

Early Detection of Pancreatic Cancer Using 3D Wavelet Analysis

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ABSTRACT

Image analysis plays a fundamental role in medical imaging. Medical imaging is very valuable in proper diagnosis of the disease. In recent times pancreatic cancer is the leading cause of death for both men and women. Pancreatic cancer does not show any symptoms or signs until the disease has progressed and it is the only major cancer with five year survival rate. So there is an urgent need of a method in diagnosis of pancreatic cancer at an early stage. In this paper a methodology is proposed for the detection of pancreatic cancer from MRI images using 3D wavelet transform analysis. Later the transform coefficient derived from the images is analyzed statistically to differentiate the normal and abnormal states of pancreatic cancer.

Keywords: Pancreatic Cancer, 3D Wavelet Transform, Transform Coefficient, Statistical Analysis.

INTRODUCTION

Cancer is defined as a group of diseases involving abnormal cell growth with the potential to invade or spread to other parts of the body. In cancer, cells split and grow uncontrollably, developing high-risk cancer, and get into nearby parts of the body. One in eight fatalities globally is due to cancer. Cancer is the second major cause of loss of life in western world and the third major cause of loss of life in building nations. Cancer, which makes unfettered cell growth, will subdivide the cells and grow wildly, forming malevolent tumors, and assault nearby parts of the body. This tumor can grow and impede the digestive, nervous, and circulatory systems and they can liberate hormones that amend body function [2].

Pancreas is an organ in the abdomen cavity that is about 6 inches long and 2 inches wide. It contains both exocrine and endocrine properties, meaning it produces enzymes and proteins to send to other parts of the body and for itself. The main function of the endocrine gland is to make insulin so the body can take up glucose. Beta cells on the islet of Langerhans produce insulin, while alpha cells make glucagon and delta cells produce somatization. Exocrine gland acinar cells make digestive enzymes. The exocrine gland epithelial cells which are responsible for making sodium bicarbonate and digestive enzymes are the cells which cause most people with pancreatic cancer to die. Pancreatic cancer is a dangerous neoplasm via modified tissues which enters into the tissues that develop the pancreas. Every day the most sort of pancreatic melanoma, accounting for 95% of these cancers, is adenocarcinoma coming up within the exocrine component of the pancreas. Pancreatic cancer is the 10th most commonly diagnosed cancer in men and 9th in women. This cancer type is the 4th leading cause of cancer death for both men and women [1]. Cancer in pancreas begins in the tissues. Pancreatic cancer is essentially a disease due to the harm within the DNA (mutations). These strains can be inherent or might occur along with the growth of the individual. There are not much symptoms or signs of pancreatic cancer until the disease has been progressed. The mild symptoms of pancreatic cancer involve pain in the middle back or abdomen; fluid in the abdomen or nausea; fatigue or loss of appetite; dark urine; weight loss; yellow skin and eyes. But commonly these symptoms are assumed as a nasty stomach virus, so much care and attention are not shown until the tumor is spread outside the pancreas to nearby blood vessels, lymph nodes or both [3].

Earlier the disease is diagnosed, the better the odds of survival rate in the case of Pancreatic Cancer. Cancer image analysis can be performed using different imaging modalities like X-rays, magnetic resonance, nuclear medicine or ultrasound. Medical imaging is the better way of pancreatic cancer diagnosis [4, 20]. The overall analysis of this project is to identify the pancreatic cancer in MRI images using 3D image processing

techniques. In this research, wavelet transform is used to work on these images. Wavelet transform coefficients are used for the detection of tumour automatically. These coefficients are compared statistically using different techniques that illustrate the significant role of the Wavelet transform coefficients in identifying the pancreatic cancer. Analysis of the MRI images of pancreatic cancer is performed in both ways among the slices and also between the images using Wavelet transform coefficients. The outcome of the statistical procedures describes that the coefficients effectively with a significance level of 95% and used to differentiate the cancer images or slices from the normal images.

Relevant Work

The research focuses in defining the abnormal cancer structures in the pancreas using 3D wavelet transform for the early diagnosis and precise identification. Min Lia, et.al., (2020) developed a computer- aided preoperative diagnostic tool which performs staging of pancreatic cancer based on an ensemble learning, support vector machine (EL-SVM). Computer tomography (CT) images are used for the study. The least absolute shrinkage and selection operator (LASSO) algorithm was used for feature extraction. Then the EL-SVM learner was used for classifying the images of normal pancreas and different stages of pancreatic cancer. The results obtained shows that a normal pancreas – pancreatic cancer early stage gives a classification accuracy of 86.61% and the accuracy increases stage by stage, the normal-pancreatic cancer images of fourth stages provide a classification accuracy of 91.63%, describing a method for identifying the stages of the pancreatic cancer [5].

Yuhing Zhang et.al., (2020) describes a method for accurate diagnosis of pediatric pancreatic cancer using support vector machine (SVM) combined with magnetic resonance imaging and machine learning. In this study they have extracted features of pancreatic lesions from the MRI images and it is then classified using clustering techniques. These extracted features are combined to construct an MRI detection model based on SVM providing an efficient method of detection of pancreatic cancer [6].

Sushant Shekar, et.al., (2018) proposed an image analysis for brain tumor detection from MRI images using discrete wavelet transform technique. The images are divided into two groups i.e. the healthy and disease images for the feature extraction by using different sub bands like LH, LL, HH, HL for determining different statistical features and their values. The results obtained are then processed through the SVM for the classification of the tumor type i.e. whether it is benign or malignant [7].

Kishor Kumar Reddy C, et.al., (2015) proposed a methodology for detection of pancreatic cancer using clustering and wavelet transform techniques. This work provides a computer aided diagnostic system for the diagnosis of the pancreatic cancer using the MRI, CT scan images. Then K- means clustering technique is adopted to segment the images for capturing the region of interest. Later Haar wavelet transform for these segmented images are considered to compute the threshold values for the region of interest. Finally, the obtained threshold value, calculated value and the mean of these two threshold values are compared. The result says that if the threshold value obtained through these three falls within the same range depicts the existence of the cancer cell or not [1].

Frank H. Miller, et.al., (2006) illustrated the strengths of MRI for evaluating pancreatic adenocarcinoma. The work says that the superior soft tissue contrast of MRI is useful in the evaluation of subtle non – contour – deforming pancreatic masses. The advances in abdominal MRI allow fast acquisition of multiple sequences free of artifacts. The excellent contrast resolution of MRI facilitates detection of a small tumor within the enhancing pancreas and also the focal pancreatic atrophy or pancreatic duct dilation can be also seen in an MRI image [8]. With these literature studies, the following details are reviewed for the work such as MRI images prominently define the cancer in pancreas and wavelet Transform can be used for the illustration of the cancerous regions for the early diagnosis. The need for an algorithm for the early diagnosis of the pancreatic cancer is analysed. Wavelet Transform used to define the fine structures in the pancreatic MRI images.

METHODOLOGY

In general, Magnetic Resonance Imaging (MRI) scan is used to generate description and analysis of the computer-generated image of body or organs. Analysis of MR imaging is required for efficient diagnosis of the

disease. MRI images are used for better characterisation of cystic lesions of the different regions especially in pancreas and can provide some indirect radiological evidence to aid in diagnosis of pancreatic cancer. The intension of this research is to process and analyse the MRI images in 3D to generate results. These results are used for the analysis and diagnosis process to state that whether the images contain cancer cells or not. The overall methodology is represented as a simple block diagram below in figure 1.



Fig 1: Block Diagram for the overall methodology

Database

In this paper, MRI images of pancreas are acquired from ‘The Cancer Imaging Archive (TCIA)’ database that contains large number of images for different categories of cancer. Images of Different modalities are available in the database including PET and SPECT images [9, 10]. In this research, the MRI images of pancreatic cancer are derived from the database. This database consists of more than 500 images of both cancerous and non-cancerous states of pancreas. The database consists of various Asian and American Demographic based T1 weighted MRI images of 1.5 Tesla shown in figure 2. In this study, T1 type of images is used for better descriptive analysis and determination of the cancer cells.

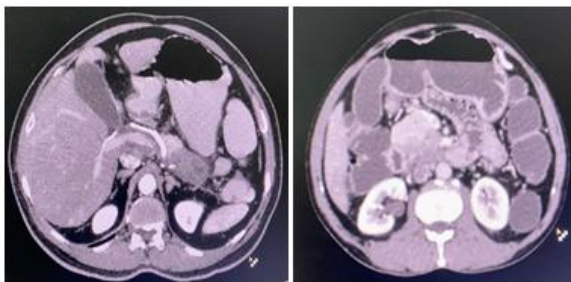


Fig 2: Input image

Luminosity method

In the state of pre-processing, luminosity method is used for the conversion of grayscale to RGB colours. Grayscale to colour image conversion is required to determine the fine details and variations in the cells of pancreas. The MRI images obtained creates an inconsistency in identifying the cancer cell because as it is in grayscale to identify the affected part is much complex, which may mislead the experimentation process, therefore the image is again converted to RGB images as shown in figure 3, which makes it easier to identify the cancer cell based on the colour. The RGB converted images have been applied with wavelet transform for further analysis [1].

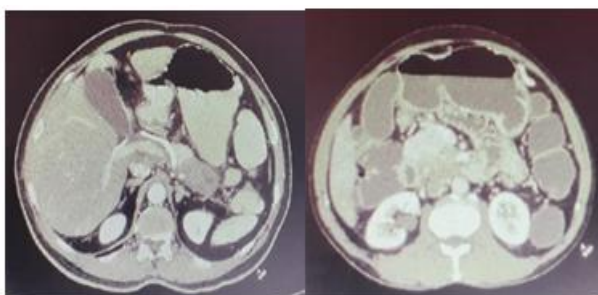


Fig 3: RGB converted image

Wavelet Transform

3D Wavelet Transform is applied to the resultant images for accurate analysis of the abrupt changes in the images that will localise mean in the time and frequency domains. The wavelet transform is a very effective method for compressing a 3D medical image data set yielding a high compression ratio of the image with good quality. The wavelet coefficients can also be used for the detection of the cancer cells in the images [11, 12]. The Wavelet Transform is applied here as it is an efficient technique, where decomposition is significant. These levels are applied to the image in rows and columns that helps in transforming from data space to wavelet space in frequency domain as shown in figure 4. The decomposition of the MRI images by applying wavelet transform based on the split in frequency levels is determined corresponding to the slices is shown in the figure given below.

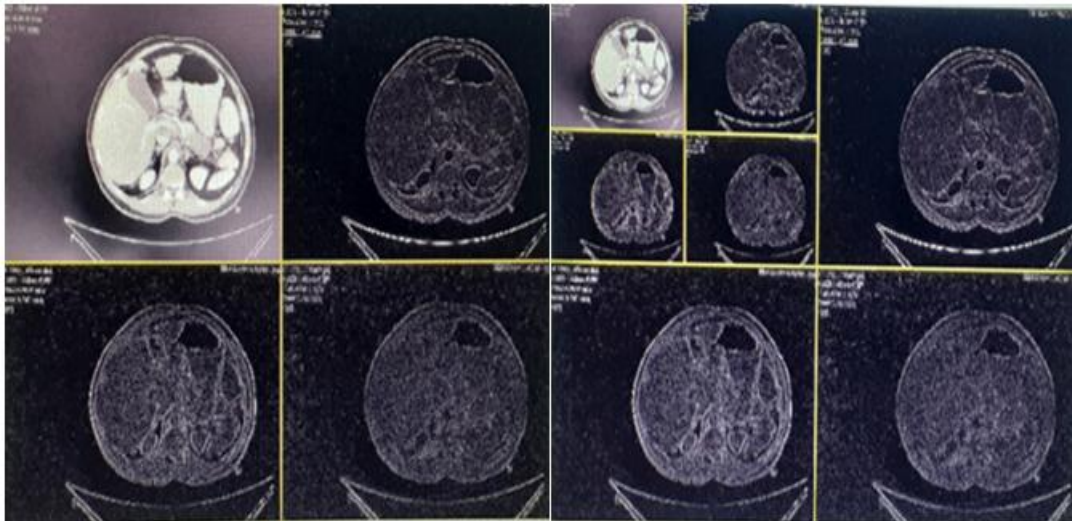


Fig 4: 3D- Wavelet transform applied for image slices

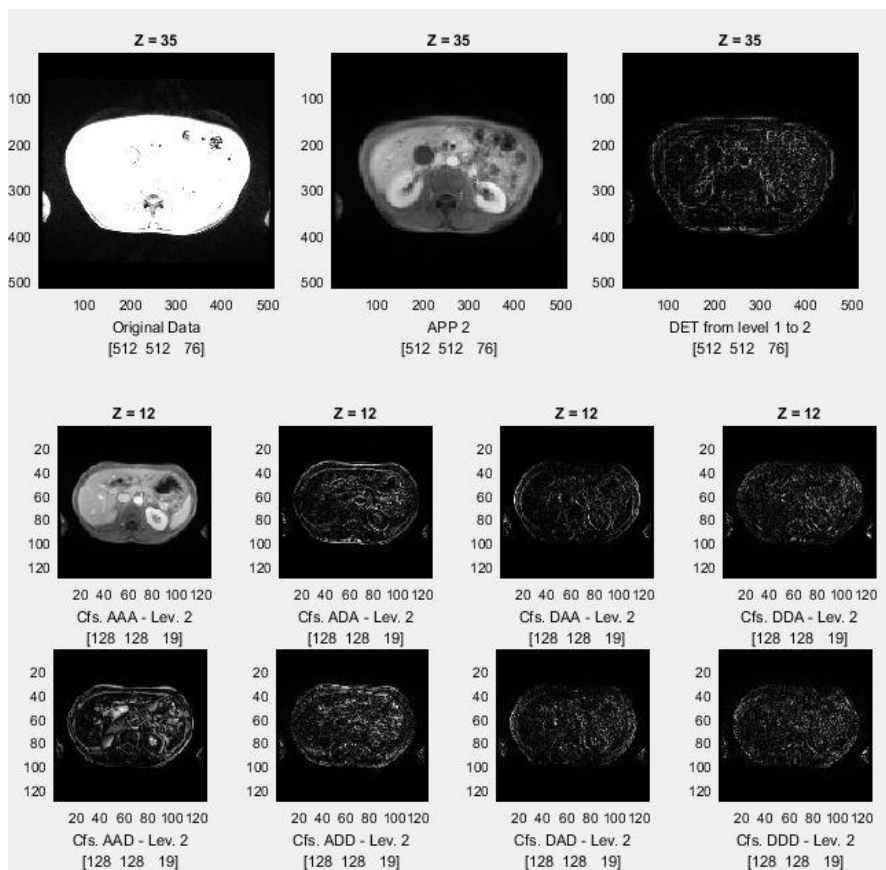


Fig 5. 3D image analysis using wavelet transform

The 3D wavelet decomposition of a typical pancreatic MRI slice is displayed in Figure 5 at full resolution ($Z = 35, 512 \times 512 \times 76$) as the original image, its level-2 approximation a smoothed version retaining coarse anatomical structure and the image detail coefficients highlighting edges and texture alongside the eight directional sub-bands obtained at a deeper slice ($Z = 128 \times 128 \times 19$). Each letter represents an approximation ("A") or detail ("D") filter applied along the x, y, and z axes. As the number of "D" components increases, the sub-bands change from smooth, organ-shaped structure, AAA to DDD, fine-grained texture detail as the number of "D" components increases; cancerous in the detail-dominant sub-bands because of greater local tissue intensity variation, which serves as the foundation for the statistical differentiation between normal and abnormal slices. Then the wavelet transforms coefficients among the image slices and images are calculated for validation. The variations in the transform coefficient of each and every slice is analysed in an image at different levels. The coefficient values define a significant difference between the slices in normal and abnormal (Pancreatic cancer) images [13, 14, and 17]. Higher the decomposition level, higher the difference between the coefficients values that illustrates the detection of cancer cells in pancreas. After the process of analysing the image slices, the mean transform coefficient value of the image slices for every MRI image in both normal and abnormal state is calculated to see the differences in the images. Both transform coefficient value for image slices and mean transform coefficient value for images are plotted graphically to see the changes in the normal and abnormal states. These coefficient values are statistically analysed using different statistical techniques.

Statistical Analysis

The statistical study is performed to both these derived coefficient values to identify the changes in the statistical features differentiating normal and abnormal states of cancer. The statistical techniques include t-Test, f-Test and ANOVA test. The statistical analysis characterizes the content of the image, texture enabling probabilistic description and classification of the images differentiating normal and abnormal states of cancer. Because of the test variance equality, mean difference between two groups, and mean difference across multiple groups/slices, respectively, the F-Test, t-Test, and ANOVA were selected together to cover to statistically validate that wavelet coefficients differ between normal and cancerous states at level.

T-test looks at the t-statistic, the t-distribution values and the degrees of freedom to determine the statistical significance and also determine if there is a significant difference between the means of two required groups. F-Test is commonly used for comparing the data that have been fitted in the dataset, in order to identify the data that best fits the population from which the data were sampled. Descriptive statistics are used to describe the basic features of the data in a study which provide basic information about the variables in the data to be analysed and also highlight the potential relationships between the variables. The one-way analysis of variance (ANOVA) test is used to determine whether there are any statistically significant differences between the means of two or more independent groups. The p value in this test is the probability of the results, and it is commonly valued to find out whether the variables in the data are statistically significant [15, 16]. Based on the results obtained the wavelet coefficient values can be used for the identification of pancreatic cancer cells in the MRI images.

RESULTS AND DISCUSSION

Pancreatic cancer detection is one of the challenging tasks that researchers, doctors, academicians and so on of present day are experiencing. These types of cancer is to be identified at the earlier stages to prevent the death toll rate to a greater extent. Mining of data from MRI images is even more challenging and cumbersome task since it involves processing of not one but hundreds of MRI images in order to extract the required results. The Pancreatic cancer images obtained from The Cancer Imaging Archive (TCIA) database for cancerous and non-cancerous are used to analyse for the identification of cancer. In the experimentation, around 450 images are analysed to compute the success rate of detection. The RGB converted input images are applied with wavelet transform at different levels for analysing the changes in the MRI images. Then the coefficients are calculated for validation. The obtained Transform Coefficient value for each slice in an image (considerably 15 slices including the cancer slices) shown in figure 6. These values are plotted graphically to visualize the changes in

the cancer region within the image among the slices. High variations are observed in the slices of image that contains the cancerous cells.

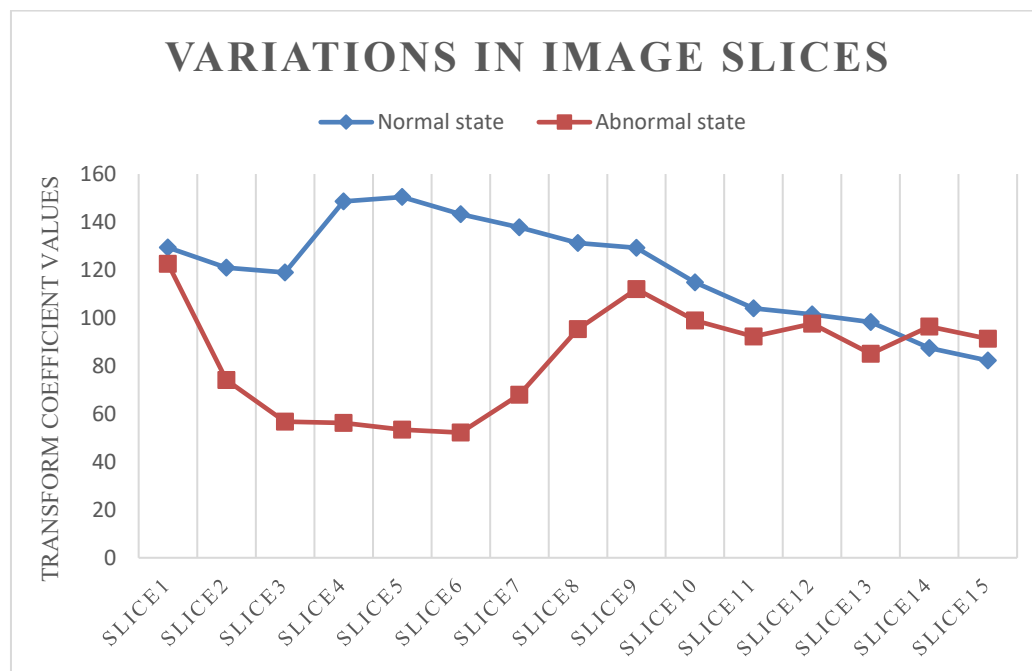


Fig 6: Graphical representation variation of coefficients among image slices

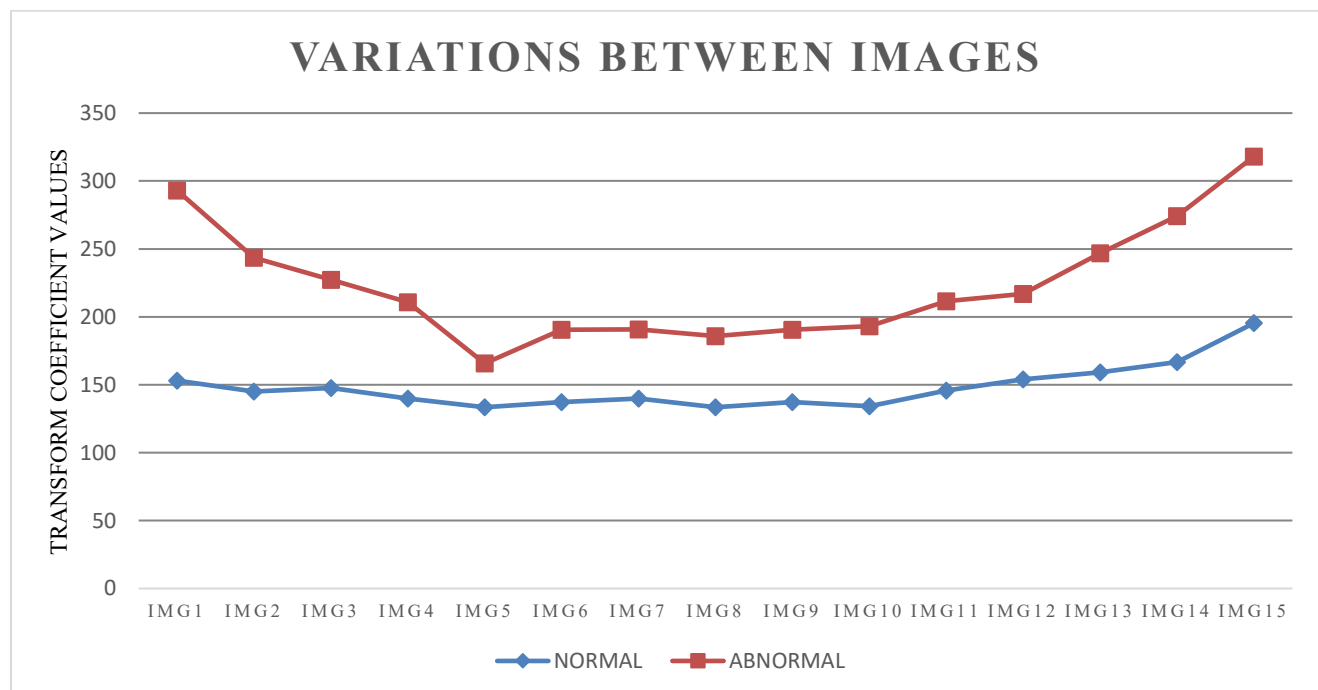


Fig 7: Graphical representation variation of mean coefficients between images

Later, to differentiate the normal and abnormal images, the mean coefficient value is calculated for every images which is plotted graphically to see the changes in the normal and abnormal images. The graphical representation is shown in figure 7. Significant variations are observed in the graphical representation stating that wavelet transform coefficients can be used for the detection and identification of the cancerous region in the pancreas.

Finally, the significance of the coefficients and the wavelet transform applied for determination of cancer region is defined using statistical study that is conducted to both data obtained from the image slices and between the images in normal and abnormal state. Basic statistical procedures performed for the analysis

process includes deriving of basic descriptive statistics, T-test, F-test and one way- ANOVA for the p-value. Descriptive statistics provide the information on the difference in the standard deviation, kurtosis and skewness values of the given data stating the changes in the normal an abnormal state. Descriptive statistical features are defined below in table 1 & 2.

Table 1. Descriptive statistical features for image slices

<i>Normal state</i>		<i>Abnormal state</i>	
Mean	119.873333	Mean	84.818
Standard Error	5.5536217	Standard Error	6.48657
Median	121	Median	91.28
Mode	#N/A	Mode	#N/A
Standard Deviation	21.5090843	Standard Deviation	25.12238
Sample Variance	462.64071	Sample Variance	631.1339
Kurtosis	-0.95512892	Kurtosis	0.445212
Skewness	-0.2808175	Skewness	0.542445
Range	68.16	Range	90.42
Minimum	82.24	Minimum	52.18
Maximum	150.4	Maximum	142.6
Sum	1798.1	Sum	1272.27
Count	15	Count	15

Table 2. Descriptive statistical features between images

NORMAL		ABNORMAL	
Mean	148.111	Mean	75.79517
Standard Error	4.240404	Standard Error	7.758839
Median	145	Median	65.8
Mode	133.45	Mode	#N/A
Standard Deviation	16.42301	Standard Deviation	30.04985
Sample Variance	269.7154	Sample Variance	902.9938
Kurtosis	4.240708	Kurtosis	0.005265
Skewness	1.878827	Skewness	0.82522

Range	61.95	Range	107.7305
Minimum	133.45	Minimum	32.2695
Maximum	195.4	Maximum	140
Sum	2221.665	Sum	1136.928
Count	15	Count	15

The obtained results of t-Test shown below in table 3 & 4, it is visible that the normal state is significant from the abnormal cancerous MRI image. Table 3 defines T-test values of the transform coefficients among the image slices and Table 4 defines T-test values of the mean transform coefficients between the images

Table 3. T-test for transform coefficients among the image slices

	<i>Normal state</i>	<i>Abnormal state</i>
Mean	119.8733333	84.818
Variance	462.6407095	631.13386
Observations	15	15
Pooled Variance	546.8872848	
Hypothesized Mean Difference	0.1	
df	28	
t Stat	4.093503505	
P(T<=t) one-tail	0.000163432	
t Critical one-tail	1.701130934	
P(T<=t) two-tail	0.000326863	
t Critical two-tail	2.048407142	

Table 4. T-test for mean transform coefficients between the images

	<i>Normal state</i>	<i>Abnormal state</i>
Mean	148.111	75.79516667
Variance	269.7153721	902.9937828
Observations	15	15
Pooled Variance	586.3545775	
Hypothesized Mean Difference	0.1	
df	28	

t Stat	8.167382569	
P(T<=t) one-tail	3.42443E-09	
t Critical one-tail	1.701130934	
P(T<=t) two-tail	6.84886E-09	
t Critical two-tail	2.048407142	

F-test is performed for derived transform coefficients from the MRI images. F-Test results is obtained and it is visible that $F > F$ Critical one-tail, stating that the variances of the two given data are unequal. These demonstrate the significance of the coefficients among the slices and between the images in normal and abnormal state. Table 5 & table 6 defines the f-test results of the coefficient values.

Table 5. F-Test for transform coefficients among the image slices

	<i>Normal state</i>	<i>Abnormal state</i>
Mean	119.8733	84.818
Variance	462.6407	631.13386
Observations	15	15
df	14	14
F	0.733031	
P(F<=f) one-tail	0.284466	
F Critical one-tail	0.402621	

Table 6. F-Test for mean transform coefficients between the images

	<i>Normal state</i>	<i>Abnormal state</i>
Mean	148.111	75.79516667
Variance	269.7154	902.9937828
Observations	15	15
df	14	14
F	0.29869	
P(F<=f) one-tail	0.015415	
F Critical one-tail	0.402621	

From the ANOVA test, the obtained p value provides the probability of obtaining the results. Here $p < 0.001$ states that there is stronger evidence in favour of changes in the normal and abnormal state images. This P value states that the methodology has a significance level of 95%.

Table 7. ANOVA for transform coefficients among the image slices

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	9216.572963	1	9216.573	16.85278	0.000317	4.195972
Within Groups	15312.84397	28	546.8873			
Total	24529.41694	29				

Table 8. ANOVA for mean transform coefficients between the images

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	39221.85	1	39221.84813	66.89100697	0.00066619209	4.195972
Within Groups	16417.93	28	586.3545775			
Total	55639.78	29				

From the above performed graphical study of the transform coefficient values and from statistical analysis results obtained for both image slices and images implies that there are significant changes in the features of images, from which we can observe that the image is of cancer in normal state or it is in abnormal state.

While the proposed 3D wavelet-based approach achieves reliable statistical separation between normal and cancerous pancreatic tissue that differs methodologically from CT-based machine learning classifiers such as the EL-SVM staging model of Li et al. [5] has 86.61–91.63% accuracy and the SVM-based MRI detection model of Zhang et al. [6], relying instead on statistical hypothesis testing of transform coefficients rather than supervised classification; however, this study has certain limitations, as the MRI images were sourced from a single database (TCIA) without controlling for variability in patient demographics (age, sex, disease stage), and the multi-slice, multi-sub-band 3D wavelet decomposition introduces notable computational overhead that may limit real-time clinical applicability. The future work will therefore focus on validating this technique and on integrating wavelet-derived coefficient features with deep learning architectures to enable automated, end-to-end classification and potentially improve diagnostic accuracy beyond statistical thresholding alone. A primary study of research for the early detection of pancreatic cancer cells using 3D wavelet transform with statistical significance level is performed.

CONCLUSION

Pancreatic cancer is predominantly developing and early diagnostic technique is required for the treatment procedures [18, 19]. Magnetic resonance imaging defines the tumour region more accurately. The MRI images of pancreatic cancer obtained from the TCIA database consists of total 450 images. In this project, analysis of MRI data that contain T1 weighted scan images of normal and abnormal state. The grayscale images are converted to RGB for better identification of cancer region and then 3D wavelet transform is applied to the images and the transform coefficient value for each image slice is obtained. Same methodology is applied to all the images to determine the mean transform coefficient value. Using this transform coefficient value, statistical analysis is performed for identifying the changes in the statistical features for normal and abnormal image slices. Then the mean value of transform coefficient for each image is calculated and tested by statistical method for analysing the changes of the features in the MRI images of normal and abnormal states. From the conducted statistical study, the analysis and prediction of the significant changes in features of normal and abnormal cancer image stating the cancer growth providing a pragmatic approach for the early detection of cancer growth with a statistical significance level of 95%.

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