Journal of Engineering and Applied Sciences 13 (Special Issue 3): 3152-3158, 2018
ISSN: 1816-949X

A Review: Supervised Technique for Automated Disease Diagnostic Using Medical Image

[1]Mazniha Berahim, [2]Noor Azah Samsudin and [1]Shelena Soosay Nathan
[1]Faculty of Computer Science and Information Technology,
Universiti Tun Hussein Onn Malaysia, 86400 Pt Raja, Batu Pahat, Johor, Malaysia
[2]Department of Information Technology, Center for Diploma Studies,
Universiti Tun Hussein Onn Malaysia, 86400 Pt Raja, Batu Pahat, Johor, Malaysia

Abstract: The result of medical images diagnostic will affect clinical decision-making for diagnostics as well as the treatment planning. Thus, an accurate classifier is needed to improve automated diagnostic result. Each design of classifier and all phases involved will lead to better classification result for the accurate diagnostic. Many techniques have been used either conventional, modification or extension. However, limited review has been done in listing the recent supervised techniques in parametric and non-parametric categories for medical diagnostic procedure. Thus, the aim of this study is to provide an overview of medical image diagnostic using supervised technique and the factors to be considered for developing an accurate classifier. This will inspire newbie researcher or radiologist for and to be used when analyzing different types of medical image. The current studies of image classification task were summarized, the prominent parametric and non-parametric supervised technique identified and discussed in this study.

Key words: Supervised technique, medical image, image classification, medical image diagnostic, prominent, task, aim

INTRODUCTION

Images of human body, organs and cells are often used to investigate and diagnose medical issues. Disease diagnostic is still a complicated task which has to be implemented accurately and efficiently (Ghadge *et al*., 2016). The application of imaging technology is increasing, especially in the area of medical diagnostic (James and Dasarathy, 2014). Machine Learning (ML) is a common strategy applied to support various medical decision making tasks (Smitha *et al*., 2011) such as design automated disease diagnosis and treatment planning (Agrawal and Agrawal, 2015). This strategy will derive a classification model (classifier) from significant class attributes (Sudhakar and Manimekalai, 2014) for making a decision without depending on medical expert. Classification is a supervised learning (Agrawal and Agrawal, 2015; Battula and Prasad, 2013; Lashari and Ibrahim, 2013) where a classifier is used to label unknown image representing of known class. However, limited review has been done in listing the recent supervised techniques in parametric and non-parametric categories for medical image classification. Thus, the aim of this paper is to provide an overview of medical image diagnostic using supervised technique and the factors to be considered for developing an accurate classifier. This will inspire newbie researcher or radiologist for and to be used when analyzing different type of medical images. Current studies in the area of medical image classification were summarized, the prominent parametric and non-parametric supervised technique identified and discussed.

MATERIALS AND METHODS

Overview medical image diagnostic: Medical imaging test is more precise in medical diagnostic compare with observation of the symptom or physical examination. Accurate symptoms are unable to be identified for all diseases. It depends on the location of the disease. Examples of the imaging test includes X-ray, Mammogram, ultrasound, Computed Tomography (CT) and Magnetic Resonance (MR) and microscopy. These images become an evidence-based guideline in providing an objective information to support diagnostics procedure. Image classification is widely used in the medical field (Hemanth *et al*., 2014) and it increases the demand for a fast, accurate and efficient classification. Various image classification techniques have been proposed in literatures which can be categorized as text-based

Corresponding Author: Mazniha Berahim, Faculty of Computer Science and Information Technology,
Universiti Tun Hussein Onn Malaysia, 86400 Pt Raja, Batu Pahat, Johor, Malaysia

and content-based (Thepade and Kalbhor, 2015; Doukim *et al*., 2014). Most of the studies in medical field is carried out on content based image classification (Xiang *et al*., 2014) which concerned more on texture features compared to color or shape of images. Textural classification can be applied to any digital image. It is useful to classify the disease patterns for selected features of image according to tissue class or category (Lashari and Ibrahim, 2013; Huber *et al*., 2012). Basically, the medical images are classified into three categories: normal, malignant and benign (Angayarkanni *et al*., 2012). Previous studies have been demonstrated as binary classification with two class either normal versus abnormal (Liu *et al*., 2016) or benign versus malignant which considered as abnormal categories (Agrawal and Agrawal, 2015). In contrast, there were studies conducted for multi-classification with stages of abnormal class.

Image classification consist of five steps: image acquisition, image preprocessing, image representation (or features extraction and selection), decision making (or classification) and performance evaluation (Lashari and Ibrahim, 2013; Kumar and Kannathasan, 2011; Fenwa *et al*., 2015). For implementing the medical image classification, the existing study is done by using image processing and ML techniques (Avula *et al*., 2014). Analysis on various medical images from different imaging modalities detect many types of abnormalities after ML technique were applied (Lashari and Ibrahim, 2013; Wang and Summers, 2012). The technique was employed in traditional (Zhang and Wu, 2012; Zhang *et al*., 2013), hybrid (Chitra and Seenivasagam, 2013; Akram *et al*., 2013) modular (Decenciere *et al*., 2013) or parallel (Kharya, 2012).

Supervised machine learning techniques: Basically, the classification system based on ML strategy consists of two stages which are training stage and testing stage (Beniwal and Arora, 2012). The objectives of training stage is to select best features that are extracted from training images and to create a classifier (Zare *et al*., 2013; Sahu and Jain, 2014). While, testing stage use the classifier to label the test images into one of the predefined class (Zare *et al*., 2013). A collection of images were composed with set of attributes and some of the attributes denote the class of image (Sahu and Jain, 2014). It will be input image for training stage and the training stage (Wang *et al*., 2012). One of the main goal of classification is to maximize the successful rate acquired by the classifier when labeling instances in the test set that are unseen during training. Developing a classification algorithm for classifying images can apply three learning approaches: supervised, unsupervised and semi-supervised. Supervised learning is used to classify unknown image pixels representing known regions and homogenous surface (known as predictive or directed classification). This learning is used when the classes is known. Each instance of image belongs to a class which is indicated by the value of a class attribute (Beniwal and Arora, 2012). Unsupervised learning is used to identify group of image based on the similarity of their attribute values, characterizing a clustering task (known as descriptive or undirected). While, semi-supervised learning normally used when a small subset of labeled data is available. Accuracy of supervised classifier is better than unsupervised classifier (Zhang and Wu, 2012; Zhang *et al*., 2013). Most of the studies in medical image classification used supervised, limited studies implemented unsupervised technique such as Avula *et al*. (2014) and Krawczyk *et al*. (2016) while a few were used semi-supervised such as Cordeiro *et al*. (2016). However, this study focus on supervised learning (Battula and Prasad, 2013) which divided into parametric and non-parametric (Lashari and Ibrahim, 2013; Kumar and Sahoo, 2012). The differentiation between both categories are listed.

Parametric characters:

- Based on the statistical parameters of the image pixels of each class
- Normal distribution assumption data and learn parameters from data

Techniques by Kumar and Sahoo (2012):
Decision Tree (DT), Support Vector Machine (SVM), Bayesian, Naive Bayes (NB), Multivariate Gaussian, linear regression.

Non-Parametric:

- Not based on statistics (used in case of unknown density function)
- No assumption is made and use fixed number of parameters

Techniques by Kumar and Sahoo (2012):
Neural Network (NN), artificial NN, k-Nearest Neighbor (kNN), kernel density estimation, multivariate, logistic regression, Multilayer Perceptron (MLP).

Selected studies on medical image classification from year 2014-2016 are reviewed and summarized in Table 1. From the review, NN-based is commonly implemented from non-parametric technique. Meanwhile, SVM is frequent parametric technique applied. These techniques contribute to make a decision for automated disease diagnostic based on image label either normal-abnormal, benign-malignant or multi-class for stages of disease.

Support vector machine classifier: SVM is one of the best classifiers (Xie *et al*., 2016), popular (Zhang *et al*., 2013), most widely applied (Xie *et al*., 2016; Hiremath and Prasannakumar, 2015) and provide a powerful ML technique (Fu *et al*., 2014). It is a parametric supervised classifier that discriminates two classes by finding the best hyperplane (Nasser *et al*., 2015) as label boundaries that separates them (Hiremath and Prasannakumar, 2015) with a maximum margin of separation (Nasser *et al*., 2015). The hyperplane can be achieved by linear or nonlinear using kernel function (Nasser *et al*., 2015; Khan *et al*., 2015). Table 2 shows that SVM is prominent (Khan *et al*., 2015) in the field of medical imaging and most relevant in breast cancer diagnostic (Hiremath and Prasannakumar, 2015). SVM have capacity to minimize both training error and the geometrical margin (Carrobles *et al*., 2015) which can handle continuous binary attributes whereas the speed of classification and accuracy is good. This technique tend to perform much better when dealing with multi-dimensions and continuous features (Huber *et al*., 2012).

Neural network classifier: NN on the other side is very useful for detection and monitoring of cancer (Mbaga and ZhiJun, 2015). It is a powerful data modeling tool that represent complex input-output relationships (Amato *et al*., 2013) NN learns from a series of an interconnected group of simulated neurons (Singh *et al*., 2015) to process information. NNs-based classifier is adaptive capable in learning, self-organization, real-time operation which carried out in parallel (Agrawal and Agrawal, 2015). Furthermore, optimized features are fed to the NN classifier to classify the disease (Aalaei *et al*., 2016). However, the disadvantages of NN reported in literature are size, complexity and training time is very high (Agrawal and Agrawal, 2015). Various NNs-based Classifier used in medical image classification as listed in Table 2. Of various neural network models, BPNN classifier (Akinola and Oyabugbe, 2015) is the most widely accepted.

Performance of a classifier is the key issue to lead modelling and to meet its quality with respect to other classifiers dealing with the same problem

Table 1: Parametric and non-parametric techniques

Parametric	Non-parametric
Characters	
Based on the statistical parameters of the image pixels of each class	Not based on statistics (used in case of unknown density function)
Normal distribution assumption data and learn parameters from data	No assumption is made and use fixed number of parameters
Techniques 33	
Decision Tree (DT), Support Vector Machine (SVM), Bayesian, Naive Bayes (NB), Multivariate Gaussian, linear regression	Neural Network (NN), Artificial NN, K- Nearest Neighbor (kNN), Kernel Density Estimation, Multivariate, Logistic Regression, Multilayer Perceptron (MLP)

Table 2: Review of medical image classification using supervised technique

Supervised techniques	Decision of classification	Accuracy result of size image dataset (%)	Image modality/dataset	References
Parametric				
SVM, NB kNN	Multi-class of tumor	SVM: 94.12, NB: 92.90 of 320 79.70 of 320	Tissue images of Meningioma tumor	AlJarrah *et al*. (2015)
Modified Counter Propagation (CP)NN	Multi-class of tumor	98 of 240	MR brain tumor	Hemanth *et al*. (2014)
ANN+Adaptive Neuro-fuzzy inference System (ANFIS)	Normal-Abnormal	98 of 144	Confocal microscopes of corneal	Sharif *et al*. (2015)
Probabilistic NN, Linear Vector Quantization (LVQ)NN and Back Propagation (BP) NN	Fatty-Cirrhosis	95, 95, 80 of 100	CT images of abdominal	Mala *et al*. (2015)
Non-parametric				
ANN	Benign-malignant	97.3 of 569	Cell image of Breast	Aalaei *et al*. (2016)
MLP-NN	Benign-malignant	90.94 of 57	Mammogram image of breast	Rouhi and Jafar (2016)
Enhanced kNN	Benign-malignant	97 of 300	MR image of lung	Thamilselvan and Sathiaseelan (2016)
kNN, NN	Normal-abnormal	kNN:70, NN:85 of 100 86 of 100	Microscopy images of cervical	Athinarayanan and Srinath (2016)
Parametric				
SVM SVM	Normal-abnormal	84.21-94.01 of 168 (varied based on different features)	Mammogram image of breast	Beheshti *et al*. (2014)
SVM	Normal-abnormal	92.96 of 917	Pap smear cell images	Mbaga and ZhiJun (2015)
SVM	Multi-class (stages of abnormal)	87.5 of 120	CT image of lung	Fenwaa *et al*. (2015)
SVM, Particle Swarm Optimization(PSO)+SVM	Benign-malignant	SVM:89.15, PSO:90.5 of 330	Mammogram image of breast	Xie *et al*. (2015)
Gaussian filters+SVM	Benign-malignant	89.33 of 75	Mammogram image of breast	Hiremath and Prasannakumar (2015)
Uniform local directional pattern+ Linear SVM	Benign-malignant	93.25 of 322	Mammogram image of breast	Abdel-Nasse *et al*. (2015)

(Krawczyk *et al*., 2016). Literature showed SVM classifier performs better than NN in terms of accuracy (Liu *et al*., 2014; Ghosh *et al*., 2014) and recognition time (Fenwa *et al*., 2015). However, NNs have similar disadvantages to the SVM classifier (Stoklasa *et al*., 2014) in terms of time consuming (Virmani *et al*., 2011). Furthermore, among the two classifier studied by (Ghosh *et al*., 2014), SVM classifier has potential to improve the conventional supervised technique significantly for applied in medical field.

RESULTS AND DISCUSSION

Main performance indicators for ML algorithms are the success classification rate and training time (Akinola and Oyabugbe, 2015). The accuracy of disease diagnostic is crucial issue in order to reduce inadequate surgeries (Mala *et al*., 2015) and unnecessary clinical procedures or treatment. Thus, this article is concern on the accuracy of a classifier for the disease diagnostic. It is a probability that the test performed correctly (Das *et al*., 2013) from the total number of images.

Even though Table 2 listed different techniques with different image dataset, every technique shows its performance within their own scope. Non-parametric classifier reach to 98% accurate result which is better than parametric classifier within its scope of studies. Kumar *et al*. (2012) also found that non-parametric classifier provide the best performance. In recent studies, in order to improve accuracy of medical image diagnostic, several extension or modification (Hemanth *et al*., 2014; Thamilselvan and Sathiaseelan, 2016; Beheshti *et al*., 2016) have been made to the conventional classifier by integration or evolutionary techniques (Battula and Prasad, 2013). Therefore, studies on that are widely explored by researchers. Besides the technique used in the classification phase, the performance of automated medical image diagnostic can also be influenced by the following issues:

- Image quality (Rouhi and Jafari, 2016; Beheshti *et al*., 2016)
- Image view either from mono-modality versus multi-modality (Liberman *et al*., 2013; Legg *et al*., 2015; Liu *et al*., 2015) or single view versus multi-view images (Battula and Prasad, 2013; Xiang *et al*., 2014)
- Number of image features either single or multi-view image features (Liu *et al*., 2016; Liu *et al*., 2015; Ganesan *et al*., 2013)
- With or without features selection task (Aalaei *et al*., 2016; Kadi, 2015)
- Stratified sampling either use k-fold cross validation (k-FCV) or percentage split (Kumar *et al*., 2012)

The above issues need to be considered when developing a classification framework. However, there was a lack of framework which considered all these issues. All classifier face the issue that the accurate labeled image are hard to obtain (Schwenker and Trentin, 2014). In future, there will be great potential to extend the existing supervised techniques to accommodate with multi-view images as issued above. Thus, a general framework for an accurate automated medical diagnostic procedure is proposed (Fig. 1) which consider above issues.

The framework shows four phases: image acquisition, pre-processing, features extraction and selected and use classifier to label. Acquisition of multi-view medical image used in this framework. The role of the second phase is to improve the quality of the images. Image quality can be optimized using enhancement, segmentation, registration, and fusion task. It is important task in order to obtain accuracy in medical image classification. Thus, the next phase is to get the best set of features for representing the input images. This goal is performed by features selection task after image features is extracted. However, selection of features for classification based on subjective criteria is depend on the Purpose or the task (Ota *et al*., 2015). Thereafter the best feature set were selected, classifier is used to label the medical image: normal or abnormal. For the labelling task, k-FCV with various number of k is propose to apply in the test. This approach can avoid bias result and improved the success classification rate in disease diagnostic.

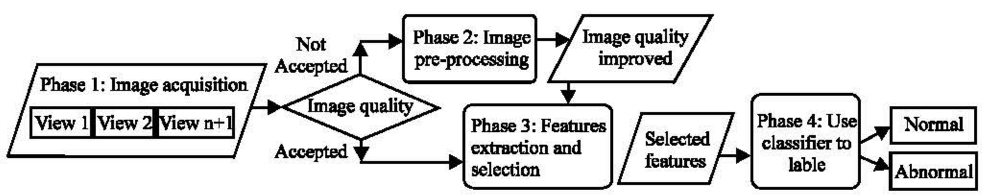

Fig. 1: General framework in medical image classification for automated diagnostic procedure

CONCLUSION

This study has reviewed current studies on classification techniques for medical image classification which applied supervised classifier and its accuracy result. The emphasis is in identifying influence factor for accurate result and generalize framework to improved accuracy of classifier. Furthermore, this study showed that the extended classifier provide better accuracy compared to conventional classifier.

RECOMMENDATIONS

It is inspiring for more research in future to identify extended strategy to be embedded into a better classifier in automating medical image diagnostic procedure.

ACKNOWLEDGEMENT

This research is supported in part by University Tun Hussein Onn Malaysia under Short Term Grant Vot U660.

REFERENCES

Aalaei, S., H. Shahraki, A. Rowhanimanesh and S. Eslami, 2016. Feature selection using genetic algorithm for breast cancer diagnosis: Experiment on three different datasets. Iran. J. Basic Med. Sci., 19: 476-482.

Agrawal, S. and J. Agrawal, 2015. Neural network techniques for cancer prediction: A survey. Procedia Comput. Sci., 60: 769-774.

Akinola, S.O. and O.J. Oyabugbe, 2015. Accuracies and training times of data mining classification algorithms: An empirical comparative study. J. Software Eng. Appl., 8: 470-477.

Akram, M.U., S. Khalid and S.A. Khan, 2013. Identification and classification of microaneurysms for early detection of diabetic retinopathy. Pattern Recognit., 46: 107-116.

Amato, F., A. Lopez, P.E.M. Mendez, P. Vanhara and A. Hampl and J. Havel, 2013. Artificial neural networks in medical diagnosis. J. Appl. Biomed., 11: 47-58.

Angayarkanni, A.S.P. and B.N.B. Kamal, 2012. Automatic classification of mammogram MRI using dendograms. Asian J. Comput. Sci. Inf. Technol. J., 4: 78-81.

Athinarayanan, S. and M.V. Srinath, 2016. Classification of cervical cancer cells in PAP smear screening test. ICTACT. J. Image Video Processing, 6: 1234-1237.

Avula, M., N.P. Lakkakula and M.P. Raja, 2014. Bone cancer detection from MRI scan imagery using mean pixel intensity. Proceedings of the 2014 8th International Conference on Asia Modelling Symposium (AMS), September 23-25, 2014, IEEE, Hyderabad, India, ISBN:978-1-4799-6487-1, pp: 141-146.

Battula, B.P. and R.S. Prasad, 2013. An overview of recent machine learning strategies in data mining. Intl. J. Adv. Comput. Sci. Appl., 4: 50-54.

Beheshti, S.M.A., H.A. Noubari, E. Fatemizadeh and M. Khalili, 2016. Classification of abnormalities in mammograms by new asymmetric fractal features. Biocybernetics Biomed. Eng., 36: 56-65.

Beniwal, S. and J. Arora, 2012. Classification and feature selection techniques in data mining. Intl. J. Eng. Res. Technol., 1: 1-6.

Bettencourt, L.A. and S.W. Brown, 2003. Role stressors and customer-oriented boundary-spanning behaviors in service organizations. J. Acad. Market. Sci., 31: 394-408.

Carrobles, F.M.M., G. Bueno, O. Deniz, J. Salido and R.M. Garcia *et al*., 2015. Frequential versus spatial colour textons for breast TMA classification. Computerized Med. Imaging Graphics, 42: 25-37.

Chitra, R. and V. Seenivasagam, 2013. Review of heart disease prediction system using data mining and hybrid intelligent techniques. ICTACT. J. Soft Comput., 3: 605-609.

Cordeiro, F.R., W.P. Santos and F.A.G. Silva, 2016. An adaptive semi-supervised fuzzy GrowCut algorithm to segment masses of regions of interest of mammographic images. Appl. Soft Comput., 46: 613-628.

Das, S., M. Chowdhury and M.K. Kundu, 2013. Brain MR image classification using multiscale geometric analysis of ripplet. Prog. Electromagnet. Res., 134: 1-17.

Decenciere, E., G. Cazuguel, X. Zhang, G. Thibault and J.C. Klein *et al*., 2013. TeleOphta: Machine learning and image processing methods for teleophthalmology. IRBM., 34: 196-203.

Doukim, C., J. Dargham and A. Chekima, 2014. State of the art of content-based image classification. Proceedings of the 2014 International Conference on Computational Science and Technology (ICCST), August 27-28, 2014, IEEE, Kota Kinabalu, Malaysia, ISBN:978-1-4799-3241-2, pp: 1-6.

Fenwa, O.D., F.A. Ajala and A.M. Aku, 2015. Performance evaluation of support vector machine and artificial neural network in the classification of liver cirhosis and hemachromatosis. Proceedings of the 2015 International Conference on Computer Vision and Image Analysis Applications (ICCVIA), January 18-20, 2015, IEEE, Ogbomoso, Nigeria, ISBN:978-1-4799-7186-2, pp: 1-6.

Fu, J.J., Y.W. Yu, H.M. Lin, J.W. Chai and C.C.C. Chen, 2014. Feature extraction and pattern classification of colorectal polyps in colonoscopic imaging. Computerized Med. Imaging Graphics, 38: 267-275.

Ganesan, K., R.U. Acharya, C.K. Chua, L.C. Min and B. Mathew *et al*., 2013. Decision support system for breast cancer detection using mammograms. Proc. Inst. Mech. Eng. Part H. J. Eng. Med., 227: 721-732.

Ghadge, P., V. Girme, K. Kokane and P. Deshmukh, 2016. Intelligent heart attack prediction system using big data. Intl. J. Recen Res. Math. Comput. Sci. Inf. Technol., 2: 73-77.

Ghosh, S., S. Mondal and B. Ghosh, 2014. A comparative study of breast cancer detection based on SVM and MLP BPN classifier. Proceedings of the 2014 1st International Conference on Automation, Control, Energy and Systems (ACES), February 1-2, 2014, IEEE, Hooghly, India, ISBN:978-1-4799-3894-0, pp: 1-4.

Hemanth, D.J., C.K.S. Vijila, A.I. Selvakumar and J. Anitha, 2014. Performance improved iteration-free artificial neural networks for abnormal magnetic resonance brain image classification. Neurocomputing, 130: 98-107.

Hiremath, B. and S. Prasannakumar, 2015. Automated evaluation of breast cancer detection using svm classifier. Intl. J. Comput. Sci. Eng. Inf. Technol. Res., 5: 11-20.

Huber, M.B., K. Bunte, M.B. Nagarajan, M. Biehl and L.A. Ray *et al*., 2012. Texture feature ranking with relevance learning to classify interstitial lung disease patterns. Artif. Intell. Med., 56: 91-97.

James, A.P. and B.V. Dasarathy, 2014. Medical image fusion: A survey of the state of the art. Inf. Fusion, 19: 4-19.

Jarrah, A.O.Y., P.D. Yoo, S. Muhaidat, G.K. Karagiannidis and K. Taha, 2015. Efficient machine learning for big data: A review. Big Data Res., 2: 87-93.

Kadi, A.O.S., 2015. A multiresolution clinical decision support system based on fractal model design for classification of histological brain tumours. Computerized Med. Imaging Graphics, 41: 67-79.

Khan, A., N.A. Syed and M. Reyaz, 2015. Image processing techniques for brain tumor extraction from MRI images using SVM classifier. Int. J. Recent Innov. Trends Comput. Commun., 3: 2707-2711.

Kharya, S., 2012. Using data mining techniques for diagnosis and prognosis of cancer disease. Int. J. Comput. Sci. Eng. Inf. Technol., 2: 55-66.

Krawczyk, B., M. Galar, L. Jelen and F. Herrera, 2016. Evolutionary undersampling boosting for imbalanced classification of breast cancer malignancy. Appl. Soft Comput., 38: 714-726.

Kumar, A. and N. Kannathasan, 2011. A survey on data mining and pattern recognition techniques for soil data mining. Intl. J. Comput. Sci., 8: 422-428.

Kumar, Yugal and G. Sahoo, 2012. Analysis of Parametric and Non Parametric Classifiers for Classification Technique using WEKA. Int. J. Inf. Technol. Comput. Sci., 4: 43-49.

Lashari S.A. and R. Ibrahim, 2013. Comparative analysis of data mining techniques for medical data classification. Proceedings of the 4th International Conference on Computer Informatics Vol. 4, August 28-30, 2013, Universiti Utara Malaysia, Changlun, Malaysia, ISBN:9789832078791, pp: 365-370.

Lashari, S.A. and R. Ibrahim, 2013. A framework for medical image classification using soft set. Procedia Technol., 8: 537-545.

Legg, P.A., P.L. Rosin, D. Marshall and J.E. Morgan, 2015. Feature neighbourhood mutual information for multi-modal image registration: An application to eye fundus imaging. Pattern Recognit., 48: 1937-1946.

Liberman, G., Y. Louzoun, O. Aizenstein, D.T. Blumenthal and F. Bokstein *et al*., 2013. Automatic multi-modal MR tissue classification for the assessment of response to bevacizumab in patients with glioblastoma. European. J. Radiol., 82: e87-e94.

Liu, D., S. Wang, D. Huang, G. Deng and F. Zeng *et al*., 2016. Medical image classification using spatial adjacent histogram based on adaptive local binary patterns. Comput. Biol. Med., 72: 185-200.

Liu, L. and L. Wang, 2014. HEp-2 cell image classification with multiple linear descriptors. Pattern Recognit., 47: 2400-2408.

Liu, S., W. Cai, S. Liu, S. Pujol and R. Kikinis *et al*., 2015. Subject-centered multi-view feature fusion for neuroimaging retrieval and classification. Proceedings of the 2015 IEEE International Conference on Image Processing, September 27-30, 2015, IEEE, Sydney, Australia, ISBN:978-1-4799-8339-1, pp: 2505-2509.

Mala, K., V. Sadasivam and S. Alagappan, 2015. Neural network based texture analysis of CT images for fatty and cirrhosis liver classification. Appl. Soft Comput., 32: 80-86.

Mbaga, A.H. and P. ZhiJun, 2015. Pap smear images classification for early detection of cervical cancer. Intl. J. Comput. Appl., 118: 7-16.

Nadiri, H. and C. Tanova, 2010. An investigation of the role of justice in turnover intentions, job satisfaction and organizational citizenship behavior in hospitality industry. Int. J. Hospitality Manage., 29: 33-41.

Nasser, A.M., H.A. Rashwan, D. Puig and A. Moreno, 2015. Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern. Expert Syst. Appl., 42: 9499-9511.

Ota, K., N. Oishi, K. Ito, H. Fukuyama and J. Sead *et al*., 2015. Effects of imaging modalities, brain atlases and feature selection on prediction of Alzheimer's disease. J. Neurosci. Methods, 256: 168-183.

Owolabi, A.B., 2012. Effect of organizational justice and organizational environment on turn-over intention of health workers in Ekiti state, Nigeria. Res. World Econ., 3: 28-34.

Rouhi, R. and M. Jafari, 2016. Classification of benign and malignant breast tumors based on hybrid level set segmentation. Expert Syst. Appl., 46: 45-59.

Saaty, T. and L. Vargas, 1987. Uncertainty and rank ordering in the analytic hierarchy process. Eur. J. Operational Res., 32: 102-118.

Sahu, P. and A.K. Jain, 2014. A review on new data mining techniques for x-ray image classification. Intl. J. Adv. Technol. Eng. Res., 1: 55-60.

Schwenker, F. and E. Trentin, 2014. Pattern classification and clustering: A review of partially supervised learning approaches. Pattern Recognit. Lett., 37: 4-14.

Seetharaman, K. and S. Sathiamoorthy, 2016. A unified learning framework for content based medical image retrieval using a statistical model. J. King Saud Univ. Comput. Inf. Sci., 28: 110-124.

Sharif, M.S., R. Qahwaji, S. Ipson and A. Brahma, 2015. Medical image classification based on artificial intelligence approaches: A practical study on normal and abnormal confocal corneal images. Appl. Soft Comput., 36: 269-282.

Silverthorne, C., 2004. The impact of organizational culture and person-organization fit on organizational commitment and job satisfaction in Taiwan. Leadersh. Organiz. Dev. J., 25: 592-599.

Singh, B.K., K. Verma and A.S. Thoke, 2015. Adaptive gradient descent backpropagation for classification of breast tumors in ultrasound imaging. Procedia Comput. Sci., 46: 1601-1609.

Smitha, P., L. Shaji and M.G. Mini, 2011. A review of medical image classification techniques. Proceedings of the International Conference on VLSI, Communications and Instrumentation, Volume 11, April 7-9, 2011, Kottayam, India, pp: 34-38.

Stoklasa, R., T. Majtner and D. Svoboda, 2014. Efficient K-NN based HEp-2 cells classifier. Pattern Recognit., 47: 2409-2418.

Sudhakar, K. and D.M. Manimekalai, 2014. Study of heart disease prediction using data mining. Intl. J. Adv. Res. Comput. Sci. Software Eng., 4: 1157-1160.

Thamilselvan, P. and J. Sathiaseelan, 2016. An enhanced k nearest neighbor method to detecting and classifying MRI lung cancer images for large amount data. Int. J. Appl. Eng. Res., 11: 4223-4229.

Thamilselvan, P. and J.G.R. Sathiaseelan, 2015. Image classification using hybrid data mining algorithms-a review. Proceedings of the 2015 International Conference on Innovations in Information, Embedded and Communication Systems, March 19-20, 2015, IEEE, Tamilnadu, India, ISBN:978-1-4799-6818-3, pp: 1-6.

Thepade, S.D. and M.M. Kalbhor, 2015. Novel data mining based image classification with Bayes, tree, rule, lazy and function classifiers using fractional row mean of cosine, sine and walsh column transformed images. Proceedings of the 2015 International Conference on Communication, Information and Computing Technology (ICCICT), January 15-17, 2015, IEEE, Pune, India, ISBN:978-1-4799-5522-0, pp: 1-6.

Virmani, J., V. Kumar, N. Kalra and N. Khadelwal, 2011. A rapid approach for prediction of liver cirrhosis based on first order statistics. Proceedings of the 2011 International Conference on Multimedia, Signal Processing and Communication Technologies, December 17-19, 2011, IEEE, Roorkee, India, ISBN:978-1-4577-1107-7, pp: 212-215.

Wang, N., J. Li, D. Tao, X. Li and X. Gao, 2012. Heterogeneous image transformation. Pattern Recognit. Lett., 34: 77-84.

Wang, S. and R.M. Summers, 2012. Machine learning and radiology. Med. Image Anal., 16: 933-951.

Xiang, Z., X. Lv and K. Zhang, 2014. An image classification method based on multi-feature fusion and multi-kernel SVM. Proceedings of the 2014 7th International Symposium on Computational Intelligence and Design Vol. 2, December 13-14, 2014, IEEE, Beijing, China, ISBN:978-1-4799-7005-6, pp: 49-52.

Xie, W., Y. Li and Y. Ma, 2016. Breast mass classification in digital mammography based on extreme learning machine. Neurocomputing, 173: 930-941.

Zare, M.R., A. Mueen and W.C. Seng, 2013. Automatic classification of medical X-ray images using a bag of visual words. IET Comput. Vision, 7: 105-114.

Zhang, Y. and L. Wu, 2012. An MR brain images classifier via principal component analysis and kernel support vector machine. Prog. Electromagnet. Res., 130: 369-388.

Zhang, Y., S. Wang, G. Ji and Z. Dong, 2013. An MR brain images classifier system via particle swarm optimization and kernel support vector machine. Sci. World J., 2013: 1-9.