

Towards Better Segmentation of Abnormal Part in Multimodal Images Using Kernel Possibilistic C Means Particle Swarm Optimization With Morphological Reconstruction Filters: Combination of KFCM and PSO With Morphological Filters

Sumathi R., KARE, India

Venkatesulu Mandadi, KARE, India

ABSTRACT

The authors designed an automated framework to segment tumors with various image sequences like T1, T2, and post-processed MRI multimodal images. Contrast-limited adaptive histogram equalization method is used for preprocessing images to enhance the intensity level and view the tumor part clearly. With the combination of kernel possibilistic c means clustering with particle swarm optimization technique, a tumor part is segmented, and morphological filters are applied to remove the unrelated outlier pixels in the segmented image to detect the accurate tumor part. The authors collected various image sequences from online resources like Harvard brain dataset, BRATS, and RIDER, and a few from clinical datasets. Efficiency is ensured by computing various performance metrics like Jaccard Index MSE, PSNR, sensitivity, specificity, accuracy, and computational time. The proposed approach yields 97.06% segmentation accuracy and 98.08% classification accuracy for multimodal images with an average of 5s for all multimodal images.

KEYWORDS

Kernel Possibilistic C Means Clustering, Magnetic Resonance Imaging, Morphological Filters, Particle Swarm Optimization, Performance Measures, Support Vector Machine Classifier

INTRODUCTION

Cancer is a dangerous disease. It produces unpredictable cells, and also reproduces new cells and new cells break existing organs and cause the tumour to spread, thus harming the body. Tumor in the brain is classified as primary tumor and metastasis tumor, Primary tumor is one type of cancer which grows in the brain tissue whereas metastasis tumor affects the other organs in the human body. Primary brain tumor is further classified as benign and malignant In benign tumor structure is uniform without active cells and does not affect the nearby tissues whereas malignant tumor contains heterogeneous structure with active cells affects the other parts of the body. To predict the tumor growth in advance and reduce the death rate due to breast cancer for women's an automated frame work is necessary.

DOI: 10.4018/IJEHMC.20210501.oa4

This article, published as an Open Access article on January 15th, 2021 in the gold Open Access journal, the International Journal of E-Health and Medical Communications (IJEHMC) (converted to gold Open Access January 15th, 2021), is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

The common types of cancers that develop in breasts are ductal carcinoma in situ, invasive ductal carcinoma, inflammatory breast cancer, and metastatic breast cancer and our proposed work focus on invasive ductal carcinoma breast cancer images. For diagnostic and treatment purposes, medical professionals (radiologists and doctors) need to understand the type of tumors they are dealing with.

In this context, MRI (Magnetic Resonance Imaging) scanning is used to get the high contrast resolution images of tumors. Using MRI scanner, images with various dimensions and various angles such as T1-Axial, T2-Axial, T1-Weighted, T1 Contrast enhanced and post processed, are captured efficiently. The MRI images greatly help medical professionals study the details of various soft tissues and structures associated with the tumors in question and help them classify tumors. In the whole process, the technique of segmenting images of tumors from the MRI images plays an important role. MRI image sequences usually have non-uniform intensity variations and noise inference signals. They prevent enhanced visualisation of images and proper tumor segmentation. Image segmentation partitions images into small number of homogenous regions based on their size, texture and pixel intensity. Thus it enhances the vision of the tumor region. This helps medical professional to extract the meaningful information from scanned images. From the clinical prospective, when segmentation is done manually, it takes a lot of time. Further manual segmentation can result in human errors. To overcome the above said issues, an automated segmentation is required.

Currently, segmentation is done on image sequences pertaining only to any one single modality such as MRI brain or MRI breast. For this, bio inspired techniques such as Particle Swarm Optimization (PSO), Cuckoo Search Optimization (CSO), and Ant Bee Colony (ABC), are used. The proposed system produces better segmentation results in multimodal (specifically, MRI brain and MRI breast) with various image sequences and yields better segmentation and classification accuracy. This is achieved by integrating Kernel Possibilistic C Means (KPCM), a technique to calculate the kernel-induced distance metrics between data spaces, with PSO that provides the best optimal solution with less number of iterations to increase the efficiency of segmentation and classification of tumors. The approach also involves the removal of irrelevant pixels from the segmented output using morphological reconstruction filter. This enhanced output (feature set) is fed into Support Vector Machine classifier one of the supervised classification techniques for classifying the tumors into normal, benign, and malignant.

The major contributions of this approach in image segmentation are:

- Integration of a clustering method (KPCM) with a soft computing technique (PSO);
- Deployment of a classifier (SVM) for tumour classification;
- Ability to process image sequences of two different modalities (MRI brain and MRI breast) with less computational time.

The rest of the paper organized as follows: section II briefs the related work, Section III deals with image acquiring, types of datasets used, and working principle of KPCM-PSO with Morphological reconstruction filters and support Vector Machine (SVM) architecture in detail. Section III briefly discusses the experimental results and its performance measures and in Section IV conclusion and limitation of the proposed work is stated in a short note.

RELATED WORK

Cellular automation based seeded segmentation algorithm is used to segment the tumor part of T1 weighted images of MRI brain sequence. Fuzzy-based hybrid techniques have been applied to segment the DICOM-based MRI brain images and (Uma maheswari & Radhaman, 2012) shown to yield better results than Otsu based segmentation. Comparison between Kernel Fuzzy C Means KFCM-F feature space and (KFCM-K) kernel space proves that KFCM is highly sensible in selecting

the kernel parameters based on the clustering rate and reconstruction rate is defined by Daniel Graves & Witold Pedrycz (2010).

Hala Ali et al (2015) have segmented MRI brain images using three steps: in the first step, the spatial context is maintained, in the second step, the image is enhanced and the noise information is reduced using morphological operations and in the third step, the tumor is segmented using Fuzzy C Means. MRI brain tumors like Meningioma, Glioma, Astrocytoma, and Metastases are utilized to classify the tumor based on the attributes of the co-occurrence matrix and the histogram. Fuzzy logic-based hybrid kernel (Jayachandran & Kharmega Sundararaj, 2015) is used to test the classification for accuracy. T1-weighted MRI images are used to clustering for brain tumors with Principal Component Analysis (PCA) algorithm and compare the performance with PPCA, EM-PCA, GHA, APEX – they conclude that PPCA and EM-PPCA are efficient clustering algorithms.

Multi fractional Brownian motion approach (Artem Mikheev et al, 2008) is applied to identify the tumor part based on tumor size and its texture, The limitation in this method is that it focused on single image sequence like T1-W alone and its jaccard index is comparatively less than leading approaches (Vijayakumar & Ashish Chaturvedi, 2012). It uses three steps for detecting and classifying the MRI brain tumor with T1W and T2-W sequences. In the first step, Gaussian filter is applied for pre-processing and in the second step, fluid flow is used to segment the tumor part and in the last step support vector machine is used for classification of tumor as normal and abnormal. Using spatially constrained possibilistic fuzzy c-means classification (Hayit Greenspan et al, 2006) for segmenting the lesions present in MRI brain with T1-W and T2-W image sequences. They proved that PFCM produces better segmentation accuracy than FCM clustering in short duration of time. An hybrid approach (Aboul EllaHassanien & Tai-hoon Kim, 2012) to segment the tumor region by pulse coupled neural networks and SVM classifier is used to discriminate the tumor as cancer or not and proved its accuracy with various techniques like decision trees, rough sets, neural networks, and fuzzy artmap. SVM with KNN (Machhale et al, 2015) is combined for image classification and yield 98% of classification accuracy with 50 images. Bauer et al (2011) has utilizes 10 multispectral dataset of patients with the combination of Support Vector Machine classification using multispectral intensities and textures with subsequent hierarchical regularization based on Conditional Random Fields. Combination of wavelet transform, Genetic algorithm and SVM (Ahmed Kharrat et al, 2010) is applied for brain tumor classification. It obtains 96.2% classification accuracy. T2 spectral MRI breast image tissues (Wang et al, 2008) are classified using SVM with 5 classes namely fatty, glandular, tumor, muscle, and background with limited number of images.

Sowjanya et al (2018) has utilized adaptive wind driven optimization technique for segmenting the tumor part of brain images with Axial T2 Weighted image sequences with 10 MRI brain images, with the number of cluster=5 and number of iteration used is 80, To reduce the number of iteration WDO is replaced with adaptive wind driven optimization and proved its efficiency with PSO, DE and GA techniques, its limitation is high execution time and the choice of multilevel threshold value.

Combination of Genetic Algorithm – Ant Colony optimization-Fuzzy C means (GA-ACO-FCM) algorithms (Guru Kalyan Kanungo et al, 2014) aids in segmenting the breast tumor part and achieves high accuracy when compared with other existing techniques like GA and ACO. Weighted PSO optimization (Seetha & Santhosh baboo, 2017) applied to extract the tumor part of mammogram breast cancer images and classifies the micro calcifications into benign, malignant or normal images. Aya Hossam et al (2018) have suggested utilizing the sub-optimum Feature set algorithm with Particle Swarm Optimization (PSO) to detect the tumor part using a breast cancer dataset and to ensure the classification accuracy as better as data structure's breast first and Greedy approach. Max-min with the east variance method (Raj kumar & Raju, 2015) is applied to extract the abnormal part in breast images. Fuzzy C Means combined with a level set with PSO (Elham Gohariyan et al, 2016) is used to segment the MR brain images and proved its accuracy with limited images. Combination of Ant Bee colony– Extreme Learning Machine – Kernel Fuzzy C Means clustering (Hemalatha et al, 2018) is used for segmenting the tumor part of brain images. This method yields 97.03% of segmentation

accuracy and 95.85% of Classification accuracy. But its limitation is combination of three different approaches that leads to high computational time. Ahmed et al (2016) have used contrast enhanced MRI breast images with KNN classifier and with two classes to classify the tumors as benign and malignant with 20 patients images based on histogram feature extraction.

BAT based Interval Type-2 Fuzzy C-Means (BAT-IT2FCM) clustering (Saravanan et al, 2020) is used for brain tissue segmentation with the T1-W, T2-W, FLAIR (Fluid Attenuated Inversion Recovery) and MP(Multi- planar Reconstruction) image sequences and proved their segmentation accuracy with various existing approaches like Cuckoo based IT2FCM, PSO based FCM etc. Anitha Narayanan et al (2019) combines the particle swarm optimization (PSO) and bacteria foraging optimization (BFO) with modified fuzzy c means (MFCM) algorithm for segmenting the tumor tissue and identifies the tumor part with the T1- W, T2-W image sequences. Deep Neural network model (Yurttakal et al, 2020) is used to classify the MRI breast images in to benign and malignant and proved this classification accuracy with 98.8% with 200 sample image datasets. Ahmed et al (2020) utilized the Deep Lab and Mask RCNN (restn CNN) for classifying the Mammogram breast masses and its limitation is artifact, muscle removal and noise handling during the feature extraction.

METHODOLOGY

Scope of Our Proposed Work

The major goal of this method is to develop an automated framework by combining the two multimodal MR brain images like T1-W, T1-A, T2-W, T2-A and for breast image sequences like post-processed, T1 –A, T2-A and post-contrast images. The author investigated various techniques and proved that this automated frame work helps radiologists for early prevention and also for diagnosis using MR brain and MR breast tumor images in advance. This method uses 208 images (170 MRI brain and 38 MRI breast) and ensures the segmentation accuracy with 97.06% and classification accuracy with 98.08%. This compares the computational time with various emerging techniques like GA with K Means, FCMPSO and FCM-SVM etc.

Details of Image Dataset

In this study, the authors have used various types of images for the MR brain and breast for ensuring the validity of the proposed method.

MR Brain Images

This study uses various types of MR brain image sequence like T1 axial, T2 axial and T1 post-contrast images. These images are collected from online datasets like Harvard Brain Web Database (Alexander Dagley et al, 2017) and also from hospital datasets. To enhance the fatty portion T1-Weighted images are used to focus the image which was taken in front dimension as T1-Axial images that are used to analyze the anatomic details, whereas T2- Axial produces the detailed information about anatomic details of CSF helpful for blood flow and lesions part.

MR Breast Images

MRI scanning images of breast cancer is used to measure the accurate size of tumor part and to detect multifocal and multi centric lesions accurately. This study uses post-processed T1 post-contrast and STIR axial images for MR breast images and these samples are collected from publicly available sources like RIDER (Reference Image dataset to evaluate Therapy response) (Meyer et al, 2015) and few from hospital dataset. The authors have used Intel I5 core Vostro 3000 series with 4Ghz processor with 4 GB RAM for processing the input images.

Image Analysis

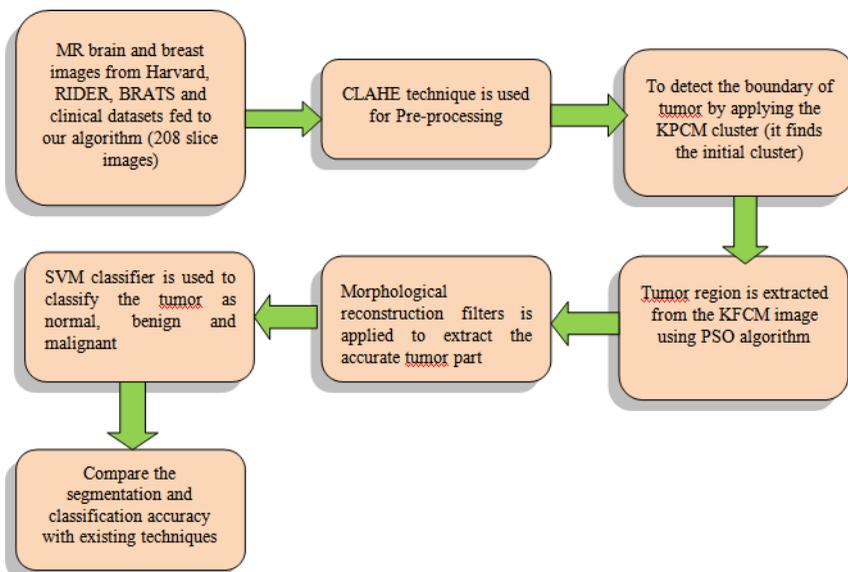
Our proposed approach steps are described as follows:

- Step 1:** Convert the input image of size 256 x 256 into grayscale image.
- Step 2:** Apply CLAHE preprocessing to enhance the contrast of tumor part and reduce noise amplification.
- Step 3:** To initialize the cluster KFCM method is used, based on kernel space all data inputs are mapped with high dimensional feature space to reduce the noise as well as outlier more accurate than FCM.
- Step 4:** To Integrate the KFCM with PSO for global solution based on the cluster centroid, which is used to extract the tumor parts.
- Step 5:** Apply morphological reconstruction filters to segment both brain and breast tumors with accurate size by removing the irrelevant pixels in the outliers.
- Step 6:** SVM classifier is used to classify the tumor as normal, benign and malignant based on the feature set obtained from the segmented output images.
- Step 7:** Compare the segmented output with expert manual segmentation and ensure 97.06% segmentation accuracy. Based on specificity, sensitivity values classification accuracy and obtained as 98.08%. The Flow diagram of our proposed work is shown in Figure 1.

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Preprocessing is very essential for the medical image to enhance the contrast level of the input images for identifying the tumor part. CLAHE is highly used to enhance the contrast and helps to identify the boundaries of tumor part. It also suppresses the noise levels other than AHE (Waleed et al, 2014):

Figure 1. Flow diagram



$$R_g = g_{min} + \left[2(\alpha^2) \ln \left(\frac{1}{1-p(f)} \right) \right]^{0.5} \quad (1)$$

where α represents the non-negative number and the authors have assigned as 0.2, which defines the distribution value and $p(f)$ is a cumulative grey level function of R.

Kernel Possibilistic C-Means

FCM is a soft computing technique that is highly suitable for medical image segmentation applications (Vishnuvarthanan & Rajasekaran, 2014). It is an iterative approach method that yields an optimal C partition by minimizing the weighted within the group sum of squared error objective function (Krishnapuram & Keller, 1993). It is denoted as:

$$J_m = \sum_{i=1}^N \sum_{j=1}^C S_{ij}^m x_i - c_j^2 \quad (2)$$

where $X = \{x_1, x_2, \dots, x_n\}$ is the data set and cluster center is represented as follows:

$$V_i = \frac{\sum_{k=1}^n \mu_{ik}^m K(x_k, V_i) x_k}{\sum_{k=1}^n \mu_{ik}^m K(x_k, V_i)} \quad (3)$$

To reduce the noise, outlier and inaccurate boundary detection, FCM is not preferable to overcome the problem and improve the robustness. KPCM objective function is defined as:

$$JFCM = \sum_{i=1}^c \sum_{k=1}^n \mu_{ik}^m d^2(x_k, V_i) + \sum_{i=1}^c n_i \sum_{k=1}^n (1 - \mu_k)^m \quad (4)$$

where d represents the Mahalanobis distance measure as:

$$d^2(x_k, V_i) = (x_k, V_i)^T S_i(x_k, V_i) \quad (5)$$

where:

$$S_i = \left| \sum_i \right|^{\frac{1}{p}} \sum_1^{-1} \quad (6)$$

where p is the problem dimension and its value is assigned as 1. From equation 3, the value of n_i is chosen using the formula:

$$n_i = K \frac{\sum_{k=1}^n \mu_{ik}^m x_k - V_i^2}{\sum_{k=1}^n \mu_{ik}^m} \quad (7)$$

where $k=1$ and the membership of PCM values are updated by:

$$\mu_{ik} = \frac{1}{1 + \left((x_k - V_i^2) / (n_i) \right)^{\frac{1}{(m-1)}}} \quad (8)$$

KPCM objective measure is represented as:

$$J_{JPCM}(U, V) = \sum_{i=1}^c \sum_{k=1}^n \mu_{ik}^m \varnothing(x_k - \varnothing(V_i))^2 + \sum_{i=1}^c n_i \sum_{k=1}^n (1 - \mu_{ik})^m \quad (9)$$

Membership is updated using:

$$\mu_{ik} = \frac{1}{1 + \left(\frac{2(1 - K(x_k, V_i))}{n_i} \right)^{\frac{1}{(m-1)}}} \quad (10)$$

Here the author's use the Gaussian function as kernel function and n_i can be estimated by using:

$$n_i = K \frac{\sum_{k=1}^n \mu_{ik}^m 2(1 - K(x_k, V_i))}{\sum_{k=1}^n \mu_{ik}^m} \quad (11)$$

Steps for KPCM is as follows:

- Step 1:** Initialize number of class $c = 3$ for the pre-processed image, $m > 1$ and $\varepsilon = 0$.
- Step 2:** Initialize $U^t = 0$.as a random value
- Step 3:** Determine the value of n_i .using equation 11
- Step 4:** See below:
 - i. Update V^t .using equation 3.
 - ii. Update U^t .using equation 10.
 - iii. Check whether $J_{KPCM}^{t+1} - J_{KPCM}^t < \varepsilon$ then stop the process else goto step 3.
- Step 5:** Stop the process

Particle Swarm Optimization

The KPCM processed images are given as input to the PSO algorithm to achieve the global solution, whereas PSO is the best for producing globally optimal solution obtained from the behaviour of

swarm. PSO is used to find the optimal cluster location from which the clustering operations are performed by the KPCM to reduce the computational complexity, particle with random position and velocity is evaluated using fitness function:

$$y_i(t+1) = \begin{cases} \{y_i(t) \text{ if } x_i(t+1) \geq f(y_i(t)) \\ x_i(t+1) \text{ if } x_i(t+1) < f(y_i(t)) \end{cases} \quad (12)$$

Global best position \hat{y} (gbest) can be obtained by applying the following equation as:

$$\hat{y}(t) \in \{y_1, y_2 \dots y_p\} = \min\{f(y_1(t)), f(y_2(t)), \dots f(y_p(t))\} \quad (13)$$

Velocity and position of the particle is updated by applying the following equation:

$$v_i(t+1) = wv_i(t) + c_1r_1(t)(y_i(t) - x_i) + c_2r_2(t)(\hat{y}(t) - x_i(t)) \quad (14)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (15)$$

where $i = 1, 2, 3, \dots, p$, are integer values and the parameter used in PSO is mentioned in Table 1.

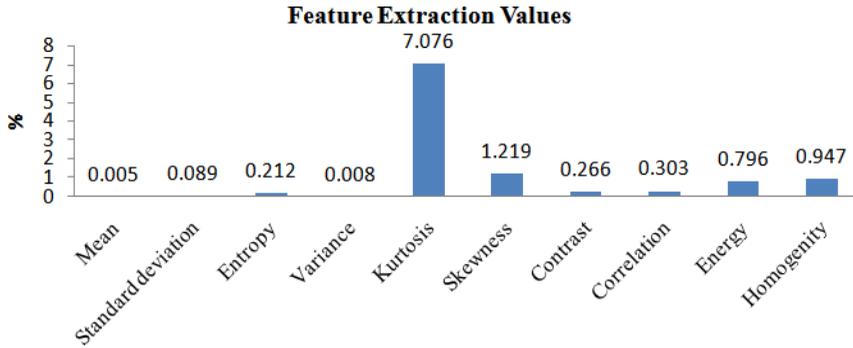
Morphological Reconstruction Filters

Mathematical morphology provides aid between the KPCM-PSO segmented image and structural element. It also briefs the structure and the shape of an object by using set theory. A more powerful class of morphological filters can also preserve the horizontal contours that are the opening and closing by reconstruction. These two operations involve an interaction between an image (A) and a structuring element (B). The morphological reconstruction filters perfectly, preserving other components and their contours. The size of removed components depends on the size of the structuring element. Among

Table 1. Parameters of PSO

Definition	Values
C	2
M	2
Iteration	60
	10^4
C_1	0.5
C_2	1.5
P	20
U_{\max}	255
W_{\max}	0.9
W_{\min}	0.4

Figure 2. Overall average values of all feature sets



the many structuring elements, ‘disc’ (Gonzalez & Woods, 2009) is more suitable for removing the unrelated pixels with 7 x7. It also preserves the edges and enhances the quality of medical images. Morphological operators like dilation and erosion are highly helpful in medical images. Erosion shrinks the extraneous pixels, and dilation escalates pixels in the segmented image.

Dilation of A by B is represented as:

$$(A \oplus B)(s, t) = \max \left\{ A(s - x, t - y) - \frac{B(x, y)}{(s + x)}, (t - y) \in D_A; (s, y) \in D_B \right\} \quad (16)$$

where D_A and D_B are the domains of A and B. whereas erosion of A by B is defined as:

$$(A \ominus B)(s, t) = \max \left\{ A(s - x, t + y) - \frac{B(x, y)}{(s + x)}, (t + y) \in D_A; (s, y) \in D_B \right\} \quad (17)$$

where D_A and D_B are the domains of A and B. opening and closing are denoted as:

$$A \circ B = (A \ominus B) \oplus B \quad (18)$$

$$A \cdot B = (A \oplus B) \ominus B \quad (19)$$

The morphological closing operator applies dilation followed by erosion, where dilation leads to brighter image and erosion leads to darker images. A morphological closing simplifies the original signal by removing the dark components that do not fit within the structural elements B, where A represents the original image and B is the structuring element applied to the KFCM PSO segmented image. Applying Morphological operations highly reduces the computational time for tumor segmentation that has been proved (Devkota et al, 2017).

SVM Classifier

SVM classifier (Mathew & Anto, 2017; Srinivas & Sasibhushana, 2019) are one of the best classifier under supervised learning technique. It is highly used in medical image classification with two types namely linear and non linear. In order to classify the tumor as normal, benign and malignant many techniques like DWT, Gabor Filter and GLCM are commonly used. The gray level co-occurrence matrix is mostly used as statistical technique for feature extraction. This study uses GLCM for classifying the tumor as normal, benign and as malignant. The statistical importance is examined using one-way ANOVAs test. Our work uses non linear classifier with the following texture features like entropy, mean, standard deviation, variance, correlation, contrast, kurtosis, energy, skewness and homogeneity for classification. The overall average values of all feature set is shown in Figure 2. The SVM classifier is suitable for classifying the tumor of multimodal images. It obtains 98.08% classification accuracy with 208 images (with 170 benign and 38 malignant) validated by expert radiologist using manual segmentation and classification.

PERFORMANCE MEASURES

Jaccard Index

Jaccard Index (Jaccard, 1912) values ensure the segmentation accuracy, and its representation is defined as:

$$J(A, B) = \frac{S(A \cap B)}{S(A \cup B)} \quad (20)$$

MSE (Mean Square Error)

It is used to measure the accumulated square error obtained between the input image A (i, j) and the segmented output image B (i, j):

$$MSE = \frac{1}{xy} \sum_{i=0}^{x-1} \sum_{j=0}^{y-1} [A(i, j) - B(i, j)]^2 \quad (21)$$

where x and y represents the row and column of the given input image.

Peak Signal to Noise Ratio (PSNR)

PSNR value is used for measuring the noise resistance level between the input and segmented output image. Its value is depended upon the MSE value obtained (Sumathi et al, 2018). The PSNR value lies in the range from 40 to 60 and ensures the quality of good segmentation. It also ensures the noise signals value of MSE as low, and PSNR value remains high. The combination of MSE and PSNR is used to degrade the noise level, PSNR computes the pixel by pixel comparison with input and segmented output images, it determines the how close the image obtained from the manual segmentation and also ensure the quality of segmented image.

The formula of PSNR is denoted as:

$$PSNR = 10 * \log_{10} \left(\frac{255}{\sqrt{MSE}} \right) \quad (22)$$

Sensitivity, Specificity and Accuracy

It measures the percentage of patients having tumors (Sumathi & Arjunan, 2014) It is calculated using:

$$Sensitivity = \frac{TP}{TP + FN} \quad (23)$$

where as specificity is the percentage of patients that is not correctly identified with tumor. It provides the percentage of patients wrongly identified with a tumor:

$$Specificity = \frac{TN}{TN + FP} \quad (24)$$

Accuracy

Accuracy is used to calculate the proposition of both TP and TN in all evaluated cases:

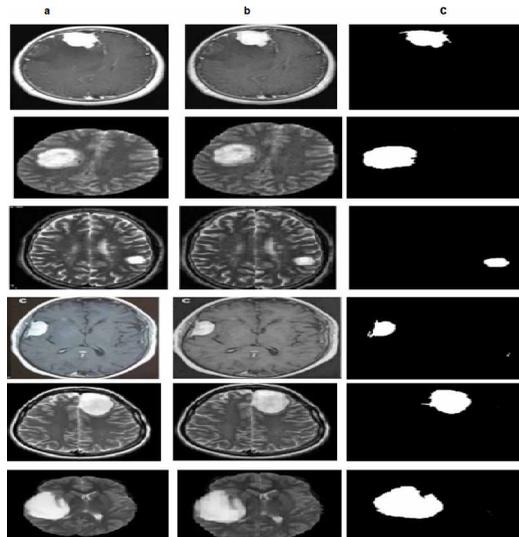
$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (25)$$

where TP (True Positive) represents the correct segmentation of tumor part; FP (False positive) represents normal region present in the input image identified wrongly as tumor region; FN (False negative) represents the wrongly segmented tumor region, and TN (True Negative) represents the correct segmentation of non-tumorous part.

RESULTS AND DISCUSSION

The proposed technique segments the tumor part of MR brain and MR breast in an efficient manner within a minimum duration by combining KPCM-PSO technique with morphological filters. Brain and breast tumor shapes are exactly segmented by applying morphological filters. It is highly preferable in biomedical research and real-time applications. Its task is to remove unrelated patches and unrelated holes in the given image. The output produced by our proposed method has been validated with ground truth images of clinical dataset. It is useful to the surgeon to get detailed information about the tumor shape, size and location in the brain and the breast within a short duration. T1- axial, T1-Enhanced, T1-Weighted, T2 -axial and T2-Weighted MRI brain images with the age group of 30-45 is shown in Figure 3. These images are collected from online dataset like Harvard Brain Dataset and BRATS 2013 challenge images. 3(a) contains input image, 3(b) contains CLAHE Pre-processed images and 3(c) contains KPCM-PSO technique with morphological reconstruction filters segmented output images. MR breast of T1 weighted, T1 Axial, T2 axial, T2 Weighted Images collected from the clinical dataset with Carcinoma tumor of the patients' age group 35 to 40 is shown in Figure 4, where 4(a) contains input image, 4(b) contains CLAHE preprocessed images that increase the contrast to enhance the tumor part clearly, 4(c) contains the segmented output images using KPCM-PSO and Morphological filters. It is observed that the proposed method is highly helpful to the radiologist to segment the tumor part in multimodal image. MRI brain segmentation accuracy is proved with comparing the output of existing methods is shown in Figure 5 whereas MRI breast images segmentation is compared with meanshift, meanshift + K Means clustering methods is shown in Figure 6. From this, it is proved that KPCM-PSO is an efficient method for segmenting both brain and breast images. Segmentation accuracy of

Figure 3. T1- axial, T1-Enhanced, T1-Weighted, T2 -axial and T2-Weighted MRI brain images with the age group of 30-45



the proposed method with existing techniques used (Hamamci et al, 2012; Priyansh Sharma et al, 2017) for both images is shown in Figure 7. The tumor segmentation performed using improved K Means clustering, and hybrid segmentation using region growing techniques. From the comparisons of existing approaches, the proposed method ensures the efficiency of segmentation. Some ground

Figure 4. MR breast of T1 weighted, T1 Axial, T2 axial, T2 Weighted Images collected from the clinical dataset with Carcinoma tumor of the patients' age group 35 to 40

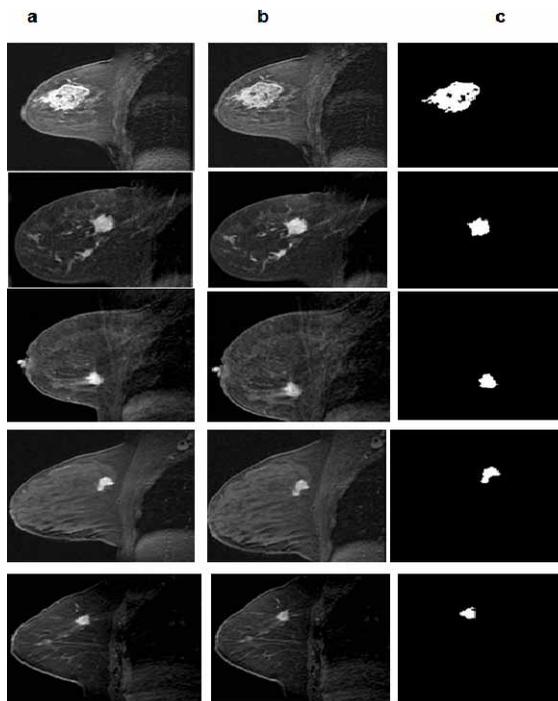


Figure 5. MRI brain segmentation accuracy is proved with comparing the output of existing methods

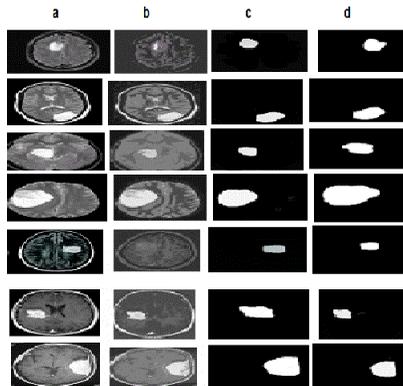


Figure 6. MRI breast images segmentation is compared with meanshift, meanshift + K Means clustering methods

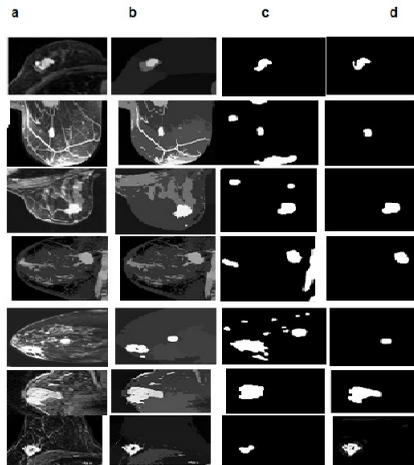


Figure 7. Segmentation accuracy of the proposed method with existing techniques

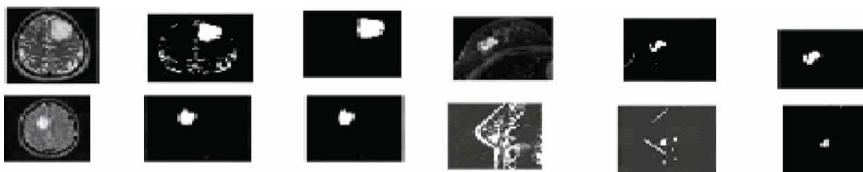


Figure 8. Some ground truth images of brain and breast



truth images of brain and breast are shown in Figure 8. Jaccard Index comparison among existing with proposed work is shown in Figure 9, whereas Jaccard index of Mean shift produces 0.09, Mean shift + K means produces 0.878 and KPCM-PSO yields 0.95. It proves that the proposed method gives vital information about the commonality among input and segmented images.

The average values of MSE and PSNR produced by various segmentation methods like Mean shift, Meanshift + K Mean and KPCM-PSOMSE values of existing methods like Mean shift produces 26.79, Meanshift+K Means produces 4.15, whereas this method yields 0.11, which is relatively less than all the existing methods is mentioned in Figure 10. By default, any segmentation efficiency is proved based on the PSNR value range between 40 and 60 decibels. This method ensures the quality of segmentation from the PSNR value of the proposed method. It is observed that the noise level is comparatively low and validates that this method is suitable for segmenting multimodal images. It can also be applied to many image processing applications like image compression, image enhancement etc., From the MSR and PSNR comparison chart, it is proved that the present work contains 44.5 overall PSNR value, whereas Mean shift produces 21.22, Mean shift + K means produces 38.5.

To ensure the segmentation specificity, sensitivity and accuracy measures are compared with existing techniques. Our present study's segmented output yields 97.06% accuracy with ground truth images, whereas Mean shift produces 93.3% and Mean shift + K Means contribute 95.3% are mentioned in Figure 11. The average computational time comparisons among all techniques are shown in Figure 12. From the comparison chart, the proposed method is found to be an efficient segmentation method among all other techniques (Kumar et al, 2018; Siyuan Lu et al, 2018). It is observed that KFCM-PSO is highly suitable for tumor segmentation with various image sequences like T1, T2, Post-processed etc, though many soft computing approaches are used in medical image segmentation, the proposed method takes minimum duration for segmenting the tumor part of brain and breast images. Classification accuracy with existing techniques like (Latif et al, 2017; Ali et al, 2015) are compared with our proposed work is shown in Figure 13. From this output, it is noticed that SVM classifier is suitable for classifying the multimodal image using BRATS data images and few from clinical dataset. It is observed that ABC-ELM-KFCM classifier is 97.03% accurate and our proposed method yields 98.08% which is far better than existing methods. From the obtained segmentation and classification outcome, it was proved that our proposed method KFCM- PSO with morphological reconstruction is highly helpful for radiologist for clinical decision support system.

The proposed method faces a shortcoming of fixed size. Since the approach fixes the size of the structural element (7x7) in the morphological reconstruction filter, it may not always accommodate shapes (especially of breast) when mass increases or decreases abnormally. The value of Jaccard index can be improved by using various other hybrid techniques like Fish Swarm Optimization and GA based optimization with deep learning techniques. There are still some open research questions to address in future:

1. Adaptive selection of structural element size for different image modalities;
2. Adaptive selection of the hybrid techniques based on the physiological structure of the various images;
3. The optimization of the parameters with respect to the features of the image segmentation.

CONCLUSION

This study has shown that the proposed automated KPCM-PSO with morphological filters has significantly able to segment both the modalities. Efficiency is proved by applying various performance measures like Jaccard index, MSE, PSNR, specificity, sensitivity, accuracy and computational time. From the MSE and PSNR values, it is proved that the segmentation results obtained by the proposed algorithm have good immunity toward noise interference. The accuracy rate of the proposed method is far better than existing approaches and also computational time comparison ensures that using KPCM-

Figure 9. Jaccard Index comparison

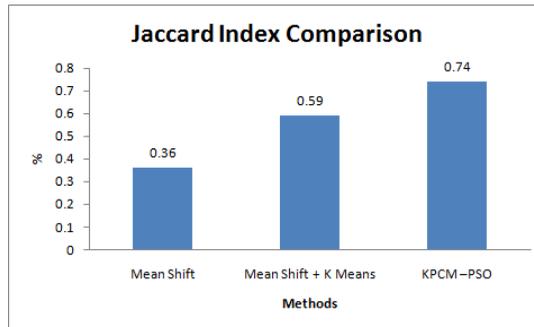


Figure 10. MSE and PSNR Comparison

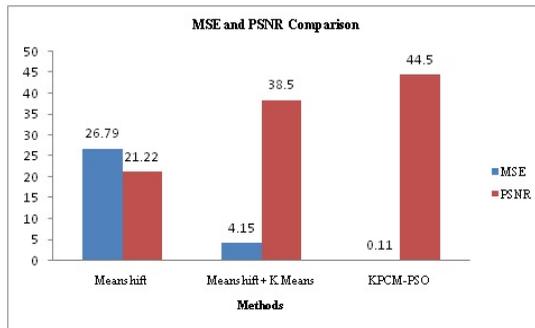
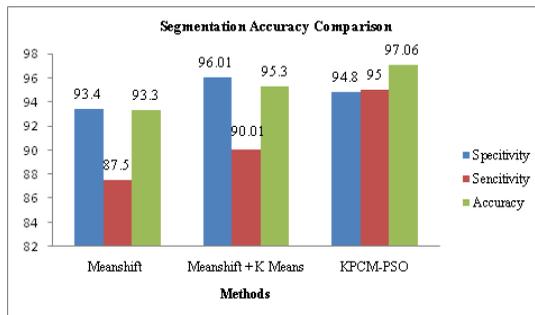


Figure 11. Mean shift produces 93.3% and Mean shift + K Means contribute 95.3%



PSO segmentation works in short duration. Our proposed method produces 97.06% segmentation and 98.08% classification accuracy for both MRI brain and breast images. The future work may focus on hybrid techniques with deep learning techniques for both segmentation and classification of multimodal images.

Figure 12. The average computational time comparisons among all techniques

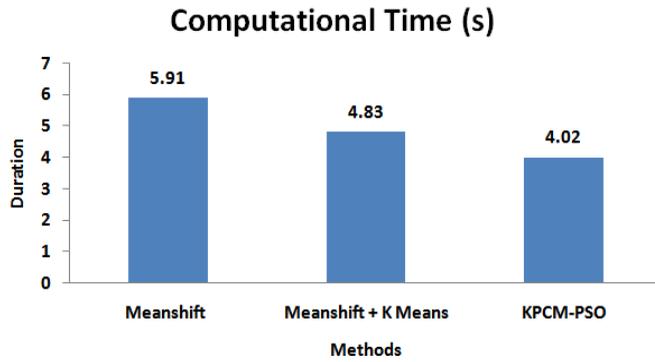
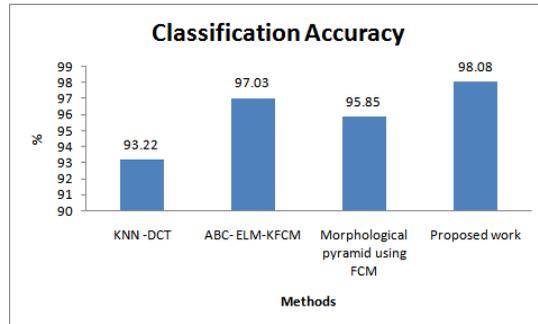


Figure 13. Classification accuracy with existing techniques



REFERENCES

- Ahmed, L., Iqbal, M. M., & Aldabbas, H. (2020). Images data practices for Semantic Segmentation of Breast Cancer using Deep Neural Network. *Journal of Ambient Intelligence and Humanized Computing, Computer*. 10.1007/s12652-020-01680-1
- Alagarsamy, , Kamatchi, , & Govindaraj, , Zhang, & Thiyagarajan. (2020). Multi-channelled MR brain image segmentation: A new automated approach combining BAT and clustering technique for better identification of heterogeneous tumors. *Biocybernetics and Biomedical Engineering*, 39(4), 1005–1035.
- Ali, H., Elmogy, M., El-Daydamony, E., & Atwan, A. (2015). Multi-resolution MRI Brain Image Segmentation Based on Morphological Pyramid and Fuzzy C-mean Clustering. *Arabian Journal for Science and Engineering*, 40, 3173–3185.
- Ali, H., Elmogy, M., El-Daydamony, E., & Atwan, A. (2015). Multi-resolution MRI brain image segmentation based on morphological pyramid and fuzzy c-mean clustering. *Arabian Journal for Science and Engineering*, 40, 3173–3185.
- Alomoush, Abdullah, Sahran, & Hussain. (2014). Segmentation of MRI Brain Images Using FCM Improved by Firefly Algorithms. *Journal of Applied Sciences (Faisalabad)*, 14, 66–71.
- Sayed, Zaghoul, & Nassef. (2016). Automatic Classification of Breast Tumor Using Features Extracted from Magnetic Resonance Images. *Procedia Computer Science*, 95, 392–398.
- Bauer, S., Nolte, L. P., & Reyes, M. (2011). Fully Automatic Segmentation of Brain Tumor Images Using Support Vector Machine Classification in Combination with Hierarchical Conditional Random Field Regularization. In MICCAI 2011, Lecture Notes in Computer Science. Springer.
- Dagley, , LaPoint, , Huijbers, , & Hedden, , McLaren, Chatwal, Papp, Amariglio, Blacker, Rentz, Johnson, Sperling, & Schultz. (2017). Harvard Aging Brain Study: Dataset and Accessibility. *NeuroImage*, 255–258.
- Devkota, Alsadoona, Prasad, Singh, & Elchouemi. (2017). Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. *Procedia Computer Science*, 125, 115–123.
- Gohariyan, E., Esmaeilpour, M., & Shirmohammadi, M. M. (2016). The Combination of Mammography and MRI for Diagnosing Breast Cancer Using Fuzzy NN and SVM. *International Journal of Interactive Multimedia and Artificial Intelligence*, 4(5), 20–24.
- Gonzalez, R. C., & Woods, R. E. (2009). Digital image processing (3rd ed.). Prentice Hall, Incorporation.
- Govindaraj, V., & Murugan, P. R. (2014). A Complete Automated Algorithm for Segmentation of Tissues and Identification of Tumor Region in T1, T2, and FLAIR Brain Images Using Optimization and Clustering Techniques. *International Journal of Imaging Systems and Technology*, 24(4), 313–325.
- Graves, D., & Pedrycz, W. (2010). Kernel-based fuzzy clustering and fuzzy clustering: A comparative experimental study. *Fuzzy Sets and Systems*, 161, 522–543.
- Greenspan, H., Ruf, A., & Goldberger, J. (2006). Constrained Gaussian Mixture Model Framework for Automatic Segmentation of MR Brain Images. *IEEE Transactions on Medical Imaging*, 25(9), 1233–1245.
- Hamamci, A., Kucuk, N., Karaman, K., Engin, K., & Unal, G. (2012). Tumor-cut: Segmentation of brain tumors on contrast enhanced MR images for radio surgery applications. *IEEE Transactions on Medical Imaging*, 31(3), 790–804.
- Hassanien & Kim. (2012). Breast cancer MRI diagnosis approach using support vector machine and pulse coupled neural networks. *Journal of Applied Logic*, 10(4), 277–284.
- Hossam, Harb, & El Kade. (2018). A Sub -Optimum Feature Selection Algorithm for Effective Breast Cancer Detection Based On Particle Swarm Optimization. *IOSR Journal of Electronics and Communication Engineering*, 13(3), 1-12.
- Jaccard, P. (1912). The distribution of the flora in the alpine zone. *The New Phytologist*, 37–50.

Jayachandran, A., & Kharmega Sundararaj, G. (2015). Abnormality Segmentation and Classification of Multiclass Brain Tumor in MR Images Using Fuzzy Logic-Based Hybrid Kernel SVM. *International Journal of Fuzzy Systems*, 17(3), 434–443.

Kanungo, G. K., Singh, N., Dash, J., & Mishra, A. (2014). Mammogram Image Segmentation Using Hybridization of Fuzzy Clustering and Optimization Algorithms. *Intelligent Computing Communication and Devices*, 2, 403–413.

Kharrat, A., Gasmi, K., Ben Messaoud, M., Benamrane, N., & Abid, M. (2010). A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and Support Vector Machine. *Leonardo. Journal of Science*, 17, 71–82.

Krishnapuram, R., & Keller, J. M. (1993). A possibilistic approach to clustering. *IEEE Transactions on Fuzzy Systems*, 1, 98–110.

Kumar, S. N., Lenin Fred, A., & Sebastin Varghese, P. (2018). Suspicious Lesion Segmentation on Brain, Mammograms and Breast MR Images Using New Optimized Spatial Feature Based Super-Pixel Fuzzy C-Means Clustering. *Journal of Digital Imaging*, 32(7), 572–579.

Latif, G., Iskandar, D. A., Jaffar, A., & Butt, M. M. (2017). Multimodal Brain Tumor Segmentation using Neighboring Image Features, Journal of Telecommunication. *Electronic and Computer Engineering*, 9, 37–42.

Lingappa, H. K., Suresh, H. N., & Manvi, S. K. (2018). Medical Image Segmentation Based on Extreme Learning Machine Algorithm in Kernel Fuzzy C-Means Using Artificial Bee Colony Method. *International Journal of Intelligent Engineering and Systems*, 11(6), 128–138.

Lu, S., Lu, Z., Yang, J., Yang, M., & Wang, S. (2018). A pathological brain detection system based on kernel based ELM. *Multimedia Tools and Applications*, 77(3), 3715–3728.

Machhale, K., Nandpuru, H. B., Kapur, V., & Kosta, L. (2015). MRI brain cancer classification using hybrid classifier (SVM-KNN). *International Conference on Industrial Instrumentation and Control (ICIC)*, 60-65. doi:10.1109/IIC.2015.7150592

Mathew, A. R., & Anto, P. B. (2017). Tumor detection and classification of MRI brain image using wavelet transform and SVM. *International Conference on Signal Processing and Communication (ICSPC)*, 75-78. doi:10.1109/CSPC.2017.8305810

Meyer, C. R., Chenevert, T. L., Galbán, C. J., Johnson, T. D., Hamstra, D. A., Rehemtulla, A., & Ross, B. D. (2015). Data From RIDER_Breast_MRI. *The Cancer Imaging Archive*. 10.7937/K9/TCIA.2015.H1SXNUXL

Mikheev, A., Nevsky, G., Govindan, S., Grossman, R., & Rusinek, H. (2008). Fully Automatic Segmentation of the Brain from T1-Weighted MRI Using Bridge Burner Algorithm. *Journal of Magnetic Resonance Imaging*, 27, 1235–1241.

Narayanan, , & Rajasekaran, , Zhang, Govindaraj, & Thiagarajan. (2019). Multi-channelled MR brain image segmentation: A novel double optimization approach combined with clustering technique for tumor identification and tissue segmentation. *Biocybernetics and Biomedical Engineering*, 39(2), 350–381.

Rajkumar, K. K., & Raju, G. (2015). Automated Mammogram Segmentation Using Seed Point Identification and Modified Region Growing Algorithm. *British Journal of Applied Science and Technology*, 6(4), 378–385.

Seetha & Baboo. (2017). A Weighted Particle Swarm Optimization technique for accurate breast cancer detection. *International Journal of Advance Engineering and Research Development*, 4(10), 454-463.

Sharma, Sharma, & Tomar. (2017). A new approach for image segmentation using improved k-means and ROI, saliency map. *Journal of Information and Optimization Sciences*, 38(6), 927–935.

Sowjanya, K., Kumar, P. R., & Kumar, I. S. (2018). Optimal Multilevel Thresholding Selection for Brain MRI Image Segmentation based on Adaptive Wind Driven Optimization. *Measurement*, 9(4), 1043–1067.

Srinivas, B., & Sasibhushana Rao, G. (2019). Performance Evaluation of Fuzzy C Means Segmentation and Support Vector Machine Classification for MRI Brain Tumor. In J. Bansal, K. Das, A. Nagar, K. Deep, & A. Ojha (Eds.), *Soft Computing for Problem Solving, Advances in Intelligent Systems and Computing*, 817. Springer.

- Sumathi, R., & Arjunan, S. (2014). Towards better segmentation of object of interest using histogram equalization and morphological reconstruction. *International Journal Signal Imaging System Engineering*, 7(3), 189–194.
- Sumathi, Venkatesulu, & Arjunan. (2018). Extracting tumor in MR brain and breast image with Kapur's entropy based Cuckoo Search Optimization and morphological reconstruction filters. *Biocybernetics and Biomedical Engineering*, 38(4), 918-930.
- Uma Maheswari, J., & Radhaman, G. (2012). A hybrid approach for DICOM image segmentation using fuzzy techniques. *International Journal of Fuzzy Logic Systems*, 2(3), 51–58. doi:10.5121/ijfls.2012.2305
- Vijayakumar & Chaturvedi. (2012). Automatic Brain Tumors Segmentation of MR Images using Fluid Vector Flow and Support Vector Machine. *Research Journal of Information Technology*, 3, 108-114.
- Wang, C., Mai, X., Lin, G., & Kuo, C. (2008) Classification for Breast MRI Using Support Vector Machine. *IEEE 8th International Conference on Computer and Information Technology Workshops*, 362-367. doi:10.1109/CIT.2008.Workshops.90
- Yurttakal, A. H., Erbay, H., & İkizceli, T. (2020). Detection of breast cancer via deep convolution neural networks using MRI images. *Multimedia Tools and Applications*, 79, 15555–15573. doi.org/10.1007/s11042-019-7479-6

M. Venkatesulu received a postgraduate degree in Mathematics from Sri Venkateswara University, Tirupati, India, in 1975, and a Ph.D. degree in mathematics from the Indian Institute of Technology, Kanpur, India, in 1979. He worked as a faculty member at Shri Sathya Sai University, Prashanthinilayam, India Between 1983 and 2003. He also worked as a consultant for Satyam Computers, Hyderabad, India, for a short period. He was a Visiting Professor at the University of Missouri, Kansas City, between August 2006 and May 2007. Currently, he is working as a Senior Professor in the Department of Information Technology at Kalasalingam Academy of Research and Education, Krishnankovil, Srivilliputtur, Tamil Nadu, and India. His area of interest includes differential equations, Image Processing, Cryptography, Bioinformatics, Big Data Analytics, and Distributed Computing.