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A study on detection of diseases using Digital Image Processing Techniques with a case study on MRI images and x-ray images of animals

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ABSTRACT
Image processing techniques plays important role in animal medical image or picture to demonstrative and recognition the disorders and screen the animal(patient) from these infections. The image processing utilizing as a part of numerous applications in the medicinal picture like Magnetic Resonance Imaging (MRI), Computerized Topography (CT), ultrasound imaging and X-ray images etc The x ray or CT or MRI are it may be on fracture of bone , hip joint, vertibrai column , Nmemonia , Fermur joint, plating, Intenstine and stomach, neck , Lungs, Periodically heart size calculating , Fixing rod etc. These images highly exception cost to the diseased animal(patient) when it do not clear the reimaging is more cost for that, then the picture operation is one of picture preparing strategies to take care of this issue by less cost and quick. Animal Medicinal pictures are normally corrupted by commotion amid picture procurement and transmission process. The primary reason for the commotion lessening strategy is to remove noise by holding the essential component of the pictures. In a run of the mill arrangement of WSN, hubs are battery worked each of the therapeutic imaging gadgets are influenced by various sorts of commotion. For instance, the x-ray images are regularly ruined by Poisson commotion, while the ultrasound pictures are influenced by Speckle noise. Dot is an intricate marvel, which debases picture quality with a back scattered wave appearance which begins from numerous tiny diffused reflections that going through inside organs and makes it more troublesome for the on looker to segregate fine detail of the pictures in analytic examinations. Accordingly, denoising or lessening this dot commotion from a loud picture has turned into the dominating stride in medicinal image processing. Magnetic resonance imaging (MRI) of brain is a noninvasive medical imaging technique used in measuring and visualizing the brain's anatomical structure, analyzing brain abnormalities, delineating pathological regions, surgical planning and image guided interventions. X-ray Different image processing techniques are applied to MRI images for identification, detection and classification of brain diseases as well as abnormalities. In this thesis, we propose an improved classification method, which can detect brain tumors and classify as normal and abnormal brain MRI images. The abnormal brain MRI images are also classified as Benign and Malignant on the basis of cancerous or non-cancerous state of brain tumors. The classification method is developed by using feature extraction process to extract the features of brain MRI images for detecting the abnormalities and brain tumors. In our proposed method, log-polar transformation (LPT) based feature extraction method is constructed to extract the features from brain MRI images which are performed as detection factor of brain abnormalities. Kernel support vector machine (KSVM) is applied as image classification tools for the tested brain MRI images. Extensive experiments are simulated over different orientation and conversion of scales in T-1 and T-2 weighted MRI images. A comparative analysis of the proposed method with other existing algorithm is then performed that clarify the significant improvement of the proposed

method.

INTRODUCTION:

Medical imaging as magnetic resonance image (MRI) is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention. Main advantages of MRI over CT scan are, MRI provides more accurate visualize of anatomical structure of tissues and it does not contain any radiation effects. Therefore it is widely used for brain imaging. The brain tumor detection from MRI images schemes works on either co-efficients of transformed domain [1] or spatial values of an image [2]. Classification of brain MRI images play vital role for analysis and interpretation of brain diseases. Many methods have been proposed to design accurate classifier to distinguish normal and abnormal brain MRIs [3-6]. Feature extraction is a prominent process to classify brain MRIs. The extraction of feature means reduce the dimensionality of input image and transform the simplified set of data for calculation. The process of feature extraction eliminates redundant data by measuring certain image properties. The extracted features provide relevant properties of the image into feature vectors and distinguish one pattern into another pattern. Image segmentation technique is applied to brain MRI for partitioning the image into meaningful simplified regions have similar attribute or feature. The features used for segmentation largely depend on the process of feature extraction. The image intensities are most common feature for tumor segmentation of brain MRIs. Segmentation can easily distinct infected region of the brain by grouping the image pixels based on the intensity level [8-10]. Our main contribution of this work is to develop an improved feature extraction based classification method for brain MRI images which can identify the abnormalities of the brain. The proposed method, firstly, applies the basic segmentation technique. Next it introduces a log-polar transform-based feature extraction method along with classification algorithm to detect the brain tumor. The scheme, thereafter, classifies the abnormal brain images and records them as benign and malignant tumor. The accurate segmentation of brain MRI images is necessary for detecting any abnormalities in MRI images as well as to diagnose them correctly. The segmentation process selected 2 abnormal brain MRI images randomly from our image dataset. The image dataset contain neoplastic and degenerative diseases: Glioma, Meningioma, Sarcoma, Alzheimer’s disease, Huntington disease, Picks disease and Alzheimer’s disease plus visual agnosia. The scheme then categorizes the abnormal brain images with a probability of having cancer tissues. Nevertheless, a benign brain tumor is a non-cancerous mass of cells that grow relatively slowly in the brain and tends to remain constant in one place. An appropriate surgery can remove a benign tumor safely. The malignant brain tumors certainly signify a cancer case. Malignancy grows faster and aggressively infects neighboring tissues. In that case the patient usually experiences a radiotherapy or chemotherapy to kill the cancerous cell. Even, the malignant tumor often eventually returns after the treatment. If it happens, cure is not possible in usual cases. Then the doctors try to improve the symptoms and prolong life. The matter of improving the symptoms depends on the accuracy of detection. The research uses rotation and scale invariant T-1 and T-2 weighted MRI images of neoplastic diseases. It successfully detects the benign and malignant tumors in the MRI images. In this thesis, firstly we apply the basic segmentation technique and then introduce a logpolar transform based feature extraction method along with classification algorithm which can detect the brain tumor and classify the tested brain primarily into two categories: normal and abnormal as well as benign and malignant tumor for abnormal brain. Our main objective of this thesis is to develop an improved classification method based on feature extraction process for brain MRI images which can identify the abnormalities of brain. It is significant that our proposed method can successfully detect rotation and scale invariant T-1 and T-2 weighted MRI images of neoplastic diseases.

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Image Classification Model

To separate the cancerous and non-cancerous state of tumor, classification of brain MRI is very essential. The target of image classification is to identify a unique gray level (or color) of the features occurring in an image in terms of the object or type of images that features actually represent the separation. Basically multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. Image classification is performed by numerical properties of image features and organizes data into categories. Classification algorithms construct using two phase of processing: i) training and ii) testing. At the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, i.e. training class, is created. In the subsequent testing phase, these feature-space partitions are used to classify image features. The description of training classes is an extremely important component of the classification process. In supervised classification, statistical processes (i.e. based on an a priori knowledge of probability distribution functions) or distribution-free processes can be used to extract class descriptors. Unsupervised classification relies on clustering algorithms to automatically segment the training data into prototype classes.

Many of the researchers introduced image classification model for identifying abnormalities of brain MRI. Y. Zhang and L. Wu et. al. [1] proposed a classification method by using principal component analysis (PCA) and kernel support vector machine (KSVM). This method was formulated in three basic steps. These steps are consequently as follows:
i) Preprocessing (including feature extraction and feature reduction)
ii) Training the Kernel SVM &
iii) Submit new MRI brains to the trained kernel SVM for output.

Two dimensional discrete wavelet transformations are applied for feature extraction and principal component analysis is used for feature reduction. Feature extraction and feature selection based classification method for MRI brain tumor detection was introduced by [4]. The pre-processing tasks are used to improve the image quality and its visual appearance. Extractions of the essential features from MRI images are prepared for training and the test phase. Primary focus of MRI image identification system is used to determine the likenesses among training MRI image sample and testing MRI image sample. Spatial Gray Level Dependence matrix (SGLDM) will be a numerical system to comprise on building Co-occurrence matrix to mirror the spatial spreading from demanding gray intensities in the ROI. This technique concentrated on the feature extraction, reduction of features which are extracted and select appropriate features for the classification. PCA and SGLDM Algorithms are used for the feature extraction and the optimized features are selected using genetic algorithm along with the joint entropy

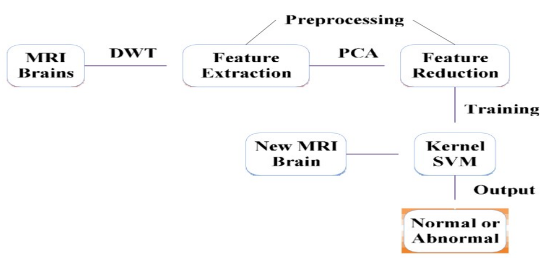

Figure 1: Algorithm for classification method

By analyzing important proposed methods, we observed four fundamental steps for classification model. The basic steps for classification model are following:

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i Preprocessing
ii Segmentation
iii Feature Extraction
iv Classification

i Preprocessing

Medical image processing encompasses the use and exploration of 3D image datasets of the human body, obtained most commonly from a Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) scanner to diagnose pathologies or guide medical interventions such as surgical planning, or for research purposes.

ii Segmentation

In brain MRI analysis, image segmentation is commonly used for measuring and visualizing the brain's anatomical structures, for analyzing brain changes, for delineating pathological regions, and for surgical planning and image-guided interventions.

iii Feature Extraction

Feature extraction is an, approximate reasoning method to recognize the tumour shape and position in MRI image using edge detection method. In the existing method many algorithms were developed for segmentation. But they are not good for all types of the MRI images.

iv Classification

SVM based classification and PCA oriented feature extraction were applied for brain tumor of MRI images by Nandpuru H. B. et al [2]. This method uses the steps of preprocessing, feature extraction, feature reduction, training, storing the database and testing. Initially MRI images are given as input to the classifiers for training, then the features of new MRI images are given as input, based on the training, trained classifier classify it efficiently. But there was a lack of conformity about feature extraction and separation of the cancerous and noncancerous tumor. It performs better than other classification method with high dimensional features and contradictory data. But the high computing cost which consumes high CPU and physical memory usage is the main disadvantage of this method.

Feature extraction and feature selection based classification method for MRI brain tumor detection was introduced by [4]. The pre-processing tasks are used to improve the image quality and its visual appearance. Feature extractions of the necessary features from MRI images are prepared for training and the test phase. Main aim of MRI image identification system is used to determine the likenesses among training MRI image sample and testing MRI image sample. SGLDM will be a numerical system to comprise on building Cooccurrence matrix to mirror the spatial spreading from demanding gray intensities in the region of interest (ROI). In this paper mainly concentrated on the feature extraction, reduction of features which are extracted and select appropriate features for the classification. PCA and Spatial Gray Level Dependence matrix Algorithms are used for the feature extraction and the optimized features is selected using genetic algorithm along with the joint entropy.

PROPOSED METHODOLOGY

Detection of a tumor by the proposed method is mainly divided into pre-processing, feature extraction, segmentation, and classification. The pre-processing is the most important step in MRI brain image analysis due to poor captured image quality. In this phase, the image is resized and converted the RGB to grayscale by eliminating the hue and saturation while existing the luminance. The noise is removed to enhance the quality of the finer details of the image. The scheme segments the image by a K-means clustering based segmentation method. The proposed LPT based feature extraction method then extract features from brain MRI image. At the final phase, the classification technique detects the tumors. The following figure presents the flowchart and the details of the proposed algorithm.

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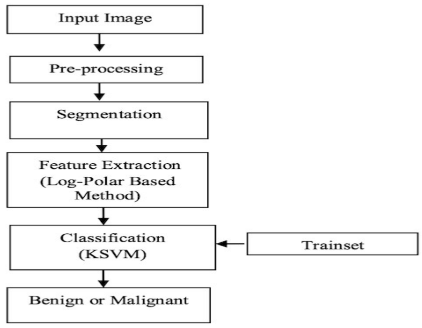

Figure 2: Flow diagram of proposed system

Pre-processing At the initial stage of the algorithm, Brain MRI image is resized for the input image. This input image is necessarily converted into RGB to grayscale. For this conversion process, the image property of hue and saturation is removed but constant the luminance. Then the grayscale image is to be converted a binary image which alters all pixels in the gray image with luminance larger than level with the value 1 (white) and replaces all other pixels with the value 0 (black).

Segmentation The target of image segmentation is partitioning an image into division or clusters for identification the region of interest and object in an actual image. The image segmentation is applied to divide the image into a mutually exclusive and exhaustive segment. It means that each segment of interest is spatially contiguous and pixels within the segment are homogeneous with respect to a predefined criterion. In this thesis work, well-known KMeans clustering technique is applied for segmentation part.

K-Means Clustering The algorithm is introduced by Macqueen in the year 1997.This is one of the unsupervised algorithms. The algorithm starts by assigning the number of cluster K randomly. Next, calculate the cluster center is called the centroid. Each pixel is compared with the centroid. Then the pixel is moved to the particular cluster, which has the shortest path among all. Continue the same process by re-estimating the centroid for the next pixel. This process is repeated until the center converges. The Algorithm steps are explained as follows
Step 1: Randomly choose the C cluster center.
Step 2: Euclidean distance has evaluated among each pixel to cluster center.
Step 3: Every pixel is allotted to the specific cluster, which has shortest distance.
Step 4: The main objective of the algorithm is to reduce the squared error. The K-Means cluster method is an iterative technique to partition an image into k cluster. The K-Means algorithm finds k groups of data that minimize the objective following function:

$$F = \sum_{i=1}^{k} \sum_{x_j \in s_i} (x_j - c_i)^t (x_j - c_i) \quad \text{...... (1)}$$

Where, *k* cluster S*i*, i=1, 2, 3,......, *k,* and c*i* is the centroid or mean points of all the points

$x_j \in s_i$.

$$d = \| p(x, y) - c_k \| \quad \text{. ...(2)}$$

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$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x,y)$$

..(3)

This method continues the process until it satisfies the tolerance or error value and reshapes the cluster pixels into the image. The selection of K-value is the challenging task in K-means clustering. The performance of the entire segmentation process strictly depends on the initial assigned K-value. The improper value provides the poor segmentation results; this can be overcome by researchers to develop the new algorithm called adaptive K-means clustering. In This process cluster grows is not depends on the initial value. The process begins with selecting the K value from the data set. This K value generates the seed point for clusters. The properties of the cluster depend on the properties of the element present in that particular cluster.

Feature Extraction

Feature extraction and reduction is necessary for image processing to reduce the complexity, data, memory and time. The extracted features are used as the input of image classifier. Generally, brain MRI images consist of three types of features:
i) shape-based features (area, perimeter, circularity, irregularity shape index etc.)
ii) intensity-based features (mean, variance, standard deviation, median, skewness, kurtosis, range, pixel orientation etc.)
iii) texture-based features (contrast, correlation, entropy, energy or uniformity, cluster shade, inverse different movement, inertia, cluster Prominence etc.).

The proposed LPT based feature extraction method works as a scale and rotation invariant feature extractor. Where, DWT is used for its multi-resolution analytic property. To reduce the dimension of feature vectors and computational cost of new data, principal component analysis (PCA) is applied as an excellent tool for feature reduction. Feature extraction calculates features on the basis of which image can be easily classified as normal or abnormal one. The feature extraction is the process to represent raw image to facilitate decision making such as pattern classification. Features will be extracted from the tumor regions from MRI images. Feature extraction involves reducing the amount of data required to describe a large set of data accurately. Features are used as inputs to classifiers that assign them to the class that they represent. The intention of feature extraction is to reduce the original data by measuring positive properties, or features, that discriminate one input sample from another sample [2].
Following features are extracted:
1. Gray Scale
2. Texture
3. Symmetrical
These features certainly have some redundancy, but the idea behind this is to find the potential by useful features.
Gray Scale features: Gray scale features that extracted are mean, variance, standard deviation, skewness and kurtosis.

i) Mean = $\sum_i \sum_j g(i,j)$

ii) Variance = $\sum_i \sum_j (i - mean)^2 g(i,j)$

iii) Standard Deviation = $\sqrt{Variance}$

iv) Skewness = $(\frac{1}{Variance^3}) \sum_{x=1}^{m} \sum_{y=1}^{n} (f(x,y) - mean)^3$

v) Kurtosis = $(\frac{1}{Variance^4}) \sum_{x=1}^{m} \sum_{y=1}^{n} (f(x,y) - mean)^4$

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Texture Features: In this work six textural features are extracted from each image. The several Haralick texture descriptors are extracted from each co-occurrence matrices which are computed. Some of the texture features are shown below.

i) Entropy = $-\sum_{i=1}^{n}\sum_{j=1}^{n} P(i,j)\log(P(i,j))$

ii) Dissimilarity = $\sum_{i,j=1}^{n} P\ (i,j) * |(i-j)|$

iii) Inverse = $\sum_{i,j=1}^{n} \frac{P(i,j)}{(i-j)^2}$

iv) Energy = $\sum_{i=1}^{n}\sum_{j=1}^{n}(P(i,j))^2$

v) Homogeneity = $\sum_{i,j} \frac{1}{1+(i-j)^2}\, g\ (i, j)$

vi) Contrast = $\sum_{i=1}^{n}\sum_{j=1}^{n}(i,j)^2\ P(i,j)$

vii) IDM = $\sum_{i=1}^{n}\sum_{j=1}^{n} \frac{1}{1+(i-j)^2}\ P(i,j)$

Symmetrical Feature:

i) Exterior Symmetry = $\frac{\sum_{i=1}^{n}(m-M)^2}{n}$

Log-Polar Transformation (LPT) LPT is an effective and validate mechanism for conversion of image geometry from Cartesian domain to log polar domain retaining the rotation and scaling invariant properties [25]. We can represent the polar coordinates (r, θ) corresponding to distance of radius and angle from the center respectively. Equation (17) does that conversion.

$$(r,\theta) = \sqrt{(x-x_c)^2-(y-y_c)^2}\ ,\ \tan^{-1}\frac{(y-y_c)}{(x-x_c)}$$

Principal Component Analysis (PCA) The PCA reduces the number of unnecessary features and dimensions in our work. PCA is used as statistical tools for providing orthogonal transformation of data to a new coordinate system and summarizing the variances that eliminate the least contributing components to the variation in data set. PCA formulate the eigenvectors of the covariance matrix of the original data and compare it by a linear combination of the leading eigenvectors. The Principal component analysis (PCA) is highly used and it essentially decomposes the set from claiming spectra under factors alternately of the central components, in weight of the score and the spectral variance, with the weight of that specific part of the structure from the spectrum. Each crucial part needs an interesting unique characteristic, speaking to the new hub of most extreme difference. The scores are those cosines (projections) from claiming every range in this new hub axis. The preference of PCA may be that, once a situated of spectra have been determined and arranged with classification by concerning illustration for having a place into specific class, whatever new. Range might be compared for this model Furthermore a chance to be ordered if it fits under that class. A standout amongst those the majority well-known types of dimensionality decrease is central parts dissection. PCA detects the typical lower dimensional manifestation of the information such that the difference of the exhilarate information will be safe guarded. Use of the combined principal component analysis system plays a vital role for the feature reduction on the feature vectors which are calculated by wavelets to limiting the selected feature vectors PCA use the supervised approach and leads to an efficient methodology. That’s why the fundamental thought behind utilizing PCA will be to decrease the dimensionality of the coefficients of the wavelet. The characteristic extraction procedure might have been conveyed out through two different and most effective steps: first is the wavelet coefficients were extracted by

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using the DWT. Feature extractions of the essential features from MRI images are prepared for training and the test phase. Main aim of MRI image identification system is used to determine the likenesses among training MRI image sample and testing MRI image sample [4]. Excessive features increase the computation time and memory storage which sometimes causes some complications in the classification process (the curse of dimensionality), and so it is required to reduce the number of features. Principal components are the projection of the original features onto the eigenvectors and correspond to the largest eigenvalues of the covariance matrix of the original feature set. PCA can be used to approximate the original data with lower dimensional feature vectors. The basic approach is to compute the eigenvectors of the covariance matrix of the original data, and approximate it by a linear combination of the leading eigenvectors.

PCA is a proficient tool to reduce the dimension of a data set consisting of a large number of interconnected variables while retaining most of the variations. Reduce dimension means reduced feature set which is act as an input to the SVM during training part as well as testing part [2].
Steps to be followed in PCA:
1. Compute the mean of the data matrix
2. Subtract the mean from each image.
3. Compute the covariance matrix.
4. Compute the Eigen vectors and values for covariance matrix.
5. Arrange the Eigen vectors according to the Eigen values and as per the threshold value.
6. Compute the feature matrix (the space that will use it to project the testing image on it)

CONLUSION AND FUTURE WORK

In this paper, feature extraction method was developed for detection and classification of tumor from brain MRI images which was validated conducting a number of experimental evaluation using a set of brain MRI dataset. Experimental results showed that, our classification method can successfully separate normal and abnormal brain MRI images. Finally, cancerous and non-cancerous tumors are classified from abnormal brain MRI images. To categorize brain tumor, it can detect tumor and classify as benign or malignant. LPT provides accurate feature extraction and PCA reduces search space without misinterpreting detection factor. It is significant that our method can classify rotation and scale invariant image as well as T-1 and T-2 weighted neoplastic and degenerative brain diseases images. The accuracy measurement of our experiment gets perfection by using four kernels (RBF, LINEAR, POLYNOMIAL and QUADRATIC) operations. Almost in all cases, the proposed method gives better performance than that of the existing process. The combined performance of feature extraction and classification by using strong dataset make our method robust and efficient.

In the future, we work in cerebro vascular and inflammatory disease. Our further analysis concentrate on different wavelet families such as complex wavelet transforms (CWT), dualtree complex wavelet transforms (DTCWT) etc. Our future focus turns to classification variety of brain disease by handling different wavelet families as well as reducing time consumption and increasing the success rate.

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