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Predictive Analytics and Retrieval Using Mri-A Recent Retrospective

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Abstract— Research in MRI is gaining attention for tumor detection, classification, retrieval which it is critical for diagnosis, surgical planning and treatment. Several techniques are proposed to address this challenge and none of the solution is yet perfect. The accuracy of the system is improved using pre-processing, determined in feature extraction, evaluated in classification and retrieval techniques. Segmentation techniques are used to extract the tumor for feature extraction. As the tumor characteristic differs on various types, different spatial, wavelet, model based techniques are adapted to capture the unique features. The objective of this paper is to present a comprehensive overview of different methods, their efficacy on predictive analytics and retrieval.

Keywords— MRI Retrieval, Feature Extraction, Classification, Tumor Detection

I. INTRODUCTION

Radiologists are smart, well experienced and rely on decisions formulated from research in depth. But compared to advance data processing techniques, human capabilities are limited. Predictive analytics fills the gap by adapting statistical and data transformation methods to search massive data volume, analyze and predict possible outcomes.

In the recent past there have been various developments for computer aided diagnosis and treatment based on the analysis and interpretation of radiological images like MRI. MRI provides anatomical and physiological details in structure and function with 3D orientation, excellent soft tissues visualization and high spatial resolution. Magnetic Resonance Imaging(MRI) is a non ionizing technique based on the phenomenon of nuclear magnetic resonance(NMR) that uses radio frequency(200 MHz – 2GHz) electromagnetic radiation and large magnetic fields around 1-2 tesla. MRI depends on the proton density and on the values of T1 and T2.Various protocols e.g., spin echo, gradient echo and inversion recovery, etc., using pulse sequence of different lengths and separations can be used to improve the contrast resolution of the image. Images produced in such a way to reflect differences primarily in tissue T1 is said to be “T1-weighted” other images might be “T2-weighted”, “proton density weighted” etc [1].The role of radiologist is crucial for recovery and survival. As human observations are probabilistic CAD(computer aided design) systems provides additional support for diagnosis by combining the domain knowledge and machine computing.

The most recent innovations in medical image analysis is Radiomics, which focuses on improvements of medical image analysis with automated high throughput feature extraction algorithms. Feature extraction algorithms can precisely represent the image features like Image intensity, pattern of pixel distribution, deviation from normal tissues, lesion boundaries. These features when combined with disease information improve differential diagnosis in radiology.

The rest of the paper is organized as follows. Challenges in MRI are discussed in section II. A short overview about feature extraction is discussed with illustration in section III. Table II analyzes the recent contributions followed by a summary in section IV.

II. CHALLENGES IN MRI TECHNIQUES

MRI poses certain challenges which are to be resolved for accurate prediction and retrieval.

1. The variation of MRI intensity from one patient to another. Intensity normalization should be done to compare different datasets to solve this issue.
2. Intensity non-uniformity, as bias field causes a slow and smooth intensity variation within the same

dataset which can be solved using retrospective correction methods.
3. Misalignment of inter and intra patient images. Registration is the solution for aligning medical data.
4. Structural abnormalities of brain, such as ventricular enlargement, cerebral atrophy and tumors.
5. High visual similarity between irrelevant and relevant segments in medical images.

III. FEATURE EXTRACTION

The success of image analysis and retrieval relies in the feature extraction algorithms. Fig. 1.a illustrates the architecture of the image retrieval system and Fig.1.b illustrates image classification system. Initially the images are preprocessed to reduce rician noise, normalize intensity variation, and other tasks like brain skull extraction etc. Pixel level, global, local and domain specific features can be used for analysis and retrieval. Global features represent the feature from image as a whole, whereas local features refer to ROI extracted features. MRI feature extraction techniques are based on intensity, texture, shape. The features can be extracted using statistical methods, wavelet based methods and structural methods. Table I provides a summary of some common techniques in MRI feature extraction.

A. *Texture*

Texture is a powerful region descriptor so it is applied after ROI segmentation. Variation, orientation, granularity of homogenous, heterogeneous, iso, hypo, hyper intensity of soft tissues can be measured using texture. The commonly used statistical texture descriptors are GLCM, LBP, LTP and Tamura feature. In wavelet approach Gabor feature, curvelet, contourlet, daubechies etc are used of which Gabor is widely used as it captures a multi level features but it suffers high dimensional problem.

B. *Shape*

Shape features can be region based or contour based. Contour based techniques can be used for edge detection algorithms. Geometric measures like circularity, aspect ratio, irregularity, speculation of edges can discriminate benign and malignant tumors. Zernike moments are predominantly used compared to Fourier descriptors, chain codes. As the nature margin of tumor has a great impact in malign or benign classification, margin information descriptors are computed based on the radial signature of boundary points.

The extracted features are stored in feature database. In online phase, the matched features of the query image with the feature database are retrieved to assist diagnosis. The results can be further improved using user feedback.

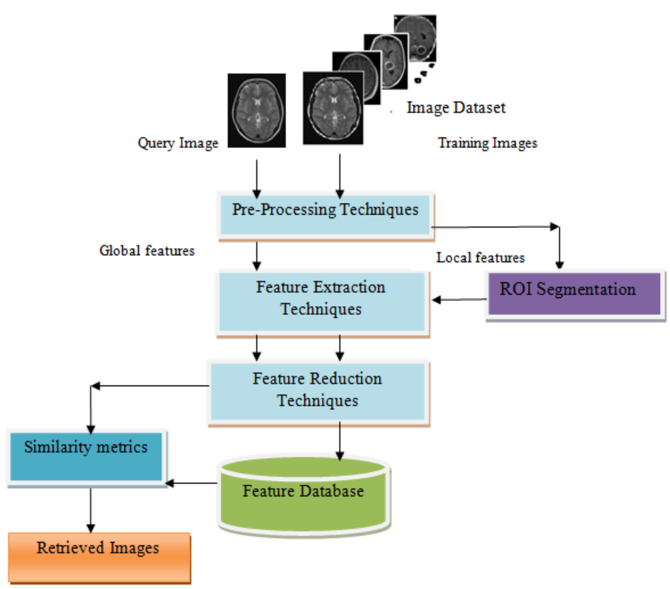

Fig. 1a Illustration of CBIR System

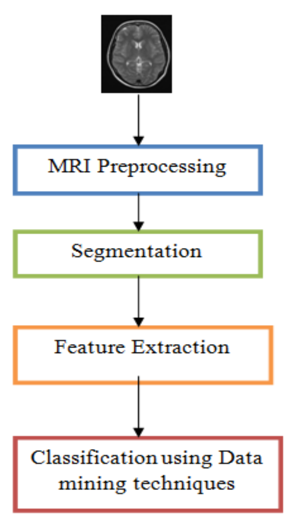

Fig. 1.b Illustration of Brain tumor Classification

Table I Summary of common Feature Extraction techniques in MRI

Techniques	Feature	Computation	Nature
Statistical measures	Intensity	Mean, Contrast, standard deviation, uniformity, Entropy, histogram skewness etc.	Statistical method
Autocorrelation	Texture	Detect repetitive patterns, fineness/coarseness	Dot product of image with shifted images
Tamura	Texture	coarseness, contrast, directionality, line-likeness, regularity and roughness	Statistical method

GLCM(Gray Level Co-occurrence Matrix)	Texture	Co-occurrence of a pixels at specified distance and orientation	Matrix computation
GLRM(Gray Level Run Length Matrix	Texture	Set of consecutive co-linear pixels in a given direction	Matrix computation
LBP(Local Binary pattern)	Texture	Detect uniform or non-uniform pattern using binary values 1,0	Thresholding and binary pattern
LTP(Local Ternary pattern)	Texture	Detect uniform or non-uniform pattern using three values -1,1,0	Thresholding and binary pattern
HOG(Histogram of Oriented Gradients)	Shape	Counts occurrences of gradient orientation in localized portions of an image	Gradient computation
Laws filter	Texture	Texture filters for image and computes texture energy	Applying masks
Gabor	Texture	Captures frequency, locality, and orientation, providing multi-resolution texture information in spatial and frequency domain	Wavelet method
Ridgelet	Shape	Straight line feature	Wavelet method
Curvelet	shape	Curve like features	Wavelet method
Contourlet	Shape	Directional multi resolution image representation, measures smoothness	Wavelet method
Moment Invariants	Shape	Shape analysis of objects irrespective of translation, scaling and orientation	Statistical method
Fourier coefficients	Shape	Contour based shape coefficients of general and fine details	Fourier transform of boundary points
Zernike moments	shape	Rotation invariant orthogonal polynomials on unit disk	Polynomial computation
Chain codes	Edge	Contour tracking using 4 or 8 connected neighborhood pixels	Pixel neighborhhod comparison

Table II. Summary of Related Works

Ref.	Objective	Methodology	Dataset	Findings
[2]	Benign Malignant Classification	1. Shape A) Degree Of Speculation Of Mass B) Local Fuzziness Of The Mass Margins 2. Texture A) Relative Gradient Orientation Of Pixels	Breast Masses Using A Set Of 319 Masses	Approximately 89% Correct Classification
[3]	Benign malignant classification	1. Segmentation using iso intensity contours 2.Feature extraction (a)contrast (b)coherency ratio (c)entropy of orientation (d)variance of coherence –weighted angular estimates 3. Classification	56 images at a resolution of 200 m including 30 benign breast masses, 13 malignant, and 13 normal cases	Detects all the 13 malignant tumors successfully
[4]	Mammogram Retrieval	1. Segmentation using region growing from brightest pixel 2. Feature extraction -shape and margin features (i) variation degrees vd of the inner and outer rings (ii) sharpness degree sd of the segmented mass 3. classification using bi-rads standards	Digital database for screening mammography (DDSM)	Zernike moments are the most discriminative for round-shape masses
[5]	Classification of gliomas from metastases, and also for grading of gliomas.	1. Manual segmentation 2. Feature extraction (i)shape features a) circularity b) irregularity c) rectangularity d) entropy of radial length e)dstribution of the boundary voxels surface-to-volume ratio (ii)texture features-gabor features 3. Classification a) lda with fisher's discriminant rule b) k-nearest neighbour c) nonlinear svms	102 Brain tumors histologically diagnosed as metastasis (24), meningiomas (4), gliomas world health organization grade ii (22), gliomas world health organization grade iii (18) and glioblastomas (34).	Classification accuracy, sensitivity, and specificity are , 85%, 87%, and 79% for discrimination of metastases from gliomas and 88%, 85%, and 96% for discrimination of high-grade (grades iii and iv) from low-grade (grade ii) neoplasms
[6]	Mammogram Retrieval within BI-RADS	1. Segmentation of mass using shape, margin, density features.	1919 mass mammograms	This approach improves the accuracy by

	standards	2. Segmentation of calcification using type and distribution features 3. Feature extraction a) shape-zernike moments b) margin- sobel operators c) density ratio of the outer and inner masses. 4. classification using svm	and 644 calcification mammograms, obtained from the digital database for screening mammography (ddsm)	as high as around 72% and 74%.
[7]	Brain Tumour Retrieval	1. Manual segmentation of tumour. 2. Feature extraction a) texture-rotation invariant glcm b) shape signature- radial distance between the centroid and tumor boundary c) statistical features from the histogram of tumor margin region is used to compute mid. 3. tumour retrieval using maximum mean average precision projection	The dataset t1-c+ mri comprising of 3108 slices from 235 patients, including 705 meningiomas, 1475 gliomas, and 928 pituitary tumours	Incorporating tumour margin information represented by mid with the distance metric maximum mean average precision projection can substantially improve the retrieval performance for brain tumours in ce-mri. retrieval precision is 89.3%
[8]	Retrieval of glioblastoma multiforme (gbm) and non-gbm tumors	1. Manual segmentation of tumour. 2. PCA feature reduction 3. Classification using svm and retrieval	GBM lesions from 40 patients and non-gbm lesions from 20 patients	Classification of tumor grade (gbm or other grade 3) was 77% achieved by svm coupled with the pca features
[9]	Two Level Hierarchical CBMIR system which first classifies the brain tumor query image as benign or malign and then searches for the most similar images within the identified class	1. Segmentation 2. Global Features: (i)Shape a) circularity b) irregularity (ii)Texture a) average gray level b) standard deviation c) entropy d) coefficient of variation, e) skewness f) kurtosis obtained from the histogram of the brain tumor image 3. local features -texture: a) wavelet based fourier descriptors b) local binary pattern 4. classification using svm and knn algorithm	820 Brain MR images benign:420, malign:400	Retrieval Precision Of 97% and Recall Of 95.78%
[10]	MRI brain tumor feature extraction and segmentation	1.Texture Features brain tumor texture is formulated using a multi resolution-fractal model known as multi fractional brownian motion 2.Segmentation multi fractal feature-based segmentation.	T1-Weighted (non-enhanced), T2-Weighted, and flair from 14 different pediatric patients with total of 309 tumor bearing image slices of two different tumor groups such as 6 patients (99 mri slices) are from astrocytoma and 8 patients (210 mri slices) are from medulloblastoma (8) tumors	ROC Plot suggest that features representing tumor regions are well separated non-tumor regions
[11]	Three-dimensional texture analysis of MRI brain datasets	Texture Analysis using Multi Sort Coccurrence Matrices, intensity, gradient and anisotropy image features	Forty-three volumetric t1 images	Extended co-occurrence descriptors can be used as an efficient tool in mri brain image analysis tasks
[12]	Texture Analysis for 3d classification of brain	1. Feature Extraction (i)image intensity, mean, standard deviation	Harvard Surgical Planning (Spl) 10	Extreme Learning Machine achieves highest

	tumor tissues and tumor into 4 classes.	(ii)texture features glcm (iii)spectral features-gabor filters 2. Feature Selection using genetic algorithm 3. classification using extreme learning machine	Benchmark Image Datasets And 35 Real Time Mri Sets	classification accuracy of 93 % with 3d glcm
[13]	Comparison of intensity, intensity histogram and glcm feature extraction method for feature extraction and classification	1. Feature extraction (i)intensity based features (ii)intensity histogram features (iii)glcm features 2. Weka tool for classification.	BRATS dataset tumor types- metastatic bronchogenic carcinoma, astrocytoma, meningioma, sarcoma	GLCM (Gray Level Co-Occurance) method is showing better results
[14]	Identifying normal and abnormal tissues in brain mri	1. Thresholding followed by morphological operations and berkeley wavelet transformation (bwt) is used for brain tumor segmentation	Tumor infected 22 dicom images, brain web dataset, 135 images of 15 patients from all modalities	Accuracy of 96.51%, Specificity of 94.2%, and Sensitivity of 97.72%
[15]	Detection of brain hemorrhage lesions	Texture Features using GLCM features a)mean b)skewness c)kurtosis entropy	high resolution t2 sequence of ten healthy patients and ten diseased patients and finally 120 rois were analyzed.	the standard deviation (7 × 7 kernel) and skewness (5 × 5 kernel) image features and energy and homogeneity textural parameters have been found as relevant for brain hemorrhage traumas detection
[16]	pca-ann for classifying six classes—five classes of brain tumors and a normal class. 1.astrocytoma- as, 2.glioblastoma multiforme- gbm, 3.medulloblastoma- med, 4.meningioma-men 5.metastases- met 6.normal region (nr).	1. ROI segmentation using content-based active contour 2. feature extraction 218 intensity and texture features a)laplacian of gaussian b) gray level co-occurrence matrix c)rotation invariant local binary patterns ‘ d)directional gabor texture features e) intensity-based features f) rotation invariant circular gabor features 3. classification using pca-ann	55 patients dataset constituting of −118 as, 59 gbm, 97 med, 88 men, 66 met, and 428 nr are taken from 428 mr brain tumor slices and 856 srois are marked by the radiologists using cbac	The accuracy obtained for each class is: as-90.74 %, GBM-88.46 %, MED-85.00 %, MEN-90.70 %, MET-96.67 %, and NR-93.78 %.
[17]	Benign and Malign Classification of mammogram masses.	1. ROI segmentation using adaptive region growing 2. Feature Extraction (i)shape features shape-radial points are normalized to calculate variance, average, roughness, zero crossing boundary moments. (ii)Texture Features empirical mode functions are used to describe the texture of the masses. 3. Classification two adaboost classifiers followed by svm, naive bayes in case of ambiguity	Mammogram Masses from MIAS and DDSM database	The Classification Accuracy is 93% for MIAS and 90% for DDSM database.
[18]	Breast Tissue Classification using DCE-MRI.	1. Segmentation using Active Contour method 2. Texture Feature Extraction a) average of glcm for five different orientations b) run length matrices. c) three-scale discrete wavelet transform 3. Feature Selection progressive feature selection scheme 4. Classification support vector machines	dynamic contrast enhanced mri (dce-mri) 20 tumors a)malignant cancers(4) b)invasive ductal carcinoma(6) c) inflammatory breast cancers (10)	1. receiver-operating characteristics (roc) analysis shows that the texture temporal sequence is much more effective than the intensity sequence 2.wavelet transform further improves the classification performance
[19]	CAD system to detect Benign or Malignant	1. Segmentation spatial-fuzzy c-means(fcm)	376 T1 and T2 based mr images (248	Accuracy is 91.49%, sensitivity is

	Brain Tumour using T1 and T2 weighted MR Images.	2.Feature Extraction (i)intensity features a)standard deviation b) entropy c) mean d)skewness, e)kurtosis f)variance (ii)Shape Features a) circularity b) eccentricity c) area d) boundig box e) centroid f) filledarea g) convexarea h) equivdiameter i) eulernumber j) extent k) perimeter l) orientation m)solidity (iii)Texture Features using GLCM 3.Feature Selection using PCA 4.Classification using Support Vector Machine(SVM)	malignant and 128 benign)	90.79% and specificity is 94.74%
[20]	Benign And Malign Classification of Brain Tumour	1.Segmentation using Feedback Pulse-Coupled Neural Network 2. Features Extraction using Discrete Wavelet Transform 3.Feature Reduction using Principal Component Analysis 4.Classification using Feed Forward Back-Propagation Neural Network	101 images consisting of 14 normal and 87 abnormal mri	Classification Accuracy on both training and test images is 99%
[21]	Benign or Malignant Classification of Brain Tumor	1.Pre-Processing using 2D-Adptive Filter 2.Segmentation using Otsu's method and morphological operations using erosion and dilation 3.Classification based on the size of the tumor	1500 images of four different types i.e. cns lymphoma, glioblastoma, meningioma, and metastases	Detection rate of 93 % with 7 % error rate
[22]	Image Retrieval Comparison using intensity and texture	Feature Extraction 1.intensity-based features using intensity histogram 2. intensity histogram with spatial context 3.texture features Local Binary Pattern (LBP) 4.LBP with spatial context	T2-Weighted Axial Brain Mr Volumes acquired from subjects with memory-related problems	Texture information with spatial context outperformed its intensity-based counterpart
[23]	MRI brain tumor retrieval	1.Texture Features a)curvelet transform b)contourlet transform c) local ternary pattern (ltp). 2.classification using deep neural network (dnn)	1000 brain tumour images with different orientations	Contourlet Transform technique perform better than curvelet transform and local ternary pattern.
[24]	Classification of normal and abnormal brain tissues	1.Segmentation adaptive pillar k-means algorithm 2.Features Extraction Using Discrete Wavelet Transform 3.Two Tier Classification a)self-organising map neural network b)k-nearest neighbour	Brain Image Dataset is partitioned into three parts which contains 40, 60 and 70 brain mri for dataset 1, dataset 2 and dataset 3 respectively	Proposed technique is higher than SVM based classification technique for all datasets.
[25]	Brain Image Retrieval	Texture Features combination of Cohen-Daubechies (CDF) 9/7 wavelet , Local Ternary Cooccurrence Patterns (LTCOP) and Gabor Feature	OASIS - MRI Database	(i) LEVEL 3 CDF 9/7 wavelet gives better performance than at

				level l and 2 (ii)Average precision & feature dimensions are improved compared to GLTCOP on OASIS MRI- brain database.
[26]	Analysis on Shape Based Brain Tumor MRI Retrieval	1)Feature Extraction process a)scale invariant feature transform (sift) b)harris corner detection c) Zernike Moments. (ii) classification a)Deep Neural Network (DNN) b) Extreme Learning Machine (ELM)	T1 weighted MRI	Highest Average Accuracy using Zernike Moments– 99%.
[27]	Detect tumor and segmentation of tumor region	(i) Wavelet Feature Extraction 1.Gabor Wavelet Feature Extraction (ii)Statistical Feature Extraction a)Gray Level Co-Occurrence Matrix b)Gray Level Run Length Matrix c)Histogram Of Oriented Gradient d)Linear Binary Pattern (iii)classification a)support vector machine b) k-nearest neighbor principle c) sparse representation classifier d) nearest subspace classifier e)k-means clustering	T1-Weighted and Fluid-Attenuated Inversion Recovery (FLAIR)	In Most cases statistical features provide higher accuracy than Gabor Wavelets Features
[28]	Brain Image Retrieval	(i)Tumor region segmentation and augumentation (ii)Sub Division of tumor region based on intensity disorders (iii)Extract image patches and pca reduction (iv) Conctenate feature vector of subregion using fisher kernel framework	T1-Weighted contrast-enhanced MRI of 3604 images with three types of brain tumors, namely, meningiomas, gliomas, and pituitary tumors	Mean Average Precision for retrieval is 94.68%.
[29]	Classification of normal, ms and tumoral images	(i) Feature Extraction Using Gray Level Co-Occurrence Matrix (Ii)Feature Reduction using PCA (iii)Classification using SVM	120 MRI with 43 MS, 36 tumors and 41 normal in axial, T2-weighted,	100 % classification for MS images, 95% for normal images and84% for tumoral images
[30]	Classification of normal and Alzheimer's disease	Feature Extraction using dataset1:GLCM, dataset2:Haralick, dataset3: Gabor Wavelet based Haralick Features (ii) Classification using Backpropagation Network	3D Brain MRI data extracted from OASIS database.	(i)Average Efficiency Of Gabor combined with Haralick features is around 97% for all types of datasets. (ii) the average efficiency value for GLCM is 86 % and Haralick features was 90%.
[31]	Fast and robust region-of-interest retrieval method for brain MR Images	Feature Extraction a)Local Binary Patterns b)Kanade–Lucas–Tomasi (KLT) feature points	T1-Weighted axial brain MR scans from 15 subjects of normal and pathological cases from private and OASIS database	Incorporating spatial information in the Local Binary Pattern substantially improved accuracy, whereas avoiding matching of KLT feature points degraded performance and dominant LBPS with spatial context consistently utperformed KLT

IV. DISCUSSION

Diagnosis of tumors or masses begins with MRI. As intensity variation depends on image acquisition, a pre-processing technique for intensity normalization should be adapted. Several methods like nuclear network algorithm, watershed, edge detection, fuzzy c means, asymmetry of brain for abnormality detection [32].Multimodal analysis of soft tissue pattern, intensity, tumor edge smoothness are computed for tumor classification. If similar techniques could be adapted the multi modal images, parallel computing architecture could be adapted for fast computation. For optimizing the results, the tumor area is segmented before feature extraction and prediction.

When it comes to feature extraction, domain specific features which significantly discriminates the different types of classes should be chosen after evaluating with feature selection methods. Mathematical morphology based shape features is used for tumor detection [33]. For ring enhancing lesions, the ring inT1C+ images is analyzed for diagnosis, so Margin information descriptors and radial signature can be used to discriminate thin or thick, smooth or spiculated edges. In some cases to detect abnormality in brain, mid line shift can be analyzed which is a global feature of a brain MRI. So both global features and global features are important to achieve good results.

Certain features like Gabor are excellent in capturing the texture but suffer from high dimensionality problem. GLCM is wide used but it is rotation variant. An average of GLCM along different orientations can be used to make it rotation invariant. Fourier descriptors need a continuous contour of image which is difficult in medical image due to intensity in homogeneity. Laws filter can enhance the texture using different masks which can be used for visualizing and computing multi patterns in texture. As there are strong concurrence of diagnosing features in MRI, multi tier classifications can be effective. In case of ambiguous prediction, additional features can be included for refining the results. Artificial neural networks can be used for training the data and its performance can be improved by increasing the no of hidden layers and adjusting the training parameters.

REFERENCES

[1] G. Dougherty,"*Digital Image Processing for Medical Applications*", Cambridge University Press,2009.

[2] Rojas-Domínguez A, Nandi AK.,"*Development of tolerant features for characterization of masses in mammograms*". Comput Biol Med Vol.39, pp. 678-688,2009.

[3] N. R. Mudigonda, Rangaraj M. Rangayyan and J. E. Leo Desautels, "*Detection of Breast Masses in Mammograms by Density Slicing and Texture Flow-Field Analysis*" ,IEEE transactions on medical imaging, Vol. 20, NO. 12, December 2001.

[4] C.H. Wei , Y.Sherry, Chen, X. Liub, "*Mammogram retrieval on similar mass lesions*", Computer methods and programs in biomedicine, pp. 234–248, 2012.

[5] E.I. Zacharaki, S. Wang, S. Chawla, D. S. Yoo, R. Wolf, E.R. Melhem, and C. Davatzikos, "*Classification of Brain Tumor Type and Grade Using MRI Texture and Shape in a Machine Learning Scheme"*, Magnetic Resonance in Medicine, pp.1609 – 1618,2009

[6] C.H.Wei , Y.Li , P. J. Huang,"*Mammogram retrieval through machine learning within BI-RADS standards"*, Journal of Biomedical Informatics, Vol 44, Issue 4, August 2011, pp. 607-614

[7] W. Yang, Q. Feng, M.Yu, Z.Lu, Y. Gao, Y.Xu, and W. Chen, "*Content-based retrieval of brain tumor in contrast-enhanced MRI images using tumor margin information and learned distance metric",* Medical Physics 39, 6929 ,2012

[8] S. Dube, S. El-Saden, T. F. Cloughesy, U. Sinha, "*Content Based Image Retrieval for MR Image Studies of Brain Tumors"*, Proceedings of the 28th IEEE EMBS Annual International Conference

[9] M. P. Arakeri, and G. R. M. Reddy, "*Medical image retrieval system for diagnosis of brain tumor based on classification and content similarity*," Annual India Conference (INDCON), 2012, pp. 416-421.

[10] A. Islam, S. M. S. Reza and K. M. Iftekharuddin, "*Multi-fractal Texture Estimation for Detection and Segmentation of Brain Tumors*", IEEE Transactions on Biomedical Engineering Vol. 60, Issue:11, Nov. 2013

[11] V. A. Kovalev, F. Kruggel, H.J. Gertz, and D. Y. von Cramon, "*Three-Dimensional Texture Analysis of MRI Brain Datasets"*, IEEE transactions on medical imaging, Vol. 20, NO. 5, MAY 2001

[12] Arunadevi,B,Deepa, S N.,"*Texture analysis for 3D classification of brain tumor tissues",*Przeglad Elektrotechniczny. . pp.338-342, 2013.

[13] B.S. Kumar, Dr.R.A. Selvi, "*Feature Extraction Using Image Mining Techniques to Identify Brain Tumors*", IEEE Sponsored 2nd International Conference on Innovations in Information Embedded and Communication Systems ,ICIIECS'15

[14] N. B. Bahadure, A. K. Ray,and ,H. . Thethi," *Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM*", Hindawi International Journal of Biomedical Imaging Vol 2017, Article ID 9749108 ,12 pages

[15] L. Morarua , S. Moldovanua., D. Bibicua and M.Stratulat , "*Hemorrhage Detection in MRI Brain Images using Images Features*", TIM 2012 Physics Conference AIP Conf. Proc. 1564, 171-177 ,2013.

[16] J.Sachdeva, V.Kumar, I.Gupta, N.Khandelwal and C.K. Ahuja,," *Segmentation, Feature Extraction, and Multiclass Brain Tumor Classification*", Journal of Digit Imaging.Vol 26(6),pp.1141–1150, Dec 2013.

[17] O. R. Seryasat and J. Haddadnia, *"Assessment of a novel computer aided mass diagnosis system in mammograms",* Biomedical Research Vo 28, Issue 7, 2017

[18] J. Yao, J. Chen, and C. Chow, "*Breast Tumor Analysis in Dynamic Contrast Enhanced MRI Using Texture Features and Wavelet Transform*" ,IEEE journal of selected topics in signal processing, Vol. 3, No. 1, February 2009

[19] E. Dandıl,, M. Çakıroğlu , and Ziya Ekşi , "*Computer-Aided Diagnosis of Malign and Benign Brain Tumors on MR Images"*, ICT Innovations. Advances in Intelligent Systems and Computing, Vol 311. Springer, 2014

[20] E. Sayed , E.Dahshan , H. M. Mohsen , Kenneth Revett , Abdel-

Badeeh M. Salem , "*Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm*", Expert Systems with Applications ,Vol 41, pp.5526–5545, 2014

[21] I. Ahmed, Q. N.U.Rehman, G.Masood, M.Nawaz, "*Analysis of Brain MRI for Tumor Detection & Segmentation*", Proceedings of the World Congress on Engineering , June 29, IWCE 2016.

[22] D. Unay, A. Ekin, "*Intensity Versus Texture For Medical Image Search And Retrival"*,Video Processing and Analysis Group,Philips Research Europe, pp. 241-244,IEEE 2008

[23] A. A. Pandian and R. Balasubramanian, "*Performance Analysis Of Texture Image Retrieval For Curvelet, Contourlet Transform And Local Ternary Pattern Using Mri Brain Tumor Image*",International Journal in Foundations of Computer Science & Technology (IJFCST) Vol.5, No.6, November 2015

[24] V. Anitha, S. Murugavalli ,"Brain Tumour Classification Using Two-Tier Classifier With Adaptive Segmentation Technique",IET Computer Vision ,ISSN 1751-9632, "in press" ,Accepted on 22nd June 2015.

[25] T.A Anju, D. A. Chandy," Brain Image Retrieval Using Local Ternary Co-Occurrence Pattern and CDF 9/7 Wavelet", International Conference on Electronics and Communication System (lCECS -2014)

[26] A. A. Pandian ,Dr. R. Balasubramanian ,I.J. Information Engineering and Electronic Business, "Analysis on Shape Image Retrieval Using DNN and ELM Classifiers for MRI Brain Tumor Images", Vol. 4, pp. 63-72 , 2016.

[27] N.Nabizadeh, M. Kubat , "Brain tumors detection and segmentation in MR images: Gabor wavelet vs. statistical features. Comput Electr Eng ,2015

[28] J. Cheng, W. Yang, M. Huang, W. Huang, J. Jiang, Y. Zhou, R. Yang, J. Zhao, Y.Feng, Q. Feng, W. Chen,"Retrieval of Brain Tumors by Adaptive Spatial Pooling and Fisher Vector Representation", PLOS ONE pone.0157112 June 6, 2016

[29] M. R. Nazari,E. Fatemizadeh,"*CBIR System for Human Brain Magnetic Resonance Image Indexing ",*International Journal of Computer Applications,*pp. 0975 – 8887,Vol 7, No.*14*, October* 2010,

[30] T.R Sivapriya., V.Saravanan, R. Jeba P.Thangaiah "*Texture Analysis of Brain MRI and Classification with BPN for the Diagnosis of Dementia*", Communications in Computer and Information Science, Vol 204. Springer, 2011.

[31] D. Unay, A. Ekin, and R. S. Jasinschi,"*Local Structure-Based Region-of-Interest Retrieval in Brain MR Images*", IEEE Transactions On Information Technology In Biomedicine, Vol. 14, No. 4, July 2010

[32] C. M. Meshram, Bapurao, "*Brain Tumor Segmentation and Classification: A Review*", International Journal of Scientific Research in Computer Sciences and Engineering, Vol. 4, Issue 1, 2018

[33] N. Jyoti, "Automatic Classification and Detection of Brain Tumor with Fuzzy Logic and MFHWT", International Journal of Scientific Research in Computer Science, Engineering and Information Technology, Vol. 2, Issue 1,2017

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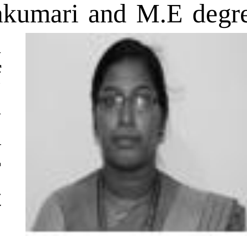

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