

A Review on Abdominal Mass Diagnosis Models

¹Shivshankar Sambhajirao Kore, ²Dr. Ankush B. Kadam

¹Research Scholar, Pacific Academy of Higher Education and Research, University, Udaipur, India

²Assistant Professor, Jawahar Arts, Science and Commerce College, Andoor. Maharashtra.India

ABSTRACT

An abdominal mass is any localized swelling or enlargement in the abdomen of human. Based on its position, the it may be occur as an hepatomegaly, a retroperitoneal mass splenomegaly, a pancreatic mass, protruding kidney, an abdominal aortic aneurysm, or different tumors, like those occurred by abdominal omental metastasis and carcinomatosis. The diagnosis is based on the reason, and may perhaps range from observant waiting to radical surgery. In this paper, various kinds of classifiers adopted for classifying the medical images related to numerous diseases are focused. As there is lack of contributions based on abdominal mass detection, this paper is focused on other various diseases and their corresponding methodologies. Accordingly, abdominal mass detection can be detected by means of any of the adopted methodologies in future.

Keywords—Medical Image Classification; Abdominal mass Detection; Features; Classifiers; Challenges

I INTRODUCTION

In the earlier period, biomedical image investigation for identification of diseases in patients was carried out by means of conventional radiological screening methods and automatic identification that are somewhat time-utilizing and endures from numerous vital restrictions together with the prejudice of the diagnosed consequence and the inconsistency among laboratories [1]. In addition, with the current extreme progressions in the biomedical image technology, numerous kinds of biomedical images have been produced in an assortment of modalities by means of highly developed medical imaging strategies, together with US (Ultrasound), MRI (Magnetic Resonance Imaging), CT (Computed Tomography) and X-Ray, MS (Microscopic). Consequently, it has turned out to be not practical for experts to label and annotate the entire images manually that are gathered from a very large quantity of patients on a daily basis. The continuing improvement of imaging technology assisted in resolving numerous challenges in medical imaging in the present day. Medical imaging has made a significant contribution to develop the exactness, appropriateness, and effectiveness of diagnosis [2]. Depending on US images, general practitioner can determine the typical sizes of organs precisely in abdominal cavity such as kidneys, pancreas, spleen, liver, etc. and identifies abnormal tumors. It assists the general practitioner to recognize cranial pathologies, particularly brain tumors and endoscopic hemorrhoids, and precisely find out masses and abnormalities in the body. A major essential task in medical imaging is known as segmentation that partitions a medical image into various segments for additional analysis on diseases [3]. For the precedent

decade, in medical imaging, significant attempts have been dedicated to intend valuable feature representation for mechanical classification. The majority of the researchers concerns on exploiting a variety of feature descriptors, namely, Local Binary Patterns (LBP), Scale-invariant Feature Transform (SIFT), etc., to take out features from medical images. Moreover, feature encoding methods such as locality-constrained linear coding and sparse coding generally integrate histogram representation or bag of words framework and multiple feature combination techniques by aggregating various feature information. As the contribution for abdominal mass detection in medical image is insufficient, this paper has look forwarded for various other diseases in medical imaging classification [4], which can be adopted for abdominal mass diagnosis.

II LITERATURE WORKS

2.1 Related Works

In 2016, Shuchao *et al.* [1] have introduced a deep convolution neural network (DCNN) for constructing a deep model; and subsequently to extend the deep learning structural design depending on the raw pixels of actual biomedical images by means of supervised training. Accordingly, the feature space was modeled, and it explores an effectual feature vector classifier or segments particular image patches and detection object that were the major technological complicatedness in the implementation of conventional image classification techniques. In addition, there was no requirement to be troubled with whether there were large training sets of interpreted biomedical images to wait for training a ideal deep model that were the major troubles to train DNN for biomedical image classification as noticed in current works.

In 2017, Solmaz Abbasi and Farshad Tajeripour [2] has developed an automatic technique in 3D images for brain tumor detection. In the initial pace, the histogram matching and bias field corrections were utilized for image preprocessing. In the subsequent pace, the region of interest (ROI) was recognized and alienated from the Flair image background. Histogram of orientation gradients (HOG-TOP) and LBP in three orthogonal planes (LBP-TOP) was exploited as the learning features. As 3D images were deployed in this study, the suggestion of LBP in three orthogonal planes for expanding HOG for 3D images was deployed. The random forest (RF) was subsequently utilized to segment the regions of cancer. Moreover, the computation of the proposed scheme on glioma images from BRATS 2013 was evaluated.

In 2017, Yangyang *et al.* [3] have introduced a scheme, which can differentiate a variety of structures in medical imaging better than a single-scale edition. Consequently, Fisher vector method was adopted to encode the obtained features to execute a fixed-length image demonstration that offers plentiful information of high-order information and improves the discriminative and descriptive capability of feature representation. Moreover, researchers were carried out on the IRMA-2009 mammographic patch and the medical collection dataset. The wide-ranging investigational outcome has revealed that the suggested technique have higher performance.

In 2017, EhsanKozegar *et al.* [4] have developed a multi-stage detection model for the objective of identifying cancer in 'ABUS' images. Early stage was to minimize the speckle noise, and it can be achieved by deploying de-speckling technique known as "OBNLM." Subsequently, a novel procedure was deployed for the

recognition of initial candidates that was dependent mainly on isocontours. With the intention of reducing the erroneously created isocontours, certain features like 'roundness,' 'hypoechoicity,' 'area strength' and 'contour strength' were utilized. Consequently, the successive candidates were further practiced by means of a cascade classifier, and the corresponding base classifiers were 'Random Under-Sampling Boosting (RUSBoost)' that was initiated for managing with the imbalanced datasets. The design was investigated depending on 'Free response Operating Characteristics (FROC)' and has revealed its enhanced performance.

In 2018, Abir *et al.* [5] have introduced a content-dependent image retrieval technique on the basis of med-level descriptors. These descriptors were mechanically produced from low-level image features by utilizing the semantic conceptions depending on the clinician medical-knowledge. Actually, the suggested technique was dependent on three major processes. First is the low-level extraction of features. Next is the med-level model extraction and last is the online retrieval depending on med-level feature vectors. The major contributions exist in the incorporation of clinician medical-knowledge with respect to the med-level features devoid of requiring radiologists interface. The implemented scheme was authenticated on the MIAS dataset, in the framework of mammogram retrieval, and the outcomes confirm its efficiency and its dominance to the distinguished techniques.

In 2017, Habib *et al.* [6] have suggested a scheme that initially identifies an preliminary set of candidates by means of a Gaussian Matched Filter and subsequently classifies the corresponding set to decrease the number of false positives. In addition, a Tree Ensemble classifier was adopted with a group of 70 features. A novel set from the MESSIDOR dataset of 32 MA ground truths depending on images was established as a public dataset for benchmarking MA detection techniques. The suggested scheme was estimated on this dataset in addition to various public dataset (DIARETDB2) and distinguishes it in opposition to the most excellent obtainable option. Outcomes demonstrate that the suggested classifier was better in eradicating false positive MA detection from the primary set of candidates.

In 2017, Bartosz *et al.* [7] have introduced a novel advanced technique of image description and an ensemble classifier for identification of mammograms in breast cancer. The non-negative matrix factorization and various techniques of image representation, which were not utilized in the area of mammogram recognition were improved and ensured in the function of investigative features. Ultimate image recognition was made by means of an ensemble classifier. In addition, the novel scheme to the combination of an ensemble was suggested. It relates the weighted majority voting together with the weights described from the optimization task described depending on the region under curve of ROC. The consequences of arithmetical experiments carried out on large database "Digital Database for Screening Mammography" enclosing higher than 10000 mammograms have established higher accuracy in recognizing the abnormal ones from the normal cases. The offered outcome of class recognition goes beyond the most excellent accomplishments for this base reported in the original publications.

In 2016, ImanElyasi *et al.* [8] have developed an algorithm for the reduction of speckle noise using the US in breast cancer images. For eradicating the noise, an amalgamation of 'homogeneity filters' and a design said to be 'Modified Bayes Shrink model (MBS) was adopted. Primarily, they have substituted the pixel intensity and

shortly they have deployed the threshold value of customized bayes shrink representation. This was made for the inequity of homogeneous regions together with speckle noise that was acquired from the process of filtering. The suggested 'Homogeneity MBS (HMBS)' has revealed its dominance over other traditional models.

In 2015, G. Mahendran and Dhanasekaran [9] has implemented a technique to identify lesion exudates mechanically with the support of non-dilated retinal funds for supporting ophthalmologists to treat the disease. The low contrast images of the exudates were recognized and localized by means of a neighborhood dependent segmentation method. A probabilistic neural network (PNN) classifiers and SVM were suggested to evaluate the rigorousness of the disease, and the consequences were distinguished with the similar segmentation method. The standard classification accurateness for the PNN and SVM classifiers were found to be 94.76% and 97.89%, correspondingly.

In 2016, PengGu *et al.* [10] have introduced a mechanized technique for the segmentation of 3D US volumes. The segmentation was categorized into three varieties known as, 'fatty tissue,' 'mass/cist' tissue, and 'fibro-glandular tissue.' They have scrutinized the effectiveness in addition to the steadiness of suggested representation by deploying them on a database of 21 test cases of all breast US. Outcomes of the research have offered improved computation of the proposed model by comparing tissues, namely non-fat or fat, and in addition, it outperformed in tissues classification also. On the whole, the design has acquired ideal consistency and potential in characterizing the tissues.

In 2017, Pedro *et al.* [11] have proposed a new method for extracting features based on radiological density patterns of the brain, called Analysis of Brain Tissue Density (ABTD). The proposed method is a specific approach applied to CT images to identify and classify the occurrence of stroke diseases. The evaluation of the results of the ABTD extractor proposed in this paper were compared with extractors already established in the literature, such as features from Gray-Level Co-Occurrence Matrix (GLCM), Local binary patterns (LBP), Central Moments (CM), Statistical Moments (SM), Hu's Moment (HM) and Zernike's Moments (ZM).

In 2014, GerardPons *et al.* [12] have implemented a 'deformable part models' (DPM) and object detection model (ODM) for the detection of cysts in breast images. They have further adopted a data set of 326 images from a variety of patients. The implemented design has outperformed numerous traditional models regarding lesion detection. Moreover, 'False positive detection' of 0.28 (per image), high sensitivity of 86% were achieved. In addition, the introduced design has demonstrated its effectiveness concerning the 'Malignant lesion detection.'

In 2017, Woo KyungMoon *et al.* [13] have suggested a design known as 'Computer-Aided Prediction (CAP)' with the exploitation of tumor close by features in US images. The design was formulated for describing the 'Axillary Lymph Node (ALN)' condition in breast cancer. The adopted dataset included 114 cases, and 49 of 114 were 'ALN metastases. Finally, the assumption design was trained and tested. From the outcomes, the set of textural features, which were obtained from close by tissue have revealed more computation than the feature sets such as intensity and morphology.

In 2017, Qi Dou *et al.* [14] has suggested a 3D DSN scheme, which was proficient in performing volume-to-volume inference and learning that can eradicate superfluous performances and lessen the risk of over-fitting on restricted training data. More significantly, the 3D deep supervision method can efficiently manage with the optimization crisis of gradients fading. The speed of convergence has enhanced the discrimination ability simultaneously. Such a method was introduced by formulating an intended function, which directs the training of both upper and lower layers directly in the network, thus the unfavorable consequences of unbalanced gradient alterations can be frustrated throughout the training process. In addition, an entirely connected conditional random field design was employed as a post-processing pace to purify the segmentation consequences.

In 2018, Alexander *et al.* [15] have offered a novel quantitative technique for detecting variations in 3D medical images. The variation among shapes was measured as a determination of the attempts it takes to distort one 3D region into another one. The evaluation of isometric and conformal deformations of mappings was major equipment among volumes. Contrasting to the majority of the conventional schemes for shape assessments, the suggested one functions both on tetrahedral and triangular meshes, and as a result can be deployed for volumetric domains homeomorphic to a ball in addition to closed simply connected surfaces with geometrically complex limitations. In addition, the major geometric deformation access to higher dimensions was evaluated in a manner, which permits for managing with spatial data at the maximal, at the entire lower dimensions.

In 2017, Sheng-Chih Yang [16] has established a novel medical image segmentation scheme, which obtains better image segmentation precision. With the intention of demonstrating the finest outcomes distributed by the suggested Progressive Support-pixel Correlation Statistical Method (PSCSM) for actual medical images. Moreover, investigational data were classified as multi-spectral breast magnetic resonance images (MRI), computer-processed images, and actual single-spectral mammograms. At last, the research consequences were distinguished with various renowned conventional and aggressive image segmentation techniques to substantiate the contributions and advantages of the suggested technique.

In 2017, Khatami *et al.* [17] have suggested a three-step architecture for classifying multiclass images related to radiography. The initial pace exploits a de-noising method depending on wavelet transform (WT) and Kolmogorov Smirnov (KS) analysis to eradicate noise and irrelevant characteristics of images. An unsupervised DBN was modeled for unlabelled feature learning in the succeeding step. Even though small-scale DBNs includes noteworthy prospective, the performance cost of training the limited Boltzmann apparatus was a most important problem when extending to large networks. In addition, noise in radiography images could make a major corruption of details that obstructs the computation of DBNs. The amalgamation of WT and KS test in the initial step assists in enhancing the computation of DBNs

TABLE I. REVIEW ON STATE OF THE ART MEDICAL IMAGE CLASSIFICATION TECHNIQUES

Author [Citation]	Adopted Methodology	Features	Challenges
Shuchao <i>et al.</i> [1]	DCNN	<ul style="list-style-type: none"> ❖ Efficiently deal with a restricted amount of labeled biomedical images ❖ Increased convergence speed 	<ul style="list-style-type: none"> ❖ Classification accuracy is not excellent and lessens most of the time
Solmaz Abbasi and Farshad Tajeripour [2]	RF	<ul style="list-style-type: none"> ❖ Enhances the contrast of the input image ❖ Decreases the space and time complication 	<ul style="list-style-type: none"> ❖ This system was not performed on BRATS 2014 dataset.
Qiling <i>et al.</i> [3]	SVM	<ul style="list-style-type: none"> ❖ Better classification accuracy ❖ Offers excellent optimal sampling 	<ul style="list-style-type: none"> ❖ No contemplation on high level feature representation
EhsanKozegar <i>et al.</i> [4]	AdaBoost	<ul style="list-style-type: none"> ❖ Achieves high sensitivity ❖ Reduces false positive. 	<ul style="list-style-type: none"> ❖ Possibility of missing cancerous masses. ❖ Not able to recognize the closed iso-contour from close by boundaries.
Abir <i>et al.</i> [5]	decision tree,	<ul style="list-style-type: none"> ❖ Improves the accuracy of the query decision ❖ Obtains the high-level features of the query image devoid of radiologist intervention 	<ul style="list-style-type: none"> ❖ No contemplations on huge sized medical datasets
Habib <i>et al.</i> [6]	SVM	<ul style="list-style-type: none"> ❖ Advanced in terms of eliminating false positives ❖ Maintains the same sensitivity 	<ul style="list-style-type: none"> ❖ No consideration on feature selection for the minimization of the feature set
Bartosz <i>et al.</i> [7]	Decision tree	<ul style="list-style-type: none"> ❖ Better specificity and sensitivity of identification system ❖ Enhances different quality factors simultaneously in an automatic system 	<ul style="list-style-type: none"> ❖ Not able to substitute the radiologists for final interpretation of mammograms.



ImanElyasi <i>et al.</i> [8]	Bayesian	<ul style="list-style-type: none"> ❖ Achieves fast running time ❖ Improves the performance by enhancing the image quality 	<ul style="list-style-type: none"> ❖ High smoothing leads to blurring the image. ❖ Complication increases in image registration process.
G. Mahendran and Dhanasekaran [9]	SVM	<ul style="list-style-type: none"> ❖ Facilitates ophthalmologists to identify the exudates in a very short time of scrutiny ❖ Low-cost and does not necessitate trained experts 	<ul style="list-style-type: none"> ❖ Requirement of features may be increased on the accumulation of the exudates with respect to the distance
PengGu <i>et al.</i> [10]	NN	<ul style="list-style-type: none"> ❖ Automatically differentiate non-fatty and fatty tissues. ❖ Outperforms in combined imaging design. 	<ul style="list-style-type: none"> ❖ Shadow separation from lesion is very complicated. ❖ Necessitates certain manual corrections for automatic segmentation.
Pedro <i>et al.</i> [11]	Bayesian	<ul style="list-style-type: none"> ❖ Simple to implement ❖ Includes low processing time ❖ Increased accuracy 	<ul style="list-style-type: none"> ❖ No contemplation on the exploitation of deep learning techniques to accelerate this scheme
GerardPons <i>et al.</i> [13]	SVM	<ul style="list-style-type: none"> ❖ Possible to execute in clinical applications ❖ Lesions are identified accurately. 	<ul style="list-style-type: none"> ❖ Cancer detection is not feasible via this design. ❖ Performance is not so promising. ❖ Proper evaluation of bounding box is not possible.
Woo KyungMoon <i>et al.</i> [13]	Fuzzy classifier	<ul style="list-style-type: none"> ❖ Contributes constructive information for the prediction of ALN status. ❖ Performance of texture feature set is extremely improved 	<ul style="list-style-type: none"> ❖ Could not predict the unidentified regions in image. ❖ Considering extra features may frequently grant worse performance.
Qi Dou <i>et al.</i> [14]	CNN	<ul style="list-style-type: none"> ❖ Proficiently carry out the dense segmentation in a volume-to-volume approach. ❖ Directly attain equal-sized output as the input data ❖ Develop the discriminative 	<ul style="list-style-type: none"> ❖ Slight adjustments have to be done owing to deviations in size and shapes



		ability of networks	
Alexander <i>et al.</i> [15]	Jacobian	<ul style="list-style-type: none"> ❖ Better detection of changes in volumetric models ❖ Can be deployed on both closed simply connected surfaces 	<ul style="list-style-type: none"> ❖ Accuracy and distortion measures have to be determined more.
Sheng-Chih Yang [16]	Fuzzy classifier	<ul style="list-style-type: none"> ❖ Segments medical images more accurately ❖ Evades statistical error occurred due to large patches of background and noise 	<ul style="list-style-type: none"> ❖ Requires more contemplation on 3D reconstruction, lesion localization, benign or malignant tumor determination
Khatami <i>et al.</i> [17]	DBN	<ul style="list-style-type: none"> ❖ Assists to discover the most practical features from raw data proficiently. ❖ Minimizes the computational time. ❖ Develops the performance of classification 	<ul style="list-style-type: none"> ❖ No investigation of other multiclass classifiers for processing noisy radiographic and high dimensional imaging data

III PROBLEM STATEMENT

The state of the art techniques regarding the medical image classification is given by Table I. At first, DCNN was implemented in [1] that deals efficiently with a restricted amount of labelled biomedical images with increased convergence speed. However, classification accuracy is not excellent and minimizes most of the time. Moreover, RF was suggested in [2], which enhances the input image contrast with decrease the space and time complication, but this scheme was not performed on BRATS 2014 dataset. In addition, SVM was proposed in [3] that provides better classification accuracy and excellent optimal sampling. Anyhow, there were limitations on best Dice coefficient in the lumen segmentation in this scheme. AdaBoost was implemented in [4] that achieves high sensitivity with reduced false positive. However, there are possibilities of missing cancerous masses and it is not able to recognize the closed iso-contour from close by boundaries. Further, decision tree was suggested in [5] that improves the accuracy of the query decision and obtains the high-level features of the query image devoid of radiologist intervention, but there were no contemplations on huge sized medical datasets. Similarly, SVM was proposed in [6] that were advanced in eliminating false positives and it also maintains the same sensitivity. However, there was no consideration on feature selection for the minimization of

the feature set. Also, decision tree was suggested in [7], which provides better specificity and sensitivity and it also enhances different quality factors simultaneously in an automatic system. Anyhow, it was not able to substitute the radiologists in final interpretation of mammograms. Similarly, Bayesian classifier was adopted in [8] that achieve fast running time and it also improves the performance by enhancing the image quality. However, high smoothing leads to blurring the image and the complication also increases in image registration process. Similarly, SVM was presented in [9], which facilitates ophthalmologists to identify the exudates in a very short time of scrutiny. It also offers low-cost and does not necessitate trained experts, but the requirement of features may be increased on the accumulation of the exudates with respect to the distance. In addition, NN was presented in [10] that differentiates non-fatty and fatty tissues and also outperforms in combined imaging design. But the Shadow separation from lesion was very complicated and it necessitates certain manual corrections for automatic segmentation. Similarly, Bayesian classifier was adopted in [11] that were simple to execute and it requires only less computing time with increased accuracy. However, there was no contemplation on the exploitation of deep learning techniques to accelerate this scheme. Moreover, SVM was suggested in [12], which was possible to be executed in medical appliances to detect the lesions accurately. Anyhow, cancer detection is not feasible via this design and the performance is not so promising. Moreover, Fuzzy classifier was suggested in [13] that enhances the texture feature set, and provides useful information for the prediction of ALN status. However, the prediction of unknown regions is impossible. In addition, CNN were proposed in [14], which proficiently carries out the dense segmentation in a volume-to-volume approach. Also, it directly attains equal-sized output as the input data and develops the discriminative ability of networks, but slight adjustments have to be done owing to deviations in size and shapes. Similarly, Jacobian based method was suggested in [15], which provides better detection of changes in volumetric models and it can be deployed on both closed simply connected surfaces. However, accuracy and distortion measures have to be determined more. Fuzzy classifier was implemented in [16] that Segments medical images more precisely and evades statistical error occurred due to large patches of background and noise. Anyhow, it requires more contemplation on 3D reconstruction, lesion localization, benign or malignant tumour determination. Furthermore, DBN was suggested in [17] that assist to discover the most practical features from raw data proficiently with minimization of computational time. Also, it develops the performance of classification, but there was no investigation of other multiclass classifiers for processing noisy radiographic and high dimensional imaging data. These limitations have to be considered for improving the abdominal mass diagnosis performance.

3.1 Contribution on Feature Extraction

The contribution of the feature extraction methods considered in this paper is provided in graphical representation by Fig. 1. Various researchers have diagnosed multiple diseases based on several features, in which the contribution on texture feature is 53%, GLOH is 6%, and GLCM is 12%, SIFT is 12%, wavelet is 6%, structural features is 6%, and geometrical features are 6%. Thus the texture features are found to be adopted more than other features.

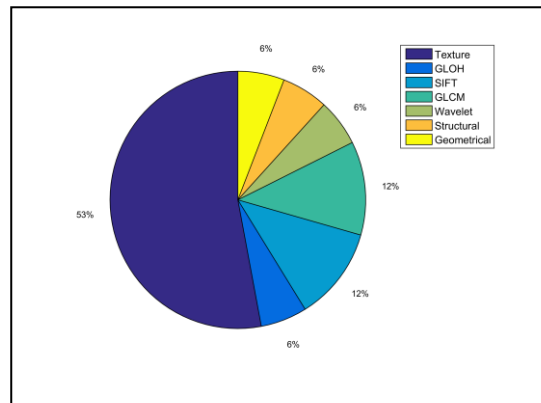


Fig. 1 Graphical representation of feature extraction methods

3.2 Medical Disease Diagnosis

The bar chart representation of the medical disease diagnosis is given by Fig. 2. From Fig. 2, 59% contribution is based on breast cancer, 16% contribution is based on brain tumor, 5% contribution is based on diabetes, and 12% contribution is based on heart disease and 6% contribution is based on retinal disorder. Thus the contribution by found to be more than other disorders verified in this paper.

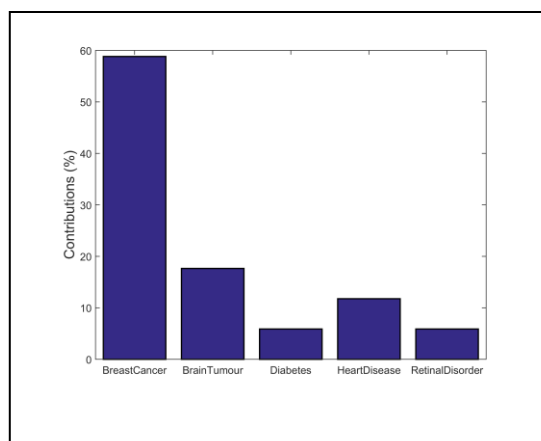


Fig. 2 Bar chart representation of medical disease diagnosis

IV RESEARCH GAPS AND CHALLENGES

The exact diagnosis of the variety of disorder is essential to construct a preparation for treatment that can reduce the deadly consequences. The conventional image classification techniques merged with a variety of classifiers and hand-crafted image feature descriptors were not capable of improving the precision rate efficiently and meet the major prerequisites of classifying biomedical images. The similar also holds the same for artificial NN designs that were directly trained with restricted biomedical images adopted as training data. In numerous techniques, the brain tumor image segmentation was done depending on the intensity of neighborhood information and the voxels. Such techniques have to be improved further based on their accuracy. Other sorts of

systems, which were dependent on local limits or object detection, were considered as less effectual than preceding group of methods. They have reduced flexibility on various kinds of tumor and diverse information. On the other hand, the chief restriction of medical image classification systems is the semantic gap that was the differentiation among high-level semantics and their low-level features of images in a specified circumstance. In addition, RF has been seemed to have more complexity, and hence in several cases, ensemble classifiers and fuzzy based classifiers were adopted. There were several contributions for various diseases as given in the literature, but the contribution with respect to abdominal mass detection was not focused more by the researchers. Hence, this paper mostly concerns on different type of classifiers, which could be adopted for better classification of medical images regarding abdominal mass detection in future.

V CONCLUSION

This paper has presented a survey on medical image classification for various diseases. In addition, several types of feature extraction techniques and classifiers, which were exploited for classifying the medical images associated with numerous diseases, were focused. Since there was lack of classifications depending on abdominal mass detection, this paper has concerned on other various diseases and their corresponding methodologies. Furthermore, by means of any of the classification schemes mentioned in the literature works, abdominal mass detection can be detected in future.

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