Early Diagnosis of Chronic and Acute Pancreatitis using Modern Soft Computing Techniques

R. Balakrishna, R. Anandan

Abstract: ***The analysis of pancreatic cancer at an incipient stage is very crucial for raising the endurance of the patients. The infection of pancreas is called as Pancreatitis, either be acute (sudden and severe) or chronic (ongoing). Across the globe, Pancreatic cancer is the fourth most cause of cancer related to death and the most challenging aspect of pancreatic cancer is diagnosing at an incipient stage. The pancreas is a gland that disguises digestive enzymes as well as important hormones and the most common causes of chronic pancreatitis is heavy consumption of alcohol, followed by gallstones. Current work presents the creation of datasets which comprises of pancreas images and it is segregated by using Big Data analytics tools like Hadoop, Next the segregated images are preprocessed for removal of noises or any other disturbance which occurs in the images. The preprocessing is done by Wiener's filter and the PSNR, MSE and SNR values are noted. Next the preprocessed image is segmented, In order to find the region of interest and the segmentation is performed by machine learning algorithm called Support Vector Machine (SVM).Finally we need to extract the features of the images in the region of interest identified in the segmentation process. The promising results indicate that pancreatic cancer can be diagnosed with high accuracy.***

Keywords: ***Pancreas, Preprocessing, Pancreatitis, Segmentation, Extraction, Prediction and Incipient.***

I. INTRODUCTION

At the start of the 21st century, pancreatic cancer is one of the most dangerous human cancers and becomes a major unsolved health problem. The infection of pancreas is called as Pancreatitis, Which can be temporary or it can be a lifelong problem and the treatment will depends on whether the infection of the pancreas is severe(acute) or ongoing(chronic) [2]. The onslaught of acute pancreatitis will be sudden or severe and the infection generally removed within days of analysis begins. According to the report of National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK), every year nearly 250,000 Americans were reported to the hospital for acute (severe or sudden) pancreatitis and in that 95% were adults, Fig. 1 illustrates the structure of pancreas. Acute pancreatitis generally occurs by Gallstones, Which are small, solid masses that developed from enmity.

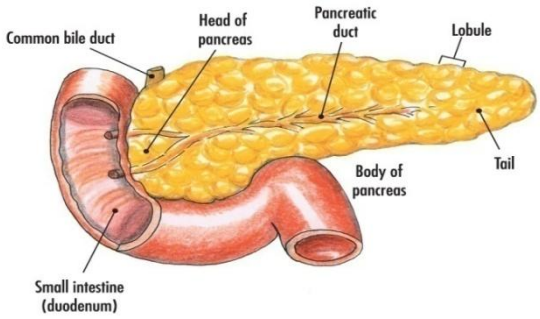

Fig. 1: Structure of Pancreas

A big gallstone will get stuck at the intersection where the primary pancreatic tube and the neutral enmity tube combines together to create another tube called the Ampulla of Vater [10]. These tubes empty into the duodenum, the primary section of the small intestine. The purpose of pancreatic tube is to carry the digestive impetus from the pancreas. The neutral enmity tube will carry enmity or other substances from the liver and gallbladder. When a gallstone gets stuck here, a copy of these substances is form by gallstone which causes infection in both the pancreatic and neutral enmity tubes.

Chronic (ongoing) pancreatitis is an infection of the pancreas that occurs continuously over the long period. Public chronic (ongoing) pancreatitis can have a stable blow to their pancreas and a scar tissue forms from this long-term infection. Severe scar tissue will root your pancreas to stop making the regular quantities of digestive impetus or glucose-monitoring hormones. As a result, people will have trouble in digesting fats (which are requires impetus for digestion) and there is a chance of diabetes. The most common cause for both acute and chronic pancreatitis in adults is Alcohol. Long-term alcohol consumption is the major root of chronic pancreatitis in adults. Along with alcohol, Autoimmune and genetic diseases, such as cystic fibrosis, can also root chronic (ongoing) pancreatitis in some people.

The primary symptom of acute or chronic pancreatitis is people will feel the pain on middle-left upper abdominal. The symptoms of People who are suffering from chronic pancreatitis are diagnosed by imaging scans or else we can't identify the symptoms. Other symptoms of pancreatitis may include:

Revised Manuscript Received on December 30, 2018.

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- pain that wraps around the upper body and involves the back in a band-like pattern
- indigestion
- nausea or vomiting
- abdominal tenderness
- unintentional weight loss
- bloating with a distended (swollen) abdomen
- hiccups
- fever

Diagnosing and Treating Pancreatitis

Your doctor will likely use a combination of blood tests and imaging studies to make a diagnosis. If you have acute pancreatitis, you'll have severe abdominal pain and blood tests may show a significant rise in your level of pancreatic enzymes [3]. There are many techniques or methods like Ultrasound, MRI, and CT scans can identify the anatomy of your pancreas, signs of infection and the knowledge about the pancreatic tubes. We can also determine whether our stools have fat content that's higher than normal or not by fecal fat test.

Hospitalization is required for treating both acute (sudden) and chronic (ongoing) pancreatitis. Since pancreas is an important factor for our digestive processes and also needs to rest to heal. For this reason, you may receive specifically tailored fluids and nutrition intravenously (IV) or through a tube that goes from your nose directly into your stomach. This is called a nasogastric feeding tube. Restarting an oral diet depends on your condition. Some people feel better after a couple of days. Other people need a week or two to heal sufficiently.

II. RELATED WORKS

Pre-processing of images is the primary steps in image processing, in this work preprocessing are done by median filters and then the features are extracted by genetic algorithm [8]. Naïve bayes and Decision tree classifiers are used to train, verify and differentiate the performance quota, the results shows that decision tree classifier yields more accurate results than the naïve bayes classifier. Once the pre-processing of images is completed, next we need to segment the images for identifying the region of interest and this can be done by any one of the image segmentation techniques. In this work, a new technique for 3D lesion segmentation was used without using MRI- atlas. A geometric exemplary for brain which is less sensitive to spatial variability's of a brain's etiology is proposed. As a result, the effect of model-over fitting is less definite at the interface of surrounding brain areas.

In the existing work, there are many trained systems or models for predicting the cancer but in each system there are some cavity in identifying or predicting the cancer at an incipient stage. There are several ways to identify the stages of cancer like using UltraSound (US), Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Magnetic Resonance Cholangio Pancreatography (MRCP), etc.

The analysis and process of medical images requires a separate platform for data entry, analysis of data, processing and developing new algorithms for predicting the cancer. In order to analyze the cancer, we require data's related to that cancer and medical imaging is the method used to generate images of human body for diagnosis and analysis [9]. MS imaging pathology, which is frequently used for disease diagnosis, shows typical anomaly. Lesion identification is a important process in computing the burden of the disease. Earlier, lesion is manually measured for clinical routine and this process is time consuming and lack of reproducibility. Atlas driven pre- segmentation is used for producing the exact boundary between WM and Grey Matter (GM) but it is difficult to compute because of brain variability. Therefore, the computed WM contains GM which might be segmented as lesion and also pre-planned computation of exact location of lesions is difficulty, as a result it is arduous in applying a purely atlas – driven method for segmentation

III. MATERIALS AND METHODOLOGY

Current work presents the creation of datasets which comprises of pancreas images and it is segregated by using Big Data analytics tools like Hadoop, Next the segregated images are preprocessed for removal of noises or any other disturbance which occurs in the images. The preprocessing is done by Wiener's filter and the PSNR, MSE and SNR values are noted. Next the preprocessed image is segmented, In order to find the region of interest and the segmentation is performed by machine learning algorithm called Support Vector Machine (SVM).Finally we need to extract the features of the images in the region of interest identified in the segmentation process. Fig. 2 illustrates the system architecture of the current work.

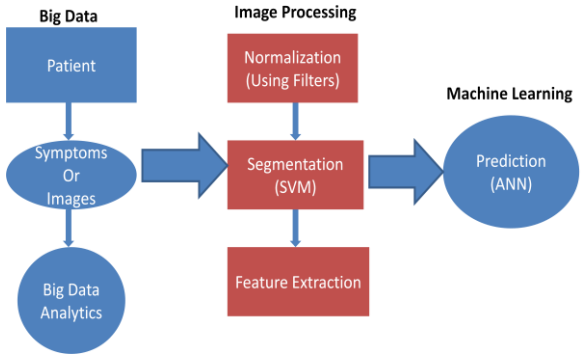

Fig. 2: System Architecture

Preprocessing of Images

One of the challenging aspects in image processing is removing unwanted features or noise from images because many images were defected to some region by noise in the form of un-described deviation in information, variation in image intensity which are either uninterruptable or not of interest. To overcome the above drawback, Normalization is performed, in which the preprocessing of images are performed. The basic idea of preprocessing (noise filtering) is to change every pixel intensity value with a new value chosen from the surrounding pixel of static size. Several techniques there for preprocessing and in that we considered wiener's filter for removing the unwanted noise.

The rebuilding or recovery technique for deconvolution is known as inverse filtering.

The concept of inverse filtering is to recover the images which are blurred by a known low pass filter and it is also called as derived inverse filtering. However, inverse filtering is very receptive to supplement noises and as a result we move on to wiener filtering technique where it executes a resolution among inverse filtering and noise flushing. Wiener filter will simultaneously remove supplement noise as well as recovering the blurred images and overall it reduces the mean square error (MSE) in the process of filtering. The Fourier domain for wiener filter is,

Wiener (freq1, freq2) =

$$\frac{K^*(freq1, freq2)R_{YY}(freq1, freq2)}{|K(freq1, freq2)|^2 R_{yy}(freq1, freq2) + R_{mm}(freq1, freq2)},$$

Where,

K (freq1, freq2) is for removing the blur of the images, $R_{yy}(freq1, freq2) and\ R_{mm}(freq1, freq2)$ is the power spectra and supplement noise of the images.

Segmentation of Images

The phrase image segmentation indicates segregation of images into regions or categories which as several objects or a portion of objects. Each pixel in an image is designated to any one of these regions or categories. An ideal segmentation is typically one in which,

- Pixels with similar grayscale values are grouped together in a region and form connected categories,
- Pixels in different regions or categories will have different grayscale values.

Region-based segmentation algorithm works on grouping the pixels with similar grayscale values in a region and dividing group of pixels with different values.

Segmentation algorithm

Step 1: Splitting of images is the first process of segmentation and for that variance (ȯ) of the image is calculated. If the variance crossed the specified limit, then the image is subdivided into five quadrants and the variance of each quadrant should not cross the specified variance limit. The default variance limit is 0.70 and not the speckle variance value 0.35 because the result of later will be very small in region.

Step 2: Next steps is grouping or merging of images which have common edges into new a region of interest. The most important point in this step is we should form the new region whose variance should not exceed the default or specified variance value (0.70).

Features Extraction of Images

One of the major drawbacks in analyzing large volume of complicated data is the number of variables involved. Large volume of memory and high computation power required to compute large quantity of variables, to overcome this problem feature extraction concept has been introduced [1]. Features refer to piece of information or knowledge which is helpful in solving the computational task involved in that application. Feature extraction is the term used for capturing the content of images for better and easy computation as well as reducing the overall dimension of the images to yield high accuracy in the result. In order words we can describe feature extraction is the process of minimizing the dimensions of input image data by capturing only the required information from the segmented images.

In the current work, Gray level co-occurrence matrix (GLCM) is used to extract the texture features of images. The spatial relationship between variable values or location is called as spatial dependency in which the results of different location will dependent on each other. The purpose of GLCM (Gray Level Co-occurrence Matrix) is to measure the spatial dependencies of images for further analysis and it is also to converts the RGB values of an image into a matrix where the number of rows and columns are identical to the gray levels in the image for extracting the features. Let us consider Q_{nm} be the co-occurrence matrix and (S X S) be the size of matrix, in the matrix each and every element (n, m) shows the spatial dependencies among pixel with gray level n and m. Fig. 3 illustrates the transformation of gray scale image into Gray Level Co-occurrence Matrix (GLCM).

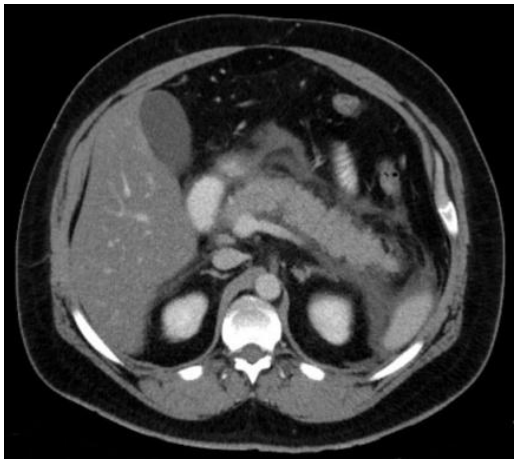

Fig. 3.a: Sample Input Image

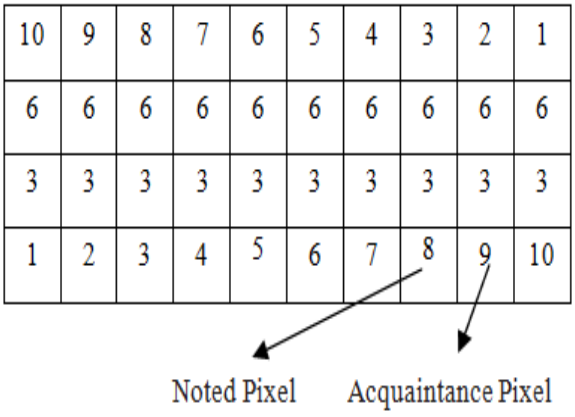

Fig. 3.b: Gray Level values of sample input image

There are 10 gray levels present in the sample input image and Fig. 3.c shows the Gray Level Co-occurrence Matrix (GLCM) which presents the relationship among the noted (n) and acquaintance pixels (m). At the start of the process, the values of each and every element of the Gray Level Co-occurrence Matrix (GLCM) are zero and later on it is updated as per the occupancy of the pixels togetherness.

NOTEDPIXEL	1	2	3	4	5	6	7	8	9	10
1	1	0	1	0	0	0	0	0	0	0
2	0	1	0	1	0	0	0	1	0	0
3	0	0	1	0	1	0	0	0	0	0
4	0	1	0	1	0	3	0	0	0	1
5	0	0	1	0	1	0	0	0	0	0
6	0	0	0	0	1	0	1	0	0	0
7	0	0	0	0	0	1	0	0	0	0
8	0	1	0	0	0	0	1	8	1	0
9	1	0	0	0	0	0	0	1	0	1
10	0	0	0	0	1	0	0	0	1	0

$Q_{nm} = Q_{89} = 1$

Fig. 3.c: GLCM for The Sample Input

By using the above Gray Level Co-occurrence Matrix (GLCM) values we can calculate the texture features like Dissimilarity, Entropy, Energy, Contrast, Correlation, Homogeneity, Standard deviation, Mean and Variance. Table 1 describes the equations for measuring the above mentioned texture features from Gray Level Co-occurrence Matrix (GLCM).

IV. RESULTS AND DISCUSSIONS

Preprocessing of Images

In preprocessing stage, various filters are used for processing the images to remove the

Table 1: Equations to measure the texture features from Gray Level Co-occurrence Matrix (GLCM)

S.NO.	Gray Level Co-occurrence Matrix (GLCM) Features	Equation
1	Dissimilarity	$\sum_{n,m=0}^{R-1} Q_{n,m}\lvert n-m\rvert$
2	Entropy	$\sum_{n,m=0}^{R-1} Q_{n,m}(-\ln Q_{n,m})$
3	Energy	$\sum_{n,m=0}^{R-1} Q_{n,m}^2$
4	Contrast	$\sum_{n,m=0}^{R-1} Q_{n,m}(n-m)^2$
5	Correlation	$\sum_{n,m=0}^{R-1} Q_{n,m}\left[\frac{(n-\varphi_n)(m-\varphi_m)}{\sqrt{(\rho_n^2)(\rho_m^2)}}\right]$
6	Homogeneity	$\sum_{n,m=0}^{R-1} \frac{Q_{n,m}}{1+(n-m)^2}$
7	Standard deviation	$\rho_n = \sqrt{\rho_n^2}$, $\rho_m = \sqrt{\rho_m^2}$
8	Mean	$\varphi_n = \sum_{n,m=0}^{R-1} n(Q_{n,m})$, $\varphi_m = \sum_{n,m=0}^{R-1} m(Q_{n,m})$
9	Variance	$\rho_n^2 = \sum_{n,m=0}^{R-1} Q_{n,m}(n-\varphi_n)^2$, $\rho_m^2 = \sum_{n,m=0}^{R-1} Q_{n,m}(m-\varphi_m)^2$

unwanted disturbance or noise for better analysis and accurate results. By considering the Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR) and Mean Square Error (MSE) parameters for all the filters, Wiener filter gives maximum PSNR value when compared to other filters.

Fig 4.a and Fig 4.b illustrates the output obtained for wiener's filter through MATLAB and graph formed according to the three parameters value obtained for the image. Table 2 illustrates the values obtained for various parameters for the images.

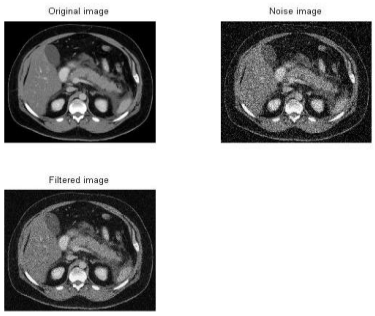

Fig. 4.a: Wiener Filter's Output

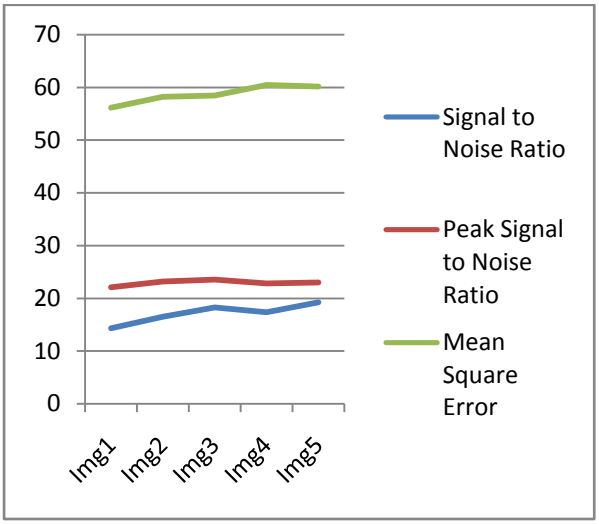

Fig. 4.b Wiener filter's graph

Table 2: Parameter values for wiener filter

IMAGE(Img)	Signal to Noise Ratio	Peak Signal to Noise Ratio	Mean Square Error
Img1	14.3	22.06	56.15
Img2	16.47	23.15	58.23
Img3	18.24	23.54	58.47
Img4	17.35	22.78	60.47
Img5	19.24	22.96	60.14

Segmentation of Images

Fig. 5 shows the output of segmentation process on the preprocessed images by using splitting and grouping or merging of pixels based on default variance value.

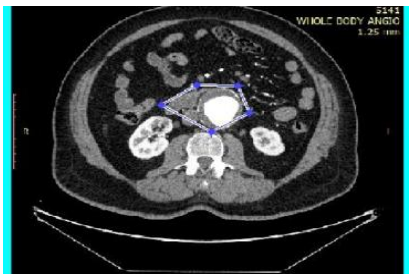

Fig. 5: Segmentation Output

Features Extraction of Images

The below table 3 describes the various texture features values like Dissimilarity, Entropy, Energy, Contrast, Correlation, Homogeneity, Standard deviation, Mean and Variance which are obtained from Gray Level Co-occurrence Matrix (GLCM).

V. CONCLUSION

In the current work, more than 100 MRI images as been used for early diagnosis of pancreatic cancer. The proposed methodology for preprocessing, segmentation and feature extraction is agile and efficient contrast to existing works. Preprocessing is done by wiener's filter and the filtered image is segmented by splitting and grouping of pixels to find the region of interest. Texture features are extracted from the segmented region by GLCM and obtained results are highly accurate and authentic. Our future work is to develop a prediction algorithm based on Artificial Neural Network (ANN) to predict the stage of pancreatic cancer from the obtained texture features values.

Table 3: Texture Features Values using GLCM

IMAGE (Img)	Texture Features							
	Dissi-milarity	Entropy	Energy	Contrast	Correlation	Homo-geneity	Standard deviation	Variance
Img1	0.615	0.201	0.878	62.114	0.978	0.897	16.124	228.741
Img2	0.596	0.230	0.850	62.478	0.945	0.841	16.748	228.847
Img3	0.664	0.239	0.815	63.117	0.910	0.879	16.496	227.124
Img4	0.647	0.210	0.798	62.145	0.897	0.852	15.998	228.145
Img5	0.599	0.214	0.884	61.987	0.945	0.812	16.884	227.987
Img6	0.621	0.197	0.917	62.254	0.914	0.798	16.950	228.478
Img7	0.601	0.254	0.816	63.114	0.956	0.884	16.118	229.147
Img8	0.666	0.287	0.874	62.147	1.001	0.845	16.247	229.105

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