which is the biggest advantage of this classifier overother classifiers like Maximum Likelihood Classifier [52].

4.2.3. Deep learning Neural Networks (DNN)

Deep learning is an algorithmic object of machine learning based on the structure and function of the brain called the artificial neural network. 'Deep' refers to the use of multiple network layers. Early research shows that a linear perceptron cannot be a global classifier, so the network with non-polynomial implementation in the hidden layer will be unlimited. Deep learning is a modern variation on a myriad of layers that allows for the processing and optimal application of technology while at the same time keeping the universal theory under slight situations.In the analysis of deep layers, for performance, training and comprehension, the 'structured area' may be diversified and widely deviated from the biologically informed linkage model [53].

4.2.4. Convolutional Neural Networks (CNN)

Deep learning is a subset of convolutional neural networks (CNN) that are often used to analyze visual imaging as a transient neural network [54]. They are also called space invariant artificial neural networks (SIANN), based on the variation of their shared weight structure and translation properties.They are used to identify photographs, video, counseling systems, photo identification, image segmentations, medical imaging analysis, natural language processing, brain and computer interface, and time sequences.

4.2.5. Back propagation neural network

The core of neural net training is back- propagation. This is the way to finalize the weight of the neural web based on the error rate achieved in the before iteration. Allows you to reduce error rates and make the correct weight adjustment model more general [55].

5.DISCUSSION

TABLE 2 shows classification system of medical image classification for each image classification technique.

Neuralnetwork classifier and SVM are the most used technique forimage classification and they could classify image fromalmost all image modalities, additionally, many researchersthat used this technique showed high accuracy and sensitivity,reasonable prediction and high classification performanceresult [24-26, 28-30, 33-39, 42, 44-45,47,48]. In addition, high sensitivityand the specificity value of the research should be completedwith a suitable number of datasets with the purpose of thefeasibility to be employed for computer-aided-diagnosis.Furthermore, many medical image analysis researchers usedimage data from X-Ray, CT, MR and ultrasound imaging modalities, since these fourimaging modalities could be used to determine the presence orabsence of the lesion based on a patient history[40].

Additionally, Magnetic Resonance Imaging does not use X-Rays. For the future work, the neural network plays animportant role in classification since it can be used with itssupervised and unsupervised techniques[41].Another interesting challenge is better classification result (above 90%)[24][27][36].

Table 2 Classification System of Medical Image Classification for Each Image Classification Technique

Image classification Methods	**Image Modalities**			
Statistical Classification Methods	**X-Rays**	**CT**	**MRI**	**Ultra sound**
Jiménez-Sánchez et al.[27]	✓			
Nisha V M et al. [43]	✓			
CNN Classifier				
Q. Dou et al [36]			✓	
M. Anthimopoulos etal. [38]		✓		
Kamil Dimilileret al.[10]	✓			
SVM				
K. Seetharaman and S.Sathiamoorthy[40]	✓	✓	✓	✓
Feng Yang et al. [44]	✓			
S. Yazdani, R. Yusof, A.Riazi, and A.Karimian [49] .			✓	

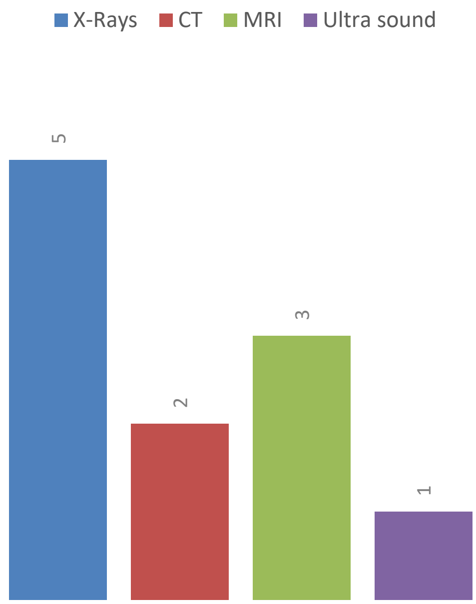

Fig 1. Graphical representation of Each image classification Technique's

6. HIGH ACCURACY PERFORMANCE ANALYSIS

Here to discuss about different algorithms and the Higher accuracy recorded by the techniques shown in table III.

Table III. High Accuracy performance Analysis above 90%

SNO.	Algorithm	Accuracy
1	Deep Neural Network (DNN)	95%
2	Convolutional Neural Networks (CNN)	91%
3	backpropagation neural network	94.3%
4	Artificial Neural Network (ANN)	92.24%
5	Support Vector Machine (SVM)	95%

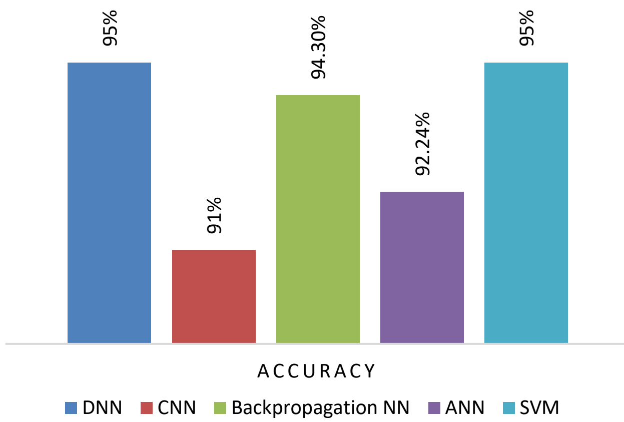

Fig 2. HigherAccuracyGraphical Representation

7.CONCLUSION AND FUTURE WORK

Medical image classification is an interesting research area,it combines the diagnosis problem and analysis purposes in themedical field. This paper has provided the detailed review ofimage classification techniques for diagnosis of human bodydisease include imaging modalities used, each dataset and prosand cons for each technique. For the future work, theimprovement of image classification techniques will increaseaccuracy value and subsequently feasible to be employed forcomputer-aided-diagnosis, and more robust methods are beingdeveloped.

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