OPEN ACCESS

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-3, January 2020

Probabilistic Neural Network and Genetic Algorithm for Abdominal Aorta Aneurysm Identification

S. Anandh, R. Vasuki, Raid Al Baradie

Abstract*: An abdominal aorta aneurysm (AAA) can cause severe threat if it burst. Doctors can detect the presence of AAA by using abdominal ultrasound. As the treatment depends on the location and size, accuracy plays a significant role. To prevent devastating clinical outcome in this proposed work, new approaches and algorithms were used for generating the infallible result. After processing the AAA image by using notch filter, exudate based segmentation is performed and the selected features gets classified by using probabilistic neural network classifier. By using PNN classifier, accuracy and sensitivity gets enhanced in this work. The achieved accuracy is 98% and sensitivity 97.5%. While analogizing the proposed work with other existing work. It's very facile to perform and expected target gets achieved.

Keywords* : Notch filter, Exudate segmentation, Gabor based region covariance matrix (GRCM), Genetic feature selection and Probabilistic neural network (PNN).

I. INTRODUCTION

Abdominal aortic aneurysm is the largest blood vessel which is present in the human body. It circulates blood throughout the body. It is the most common form of arterial aneurysm and it accounted for 151,000 deaths in the United States in the year 2013. It occurs mostly below the renal arteries. If it becomes weak, it swell or bulge out. The burst out aneurysm causes a severe threat. Aortic aneurysm is classified based on their size. If it less than 5.5 cm, it causes less risk than larger aneurysm (which is greater than 5.5 cm)[14], [15]. Doctors use the abdominal MRI image to find out the size and exact location of the aneurysm [1]. To generate an infalliable result. In this proposed work, certain new approaches and algorithm were used to generate a high level information about the abdominal aneurysm.

Revised Manuscript Received on January 30, 2020.
***** Correspondence Author

S.Anandh*, Research Scholar, Department of Biomedical Engineering, Bharath University, Chennai, India.

Dr. R. Vasuki, Professor and Head, Department of Biomedical Engineering, Bharath University, Chennai, India.

Dr. Raid Al Baradie, Associate Professor, Department of Medical Lab, Majmaah University, Kingdom of Saudi Arabia.

The success of treatment and recovery widely depends on whether or not the AAA is found before it burst out. Prognosis is usually good if the AAA is found with high information for better treatment plan.

In this proposed work, to the obtained AAA image, it applies the notch filter to eliminate the signal which cause disturbances for post processing. Exudate based segmentation is applied in the AAA image and the feature is selected by using GRCM [3]. It selects the best feature among the existing features. To the selected feature, it applies genetic algorithm for the better classification and recognition [10], [11] and finally probabilistic neural network classifier is applied. In the existing work they used Convolutional Neural Network (CNN) classifier for performing classification. Even though it performs well in many real time application, it is computationally expensive, they need a lot of training data for processing and if we do not have good GPU they are quite slow to train the data. To overcome the drawback of CNN classifier, Probabilistic neural network classifier is used. It performs computation in a faster way and it generate accurate predicted target probability scores.

II. RELATED WORKS

Huan N. Do et al [2018] proposed a prediction of abdominal aortic aneurysm growth using dynamical gaussian process implicit surface. In this paper, in a patient-specific way, the growth of AAA in future time can be predicted using the longitudinal computer tomography (CT) scans. Estimation from the point cloud's hidden field is done by utilizing the spatio-temporal field from the CT training image data. Issues like the prediction done through this study may end up in uncertainty quantification as this is the first study that predicts the 3D shape of AAA growth appears. Hahn, S et al [2019] proposed deep learning for recognition of Endoleak after endovascular abdominal aortic aneurysm repair. In this paper, to identify the presence of Endoleak and localize the abdominal aortic aneurysm a cascaded deep neural network was proposed. To predict the axial slice by slice based on the Endoleak, binary cross entropy loss function is used to train the network. Using deep learning identifying the Endoleak is both difficult and novel task, and the small Endoleak have no specific efforts to remove.

Hong, H. et al [2016] proposed automatic detection, segmentation and classification of abdominal aortic aneurysm using deep learning.

In this paper, utilizing the deep learning technique, adnominal aortic aneurysm is detected, segmented, and classified in an automated manner. During thrombus segmentation, the detection of calcification process is of much significance and the classification is easily identified as they are brighter than the blood vessels and lumen. The accuracy of the contour may end up in issue, if only one side of the lumen hosts a large number of thrombus.

Maeda, K et al [2017] discussed about comparison between open and endovascular repair for the treatment of juxtarenal abdominal aortic aneurysms: a single-center experience with midterm results. In this paper, for the treatment of juxtarenal abdominal aortic aneurysm, rather than using EVAR (which often complicates the presence of short proximal neck OSR is used. 30% of re-intervention rate is recorded at 3 years following FEVAR. Patients with high-risk and EVAR are not advised under this method as the patients underwent OSR are mostly comparability young.

Sassani. S. G et al [2015] proposed layer-dependent wall properties of abdominal aortic aneurysms: experimental study and material characterization. In this paper, to identify the organization of the collagen-fiber network spatially, a quantitative microscopic evaluation technique is performed. For reliable simulation of traverse stress-stretch data for maximum specimens, the diagonal fiber-family must be presented. Biaxial testing which is more like physiologic conditions, is needed to obtain more best-fit value of material parameters.

Behrendt, C.A.et al [2017] proposed lower extremity ischemia after abdominal aortic aneurysm repair. In this paper, the patients suffering from AAA may develop lower extremely ischemia after the treatment for AAA, therefore to understand the incidence and outcomes of LEI patients after AAA repair was discussed. The complications due to Ischemia have gradually decreased over time. As the complications arose when the patient suffers LEI (Lower Extremely Ischemia), the methods to avoid or treat this case have not been identified yet.

III. PROPOSED METHODOLOGY

This proposed methodology objective is to detect the AAA image in a more accurate manner because of the reason treatment depends on the size and location. By keeping this information, doctors predict the presence of AAA. For high accuracy it undergoes five step process. After obtaining the input AAA image, it applies notch filter to eliminate the unwanted signal in between the two cutoff frequency. This notch filter is a combination of high and low pass filter. It is also said to be band stop filter. After the removal of unwanted signal, exudate based segmentation is performed. By applying segmentation, the initial AAA image is subdivided into smaller sub images. For each image it performs computing threshold value then it is classified based on the threshold obtained in each image. GRCM helps to extract the feature. It overcomes the drawback of existing related works in feature extraction technique. It avoids duplication of activities, it provides high information quality and it achieved greater ability to collect more information quickly and efficiently. After extraction, it is optimized by using genetic algorithm. It's an advanced technique widely used in real time application. It has a power to select a best feature out of various extracted features. Finally probabilistic neural network classifier is used for classification. When analogizing with CNN (Convolutional Neural Network). It achieved high accuracy. It outperforms well when compared to other classifier. By using new algorithm and approaches, the image which is obtained undergoes various steps and it produces a high information to doctors for the better treatment plan.

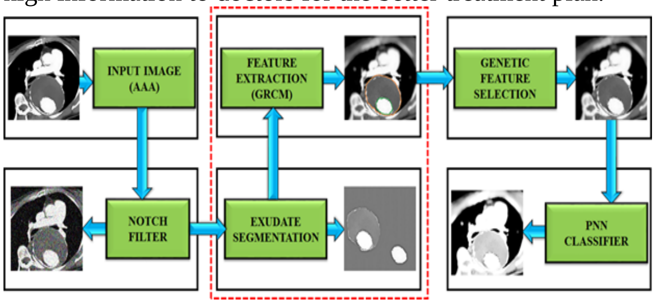


Fig 1: Block diagram of proposed work

A. Preprocessing:

To get a high quality image for processing, the obtained RGB image is transferred to the gray scale image. It is done by using the formula,

$$\text{Gray scale}= (R+G+B\backslash 3) \quad (1)$$

To give more soothing effect to the eye, it can be rewritten as

$$= ((0.3*R)+(0.59*G)+(0.11*B)) \quad (2)$$

B. Notch filter:

A notch filter is also said to be Band Stop Filter. It's a combination of high pass and low pass filter. This filter works by eliminate the signal which is present in between the two cutoff frequency. The notch filter is a very linear bandwidth filter. While comparing with flattened wider band, it shows a high frequency response where there is a deep notch with high selectivity. It passes through frequencies from 0 to lower cutoff frequency (f_L) and also it passes above the upper cutoff frequency (f_H) but it eliminate the frequencies which is present in between it.

$$\text{Bandwidth}= f_H - f_L \quad (3)$$

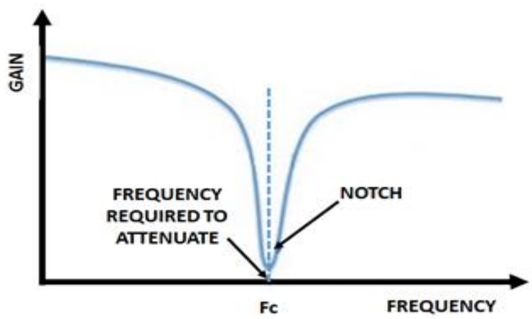


Fig 2 Frequency vs Gain graph

Retrieval Number: C9123019320/2020©BEIESP
DOI: 10.35940/ijitee.C9123.019320
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The simple notch filter is computed by using,

$$H(s)=\frac{S^2+w_z^2}{s^2+\frac{w_p}{Q}s+w_p^2} \quad (4)$$

In case of low pass filter,

$$W_z > w_p$$

In case of high pass filter,

$$W_z < w_p$$

In a standard way, it can be rewritten as,

$$H(s) = \frac{s^2+w_0^2}{s^2+w_c^s+w_0^2} \quad (5)$$

w_0 represents the eliminated frequency and w_c indicates the width of eliminated band.

C. Exudate Segmentation by using histogram and adaptive threshold:

It's a challenging task for performing segmentation in abdominal aortic aneurysm because of the reason, it has high pixel similarity to adjacent tissue. Segmentation's main objective is to categorize the image into various sectors each of which indicates various information in the image such as color, intensity or texture. Segmentation approach depend on two properties,

1) Identifying discontinuities and
2) Similarities.

In computer aided diagnosis, automatic exudate segmentation is an important task. The main contribution of this proposed work is, segmentation of exudation from AAA image by using adaptive threshold. After the process of histogram, an adaptive threshold has been selected by using first order statistical parameters such as mean and standard deviation. Histogram is constructed by partitioning the image into equal sized classes. Then for each classes, the number of points from the dataset that lies under each classes are counted.
Vertical axis: Frequency
Horizontal axis: response variable

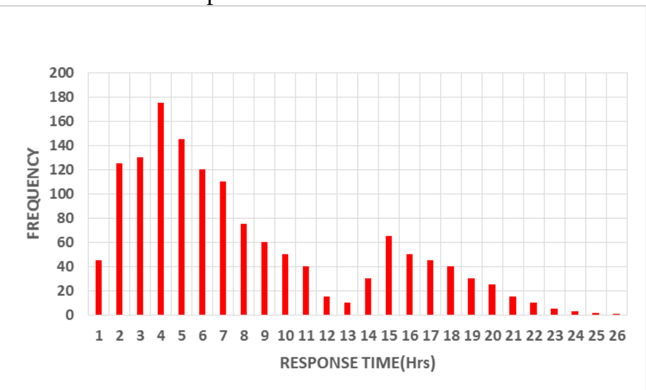


Fig 3: Histogram representation

Adaptive threshold is performed as follows,

(1) Choose an initial estimate
(2) Split the obtained gray scale image using T. It generates two group of pixels.
S_1 consisting of pixels having values greater than T.
S_2 consisting of pixels having values less than T.
(3) Calculate the average gray level value m1 and m2 for the pixels which is present in S_1 and S_2.
(4) Calculate the new threshold (T) value by using the equation,

$$T=(1/2)(m1+m2) \quad (6)$$

(5) Iterate step 2 and 4 until difference in T in continuous iteration is smaller than a predefined parameter p_0.

This technique is very efficient and takes a short span of time for performing segmentation of exudate in a real time situation. The AAA image which is converted to gray scale image undergoes the process of histogram. It is analyzed and used to determine a suitable threshold for segmentation of exudates.
The threshold used for segmenting the exudates are as follows,

$$\mathrm{Th} = [\{0.8 * \mathrm{mean(I)} + \mathrm{std(I)}\}/255] + \mathrm{graythresh(I)} \quad (7)$$

Where Th represents the adaptive threshold.
I indicates the normalized gray color channel.
From the threshold binary image, false positive pixels were removed for the accurate segmentation of exudates.

IV. GABOR BASED REGION COVARIANCE MATRIX:

In GRCM, it is initially performed to extract the discriminative information by convolution between the original AAA image and a set of Gabor kernels by using different scales and orientation. A 2- dimensional Gabor wavelet is the product of an elliptical Gaussian and plane wave is defined as follows,

$$\varphi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{-\frac{\|k_{u,v}\|^2[z]^2}{2\sigma^2}} [e^{ik_{u,v}z} - e^{-\frac{\sigma^2}{2}}] \quad (8)$$

Where μ *and* v represent the orientation and scale of Gabor kernels.

GRCM is capable to capture the geometrical and statistical properties of an AAA image after segmentation. Both pixel location and Gabor coefficients helps to form the covariance matrix. From each pixel, Gabor features were extracted. By applying GRCM, several feature derivatives were extracted from the image. Color, texture and shape are normally used for region description. To recognize and classify the object, Texture is one of the significant feature. Contrast, Homogeneity, dissimilarity, energy and entropy are very much useful to describe the texture. Texture feature uses GRCM to measure the variation in intensity.

4.1 Texture feature:

Contrast: It measures the contrast between a pixel and its neighborhood value. It is computed by using the equation,

$$Contrast = \sum_{i,j} |i-j|^2 p(i,j) \quad (9)$$

Energy: For constant image, energy value set to1. It returns the sum of squared elements. It is calculated by using,

$$Energy = \sum_{i,j} p(i,j)^2 \quad (10)$$

Homogeneity: It measures the closeness of the distribution of elements. It ranges from 0 to 1.

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (11)$$

Correlation: It measures a pixel to its neighbor value. It ranges from -1 to 1 for a perfect positive and negative correlation.

$$Correlation = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \qquad (12)$$

Entropy: It is used to characterize the texture of an input AAA image. Its value remains high when all the elements of covariance matrix remains constant. It is computed as follows,

$$Entropy = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)(-\ln(p(i,j))) \qquad (13)$$

These statistics provides information about the texture of an image.

4.2 Genetic feature selection:

It's the most advanced algorithm for selecting the feature. By selecting the most similar feature, genetic algorithm applies optimization. By using this algorithm, it minimizes the error of the model. Genetic algorithm initially operate on a population of individuals. At each generation, a new population is generated by selecting individuals. It is done based on their level of fitness in the problem domain and it recombines by using operators which is taken from natural genetics. The offspring may also undergo the process of mutation.

A state diagram for the training process with the training algorithm is shown below,

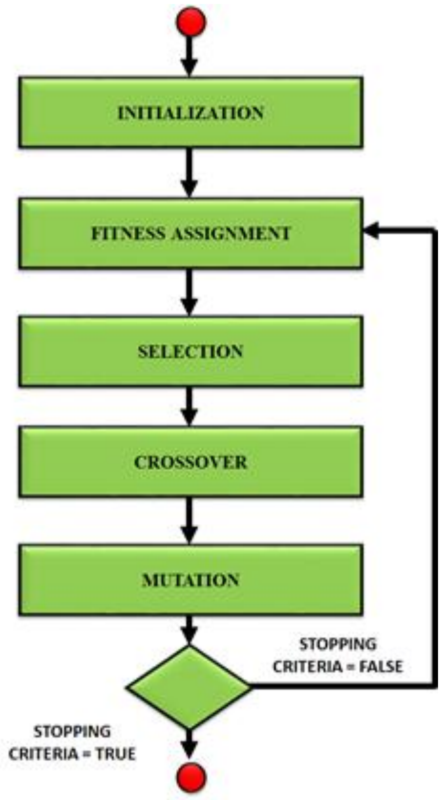


Fig 4: A state diagram of genetic feature selection

Initialization:

The initial step is to generate and initialize the individuals. Initialization is performed randomly. Initialization of individual is shown below,

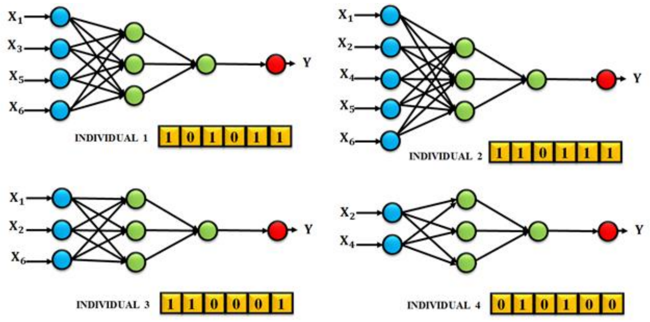


FIG: 5 Initialization Step

Fitness operation: Once it generated, we need to perform fitness operation in each individual. To evaluate train the predictive model with the training data and then evaluate, is there any selection error. If it shows a high selection error it represents a low fitness and if there is an individual with high fitness there is high probability of selecting for recombination.

By using Rank based method, the fitness operation is computed by,

$$\emptyset(i) = K.R(i) \qquad (14)$$

Where i denote i=1,…,N and K represents constant which is called selective pressure. It is shown below,

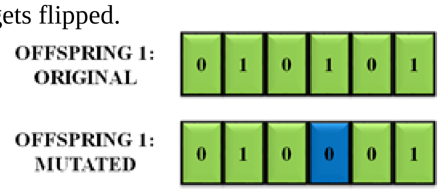
	SELECTION ERROR	RANK	FITNESS
INDIVIDUAL 1	0.9	1	1.5
INDIVIDUAL 2	0.6	3	4.5
INDIVIDUAL 3	0.7	2	3
INDIVIDUAL 4	0.5	4	6

Fig: 6 Fitness Operator

Selection: Based on the fitness value, the selection operator selects the individual. The number of selected individual is half of the size of population.

Crossover: The individuals which were selected recombines to form next generation. It randomly chose two individuals and combine their features to produce four offspring.

Mutation: In mutation process, to decide whether the feature gets mutated or not. We create a random number between 0 to1. If their number falls below the value of mutation rate, this variable gets flipped.



In this figure, the forth feature of the offspring gets mutated. By using this algorithm, The best feature is selected. The main advantage of using genetic algorithm is, it can manage dataset with many features and it don't need any specific knowledge about the problem.

4.3 Probabilistic neural network:

It's a type of feed forward neural network. It is generally used in classification and pattern recognition. It is a four layer neural network. It can take any input pattern to any number of classification.

A set of data points are given, The objective is to classify any new data sample into one of the class.

A schematic representation of a PNN is shown below,

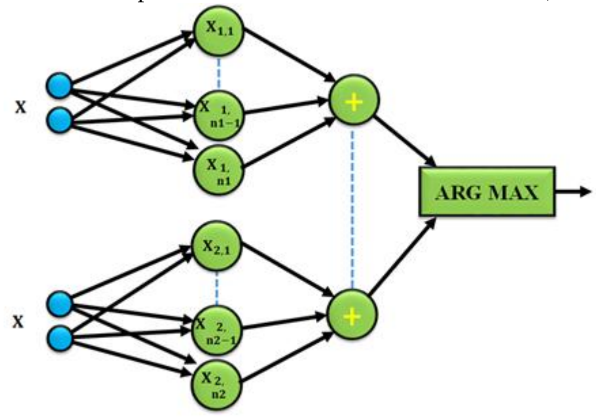


Fig 7: Schematic illustration of PNN

The algorithm of probabilistic neural network are as follows,

(1) PNN consist of several sub networks. The input nodes are the set of measurements.

(2) The second layer contains Gaussian function. It is created by using the given data of points.

(3) In third layer, from all the output, average operation is performed for each class.

(4) Finally it performs a vote by taking the highest value and then associated class label is determined.

In this proposed algorithm, In class 1, it contains 8 data points and in class 2, it contains 5 data points.

Using Gaussian function with $\sigma = 1$

$$y_1(x) = \frac{1}{8}\sum_{i=1}^{8} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x_{1,i}-x)^2}{2}\right) \qquad (15)$$

and

$$y_2(x) = \frac{1}{5}\sum_{i=1}^{5} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x_{2,i}-x)^2}{2}\right) \quad (16)$$

The PNN classifies a new x by analogizing the value of $y_1(x)$ and $y_2(x)$.

If $y_1(x) > y_2(x)$, then x is assigned to class1;

Class2.

The decision boundary of the PNN is given by

$Y_1(x) = Y_2(x)$ (17)

The solution of x can be found numerically. This is an optimal solution, reduces misclassification rate. While analogizing with CNN, it computes in a faster way. It produces an accurate output.

V. RESULTS AND DISCUSSION

The surface assessment to suggest the existence of particular repeat content in the image is performed by notch filter and the specific courses in a constrained region around the point of examination is separated to get the yield of MRI AAA picture.

Exudate-based picture division is the minimum troublesome segmentation approach of image processing in which histogram is used to select the dark levels in the pixels. The establishment and the dissent are the two feature of the proposed work. The dark portion contains maximum AAA content in the image. In histogram, dull level is tremendously zenith. By observing at the histogram for a particular picture, the witness can judge on the whole tonal dispersing from the outset. As the data contained in the framework is a portrayal of pixel motion as a segment of tonal variety, image histogram is broken down into peak or valley.

A hereditary calculation is proposed to extract the features from the gathering of uneven pixel groups. Genetic calculation is the reasonably improved system. It is valuable in image optimization and segmentation. It is an impressive broad plan space. This clarifies the expanding reputation of GAs application in image processing field. Finally PNN is implemented to classify the AAA images.

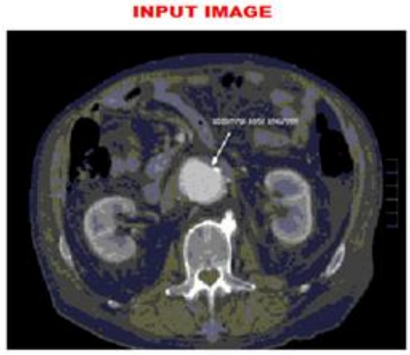


Fig. 8 Input image for the proposed analysis

The figure 8 is the input AAA image which has blur noise and radiation noise. These can be eliminated by notch filter.

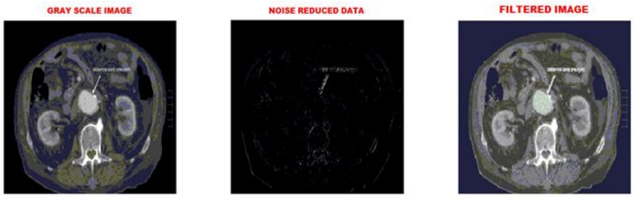


Fig 9. Noise reduced image using Notch filter

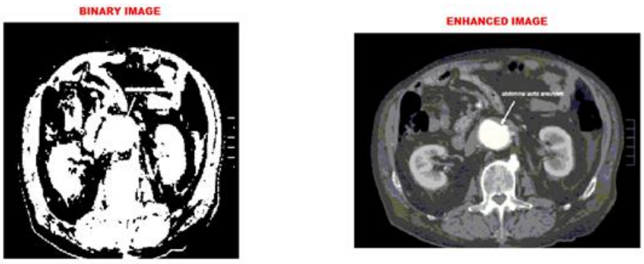


Fig 10. Binary pattern output image

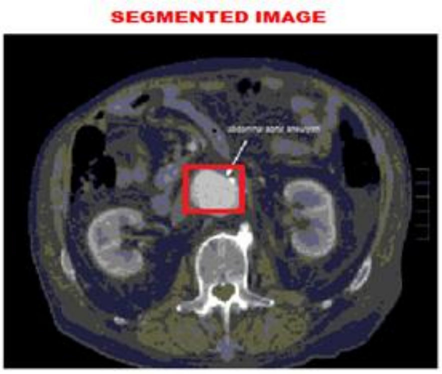


Fig 12. Segmented result from the input image

Preprocessing of data normalizes pictures. The division and ordering of medicinal MRI AAA pictures gives a chance to acknowledge zone and thickness observing by utilizing the locale removed progressively condition. This examination investigates the plausibility of tumor acknowledgment utilizing pixel (seed) point highlights for recognizing the influenced districts in the cell. The aftereffects of AAA division and the acknowledgment of human and AI calculations are compared and evaluated to prove our execution superior to the other highlight based division and identification.

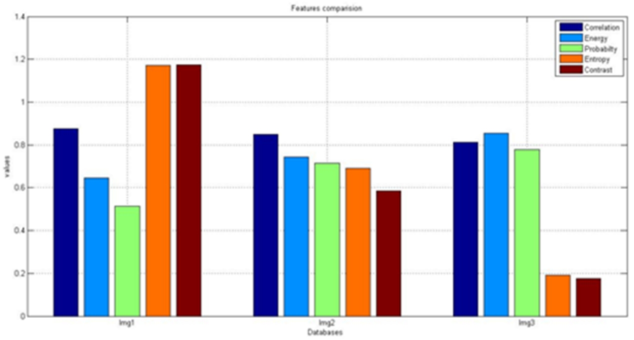


Fig 11. Feature Extraction using Genetic based feature extraction

5.1 Performance Parameters Comparison

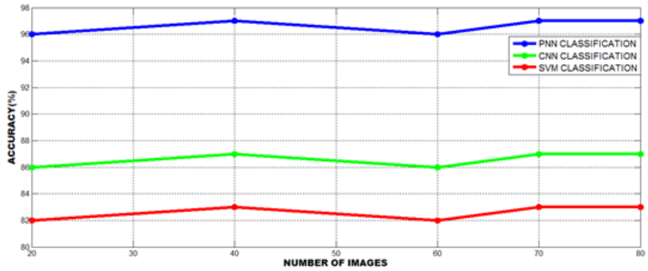


Fig 12: Accuracy

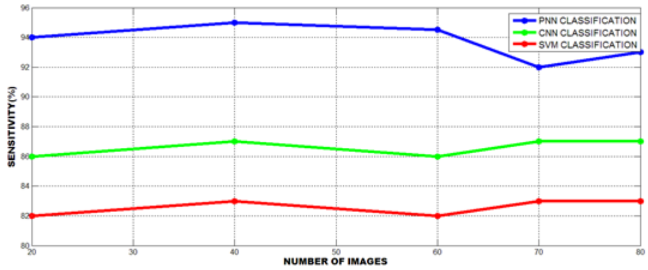


Fig 13: Sensitivity

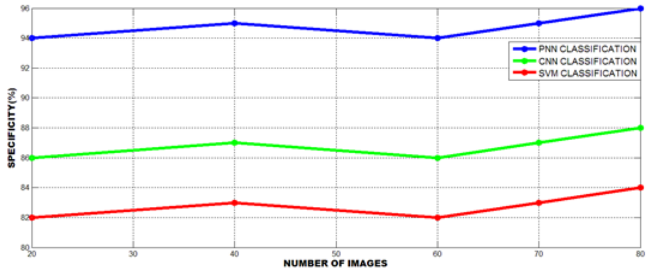


Fig 14: Specificity

Table 1 and 2. Accuracy, precision, F-Score and computational time comparison table.

IMAGE NO.	ACCURACY		PRECISION	
	WITHOUT OPTIMIZATION	WITH OPTIMIZATION	WITHOUT OPTIMIZATION	WITH OPTIMIZATION
IMAGE 1	88.6	94.3	87.32	95.6
IMAGE 2	88.3	95.4	86.43	95.6
IMAGE 3	89.4	95.6	88.2	96.8
IMAGE 4	90.9	95.1	89.3	96.1
IMAGE 5	91.3	97.23	88.67	97.87

The above table gives the deviation in ordering of MRI AAA images with single level segmentation and conducting with the similar pictures in our proposed Gabor segmentation

IMAGE NO.	F- SCORE		COMPUTATION TIME(ns)	
	WITHOUT OPTIMIZATION	WITH OPTIMIZATION	WITHOUT OPTIMIZATION	WITH OPTIMIZATION
IMAGE 1	89.4	93.6	0.82	0.91
IMAGE 2	89.65	94.2	0.84	0.93
IMAGE 3	90.34	95.2	0.88	0.94
IMAGE 4	89.43	96.6	0.82	0.932
IMAGE 5	91.32	97.34	0.85	0.961

VI. CONCLUSION:

In this proposed work, for a reliable estimate of AAA rupture, accurate measurement of geometric characteristics is achieved. The versatility of the method is tested by using trained dataset. Certain new algorithms were used and finally for the purpose of classification, Probabilistic neural network classifier is used in this proposed work. It performs computation in a faster way and it generates a high accuracy. The experimental result shows that our method achieves 91.3% accuracy. While analogizing with other proposed work it outperforms well and expected accuracy is achieved.

REFERENCE:

1. Do, H. N., Ijaz, A., Gharahi, H., Zambrano, B., Choi, J., Lee, W., & Baek, S., 2018, ‘ Prediction of Abdominal Aortic Aneurysm Growth using Dynamical Gaussian Process Implicit Surface’, IEEE Transactions on Biomedical Engineering, Vol. 66 , no. 3 , pp. 609 – 622.
2. Polanczyk, A., Podgorski, M., Polanczyk, M., Piechota-Polanczyk, A., Neumayer, C., & Stefanczyk, L., 2018, “A novel patient-specific Human Cardiovascular System Phantom (HCSP) for reconstructions of pulsatile blood hemodynamic inside abdominal aortic aneurysm’, IEEE Access, Vol: 6, pp. 61896 – 61903.
3. Roy, D., Holzapfel, G. A., Kauffmann, C., & Soulez, G., 2014, “Finite element analysis of abdominal aortic aneurysms: geometrical and structural reconstruction with application of an anisotropic material model’, IMA Journal of Applied Mathematics, vol.79, no.5, pp. 1011–1026.
4. Joris, P., Develter, W., Van De Voorde, W., Suetens, P., Maes, F., Vandermeulen, D., & Claes, P., 2018, “Preprocessing of Heteroscedastic Medical Images’, IEEE Access, vol.6, pp.26047–26058.
5. Nakhjavanlo, B. B., Ellis, T. J., Soan, P. H., & Dehmeshki, J., 2011, ‘3D Medical Image Segmentation Using Level Set Models and Anisotropic Diffusion’, 2011 Seventh International Conference on Signal Image Technology & Internet-Based Systems.
6. Pham, T. D., & Golledge, J., 2013, ‘Pattern analysis of imaging markers in abdominal aortic aneurysms’, 2013 6th International Conference on Biomedical Engineering and Informatics.
7. Lei, T., Jia, X., Liu, T., Liu, S., Meng, H., & Nandi, A. K., 2019, ‘Adaptive Morphological Reconstruction for Seeded Image Segmentation’, IEEE Transactions on Image Processing, vol.28, no. 11, pp. 5510 – 5523.
8. Weidong Liu1 , Caixia Qin2 , Kun Gao1 , Heng Li1 , Zuen Qin3 , Yafei Cao 1 , And Wen Si, 2019, ‘Research On Medical Data Feature Extraction And Intelligent Recognition Technology Based On Convolutional Neural Network’.,IEEE Access, Vol.7, pp.150157 – 150167.
9. Baali, H., Khorshidtalab, A., Mesbah, M., & Salami, M. J. E., 2015, ‘A Transform-Based Feature Extraction Approach for Motor Imagery Tasks Classification’, IEEE Journal of Translational Engineering in Health and Medicine, vol.3, pp.1–8.
10. Hong, H. A., & Sheikh, U. U., 2016, ‘Automatic detection, segmentation and classification of abdominal aortic aneurysm using deep learning’, 2016 IEEE 12th International Colloquium on Signal Processing & Its Applications (CSPA).
11. Hahn, S., Morris, C. S., Bertges, D. J., & Wshah, S., 2019, ‘Deep Learning for Recognition of Endoleak After Endovascular Abdominal Aortic Aneurysm Repair’, 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), vol.3, pp.1-8.
12. Zhe Luo, Junfeng Cai, Peters, T. M., & Lixu Gu., 2013, ‘Intra-Operative 2-D Ultrasound and Dynamic 3-D Aortic Model Registration for Magnetic Navigation of Transcatheter Aortic Valve Implantation’, IEEE Transactions on Medical Imaging, vol.32, no.11, pp.2152–2165.
13. Maeda, K., Ohki, T., Kanaoka, Y., Baba, T., Kaneko, K., & Shukuzawa, K., 2017, ‘Comparison between Open and Endovascular Repair for the Treatment of Juxtarenal Abdominal Aortic Aneurysms: A Single-Center Experience with Midterm Results’, Annals of Vascular Surgery, vol.41, pp. 96–104.
14. Behrendt, C.-A., Dayama, A., Debus, E. S., Heidemann, F., Matolo, N. M., Kölbel, T., & Tsilimparis, N., 2017, ‘Lower Extremity Ischemia after Abdominal Aortic Aneurysm Repair’, Annals of Vascular Surgery, vol.45, pp.206–212.
15. Sassani, S. G., Kakisis, J., Tsangaris, S., & Sokolis, D. P., 2015, ‘Layer-dependent wall properties of abdominal aortic aneurysms: Experimental study and material characterization’, Journal of the Mechanical Behavior of Biomedical Materials, vol.49, pp.141–161.

AUTHORS PROFILE

S.Anandh is a research scholar in the Department of Biomedical Engineering, Bharath University, Chennai. He has teaching experience of 15 years. His area of interest are Medical Image processing, Medical Signal processing and biomedical Instrumentation.

Dr. R. Vasuki is working as a Professor and Head in the Department of Biomedical Engineering, BharathUniversity, Chennai. She has 20+ years of teaching experience.Her areas of interest are Bioinformatics, Bio-signal processing and Image processing

Dr. Raid Al Baradie is working as an Associate Professor in the Department of Medical Lab, Majmaah University, Kingdom of Saudi Arabia. He has received Doctorate in the Faculty of Medicine and Human Sciences, Manchester University, United Kingdom. His areas of interest are human Anatomy and Physiology, Pathology and Histology.