A Survey of Medical Image Classification Techniques

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***Abstract*— Medical informatics is the study that combines two medical data sources: biomedical record and imaging data. Medical image data is formed by pixels that correspond to a part of a physical object and produced by imaging modalities. Exploration of medical image data methods is a challenge in the sense of getting their insight value, analyzing and diagnosing of a specific disease. Image classification plays an important role in computer-aided-diagnosis and is a big challenge on image analysis tasks. This challenge related to the usage of methods and techniques in exploiting image processing result, pattern recognition result and classification methods and subsequently validating the image classification result into medical expert knowledge. The main objective of medical images classification is not only to reach high accuracy but also to identify which parts of human body are infected by the disease. This paper reviewed the state-of-the-art of image classification techniques to diagnose human body disease. The review covered identification of medical image classification techniques, image modalities used, the dataset and trade off for each technique. At the end, the reviews showed the improvement of image classification techniques such as to increase accuracy and sensitivity value and to be feasible employed for computer-aided-diagnosis are a big challenge and an open research.**

Keywords—medical informatics; image classification; disease diagnosis

I. INTRODUCTION

Medical Informatics is the study that intersects Information Technology and healthcare [1]. In the implementation of field research, medical informatics combines two medical data sources. They are the biomedical record and imaging data, which have specific characteristic [2]. Digital image data is formed by pixels that correspond to a part of a physical object as a result of imaging modalities [2]. In contrast biomedical record is formed by record from patient medical tests. The difference characteristic between biomedical record and imaging data makes difference methodologies and techniques needed to explore them. Researchers and methods to explore biomedical record have already exploited [3, 4].

Medical image data is produced by imaging modalities. The issue of this field is how to extract the image and classify the extraction result into the similar pattern then identify and understand which parts of human body are affected by the specific disease from image classification result [5].

There are three stages of Medical Image analysis tasks include (1) feature extraction and representation, (2) feature selection that will be used for classification, and (3) feature and image classification [6]. Moreover, computer-aided-diagnosis needs the important role of image classification. Furthermore medical image classification has three main steps: pre-processing, feature extraction and classification [7]. After pre-processing step then it needs to extract features of interest part from the image for further analysis. The purpose of the pattern classification system is to map the input variables (such as record data or image data) become the output variables (to represent one specific class (with a disease or with no a disease class) [6].

Image classification is a big challenge on image analysis tasks, especially the selection of methods and techniques in exploiting the result of image processing and pattern recognition, classification methods, subsequently validating the image classification result into medical expert knowledge [7]. The main objective of medical images classification is not only to reach high accuracy but also to identify which parts of human body are infected by the disease. [8]. In the future, an automatic diagnosis technique with image data is needed to be developed for better clinical care [7].

Since image classification research is still an open area and big challenge to validate the image classification result into medical expert knowledge, this paper focuses only on detailed review of mining medical image classification technique with the state-of-the-art that addressing this issue. This paper will not review about feature extraction and feature selection. The aim of the review is to give the reader wide-ranging review of mining medical image classification techniques includes their pros and cons.

II. IMAGING MODALITIES

The source of medical images data is generated from Biomedical Devices, which use the imaging techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and mammogram [9].

There are several medical imaging modalities that involve ionizing radiation, nuclear medicine, magnetic resonance, ultrasound, and optical methods as a modality media. Each modality media has a special characteristic and differences

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response to human body structure and organs tissue [5]. There are four imaging modalities [9]:

A. Projectional 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 [9].

B. Computed Tomography (CT)

The conventional x-ray imaging projection sometimes fails in achieving good results because of tiny differences in attenuation (less than 5%). CT improves the subject contrast using discrimination less than 1%. The application for cancer screening such as lung and virtual colonoscopy often uses CT. There are several variations of CT imaging, namely: Positron emission tomography (PET) / CT, CT perfusion, CT angiography, Dual source and dual energy CT [9].

C. Magnetic Resonance (MR)

A powerful magnetic field is used in Magnetic Resonance Imaging method (MR) for the nuclear magnetization alignment of hydrogen atoms in water molecules. MR became the standard of cross-sectional imaging modalities that useful to visualize soft tissues (such as muscle, brain), fat and bone (especially marrow bone) [9].

D. Ultrasound Imaging

The high- sound waves with the frequency range from 1-20 MHz that can be applied to produce cross-sectional images of the human body. The strength of the echo ultrasound return depends on the characteristics of biological tissue which they pass through.

III. Medical Image Analysis Tasks

An image is considered as a representation of an object with specific properties that are employed in image processing. The medical image analysis tasks consist of Feature extraction and representation, Feature selection that will be used for classification, and Feature and image classification.

A. Feature Extraction and Representation

Features are an important measurement for image understanding, especially the feature representation of the segmented region that used for object classification and analysis [10]. The techniques for Feature extraction and representation include:

- Statistical Pixel-Level (SPL) Features

  These features provide quantitative information about the pixels within a segmented region. The SPL features include: mean, variance, and a histogram of the gray values of pixels in the region, and additionally: the area of the region and information about the contrast of pixels within the region and edge gradient of boundary pixels [10].

- Shape Feature

  These features provide information about shape characteristic of the region boundary, include circularity, compactness, moments, chain-codes, and Hough transform. Morphological processing methods have also been used for shape description [10].

- Texture Features

  These features provide information about the local texture within the region or related area of the image, which are calculated using the second-order statistical histogram or co-occurrence matrices. Besides wavelet processing method for spatial-frequency analysis is employed for local texture information representation [10].

- Relational Features

  These features provide information about the relational and hierarchical structure of the regions related to a single object or a group of objects [10].

B. Feature Selection for Classification

Feature selection used to discover the important features that most appropriate for the classification task. Selection of correlated features for dimensionality reduction in the classification task can improve the computational efficiency and classification performance. The final set of features can be determined through data correlation, clustering, and analysis algorithms to explore similarity patterns in the training data [10]. A typical classification system showed in Fig.1.

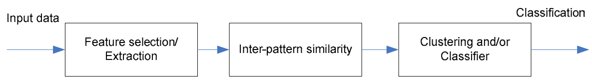

Fig. 1. A classification system [6]

Feature selection for classification techniques are:

- Linear Discriminant Analysis (LDA)

  The purpose of LDA method is to discovery a linear combination of features which able to give the best possible separation among different classes of data in the feature space. It can reduce dimensionality space for classification and also give better classification accuracy [10].

- Principal Component Analysis (PCA)

  It is an efficient method of dimensionality reduction of a data set with a big number of interrelated variables. However, for data with sparse distribution and noise, PCA method may not provide optimal selection of features [10].

- GA (Genetic Algorithms)-Based Optimization

  It is a robust technique for search optimization that uses natural selection principles. It utilizes prior information and using selection for survival, and is able to adapt to the specific parameter issues. The parameters are encoded as binary strings that are associated with the fitness measurement [10].

TABLE I. COMPILATION OF MEDICAL IMAGE CLASSIFICATION TECHNIQUES

Author Name	Year	Methodology		Pros and Cons
		Method	Imaging Modalities	
A. A. A. Setio et al [11]	2016	Multi-View Convolutional Networks (ConvNets)	Pulmonary CT	False positive reduction. The CAD sensitivity performance should be enhanced.
D. Mittal and A. Rani [12]	2016	SVM	Ultrasound image	High accuracy. Each classifier being trained on only two out of N classes.
G. Van Tulder and M. De Bruijne [13]	2016	Convolutional classification Restricted Boltzmann Machine (RBM).	Lung CT	High mean classification accuracy. Suitable for smaller representations learning with smaller filters or hidden nodes**.**
J. Hong et al [14]	2016	Principal Nested Spheres (PNS), Distance Weighted Discrimination(DWD)	MRI	AUC > 0.600. Apply PNS separately.
K. Seetharaman and S. Sathiamoorthy [15]	2016	Adaptive Binary Tree Based Support Vector Machine (ABTSVM)	CT, MRI, Microscopy, Mammogram, Ultrasound, X-ray and Endoscopy images	Low computational and storage cost. The relevance judgments are performed using the ground truth and the subjectivity of the individual user.
K. Sirinukunwattana et al [16]	2016	Neighboring Ensemble Predictor (NEP) + Convolutional Neural Network (CNN)	Histopathology images	Accurately predict. The Weighted Average F1 score and Multiclass AUC result not considerably different with softmax CNN + SSPP.
M. Anthimopoulos et al [17]	2016	Convolutional Neural Network (CNN)	Lung CT Scan Drawback	High classification performance. The training time becomes slower due to very large number of parameters.
M. J. J. P. Van Grinsven et al [18]	2016	Convolutional neural networks (CNNs) + Selective Sampling (SeS)	Color fundus image	High performance. Uses the reference guide from a single expert.
Q. Dou et al [19]	2016	3D Convolutional Neural Network (CNN)	Cerebral micro-bleeds (CMBs) MRI	High sensitivity 93:16%. The accuracy and detection speed are not balance.
A. Masood and A. Al-jumaily [20]	2015	SVM	Biopsy samples	High accuracy. The error rate of classification decreased about 16.5% for Histopathological and 6% for Dermoscopic images.
F. Khalvati, A. Wong, and M. A. Haider [21]	2015	SVM classifier.	Multi-parametric magnetic resonance imaging (MP-MRI)	High sensitivity and specificity (>80%). A limited number of datasets and the target of Gleason score is >= 7, the proposed model was not assessed by clinicians.
K. Chung et al [22]	2015	Pre-Trained Convolutional Neural Networks (CNN)	CT scan	AUC = 0.868. Time-consuming since Peri-Fissural Nodules (PFN) characterization was subjective, it suggests the increment of the number of 2D views may give the higher accuracy of characterization.
V. Gopalakrishnan, P. G. Menon, and S. Madan [23]	2015	Bayesian rule learning (BRL) methods	Cardiovascular Magnetic Resonance Imaging (cMRI)	High accuracy. A limited number of datasets.
Y. Iwahori et al [24]	2015	K-means++	Endoscope	The accuracy is higher because using the edge-based features. The computational time was decreased if HOG features used to detect the polyp region.
Y. Song et al [25]	2015	Locality-constrained Sub-cluster Representation Ensemble (LSRE)	High Resolution Computed Tomography (HRCT)	High accuracy. The Locality-constrained Linear Coding (LLC) did not use advanced distance function.
B. Manju, K. Meenakshy, and R. Gopikakumari [26]	2014	KNN classifier	CT images	High accuracy. A limited number of datasets.
G. N. Balaji, T. S. Subashini, and N. Chidambaram [27]	2014	BPNN, SVM	Echocardiogram	High performance (87.5%). Exclude other views include subcostal and Doppler view.
L. Ai, X. Gao, and J. Xiong [28]	2014	Mean-Shift Clustering (MSC)	Functional magnetic resonance imaging (fMRI)	Low false positive rate. The significance levels could not be easily theoretically measured. Still, it may show some challenges when it needs very accurate comparisons.
S. Yazdani, R. Yusof, A. Riazi, and A. Karimian [29]	2014	SVM	Magnetic Resonance Images (MRI)	Desirable performance. Not consider sub-cortical structures and 3 T images. Reduce error rate from 30% down to less than 10%. .
L. Tan et al [30]	2013	SVM classifiers for sMRI, SVM classifiers and Hierarchical clustering for fMRI.	The structural MR images (sMRI) and functional MR images (fMRI)	High accuracy. Not include tissue density maps and functional connectivity networks. fMRI classifier had difficulty in classifying some of the negative subjects.
R. Tomari et al [31]	2014	ANN	Light microscope that equipped with DinoEye Eyepiece	High accuracy. A limited number of datasets.

			Camera	
A. Andrade et al [32]	2012	Compare ANN, SVM and kNN classifier.	Ultrasound Images	Higher accuracy for SVM classifier. A limited number of datasets.
J. Miguel, P. Dias, C. Manta, A. Luís, and S. Cruz [33]	2012	Feed-Forward Backpropagation Neural Network	Digital Retinal Images	High sensitivity and specificity. The classification is not significantly affected by the randomized initialization of the neural networks weights.
M. A. Dabbah et al [34]	2011	The multi-scale dual-model using the NNT pixel classification	Corneal confocal microscopy (CCM) image	Maximum sensitivity and specificity is the EER of 15.44%. Compared to manual analysis delivers equivalent results.
E. J. Ciaccio et al [35]	2010	Classification method (using threshold or incremental learning)	Capsule endoscopy video clip images	High threshold classifier and high incremental classifier (high sensitivity and specificity).
H. Wang and B. Fei [36]	2009	Multiscale fuzzy C-means (MsFCM) classification method	MR images	Overlap ratio is greater than 90% and validated by the ground truth. Classification method was not sensitive to the threshold between 0.8 and 0.9.
M. Mete, L. Hennings, H. J. Spencer, and U. Topaloglu [37]	2009	Support Vector Machines	Regular digital camera which is attached to a microscope	Achieving 0.90 for overall f-measure. Only measures set-based dimensional fraction component. Sub-image has the same opportunities to be categorized as the positive or negative value.
R. Marée, P. Geurts, and L. Wehenkel [38]	2007	Random sub windows and extremely randomized trees	biology cell image	The accuracy is good enough without a specific pre-processing neither the domain knowledge. The issue is misclassification error rates
M. Niemeijer, M. D. Abra, and B. Van Ginneken [39]	2006	Support Vector Machine	Retinopathy screening	The ROC curve is 0.9968 and the accuracy is 0.974. The attained accuracy of 0.974 is still can be improved.
S. P. Awate, T. Tasdizen, N. Foster, and R. T. Whitaker [40]	2006	Markov statistics non-parametrically	Magnetic Resonance (MR) images	Higher mean (by a couple of percents) and lower standard deviation Only use one algorithm "nearest neighbors" in Markov neighborhood technique

C. Feature and Image Classification

The selected features of image representation that are generated from feature selection, are used in object recognition and characterization. In the medical imaging analysis, features and measurements can also be used for region segmentation to extract meaningful structures, subsequently, interpret the result using knowledge-based model and classification methods [6]. Feature and image classification techniques namely:

- Statistical Classification Methods

  The categories of these methods are an unsupervised and supervised approach. The unsupervised methods cluster the data based on their separation in the feature space, include K-means and fuzzy clustering. On the other hand, a supervised approach needs training data, test data, and class label to classify the data, include probabilistic methods like the nearest neighbor and Bayesian classifier [6].

- Rule-Based Systems

  The system analyzes the feature vector using multiple sets of rules that are designed to test specific conditions in the feature vector database to set off an action. The rules consist of two parts: condition premises and actions, which are generated based on an expert knowledge to deduce the action when the conditions are satisfied. The action which part of the rule could change the database state or label of a feature vector based on a specific state of analysis. Usually, a rule-based system consists of three sets of rules: supervisory or strategy rules, a focus of attention rules, and knowledge rules. The supervisory or strategy rules control the analysis process and provide the control actions include starting and stopping action. The strategy rules determine which rules would be tested during the analysis process. The focus-of-attention rules provide specific features within analysis process by accessing and extracting the information or features from the database. Subsequently, the rules convey the information from the input (database) into the activity center where the implementations of knowledge rules are scheduled. Finally, the knowledge rules analyze the information related to the required conditions then execute an action that changes the output database [6].

- Neural Network Classifiers

  Artificial neural network paradigms for feature classification, object recognition and image interpretation namely back-propagation, radial basis function, associative memories, and self-organizing feature maps. At that time fuzzy system-based approaches have been applied in artificial neural networks for better classification and generalization result [6].

- Support Vector Machine (SVM) for Classification

  The Relevance Vector Machine (RVM) combines regression, classification, and a Bayesian probabilistic principle. The other models for pattern classification utilizing theoretical approaches include kernel-based classifier and linear programming perturbation-based methods [6].

Compilation of medical image classification techniques showed in TABLE I.

IV. Discussion

There are several challenges for the computer to understand an image. First: diversity and number of image data increase continuously, Second: mathematical and statistical formulation and techniques, and how they could be adjusted in the medical domain, Third: computing power [2].

Subsequently, the challenge of medical image analysis model development comes from: (1) Complexity of the image data: Although the quality of an image generated by medical imaging modalities could be improved, the information captured by medical imaging modalities not always complete and clear. This problem due to lack of technology and imaging process which produce incompetent resolution and artifacts [2], (2) Complexity of the model or prototype: Medical imaging analysis involves various human body structures, features on the different application. The objects of medical imaging analysis could be atomic structures (e.g., spine, brain cortex, coronary arteries), pathological tissue (e.g., tumor, myocardial infarction, inflammation, edema), functional areas (e.g., motor cortex, glucose metabolism), or artificial objects (e.g., implants, electrodes, catheter tips) which show important biological variability of a subject. Medical imaging model or prototype explains the object based on previous knowledge that must identify diverse human body visualization [2], (3) Validation: A common problem in medical imaging analysis is data validation [2]. Human measurements are not absolutely accurate. Medical imaging algorithm requires a ground truth standard to validate their result [41-42].

TABLE II shows classification scheme of medical image classification for each image classification technique. Neural network classifier and SVM are the most used technique for image classification and they could classify image from almost all image modalities, additionally, many researchers that used this technique showed high accuracy and sensitivity, reasonable prediction and high classification performance result [12, 16-21, 26-27, 29-34]. In addition, high sensitivity and the specificity value of the research should be completed with a suitable number of datasets with the purpose of the feasibility to be employed for computer-aided-diagnosis. Furthermore, many medical image analysis researchers used image data from CT, MR and ultrasound imaging modalities [11-15,17,19,21-23,25,26,28-30,32,36,40], since these three imaging modalities could be used to determine the presence or absence of the lesion based on a patient history [9]. Additionally, Magnetic Resonance Imaging does not use x-rays [9]. For the future work, the neural network plays an important role in classification since it can be used with its supervised and unsupervised techniques [16]. Additionally, fuzzy system-based approaches have been applied in the artificial neural network for better classification result [6, 36]. Another interesting challenge is reducing an error rate by applying hybrid approach since applying single approach still give a high error rate result (above 10%) [20, 29, 30, 37].

TABLE II. CLASSIFICATION SCHEME OF MEDICAL IMAGE CLASSIFICATION TECHNIQUE

Image Classification Techniques	Imaging Modalities			
Statistical Classification Methods	X-Ray	CT	MR	Ultrasound
V. Gopalakrishnan, P. G. Menon, and S. Madan [23]			√	
Y. Iwahori et al [24]		√		
H. Wang and B. Fei [36]			√	
S. P. Awate, T. Tasdizen, N. Foster, and R. T. Whitaker [40]			√	
Neural Network Classifiers				
M. Anthimopoulos et al [17]		√		
M. J. J. P. Van Grinsven et al [18]		√		
Q. Dou et al [19]			√	
Support Vector Machine (SVM)				
D. Mittal and A. Rani [12]				√
A. Masood and A. Al-jumaily [20]		√		
F. Khalvati, A. Wong, and M. A. Haider [21]			√	
K. Chung et al [22]		√		
B. Manju, K. Meenakshy, and R. Gopikakumari [26]		√		
S. Yazdani, R. Yusof, A. Riazi, and A. Karimian [29]			√	
M. Niemeijer, M. D. Abra, and B. Van Ginneken [39]		√		

V. CONCLUSION AND FUTURE WORK

Medical image classification is an interesting research area, it combines the diagnosis problem and analysis purposes in the medical field. This paper has provided the detailed review of image classification techniques for diagnosis of human body disease include imaging modalities used, each dataset and pros and cons for each technique. For the future work, the improvement of image classification techniques will increase accuracy value and subsequently feasible to be employed for computer-aided-diagnosis, and more robust methods are being developed.

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