Research paper **UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023**

PSNR Based Evalution of Spatial Guassian Kernals for FCM Algorithm With Mean and Median Filtering Based Denoising For MRI Segmentation

Dr. Nookala Venu
Professor, Department of Electronics and Communication Engineering, Balaji Institute of Technology and Science, Warangal-506 331, Telangana, India
Corresponding Author Mail id: venunookala@gmail.com

***Abstract*:**

In this paper, a new segmentation algorithm with the integration of mean and peak-and-valley filtering based denoising and Gaussian kernels based fuzzy c-means (MPVKFCM) algorithm is proposed for medical image segmentation. First, the image is denoised by using the mean and peak-and-valley filtering algorithm. Secondly, image segmentation algorithm with Gaussian kernels based fuzzy c-means is performed on the denoised image. The performance of the proposed algorithm is tested on OASIS-MRI image dataset. The performance is tested in terms of Score, Number of iterations (NI), Execution time (TM) and PSNR values under different Gaussian noises on OASIS-MRI dataset. The results after investigation, the proposed method shows a significant improvement as compared to other existing methods in terms of PSNR, Score, NI and TM under different Gaussian noises on OASIS-MRI dataset.

Keywords: *FCM, Mean Filtering,median filtering, Image Segmentation, Gaussian Kernal, fuzzy, multiple-kernal.*

1.Introduction

Image segmentation is an active research area in medical image processing [1] and computer vision applications. Image segmentation is the process of dividing the image into non-overlapped, unfailing regions. The divided or segmented regions are uniform with respect to some characteristics like color, texture, intensity etc. Based on the characteristics, image segmentation is divided into four categories: thresholding (*intensity*), clustering (*intensity*), edge detection (*texture*) and region extraction (*color or texture*).

So many image segmentation algorithms are available in the literature. The brief survey of available techniques can be seen as follows: intensity based or thresholding algorithm [2], clustering based algorithm [3], classification [4], region growing [5], artificial neural networks (ANNs) [6], Markov Random Field (MRF) [7] based algorithms etc. From literature survey, we observed that the clustering based image segmentation algorithms are best as compared to other algorithms. This observation is motivated us to work in the direction of clustering algorithm based image segmentation [8].

Clustering is a process for classifying or segmenting the regions or objects in an image. The samples of classified objects or regions are contain the more similar content to one another than samples belonging to different clusters. There are two types of clustering strategies are available in the literature which are the hard clustering scheme and the fuzzy clustering scheme [9]. The hard clustering scheme called k-mean algorithm is proposed by MacQueen [10]. The k-mean clustering method classifies each point of the data set just to one cluster. As The outcome of the results are

  UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

repeatedly very hard, i.e., in image clustering each pixel of the image belongs just to one cluster [11]. However, in many real conditions, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity in homogeneities reduce the effectiveness of hard (crisp) clustering methods. To avoid the problem of hard clustring (k-mean) algorithm, the fuzzy set theory is introduced in [9]. The fuzzy set theory is based on the fuzzy membership, described by a membership function. The Fuzzy clustering is considered as a soft segmentation method. The brief literature survey about the fuzzy set theory for image segmentation can be seen in [12-15]. From literature, it is observed that the fuzzy c-means (FCM) algorithm [16-18] is more popular among the fuzzy clustering methods. In image segmentation, FCM is the most popular method because it has robust characteristics for vagueness and can hold much more information than hard segmentation methods [19-20]. However, the standard FCM algorithm is more suitable for noise-free images and it is very sensitive to noise and other imaging artifacts, since it does not consider any information about spatial context [21-23].

Tolias and Panas [24-26] have developed the ruled-based neighborhood enhancement system based on fuzzy rule-based scheme which imposes the spatial constraints by post processing the FCM clustering results. A geometrically guided FCM (GG-FCM) algorithm is proposed by Noordam et al. [27-28]. It is a semi-supervised FCM technique which considers the geometrical condition by taking into account the local neighborhood of each pixel. The FCM objective function is modified by Pham [29-30] where he included the spatial penalty on the membership functions. The penalty term shows the way for an iterative algorithm which is very similar to the original FCM algorithm. It is also allows the estimation of spatially smooth membership functions. Ahmed et al. [31-34] have proposed the FCM_S algorithm where the objective function of the classical FCM is modified in order to compensate the intensity in homogeneity and allow the labeling of a pixel to be influenced by the labels in its immediate neighborhood. The main disadvantage of FCM_S is computational more complex, because the neighborhood labeling need to calculate in each iteration step.

Chen and Zhang [35] have proposed two variants of the FCM_S algorithm (FCM_S1 and FCM_S2) in order to reduce the computational time. These two algorithms introduced the concepts of mean and median-filtered image, respectively [36]. These values are calculated in advance, to replace the neighborhood term of FCM_S. With this, the execution times of both FCM_S1 and FCM_S2 are considerably reduced. Further, they have improved the objective function of FCM_S to more likely reveal inherent non-Euclidean structures in data and more robustness to the noise. They have used the kernel-induced distance in place of the Euclidean distance. Further, they have proposed the kernel versions of FCM with spatial constraints, called KFCM_S1 and KFCM_S2 [37]. However, the main drawback of FCM_S and its variants FCM_S1, FCM_S2, KFCM_S1 and KFCM_S2 is that their parameters heavily affect the final clustering results.

To accelerate the image segmentation process, Szilagyi et al. [38-39] have proposed the enhanced FCM (EnFCM) algorithm. The structure of the proposed EnFCM algorithm is different from the FCM_S and its variants. First, a linearly-weighted sum image is formed by using both original image and each pixel's with local neighborhood mean gray level. Then clustering is performed on the basis of the gray level histogram instead of pixels of the summed image. The main reason behind this is that the number of gray levels in an image is generally much smaller than the number of its pixels, with this the computational time of EnFCM algorithm is reduced, while the quality of the segmented image is comparable to that of FCM_S [40]. Cai et al. [41] have proposed the fast generalized FCM algorithm (FGFCM) which incorporates the intensity of the local pixel neighborhood, the spatial information and the number of gray levels in an image. As compared to ref. [42], here they have calculated the image by nonlinearly-weighted sum from both original image and its local spatial and gray level neighborhood. The computational time of FGFCM is very small, because clustering is operated on the basis of the gray level histogram. The quality of the segmented image is well enhanced [43] as compared to [44]. The Gaussian kernel based FCM (GKFCM) for medical image segmentation is proposed by Yang and Tsai [45]. The proposed GKFCM algorithm becomes a generalized form of FCM, KFCM_S1 and KFCM_S2 algorithms and proposed with more efficiency and robustness. Chen et al. [46] have proposed the multiple-kernel fuzzy C-means (FCM) (MKFCM) for image-segmentation problems. They have used the linear combination of multiple kernels as composite kernel [47].

The hyper tangent FCM (HTFCM) based image segmentation for breast images is proposed by Kannan et al. [48]. They have used the hyper tangent function in place of Euclidean distance as objective function on feature space.

The main contributions of this paper are given as follows. (a) Mean filtering and Gaussian kernel based FCM (GKFCM) are integrated for medical image segmentation under different noise conditions. (b) The performance of the proposed method is tested on OASIS-MRI image data under different noise conditions. (c) The segmentation results show a significant improvement as compared to other existing methods [49-50].

The organization of the paper is given as follows. Sections I, presents the literature and related work of proposed clustering algorithms. The various methods which are available for cluster based segmentations are given in section II, Section III, presents the evaluation measures and dataset used in this paper. The experimental results and discussions are given in section IV. Conclusions are derived in section V.

2.Methods

2.1 Fuzzy C-means Algorithm

To avoid the problem of k-means algorithm, the fuzzy c-means clustering (FCM) algorithm is proposed. FCM shows extremely good results in image segmentation and object classification [51]. As in hard k-means algorithm, Fuzzy C-means algorithm is based on the minimization of a criterion function [52].

Suppose a data of n elements (image pixels), each of size $s(s=1)$ is represented as $X=(x_1,x_2,.....,x_n)$. FCM estimates the clusters iteratively by minimizing the objective function as given in Eq. (1).

Objective function: $$O_m(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}D^2(x_j,C_i) \tag{1}$$

Constraint: $$\sum_{i=1}^{c}U_{ij}=1;\quad \forall j \tag{2}$$

Where, U_{ij} is membership of the j^{th} data in the i^{th} cluster C_i, m is fuzziness of the system (m=2) and D is the distance between the cluster center and pixel.

FCM algorithm

Fig. 1 illustrates the flow chart of FCM algorithm and the algorithm for the same is given bellow.

Input: Raw image; Output: Segmented image;

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

- Randomly initialize the cluster centers C_i ($c = 3$ clusters).
- The distance D between the cluster center and pixel is calculated by using Eq. (3).

$$D^2(x_j, C_i) = \left\| x_j - C_i \right\|^2 \tag{3}$$

- The membership values are calculated by using Eq. (4).

$$U_{ij} = \frac{\left(D(x_j, C_i)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(D(x_j, C_k)\right)^{-1/(m-1)}} \tag{4}$$

- Update the cluster centers.

$$C_i = \frac{\sum_{j=1}^{n} U_{ij}^m x_j}{\sum_{j=1}^{n} U_{ij}^m} \tag{5}$$

- The iterative process starts:

1. Update the membership values U_{ij} by using Eq. (4).
2. Update the cluster centers C_i by using Eq. (5).
3. Update the distance D using Eq. (3).
4. If $\left| C_{new} - C_{old} \right| > \varepsilon; \quad (\varepsilon = 0.001)$ then go to step1
5. Else stop

Assign each pixel to a specific cluster for which the membership value is maximal

A. Kernel Based FCM

Kernel based FCM uses the kernel function in place of Euclidean distance [53-55]. The objective function with the mapping is as follows:

$$\text{Objective function: } O_m(U, C) = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}^m (1 - K(x_j, C_i))$$

The iterative updating of the cluster centers and membership functions for minimizing the objective function $O_m(U, C)$ are as follows:

$$C_i = \frac{\sum_{j=1}^{n} U_{ij}^m K(x_j, C_i) x_j}{\sum_{j=1}^{n} U_{ij}^m K(x_j, C_i)}; \; i = 1, 2, \ldots. C \tag{6}$$

$$U_{ij} = \frac{\left(1 - K(x_j, C_i)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1 - K(x_j, C_i)\right)^{-1/(m-1)}}; \quad \begin{array}{l} i = 1, 2, \ldots. C \\ j = 1, 2, .., n \end{array} \tag{7}$$

Here, the kernel function K is the Gaussian function with $K(x_j, C_i) = \exp(-\| x_j - C_i \|^2 / \sigma^2)$. The Gaussian kernel is suitable for clustering in which it can actually induce the necessary conditions. However, the KFCM algorithm is very sensitive to the noise [56-58]. To address this problem Chen and Zhang [59-60] have proposed the KFCM_S1 and KFCM_S2 algorithms which have utilized the spatial neigh pixel information by introducing α parameter.

B. Gaussian Kernal FCM (GKFCM)

Yang and Tsai [61] have proposed the GKFCM which is the generalized type of FCM, KFCM_S1 and KFCM_S2 algorithms. Here, they replace the parameter α with η_i which correlates the each cluster i. In this sense, Yang and Tsai [63] have considered the modified objective function $O_m^G(U,C)$ with the following constraints.

$$O_m^G(U,C) = \sum_{i=1}^{c}\sum_{j=1}^{n} U_{ij}^m (1 - K(x_j, C_i)) + \sum_{i=1}^{c}\sum_{j=1}^{n} \eta_i U_{ij}^m (1 - K(\bar{x}_j, C_i)) \quad (8)$$

where $K(x_j, C_i) = \exp(-\| x_j - C_i \|^2 / \sigma^2)$, $\bar{x}_j$ is the mean of the neighbor pixels, σ^2 is the variance of the total image.

$$C_i = \frac{\sum_{j=1}^{n} U_{ij}^m \left(K(x_j, C_i) x_j + \eta_i K(\bar{x}_j, C_i) \vec{x}_j \right)}{\sum_{j=1}^{n} U_{ij}^m \left(K(x_j, C_i) + \eta_i K(\bar{x}_j, C_i) \right)}; \; i = 1, 2, \ldots . C \quad (9)$$

$$U_{ij} = \frac{\left((1 - K(x_j, C_i)) + \eta_i (1 - K(\bar{x}_j, C_i)) \right)^{-1/(m-1)}}{\sum_{k=1}^{c} \left((1 - K(x_j, C_i)) + \eta_i (1 - K(\bar{x}_j, C_i)) \right)^{-1/(m-1)}}; \; \begin{matrix} i = 1, 2, \ldots . C \\ j = 1, 2, \ldots, n \end{matrix} \quad (10)$$

C. Integration of Mean and Peak-and-Valley Filtering and GKFCM

The ideas which are presented in mean filtering based image denoising [64] and GKFCM [65] are motivated us to propose the MPVFCM Algorithm.

Review of Mean Filtering

The earliest median filter proposed is the standard mean filter. In this method, there is a square window for filtering, and the window size is variable [66]. The center pixel in the scan window is to be de-noised. The first step is to sort all the pixel values in the scan window, and the second step is to change the value into the standard mean of the sorted sequence. The standard mean filter method is a simple and efficient technique to remove impulse noise, and it has lasted used for a long time [67].

Review of Peak-and-Valley Filtering

The Peak-and-Valley filter is a new filter algorithm that has been put forward lately; it differs from the Median filter and adopts a series of operations based on min-max operators [68]. Its core algorithm is following: first, it finds out the minimum and the maximum of the eight pixels surrounding the central pixel within a 3×3 window, then, compares the value of the central pixel with the minimum and the maximum, if the central pixel has a gray level which is much higher than the maximum, this means that the central pixel has been noised, and its gray level is replaced by the maximum, on the contrary, if the central pixel has a gray level which is much smaller than the

 UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

minimum, its gray level is replaced by the minimum [69]. Compared with the Median filter, the filter algorithm has a noise detection function; it is found to be adaptive to noise density variation and prone to protecting the details of the image better [70].

After calculaton of mean and peak-and-valley filtering, the resultant image is used for the segmentation with GKFCM algorithm. The algorithm for the proposed segmentation method is given bellow.

MPVFCM Algorithm

Input: Raw image; Output: Segmented image;

- Apply the mean and peak-valley filter based denoising.
- Apply the GKFCM using the following steps.
- Randomly initialize the cluster centers C_i ($c = 3$ clusters)
- Membership values calculation using Eq. (11).
- Cluster centers updating using Eq. (12).
- The iterative process starts:
  1. Membership values updating U_{ij} using Eq. (11).
  2. Update the cluster centers C_i by using Eq. (12).
  3. If $|C_{new} - C_{old}| > \xi$; ($\xi = 0.001$) then go to step1
  4. Else stop
- Assign each pixel to a specific cluster for which the membership value is maximal

3.Evaluation Measures and Dataset.

3.1 Segmentation accuracy/Score

In order to analyze the performance of the proposed method, we use the score which is defined in [71] and [72]. The score S_{ik} is defined as:

$$S_{ik} = \frac{A_{ik} \cap A_{refk}}{A_{ik} \cup A_{refk}} \quad (13)$$

Where A_{ik} represents the set of pixels belonging to the k^{th} class calculated by the i^{th} algorithm and A_{refk} represents the set of pixels belonging to the k^{th} class in the reference segmented image.

In this paper, we also used the number of iterations (NI) and execution time which are required for the convergence of the algorithm.

TABLE I: MRI DATA ACQUISITION DETAILS [27]

Sequence	MP-RAGE
TR (msec)	9.7
TE (msec)	4.0
Flip angle (o)	10
TI (msec)	20
TD (msec)	200

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

Orientation	**Sagittal**
Thickness, gap (mm)	**1.25, 0**
Resolution (pixels)	**176×208**

3.2 MRI Dataset

The Open Access Series of Imaging Studies (OASIS) [62] is a series of magnetic resonance imaging (MRI) dataset that is publicly available for study and analysis. This dataset consists of a cross-sectional collection of 421 subjects aged 18 to 96 years. The MRI acquisition details are given in Table 1. The performance of the proposed method is measures in terms of score, number of iterations and execution time. Fig. 1 illustrates two sample images selected for experimentation.

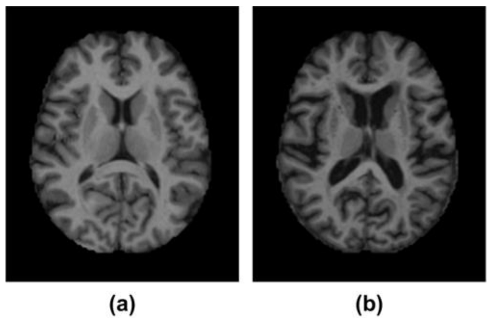

Fig. 1: Sample images used for experiments

4. Results and Discussions

In order to prove the effectiveness of the proposed algorithm, experiments were conducted on two brain MRIs [26]. The performance of the proposed algorithm is tested in terms of score, number of iterations (NI) and computational time (CT) and PSNR as compared to other existing FCM varient methods on OASIS-MRI dataset.

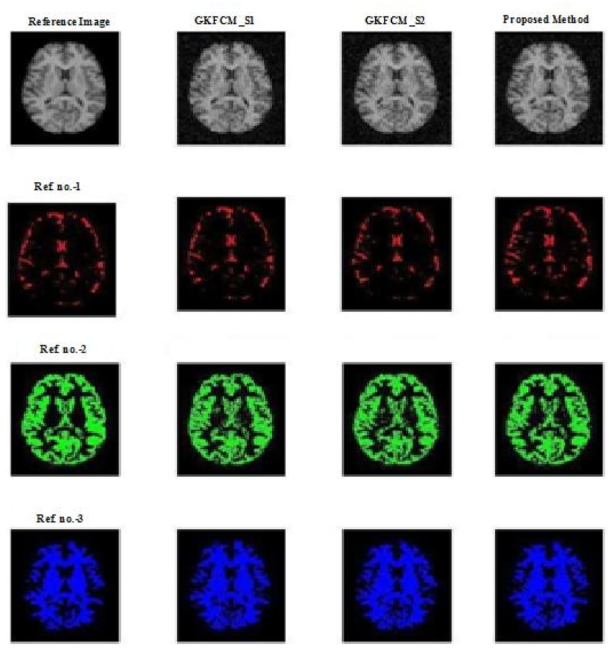

Fig. 2: Comparison of proposed method with other existing methods (GKFCM_S1 and GKFCM_S2) in terms of three segmented clusters. The original image (*Image (a)*) are corrupted with 5% of Gaussian noise.

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

TABLE II: COMPARISON OF VARIOUS TECHNIQUES IN TERMS OF SCORE ON IMAGE (A) AT DIFFERENT GAUSSIAN NOISES
CL: CLUSTER

Method	Gaussian Noise (%)											
	5%			10%			15%			20%		
	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3	Cl-1	Cl-2	Cl-3
GKFCM-S1	0.50	0.69	0.85	0.50	0.62	0.78	0.51	0.49	0.79	0.45	0.53	0.71
GKFCM-S2	0.49	0.65	0.87	0.42	0.55	0.80	0.50	0.55	0.79	0.47	0.44	0.69
Proposed Method	0.48	0.63	0.83	0.44	0.58	0.76	0.36	0.54	0.68	0.27	0.43	0.65

TABLE III: COMPARISON OF VARIOUS TECHNIQUES IN TERMS OF NUMBER OF ITERATIONS AND EXECUTION TIME AT DIFFERENT GAUSSIAN NOISE ON IMAGE (B)
NI: NUMBER OF ITERATIONS; TM: EXECUTION TIME (SEC.)

Method	Gaussian Noise							
	5%		10%		15%		20%	
	NI	TM	NI	TM	NI	TM	NI	TM
GKFCM-S1	17	0.28	16	0.31	18	0.32	22	0.43
GKFCM-S2	25	0.54	22	0.48	27	0.58	27	0.52
Proposed Method	29	0.65	28	0.65	30	0.61	30	0.66

TABLE IV: EVALUATION OF MPVFCM INTERMS OF PSNR WITH DIFFERENT GAUSSIAN NOISE

Noise level	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
0.01	44.07	24.51	35.48	36.45	45.23	26.77	24.45
0.02	45.02	42.44	48.55	46.56	45.89	26.23	30.34
0.03	46.11	42.23	42.98	32.45	22.45	42.35	38.78
0.04	25.42	37.99	26.56	44.56	43.33	34.23	40.34
0.05	34.23	46.32	45.34	27.56	44.09	42.09	44.21

TABLE V: EVALUATION OF MPVFCM_S1 INTERMS OF PSNR WITH DIFFERENT GAUSSIAN NOISE

Noise level	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
0.01	43.09	30.34	38.78	36.89	44.56	30.77	25.78
0.02	44.89	44.09	47.78	47.24	47.78	27.89	30.76
0.03	46.76	44.77	43.23	34.56	22.46	43.21	37.89
0.04	29.99	41.77	28.09	45.78	43.45	37.43	38.99
0.05	36.45	46.87	46.87	19.89	44.76	43.90	44.89

TABLE VI: EVALUATION OF MPVFCM_S2 INTERMS OF PSNR WITH DIFFERENT GAUSSIAN NOISE

Noise level	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
0.01	43.12	31.12	39.41	36.78	45.45	41.42	38.50
0.02	45.23	44.45	46.78	44.12	46.21	40.35	37.61
0.03	45.45	44.60	44.32	35.45	42.11	42.55	37.51
0.04	31.12	41.54	29.23	43.34	42.20	43.56	41.40
0.05	34.56	47.56	46.60	39.40	43.15	43.45	44.26

Fig. 2 illustrates the cluster segmentation results of the proposed method and other existing methods with the 5% Gaussian noise on Image (a) of OASIS-MRI dataset. The performance of the proposed method is compared with the GKFCM_S1 and GKFCM_S2. Table II to Table III shows the segmentation performance in terms of score, NI,TM and PSNR on image (a) and Image (b) respectively under different Gaussian noise conditions. From, Fig. 2 and Tables II to VI, it is clear that the proposed method outperforms the other existing algorithms in terms of score, NI,TM and PSNR.

4. Conclusions:

In this paper, new image segmentation algorithms (*MPVFCM*) which are increasing the performance and decreasing the computational complexity is proposed. The algorithm utilizes the integration of mean filtering and GKFCM algorithms for segmentation. The proposed algorithm is applied on brain MRI which degraded by Gaussian noise. The segmentation results demonstrate that the proposed algorithm shows the robustness under different noises as compared to other existing image segmentation algorithms from FCM family.

References:

[1] Vaigandla, K. K., & Venu, D. N. (2021). A survey on future generation wireless communications-5G: multiple access techniques, physical layer security, beamforming approach. *Journal of Information and Computational Science*, *11*(9), 449-474.

[2] Venu, D., Arun Kumar, A., & Vaigandla, K. K. (2022). Review of Internet of Things (IoT) for Future Generation Wireless Communications. *International Journal for Modern Trends in Science and Technology*, *8*(03), 01-08.

[3] Sujith, A. V. L. N., Swathi, R., Venkatasubramanian, R., Venu, N., Hemalatha, S., George, T., & Osman, S. M. (2022). Integrating nanomaterial and high-performance fuzzy-based machine learning approach for green energy conversion. *Journal of Nanomaterials*, *2022*, 1-11.

[4] Venu, N., & Anuradha, B. (2013, December). Integration of hyperbolic tangent and Gaussian kernels for fuzzy C-means algorithm with spatial information for MRI segmentation. In *2013 Fifth International Conference on Advanced Computing (ICoAC)* (pp. 280-285). IEEE.

[5] Vaigandla, K. K., & Venu, D. N. (2021). Ber, snr and papr analysis of ofdma and sc-fdma. GIS Science Journal, ISSN, (1869-9391), 970-977.

[6] Venu, N. (2014, April). Performance and evalution of Guassian kernals for FCM algorithm with mean filtering based denoising for MRI segmentation. In *2014 International Conference on Communication and Signal Processing* (pp. 1680-1685). IEEE.

[7] Karthik Kumar Vaigandla, D. (2021, November). Survey on Massive MIMO: Technology, Challenges, Opportunities and Benefits. *YMER* , 271-282.

[8] Venu, N., & Anuradha, B. (2015). Multi-Kernels Integration for FCM algorithm for Medical Image Segmentation Using Histogram Analysis. *Indian Journal of Science and Technology*, *8*(34), 1-8.

[9] Venu, N., Yuvaraj, D., Barnabas Paul Glady, J., Pattnaik, O., Singh, G., Singh, M., & Adigo, A. G. (2022). Execution of Multitarget Node Selection Scheme for Target Position Alteration Monitoring in MANET. *Wireless Communications and Mobile Computing*, *2022*.

[10] Venu, N., Swathi, R., Sarangi, S. K., Subashini, V., Arulkumar, D., Ralhan, S., & Debtera, B. (2022). Optimization of Hello Message Broadcasting Prediction Model for Stability Analysis. *Wireless Communications & Mobile Computing (Online)*, *2022*.

[11] Venu, D. N. (2015). Analysis of Xtrinsic Sense MEMS Sensors. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering* , *4* (8), 7228-7234.

[12] Venu, N., & Anuradha, B. (2013). A novel multiple-kernel based fuzzy c-means algorithm with spatial information for medical image segmentation. *International Journal of Image Processing (IJIP)*, *7*(3), 286.

[13] Nookala Venu, A. (2018). Local mesh patterns for medical image segmentation. *Asian Pacific Journal of Health Sciences*, *5*(1), 123-127.

[14] Venu, N., & Anuradha, B. (2013). PSNR Based Fuzzy Clustering Algorithms for MRI Medical Image Segmentation. *International Journal of Image Processing and Visual Communication*, *2*(2), 01-07.

[15] Thouti, S., Venu, N., Rinku, D. R., Arora, A., & Rajeswaran, N. (2022). Investigation on identify the multiple issues in IoT devices using Convolutional Neural Network. *Measurement: Sensors*, *24*, 100509.

[16] Venu, N., Revanesh, M., Supriya, M., Talawar, M. B., Asha, A., Isaac, L. D., & Ferede, A. W. (2022). Energy Auditing and Broken Path Identification for Routing in Large-Scale Mobile Networks Using Machine Learning. *Wireless Communications and Mobile Computing*, *2022*.

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023

[17] Kesavaiah, D. C., Goud, T. R., Rao, Y. S., & Venu, N. (2019). Radiation effect to MHD oscillatory flow in a channel filled through a porous medium with heat generation. *Journal of Mathematical Control Science and Applications*, *5*(2), 71-80.

[18] Nookala Venu, B. A. (2015). Medical Image Segmentation Using Kernal Based Fuzzy C-Means Algorithm. *International Journal of Engineering Innovation & Research , 4* (1), 207-212.

[19] Nookala Venu, D., Kumar, A., & Rao, M. A. S. (2022). BOTNET Attacks Detection in Internet of Things Using Machine Learning. *Neuroquantology*, *20*(4), 743-754.

[20] Venu, N., & Anuradha, B. (2014, February). Multi-Hyperbolic Tangent Fuzzy C-means Algorithm for MRI Segmentation. In *Proceedings of International Conference on Advances in Communication, Network and Computing (CNC-2014), Elsevier* (pp. 22-24).

[21] Nookala Venu, S. W. (2022). A Wearable Medicines Recognition System using Deep Learning for People with Visual Impairment. *IJFANS*, *12*(1), 2340-2348.

[22] Nookala Venu, G. R. (2022). Smart Road Safety and Vehicle Accidents Prevention System for Mountain Road. *International Journal for Innovative Engineering Management and Research , 11* (06), 209-214.

[23] Nookala Venu, D., Kumar, A., & Rao, M. A. S. (2022). Smart Agriculture with Internet of Things and Unmanned Aerial Vehicles. *Neuroquantology*, *20*(6), 9904-9914.

[24] Nookala Venu, D., Kumar, A., & Rao, M. A. S. (2022). Internet of Things Based Pulse Oximeter For Health Monitoring System. *NeuroQuantology*, *20*(5), 5056-5066.

[25] Venu, D. N. DA (2021). Comparison of Traditional Method with watershed threshold segmentation Technique. *The International journal of analytical and experimental modal analysis*, *13*, 181-187.

[26] Dr.Nookala Venu, D. K. (2022). Investigation on Internet of Things (IoT):Technologies, Challenges and Applications in Healthcare. *International Journal of Research , XI* (II), 143-153.

[27] Kesavaiah, D. C., Goud, T. R., Venu, N., & Rao, Y. S. (2021). MHD Effect on Convective Flow Of Dusty Viscous Fluid With Fraction In A Porous Medium And Heat Generation. *Journal of Mathematical Control Science and Applications*, *7*(2).

[28] Babu, K. R., Kesavaiah, D. C., Devika, B., & Venu, D. N. (2022). Radiation effect on MHD free convective heat absorbing Newtonian fluid with variable temperature. *NeuroQuantology*, *20*(20), 1591-1599.

[29] Kesavaiah, D. C., Ahmed, M., Reddy, K. V., & Venu, D. N. (2022). Heat and mass transfer effects over isothermal infinite vertical plate of Newtonian fluid with chemical reaction. *NeuroQuantology*, *20*(20), 957-967.

[30] Reddy, G. B., Kesavaiah, D. C., Reddy, G. B., & Venu, D. N. (2022). A note on heat transfer of MHD Jeffrey fluid over a stretching vertical surface through porous plate. *NeuroQuantology*, *20*(15), 3472-3486.

[31] Chenna Kesavaiah, D., Govinda Chowdary, P., Rami Reddy, G., & Nookala, V. (2022). Radiation, radiation absorption, chemical reaction and hall effects on unsteady flow past an isothermal vertical plate in a rotating fluid with variable mass diffusion with heat source. *NeuroQuantology*, *20*(11), 800-815.

[32] Kesavaiah, D. C., Prasad, M. K., Reddy, G. B., & Venu, N. (2022). Chemical Reaction, Heat and Mass Transfer Effects on MHD Peristaltic Transport in A Vertical Channel Through Space Porosity And Wall Properties. *NeuroQuantology*, , *20*(11), 781-794.

[33] Kesavaiah, D. C., Reddy, G. B., Kiran, A., & Venu, D. N. (2022). MHD effect on boundary layer flow of an unsteady incompressible micropolar fluid over a stretching surface. *NeuroQuantology*, , *20*(8), 9442-9452.

[34] Kesavaiah, D. C., Chowdary, P. G., Chitra, M., & Venu, D. N. (2022). Chemical reaction and MHD effects on free convection flow of a viscoelastic dusty gas through a semi infinite plate moving with radiative heat transfer. *NeuroQuantology*, *20*(8), 9425-9434.

[35] Mr.RadhaKrishna Karne, M. M. (2022). Applications of IoT on Intrusion Detection System with Deep Learning Analysis. *International Jourfor Innovative Engineering and Management Research , 11* (06), 227-232.

[36] Venu, N., & Anuradha, B. (2015). Two different multi-kernels for fuzzy C-means algorithm for medical image segmentation. *Int. J. Eng. Trends Technol.(IJETT)*, *20*, 77-82.

[37] Kesavaiah, D. C., Goud, T. R., Venu, N., & Rao, Y. S. (2017). Analytical Study on Induced Magnetic Field With Radiating Fluid Over A Porous Vertical Plate With Heat Generation. *Journal of Mathematical Control Science and Applications*, *3*(2).

[38] Dr. Nookala Venu, D. A. (2022, March). Routing and Self-Directed Vehicle Data Collection for Minimizing Data Loss in Underwater Network. *IJFANS International Journal of Food and Nutritional Sciences* , 170-183.

[39] Dr. Nookala Venu, D. A. (2022). Fuzzy Based Resource Management Approach for the Selection of Biomass Material. *IJFANS International Journal of Food and Nutritional Sciences* , *12* (2), 83-97.

[40] Ravindra Kumar Agarwal, D. S. (2022). A Novel Dates Palm Processing and Packaging Management System based on IoT and Deep Learning Approaches. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (8), 1139-1151.

[41] Manthur Sreeramulu Manjunath, P. K. (2022). An Enhanced Machine Learning Approach For Identifying Paddy Crop Blast Disease Management Using Fuzzy Logic. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (8), 1152-1163.

[42] K.P.Senthilkumar, K. C. (2022). Machine Learning Based Analysis and Classification of Rhizome Rot Disease in Turmeric Plants. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (8), 1179-1190.

[43] Sowmya Jagadeesan, B. B. (2022). A Perishable Food Monitoring Model Based on IoT and Deep Learning to Improve Food Hygiene and Safety Management. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (8), 1164-1178.

[44] Nookala Venu, S. K. (2022). Machine Learning Application for Medicine Distribution Management System. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (1), 2323-2330.

[45] Reddy, A. V., Kumar, A. A., Venu, N., & Reddy, R. V. K. (2022). On optimization efficiency of scalability and availability of cloud-based software services using scale rate limiting algorithm. *Measurement: Sensors*, *24*, 100468.

[46] Venu, D. (2022). Radiation Effect to Mhd Oscillatory Flow in a Channel Filled Through a Porous Medium with Heat Generation. *Radiation Effect to Mhd Oscillatory Flow in a Channel Filled Through a Porous Medium with Heat Generation (August 27, 2022).*

[47] Venu, D. N. (2022). Smart Agriculture Remote Monitoring System Using Low Power IOT Network. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (6), 327-340.

[48] Venu, D. N. (2022). IOT Surveillance Robot Using ESP-32 Wi-Fi CAM & Arduino. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (5), 198-205.

[49] Nookala Venu, N. S. (2022). Study and Experimental Analysis on FBMC and OFDM. *International Journal for Innovative Engineering and Management Research* , *11* (06), 49-53.

[50] Sandhya rani B, S. K. (2022). Vehicle Fuel Level Monitor and Locate the Nearest Petrol Pumps using IoT. *International Journal for Innovative Engineering and Management Research* , *11* (06), 233-240.

[51] Nookala Venu, K. A. (2022). Face Mask Detection System Using Python Open CV, *International Journal for Innovative Engineering and Management Research*, *11* (6), 28-32.

[52] Nookala Venu, V. M. (2022). Alcohol Detection and Engine Locking System. *International Journal for Innovative Engineering and Management Research* , *11* (06), 157-160.

[53] Nookala Venu, C. B. (2022). Wireless Night Vision Camera on War Spying Robot. *International Journal for Innovative Engineering and Management Research* , *11* (06), 123-128.

[54] Venu, D. N. (2022). IOT Based Enabled Parking System in Public Areas. *IJFANS International Journal of Food and Nutritional Sciences, 11* (4), 162-174.

[55] Venu, D. N. (2022). IOT Based Speech Recognition System to Improve the Performance of Emotion Detection. *IJFANS International Journal of Food and Nutritional Sciences, 11* (3), 92-102.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper **UGC CARE Listed (Group -I) Journal Volume 12, Iss 1, Jan 2023**

[56] Dr.Nookala Venu, M. S. (2018). Local Maximum Edge Binary Patterns for Medical Image Segmentation. *International Journal of Engineering and Techniques*, *4* (1), 504-509.

[57] Venu, N., & Anuradha, B. (2016). Multi-hyperbolic tangent fuzzy c-means algorithm with spatial information for MRI segmentation. *International Journal of Signal and Imaging Systems Engineering*, *9*(3), 135-145.

[58] Venu, N., & Anuradha, B. (2015). Hyperbolic Tangent Fuzzy C-Means Algorithm with Spatial Information for MRI Segmentation. *International Journal of Applied Engineering Research*, *10*(7), 18241-18257.

[59] Venu, N., & Anuradha, B. (2015, April). Two different multi-kernels integration with spatial information in fuzzy C-means algorithm for medical image segmentation. In *2015 International Conference on Communications and Signal Processing (ICCSP)* (pp. 0020-0025). IEEE.

[60] Nookala Venu, B. (2015). MRI Image Segmentation Using Gaussian Kernel Based Fuzzy C-Means Algorithm. *International Journal of Electronics Communication and Computer Engineering* , *6* (1), 140-145.

[61] Venu, N., & Anuradha, B. (2015). Evaluation of Integrated Hyperbolic Tangent and Gaussian Kernels Functions for Medical Image Segmentation. *International Journal of Applied Engineering Research*, *10*(18), 38684-38689.

[62] Anita Tuljappa, V. N. (2022). Dufour and Chemical Reaction Effects on Two Dimensional incompressible flow of a Viscous fluid over Moving vertical surface. *NeuroQuantology* , 63-74.

[63] Ch. Achi Reddy, V. N. (2022). Magnetic Field And Chemical Reaction Effects on Unsteady Flow Past A Stimulate Isothermal Infinite Vertical Plate. *NeuroQuantology* , *20* (16), 5360- 5373.

[64] Sowmya Jagadeesan, M. K. (2022). Implementation of an Internet of Things and Machine learning Based Smart Medicine Assistive System for Patients with Memory Impairment. *IJFANS International Journal of Food and Nutritional Sciences* , 1191-1202.

[65] Venu, D. N. (2023). Design Analysis and Classification of Digital Transmission Based Composite Relay and Artificial Neural Network Approach. *IJFANS International Journal of Food and Nutritional Sciences* , *12* (1), 680-63.

[66] Venu, D. N. (2023). Biomass Studies on Pyrolysis of Sugarcane Bagasse and Cashew Nut Shell for Liquid Fuels. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (1), 695-706.

[67] Venu, D. N. (2023). Synthesis and Study on Feasibility of Ethanol Production from Leachate of Pretreatment of Sugarcane Bagasse. *IJFANS International Journal of Food and Nutritional Sciences* , *12* (1), 707-715.

[68] Venu, D. N. (2022). Design and Performance Analysis of Super Critical Fluid Extraction for SC-CO2. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (12), 3854-3865.

[69] Venu, D. N. (2022). Supercritical Fluid Evaluation and Extraction of Phenol from Sugarcane Bagasse Pyrolysis Oil. *IJFANS International Journal of Food and Nutritional Sciences* , *11* (12), 3866-3876.

[70] Sandhya rani, D. V. (2022). IOT Based Smart Irrigation System Using Node MCU. *International Journal For Innovative Engineering and Management Research* , *11* (06), 100-106.

[71] Dr.Nookala Venu, A. E. (2022). Low Power Area Efficient ALU with Low Power Full Adder. *International Journal For Innovative Engineering and Management Research* , *11* (06), 167-170.

[72] Nookala Venu, B. (2015). Brain MRI Medical Image Segmentation Using Fuzzy Based Clustering Algorithms. International Journal of Engineering Trends and Technology, 22 (2), 83-88.