A Survey on Medical Digital Imaging of Endoscopic Gastritis

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***Abstract*— This paper focuses on researches related to medical digital imaging of endoscopic gastritis. It provides suffice information on endoscopic procedure and types of gastritis. Besides that, it also briefly addressed feature extraction methods. Feature selection and Multiple Instance Learning (MIL) concept are also reviewed. As a conclusion, this paper become a basis to propose an improved artificial intelligence algorithm to perform endoscopic gastritis diagnosis.**

Keywords-feature extraction; feature selection; MIL; endoscopic gastritis

I. Introduction

Gastritis is one of the most common stomach related disorder. Unless treated, this ailment can be fatal. According to Health Facts 2006 (Malaysian Ministry of Health), one out of ten primary causes of hospitalization in MOH hospital is disease of digestive system which account for 5.20%. Meanwhile, one out of ten principal factors of death in MOH hospitals is disease of digestive system which was recorded at 4.47% [1]. In addition, according to American Cancer Society Facts and Figures 2008, estimated new cases of digestive system cancer is at 271,000 and death is estimated at 135,130 cases [2].

Gastrointestinal endoscopy is a rapid expanding specialty in medicine which sees a great progress in diagnostic technology. Previously, biopsy is a gold standard for affirmation of what endoscopists see but in the future, endoscopy alone with the aid of technology including Narrow-Band Imaging (NBI), autofluorescence and confocal imaging, is sufficient for diagnosis without the need for biopsy [3]. Downside of biopsies is it does not provide information for the entire stomach. Endoscopic examination for gastritis is considered a non-invasive investigation and provides overall observation of the stomach not as a “point” but as a “field” [4]. There have been some debates on whether endoscopic findings have strong correlation with histologic findings. There are mixed findings deduced from different sources of journals and articles. Nevertheless, this issue is not discussed further in this paper.

Another compelling fact is the incidental discovery in 1983, of a gastric bacterium which led to a drastic change in the field of gastroenterology. Helicobacter pylori (H.pylori) infects more than half the world population, inducing peptic ulcer disease and chronic gastritis; it is also strongly associated with gastric malignancies. In fact, H.pylori has been categorized as a class I carcinogen [5]. Based on the aforementioned background, a reliable system that would be capable of supporting the classification of gastritis could increase the endoscopist’s ability to accurately classify them, and could contribute to the medical advancement. Moreover, such a system would diminish the expert’s subjectivity introduced in the evaluation of the clinical characteristics of the examined tissue.

To date, most research on endoscopic gastritis conducted are related to histologic findings. This paper intends to converse a survey on medical digital imaging research which acts as a literature survey of endoscopic gastritis study. The paper is arranged as such, firstly, facts and information related to endoscopic gastritis will be presented. Then, a few insights on feature extraction method such as the statistical histogram properties are conferred. On top of that, some studies on feature selection algorithm and MIL-based concept are deliberated. Colour model transformation, segmentation and feature generation were also simulated.

II. ENDOSCOPIC GASTRITIS

A. Endoscopy

Endoscopy is an assessment where a doctor or nurse, glance through the upper part of the gut (the upper gastrointestinal tract). An endoscope is a thin, flexible telescope. The endoscope travels through the mouth, into the oesophagus and down towards the stomach and duodenum. The tip of the endoscope contains a light and a tiny video camera that enables the operator to view inside the gut. The endoscope also has a 'side channel' which various instruments can pass. These can be manipulated by the operator. For example, the operator may grasp a small sample (biopsy) from the inside lining of the stomach by using a thin 'grabbing' instrument which is passed down a side channel [6]. Areas in the gut includes cardia, body and antrum. The area of interest in this study is the antrum. Histopathology or biopsy is an invasive procedure. In addition, the technology in digital imaging is so advanced that the clarity, colour and details of video image is as good as we see inside the body itself. The breakthrough in lens and scope systems with the support of industry players will see a better clearer image [7]. Due to this, there is a need to study characterization of endoscopic gastritis image because it can avoid extra cost in terms of time and money due to delay in analysis.

B. Gastritis

Gastritis, also called dyspepsia, is an inflammation of the lining of the stomach. It can happen abruptly (acute) or steadily (chronic) [8]. Acute gastritis is considered one of the most common types of gastritis. Sudden painful inflammation of stomach lining may involve bleeding of the stomach mucosa. The main cause of acute gastritis is the Helicobacter pylori bacteria, which accounts for 90% of the cases. Whereas chronic gastritis involves long term inflammation of mucosal lining of the stomach and the inflammatory condition of the upper digestive system can hold for years. Helicobacter pylori bacteria are found to be the principal reason. There are two major types of chronic gastritis known as chronic erosive gastritis and chronic non-erosive gastritis. Chronic erosive gastritis is actually gastric mucosal erosion caused due to damage of mucosal defenses. Gastric ulcer or stomach ulcer is one of the example. Whereas, chronic non erosive refers to a variety of histologic abnormalities that are mostly the result of Helicobacter pylori infection. The body accidentally aims the stomach as a foreign protein or infection and produces antibodies against it and thus severely damages the stomach and/or its lining. Atrophic gastritis is a chronic form whereby gastric mucosa become very thin and most of the cells that generates digestive acids and enzymes are lost. Apart from the above mentioned types of gastritis, there are also rare type of gastritis such as Crohn's disease, Menetrier's disease and Barret's eosophagus [9].

C. Helicobacter Pylori (H.pylori)

Helicobacter pylori, or H. pylori, is a spiral-shaped bacterium that is capable of breeding in the human stomach. Normally, the acidic stomach environment restrain the survival of viruses, bacteria, and other microorganisms. However, H. pylori has evolved to be uniquely conform to grow vigorously in the harsh stomach environment. H. pylori bacteria secrete urease, a special enzyme that transforms urea to ammonia. Ammonia then lessen the acidity of the stomach, making it a more suitable place for H. pylori [10].

H. pylori infection is a main risk factor for peptic ulcer disease. These bacteria are culpable for the large majority of stomach (gastric) ulcers and upper small intestine (duodenal) ulcers. Research has shown that infection with H. pylori increases the risk of gastric cancer, gastric mucosa-associated lymphoid tissue (MALT) lymphoma, and possibly pancreatic cancer [10].

III. FEATURE EXTRACTION

There are many feature extraction methods published. These methods include statistical histogram properties and others. This section will discuss features that are related to endoscopic images of internal organs.

Previously in 2003, Karkanis et al. employed Karhunen-Loeve (K-L) colour space transformation on colonoscopic video. Discrete Wavelet Transform (DWT) was chosen since the low frequency image produced by the transformation does not contain major texture information. Features from co-occurrence matrix and statistical measures such as angular second moment, correlation and entropy were applied in the study [11]. Still in the same year, Tjoa et al. conducted a study to extract feature for the analysis of colon status from the endoscopic images. The hybrid texture and colour features with PCA where used whereby the average classification accuracy was at 97% [12]. Then in 2005, Iakovidisa et al. performed a comparative study of texture feature for discrimination of gastric polyps in endoscopic video. Four texture features extraction methods which are Texture Spectrum Histogram, Texture Spectrum and Colour Histogram Statistics, Local Binary Pattern, and last but not least Color Wavelet Covariance (CWC) were employed in the research [13]. Then, a year later, two methods were proposed to detect gastrointestinal adenomas from video endoscopy. The first method is to utilize color model transformation and the second one is to employ grey-level and color texture feature extraction. The study suggested to apply K-L, HSV and CIE-Lab colour model transformation. Those colour models were suggested from previous experimental result based on colour-texture analysis, and as well as endoscopic image and video analysis [11][14][15]. On the other hand, for grey-level and color texture feature extraction, the authors suggested to employ four features that are Wavelet Energy (WE) features, Wavelet Correlation Signatures (WCS), Colour Wavelet Covariance (CWC) features and Local Binary Pattern (LBP) features. Surprisingly, the system's accuracy surpassed 94% when estimated with ROC analysis in detecting and locating the gastrointestinal edenomas from endoscopic video [16].

In 2008, Bugatti et al. mentioned that the MRI heart angiogram study employed two types of feature extractors. The first type is the texture-based extractor which is based on Haralick descriptors. Then, the authors utilized the shape-based extractor which employed the improved EM/MPM algorithm [17]. On top of that, Huang et al. indicated usage of three colour spaces which are RGB, HSI and YCbCr for the endoscopic gastritis experiments. Besides that, the investigator also applied colour and texture features. The colour of ROIs are separated into four individual sub images and for each sub images, five features were computed [18]. Still in the same year, Cheng et al. conducted a study on colorectal polyps detection using texture features and Support Vector Machine (SVM). Gray Level Co-occurrence Matrix (GLCM) and colour texture feature were utilized in the study [19].

From the abovementioned studies, a lot of Karkanis and Iakovidis' works were the most relevant reference to the current study. The methods were precise and clear because the researchers disclosed the usage of certain colour model such as K-L, HSV and CIE-Lab from experimental evidence. Besides texture features, based on evidence from previous experimental studies, colour should be considered as additional features. The work stated valuable guidelines on colour and texture feature methods including CWC that made the experimental results excellent. Tjoa's contribution is much appreciated as the study reminded that classification using feature only or colour only in endoscopic studies is an incomplete classification. This is because endoscopic images carry both textural and colour characteristics. On the other hand, Bugatti did not mention which colour model being employed, yet, indicated utilizing statistical histogram measures. This is because, although the study was based on MRI, it is suffice to use gray-level feature descriptors. As for Huang's paper, the classification accuracy was quite impressive and also revealed the colour models that was employed. Nevertheless, the paper did not cite any reference to Karkanis and Iakovidis' works eventhough it was relevant to the study and published prior to Huang's paper. The study overlooked the usage of K-L colour model and CWC feature which are quite important method and proven experimentally useful in the Karkanis and Iakovidis' studies. Meanwhile, Cheng used the renowned co-occurrence matrix, yet, missed out the CWC feature. The research did not mention employing any colour model transformation eventhough it is an important element in texture feature extraction.

The current research intend to use the RGB color model as the base, yet employ colour model tansformation such as YIQ, K-L, HSV and CIE Lab. This is because Iakovidis claimed that the RGB model was proven inadequate for various medical diagnostics tasks including detection and diagnosis of early stage of lesions in endoscopic images [16]. The current study will also utilize various statistical histogram measures including Co-occurrence matrix, Local Binary Pattern and Colour Wavelet Covariance. Following that, the current research will perform comparative studies to decide the suitable colour model and, colour and textural features.

IV. FEATURE SELECTION

Feature selection is a routine that excerpts a subset of primitive features. Evaluation criterion act as a measuring tool to generate optimum feature subset from the extraction. The performance of classification algorithms is governed by the features used. Currently, there are not many researches perform on endoscopic gastritis because histologic findings still become the first option in diagnosis. Indeed, researches that employed feature selection on endoscopic gastritis images are also scarce. The purpose of this study is to extract new features from endoscopic gastritis images using novel Feature Selection algorithm.

Brief idea of feature selection have been described and the next few paragraphs will discuss and critique feature selection research applied to medical images. In 1997, Kupinski et al. performed a study using mammogram images. The study investigated various feature selection algorithms namely: stepwise selection method, genetic algorithm and individual feature analysis. Those algorithms were compared with Linear Discriminant, namely Fischer discriminant, and Artificial Neural Network (ANN) [20]. Later in 2004, Bin Ni et al. proposed hybrid gene selection method which consist of two steps. In the filter step, the top-ranked genes were preselected and in the wrapper step, Genetic Algorithm (GA) was used to select the optimized gene subsets from the topranked genes [21]. Next, in 2007, Poonghuzali et al. employed automatic optimal feature selection process which was based on the Principal Component Analysis (PCA). The process was aimed to classify abnormal masses in ultrasound liver images [22]. Meanwhile, Bugatti et al. in 2008 performed study applied to Magnetic Resonance Imaging (MRI) of the heart. The study proposed a supervised method for continuous feature selection and used the mined patterns to discover the weight of the features. By using the feature weighting with statistical association rules, it decreases the semantic gap that exists between low-level features and the high-level. Simultaneously this action made the precision of the content-based queries become better [17].

Indeed, next facts also discusses about feature selection researches from medical imaging. In 2008, Huang et al. developed a Computer-Aided Diagnosis (CAD) system using Sequential Forward Floating Selection (SFFS) with SVM. Its purpose was to diagnose gastritis caused by Helicobacter pylori (H. pylori) extracted from endoscopic images. The study was a prominent guide to the current research since both study have similar interest in feature selection algorithm and area of endoscopy specifically in the upper gastrointestinal tract (upper GI) [18]. Meanwhile, in 2009, Bacausekiene et al. study was concerned with two phase procedures to choose essential features for classification committees. The research applied to five real world problem including Wisconsin Diagnostic Breast Cancer (WDBC) and classification of laryngeal images. In terms of feature selection, both filter and wrapper were combined in his work. In the first phase, redundant features were eradicated based on the paired *t*-test. The test compared the eminenity of the candidate and the noise features. Genetic search was employed in the second phase. The search integrated the steps of training, aggregation of committee members, selection of hyper- parameters, and selection of prominence features into the same learning process [23].

A general concept of feature selection is to perform feature reduction, thus lessen the computational time and may improve classification rate. Nevertheless, one need to keep in mind that the feature selection algorithm need to search the most discriminative features, thus may improve the accuracy rate. Kupinski and Poonguzhali both presented an ordinary feature selection method. Kupinski performed a comparative study among the feature selection methods and concluded based on ROC curve that the Genetic Algorithm feature selection was comparably good and may be better than the stepwise method. The researchers admitted a possible overfitting, yet acted upon it by applying cross validation or leave-one-out tests. Whereas, Poonguzhali used Principle Component Analysis (PCA) to reduce features and obtained dissatisfied result of 68% correct classification rate. On the other hand, Bin Ni et. al. generated impressive classification rate for 3 medical data sets, up to 100%. Nevertheless, the sample data was small; less than 100. The researchers were aware of the small sample size and implemented leave-one-out-cross- validation (LOOCV) test. Next, Bugatti's study had an appealing result as the proposed method enhanced the accuracy rate up to 38%. The study had more than 700 image samples. The procedure of feature selection method are explained clearly and one can understand the logic of the algorithm. Huang et al. also illustrated the SFFS method evidently whereby in the SFFS method, the algorithm will make a number of backward steps to choose the subset for each forward step. Another strength of the study was, it solved the nesting problems in sequential forward selection (SFS) and sequential backward selection (SBS). The paper highlighted that optimal methods were not suitable for high-dimensional problems. Regardless of the basic statistical histogram measures that he employed in the feature extraction, the accuracy rate was good, up to 97%. Bacauskiene summarized the feature selection procedure accordingly and can be understood well. The paper detailed out the colour, texture and other features. The classification accuracy even had a 30% increase out of 785 images.

Previous few paragraph discussed and criticized the journals from feature selection research applied to medical images. Next findings were a few image processing and feature selection studies specifically in endoscopy of gastrointestinal tract. Pioneer study on feature selection algorithm applied on endoscopic gastritis images was conducted by Huang et al. [18]. Almost similar research in terms of endoscopic images of internal human body, is on colorectal polyps, was conducted by Cheng et al. [19]. However, this study is not using feature selection but using SVM [19]. Another paper by Iakovidis et al. who perform gastric polyps study, yet focus on texture features rather than feature selection [13]. The current research plan to incorporate the idea of previously employed method by introducing hybrid feature selection technique.

V. MULTIPLE INSTANCE LEARNING (MIL)

Most of the medical imaging study incorporates conventional learning algorithm including Artificial Neural Network(ANN) and Support Vector Machine(SVM). However, there is also a comparable learning mechanism called Multiple Instance Learning(MIL). The current study intends to employ MIL as the classifier in the characterization of endoscopic gastritis images. Next section will briefly discuss MIL overview and MIL-based medical imaging studies.

A. MIL Overview

Whenever an incomplete knowledge about labels of training examples exists, Multiple Instance Learning (MIL) may become the proposed settlement. The MIL's objective is to classify unseen bags or instances based on the labeled bags as the training data. The MIL labels are only appointed to bags of instances. At least a positive instance exist in a positive labeled bag, and all negative instances in a negative labeled bag in a binary case. Individual instances are not labeled. MIL algorithms normally apt for applications which incorporates drug activity prediction, text categorization and image retrieval and classification [24]. Due to these reasons, MIL seems to be a suitable method to be applied in classification, hence may improve detection and diagnosis.

B. Content-based Image Retrieval (CBIR) using MIL method

There are several studies in content-based image retrieval (CBIR) that exerted MIL method. In 1998, Maron and Ratan segmentized natural scene pictures into fixed-sized sub-images and applied Diverse Density (DD) algorithm to classify them into semantic classes [25]. Next in 2000, Yang and Perez's work dealt with grayscale images and can cover object images besides scene images [26]. Two years later, Zhang et al. compared both DD and EM-DD algorithms for image retrieval. K-means segmentation algorithms was used to establish more meaningful image regions [27]. Then in 2007, Han et al. contributed a novel MIL algorithm inspired from Diverse Density(DD) and Expectation Maximization version (EM-DD), which was called Improved Diverse Density (I-DD). The data used were the drug activity prediction and image retrieval [28]. Later in 2008, Dundar et al. considered spatial adjacency of feature candidates and extremely fine-tune run time by making at least one instance in each bag has to be correctly classified. Convex Hull (CH) MIL and Fisher Discriminant algorithm was introduced in the study. The CH framework employed a standard hyperplane-based learning algorithm besides having both positive and negative bag information. The proposed convexity during training algorithm resolved local minima problems in previous MIL algorithms [29]. In short, CH-FD achieved accuracy on a basic standard and significantly lower run time.

Yet another important publication in 2008 presented by Raykar et al. was novel Bayesian MIL which performed automatic feature selection and joint classification. Surprisingly, the number of features chosen for optimizing the accuracy of multiple instance classification was less than its interrelated single instance learning algorithm. The method can be extended to manipulate information from other data sets while running multiple related classifiers [30]. In the same year, Liang Zhu et al. research was to diagnose and classify lung cancer into 5 major classes. A new Multi Instance Learning (MIL) algorithm which uses Ada Boost was contributed. It chooses bag of feature in a new bag feature space mapped by partial Hausdorff distance [31].

Some of the proposed methods in a journal are valuable while others are misinterpreted. A particular technique has its own strength and weaknesses and researchers need to assess the merit of the study. As for Maron and Rattan's study, it was an investigative study to consider how the MIL concept can be employed for natural-scene classification. The research highlighted eventhough colour histogram is the most popular global technique, the technique did not capture spatial relationship of colour regions, thus limiting discriminative power. The paper claimed that using DD in MIL produced results much better than global histogram approach. The idea described from the study can be useful to colour-texture feature extraction. Next, Yang and Perez applied DD to object image instead of natural-scene image. The contribution was the idea of weight factors in feature space which was comparable with Maron and Rattan's work. The weight factors had significant effects on systems performance. It is advised to use grayscale when applying DD because there was no significant improvement when the image was in colour. As for Zhang's work, the researcher performed CBIR on coloured image, thus the idea is useful for the current study. The researcher felt that wavelet filter stimulated best performance because it represent some valuable texture information. Han et al. demonstrated even better technique namely I-DD which was an improvement from DD and EM-DD. The technique was employed to coloured images and on top of that, the time complexity was better and the accuracy rose up to 90%. Thus, the method seemed practical to be applied to the current study. Next, Murat and Dundar proposed nifty idea to diminish local minima problem and concurrently achieved comparable accuracy from the current state of the art. The study utilized the positive bag idea, ignored the negative bag and resulted significantly lower run time. The work can be applied to the current study because both research applied coloured image and MIL concept. Meanwhile, Raykar's work can be employed too. This is because the current study is also proposing a joint classifier of feature selection and MIL idea. As for Liang Zhu, the research achieved up to 91% of lung cancer image classification accuracy, nevertheless, required more processing time because it is a two-level classifier. The research is also applicable to the current study because AdaBoost was used as feature selector and two-level classifier, which is what the current study plan to investigate in the future.

VI. SIMULATION

Several authors suggested to perform colour transformation to represent the images in different colour model to avoid dichromatic reflection and white illumination [11][14][15][18]. Gevers highlighted that the colour transformation is independent of the viewpoint, surface orientation, illumination direction and illumination intensity [32]. Based on this, the images were simulated in different colour models and a few of the results are shown in Figure 1(b)(c)(f)(g). Segmentation process were also simulated and some of them are demonstrated in Figure1(d)(h). The purpose of segmentation is to distinguish the differences in features specifically in the colour and texture of the antrum. Simulations regarding colour transformation and segmentation were carried out using CVIPtools software. The first two RST Invariant Moment-Based Features, Histogram Features and Texture Features were extracted in the current study. There were 12 images from normal gastric, erosive and superficial gastritis and also ulcer. Twenty seven features from 3 different colour channels were also extracted from each image. The feature data were used to perform backward feature selection using SVM learner from Rapid Miner 4.5 software. The result of the feature selection simulation is presented in Figure 2.

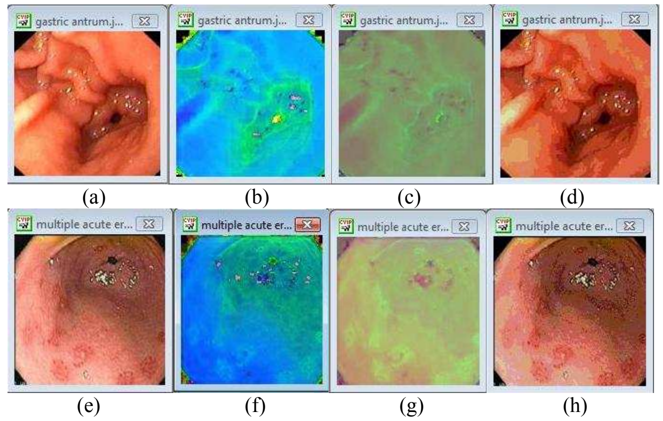

Figure 1. Images from normal and abnormal gastric whereby color model transformation and segmentation process were perfomed. (a) and (e) are normal and abnormal gastric images in RGB. (b) and (f) are normal and abnormal gastric in HSV. (c) and (g) are normal and abnormal gastric in CIE Lab.(d) and (h) are segmentation of images for normal and abnormal gastric.

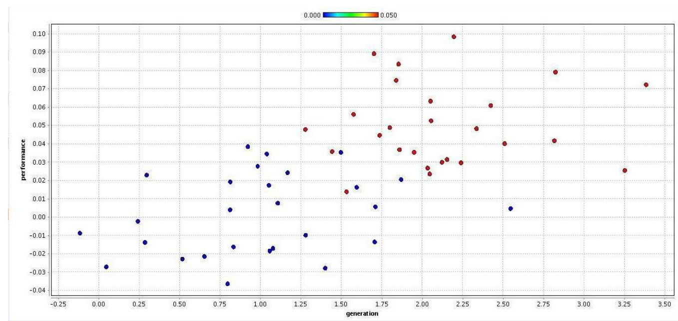

Figure 2. Scatter plot of Generation vs. Performance of features. Blue colored dots represent performance of Predicted features and red colored dots represents performance of True features.

VII. CONCLUSION

In conclusion, this paper has described relevant information which includes endoscopy and types of gastritis related to endoscopic gastritis. A brief feature extraction methods are also discussed. A new paradigm in supervised learning which are feature selection and Multiple Instance Learning (MIL) are also deliberated. On top of that, several image content based studies were also addressed. From the simulation, it was discovered that not all of the experimentally suggested colour model were suitable because certain times it does not distinguish the essential features expected. As for the feature selection, by referring to Figure 2, all of the features generated were used to classify. The current study plan to select valuable features and classify them. Regardless of the simulation, further studies need to be carried out. Currently, not many endoscopic gastritis studies are carried out using feature selection and MIL concept. Hence, this paper proposed a Hybrid Feature Selection-MIL algorithm. It acts as a joint feature selector-classifier which selects positive essential features from a bag of features that may improve the performance of the classifier.

References

[1] Health Facts 2006: Planning and Development Division (Information and Documentation System Unit), Ministry of Health Malaysia, July 2007. Retrieved from http://www.moh.gov.my

[2] American Cancer Society. *Cancer Facts & Figures 2008*. Atlanta: American Cancer Society; 2008. Retrieved from http://www.cancer.org

[3] R. Lambert. ESGE Headline News No. 6 : The challenge of high-resolution endoscopy. Retrieved on 15 April 2009 from http://www.esge.com/hln-006.html

[4] S. Kim, K. Haruma, M. Itoa, S. Tanaka, M. Yoshihara and K. Chayama. 2004. Magnifying gastroendoscopy for diagnosis of histologic gastritis in the gastric antrum. Digestive and Liver Disease, Vol. 36, pp. 286–291.

[5] Chiara Ricci, John Holton and Dino Vaira. 2007. Diagnosis of Helicobacter pylori : Invasive and non-invasive tests. Best Practice & Research Clinical Gastroenterology. Vol. 21. No. 2, pp. 299-313.

[6] Gastroscopy (Endoscopy) Retrieved on 20 April 2009 from http://www.patient.co.uk/showdoc/27000331/

[7] Anna M. Buchner and Michael B. Wallace. 2008. Novel Endoscopic Approaches in Detecting Colorectal Neoplasia: Macroscopes, Microscopes, and Metal Detectors. Gastroenterology, Volume 135, Issue 4, pp. 1035-1037.

[8] Gastritis. Retrieved on 27 May 2009 from http://my.clevelandclinic.org/disorders/Gastritis/hic_Gastritis.aspx

[9] Types of Gastritis. Retrieved on 22 May 2009 from http://www.indianetzone.com/41/types_gastritis.htm

[10] H.pylori and Cancer : Fact Sheet-National Cancer Institute. Retrieved on 22 May 2009 from http://www.cancer.gov/cancertopics/factsheet/risk/h-pylori-cancer

[11] Stavros A. Karkanis, Dimitris K. Iakovidis, Dimitris E. Maroulis, Dimitris A. Karras, and M. Tzivras. 2003. Computer-Aided Tumor Detection in Endoscopic Video Using Color Wavelet Features. IEEE Transactions On Information Technology In Biomedicine, Vol. 7, No. 3.

[12] Marta P Tjoa and Shankar M Krishnan. 2003. Feature extraction for the analysis of colon status from the endoscopic images. BioMedical Engineering OnLine, pp. 2-9.

[13] D. Iakovidisa, D. Maroulisa, S. Karkanisb, A. Brokos. 2005. A Comparative Study of Texture Features for the Discrimination of Gastric Polyps in Endoscopic Video. Proceedings of the 18th IEEE Symposium on Computer-Based Medical Systems (CBMS'05).

[14] G. Van de Wouver, P.Scheunders, S.Livens, D.Van Dyck. 1999. Wavelet correlation signatures for colour texture characterization. Pattern Recognition Vol. 32, pp. 443-451.

[15] G.Paschos. 2001. Perceptually uniform colour spaces for colour texture analysis : An empirical evaluation, IEEE Trans. Image Process Vol. 10 No. 6, pp. 932-937.

[16] Dimitris K. Iakovidis, Dimitris E. Maroulis, Stavros A. Karkanis. 2006. An intelligent system for automatic detection of gastrointestinal adenomas in video endoscopy. Computers in Biology and Medicine, Vol. 36, No. 10, pp. 1084-1103.

[17] Pedro H. Bugatti, Marcela X. Ribeiro, Agma J. M. Traina, Caetano Traina Jr. 2008. Content-based Retrieval of Medical Images by Continuous Feature Selection. 21st IEEE International Symposium on Computer-Based Medical Systems, June 17-19 2008, Jyväskylä, Finland.

[18] Chun-Rong Huang, Pau-Choo Chung, Bor-Shyang Sheu, Hsiu-Jui Kuo, and Mikul´aˇs Popper. 2008. Helicobacter Pylori-Related Gastric Histology Classification Using Support-Vector-Machine-Based Feature Selection. IEEE Transactions On Information Technology In Biomedicine, Vol. 12, No. 4.

[19] Da-Chuan Cheng, Wen-Chien Ting, Yung-Fu Chen, Qin Pu and Xiaoyi Jiang. 2008. Colorectal Polyps Detection Using Texture Features and Support Vector Machine. Lecture Notes in Computer Science (LNAI) 2008. Vol. 5108, pp. 62-72.

[20] Matthew A. Kupinski and Maryellen L. Giger. 1997. Feature Selection and Classifiers for the Computerized Detection of Mass Lesions in Digital Mammography. International Conference on Neural Networks 1997, Vol. 4, pp. 2460-2463.

[21] Bin Ni, Juan Liu. 2004. A Hybrid Filterwrapper Gene Selection Method For Microarray Classification. Proceedings of the Third Intemational Conference on Machine Learning and Cyherneucs, Shanghai, pp. 2537-2542.

[22] S. Poonguzhalil, B. Deepalakshmil and G. Ravindran . 2007. Optimal Feature Selection and Automatic Classifi'cation of Abnormal Masses in Ultrasound Liver Images. IEEE - ICSCN 2007, pp.503-506.

[23] M. Bacauskiene, A.Verikasa, A.Gelzinis, D.Valincius. 2009. A feature selection technique for generation of classification committees and its application to categorization of laryngeal images. Pattern Recognition 42, pp. 645 – 654.

[24] Yang, J. 2005. Review of multi-instance learning and its applications. Technical report, School of Computer Science Carnegie Mellon University.

[25] Maron, O. and Ratan. A. L. 1998. Multiple-Instance Learning for Natural Scene Classification. Proc. 15th Int. Conf. on Machine Learning, pp. 341-349.

[26] Yang, C. and Lozano-Perez T. 2000. Image database retrieval with multiple-instance learning techniques. Proc. of the 16th Int. Conf. on Data Engineering, pp.233- 243.

[27] Zhang, Q., Goldman, S. A.,Yu, W. and Fritts, J. E. July 2002. Content-Based Image Retrieval Using Multiple-Instance Learning. Proc. of the 19th Int. Conf. on Machine Learning.

[28] Fengqing Han, Dacheng Wang and Xiaofeng Liao. 2007. An Improved Multiple-Instance Learning Algorithm. Lecture Notes Computer Science Vol. 4491, pp. 1104-1109.

[29] Dundar, M. Murat, Fung, Glen, Krishnapuram, Balaji and Rao, R. Bharat. March 2008. Multiple-Instance Learning Algorithms for Computer-Aided Detection. IEEE Transactions on Biomedical Engineering. Vol. 55, No. 3, pp. 1015-1021.

[30] Raykar, V.C., Krishnapuram, Balaji, Jinbo Bi, Dundar, M.M, Bharat Rao, B. July 2008. Bayesian Multiple Instance Learning : Automatic Feature Selection and Inductive Transfer. Proceedings of the 25th International Conference on Machine Learning, Helsinki, Finland, 2008, ICML2008.

[31] Liang Zhu, Bo Zhao, Yang Gao. 2008. Multi-class Multi-instance Learning for Lung Cancer Image Classification Based on Bag Feature Selection. Fifth International Conference on Fuzzy Systems and Knowledge Discovery, FSKD '08, Vol. 2, pp. 487 – 492.

[32] T. Gevers and W.M. Smeulders. 2000. PicToSeek:Combining Color and shape invariant features for image retrieval. IEEE Trans. Image Processing. Vol. 9, pp. 102-119.Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].