

Brain Tumor Segmentation by Level-Set and Chan-Vese Methods using different Fusion Approaches

Rajesh Babu, K¹, T. Manjula², M. Anil Kumar³, B. Yaswanth Sai⁴, U. Sai Deepthi⁵, S. Veerabhimanyu⁶,
B.Raja⁷, Syed Inthiyaz⁸

^{1,8}Associate Professor, ²Lecturer, ³Assistant Professor, ^{4,5,6,7}Student

^{1,3,4,5,6,7,8} Department of ECE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur.

²Department of ECE, Government Polytechnic for Women (M), Badangpet, Hyderabad.

ABSTRACT

Accurate identification of tumor in brain is a challenging task in medical image processing and diagnosing the tumor with the use of Magnetic Resonance Image (MRI). So, identification tumor plays important role and there are many traditional segmentation methods which gives output, but it may or may not be accurate. So in this paper we compared two models which are segmentation with fusion and segmentation without fusion by comparing their performance metrics we can conclude which model gives more accurate performance metrics and is more preferable for Processing of image which helps to cure the tumor. The MRI grey scale image-based segmentation is a compound task because of unpredictability of brain tumors. In this clustering and segmentation methods are used. The main aim of this work is to compare two referable models, and which has better performance metrics where includes PSNR, MSE, SSIM, DC and gives the preferable model.

Key words: Brain tumour; Magnetic Resonance Image; Segmentation; K-Means; Fuzzy C Means; Chan-Vese; Level Set

1. INTRODUCTION

Brain tumor means bulk or evolution of irregular cells inside the brain. The skull which surrounds the brain is extremely inelastic. Any tumor privileged such a regulated space can cause problems. There are two (2) main forms of brain tumors, benign (non-cancerous) and Malignant (cancerous) tumors [1]. Malignant (cancerous) tumors are separated into two types primary and secondary tumors, the first tumor is which starts within the brain and secondary tumor which are spread from one location to a different location. And benign (non-cancerous) tumors are of two types Adenomas and Fibromas. Benign (non-cancerous) tumors are called as low grade and malignant (cancerous) tumors is thought as high- grade. When any sort of tumor rises, they'll

cause the burden inside skull to growth. this might cause brain harm and it's dangerous. The tumor detection is finished with the assistance of MRI's, CAT, Ultrasound, X-rays and lots of more. during this paper we are using brain MRI images for detecting tumor. Primary brain tumors originate in brain and might developed from

- Brain cells
- The membranes that mount the brain
- Nerve cells
- Glands.

Gliomas are tumor that develops from glial cells and are normally

- Supports the structure of your central system nervous
- Provide nutrition to central system nervous
- Clean cellular waste
- Break down dead neurons.

There are 4 grades in tumor

Grade I - during this grade the tumors are slowly increasing and doubtful to spread. and that they will be cured by operation.

Grade II - during this grade tumors are not as much of possible to grow and spread. and that they often grow after the treatment.

Grade III – during this grade the tumors are more expected to grow rapidly.

Grade IV – during this grade the tumors are actively dividing into a greater number of cells. and can be growing as fast because it can, it'll be the last grade of tumor and for the effected person too [2].

Why this problem occurs? It occurs thanks to inaccurately location area of tumor. And there's no specific reason for the abnormal growth of tumor and it mainly caused by damaged DNA. The tumor imaging will be done by:

- i). CT scanning i.e., computer tomography.
- ii). Ultrasound.
- iii). X-Rays.
- iv). MRI scanning i.e. magnetic resonant image.

Although surgery is that the commonest handling for brain tumors except surgery radiation and chemotherapy will be slow the expansion of tumors but cannot be removed

physically [3].

MRI (magnetic resonance imaging) is one in all the common tests used to diagnose the brain tumors which offer detailed images of brain. The MRI works as

Firstly, the patient is put in a very flux so a sender sends a electromagnetic wave through patient body where the scan is required so the electromagnetic wave shakes the protons that are present in patient body and when the electromagnetic wave ends the proton continues to shake for a few time and after then creates a brand new electromagnetic wave which is captured by an antenna (coil) at finally a computer algorithm turns it into a MR image.

2. RELATED WORK

Rajesh Babu K, et.al, [4] Studied the Chan-Vese and level set segmentation algorithms for brain tumour detection, As we have to enhance the segmentation process we test the MRI Denoised data using median filter, Then proceed to carry three stages, Three stages were developed, CNN, CT, NSCT, MWGF, GFF. A third stage includes segmentation over Fused Images. The result was performed by taking various performance metrics and Chan-vase Model gives better result than Level set before fusion.

Rajesh Babu K, et.al, [5] Analyzed the FCM algorithm and FCM is widely used in analysis of features, At first it was prone to the initialization problems and easily falls in to local minimum or saddle point on iteration, Several Techniques that are based on Global optimization That are Used to solve this problem, PSO Based FCM Clustering is a revolutionary extended clustering algorithm for image segmentation, The model focuses on Clustering of pre-processed MRI images containing brain tumour, As per Observations we noted FCM is more efficient than K-means in terms of performance.

Rajesh Babu K et.al [6] Examined the detection of brain tumour Using various methods Thresholding, K means, Clustering, Fuzzy c means, we are using genetic algorithm in paper, At first stage preprocessing method of segmentation with optimization to remove noise and increase contrast of input image, images of pre-processed and genetic algorithm are applied to PSO and DPSO algorithms of segmentation with optimization to detect error.

Muhammad Zawish, et.al [7] proposed a method which gives information on deformable contours and Modelling which separates the fore ground objects from back ground, Models given energy functions gets minimized using The level set method which guide evolving curves towards the boundaries, Among the active contour models The Chan-Vase models gets high attention to the different applications for Image Segmentations, Brain tumour segmentations in Number of Iterations 150,200 and 250, Has been clearly shown in result.

Vinay Rao, et.al. [8] Has taken a Approach to finding Tumour in images of brain by pixel wise classification, Used deep Convolution Neural Network for easy modality and

learning quality representation for pixel, Each CNN is assumed as a pixel of non-tumour, Necrosis, edema, non-enhancing, enhancing, two settings were implemented and accuracy and loss in percentages were calculated in result.

Agn, Mikael, et.al. [9] Author proposed a fully computerized method for brain tumour segmentation, with a tumour erstwhile that uses convolution controlled Boltzmann machines to model tumour shape, he have shown that methods performance associates well with current state of art on free benchmarking data sets.

Alqazzaz, et.al [10] Demonstrated that using Seg Net with 3D MRI datasets Models and the combining of four maximum feature maps with pixel concentration values of the original MRI modalities has capability to achieve well on segmentation of brain tumour.

M.S. Sarabi, et.al. [11] evaluates the performance of HNNs-based method for brain tumour separation in MRI images, The evaluation was performed for different data sets using two-fold cross validation on BRATS 2013, The proposed method out forms the common completely convolutionary network (FCN) method, In terms of the efficiency.

B. Fischl et.al [12] compared with manual segmentation in order to validate the automated segmentation, Results of automatic to manually labelling data sets, each of these labelling were compared to two criteria of percent overlap and percent columns.

Rolf A. Heckemann, et.al [13] illustrated MRI segmentation by combining label circulation and decision fusion, Label propagation is approach to provide anatomical segmentation without requiring interactive human input, drawing on concepts and principles from pattern recognition field, Suggest the results of the process.

2.1 Dataset

One of the main encounters of any scheme is to find the suitable dataset. Bio medical images are hard to find due to privacy issues. But the dataset we have used for this model was taken from BRATS (Brain Tumor Segmentation) dataset from 2015.

BRATS are a challenge that has been started from 2015 and has been done every year.

For our model we have taken 250 image samples which consist of tumor and no tumor. The images are MRI scans. This has to classes:

- NO- no tumor, encoded as 0
- YES- tumor, encoded as 1.

The entire dataset is separated into two parts training set and testing set. And each set consist of both tumor and no tumor images. The whole 100% data is divided as 65% of the total data is given for training of the model, and the remaining 35% is given for testing the model. We are modelling the model with the help of dataset by using python tensor flow. This gives more accuracy and also less computational time.

3. METHODOLOGY

In order to enhance segmentation prospects, test MRI data is de-noised using median filter. Further processing has been carried in next stages. In the first step for dimensionality reduction by using Random Projection Technique (RPT) model and in the next step clustering algorithms takes place and the methods used are K-Means and Fuzzy C-Means. And after clustering the output image is undergone both segmentation without fusion and with fusion. In segmentation the methods are Level-Set and Chan-Vese and fusion cell CNN, CVT, NSCT, MEGF methods are used to find segmented image.

3.1 Pre-Processing

In this step de- noising the input 2D MRI image is done by using median filter. Median filter is a non-linear filtering technique. It is used to eliminate noise from the image or for a signal. This type of techniques is used in pre-processing phase to improve the results for letter processing. Median filter is an actual method that can differentiate isolated out - of-range noise from valid image features such as boundaries and lines in some way. The median filter explicitly swaps a pixel by the median value of altogether neighborhood pixels.

The expression is

$$y [p, q] = \text{median} \{ x [m, n], (m, n) \in U \} \quad (1)$$

Where u represents a neighborhood defined by the operator, centered around position $[p, q]$ in the image.

3.2 Clustering Methods

3.2.1 K-Means Clustering Algorithm

K-Means is one of the clustering methods. Clustering is an unsupervised machine learning algorithm. Clustering means grouping of similar records together in each dataset. This is a non-hierarchical clustering technique and an iterative algorithm that attempts to partition the dataset into a predefined amount of non-overlapping clusters by minimizing the square distance from each information point to the centroid cluster. It's a single type of clustering [14]

$$F = \sum_{i=1}^k \sum_{j=1}^n \|x_j - \mu_i\|^2 \quad (2)$$

x_j is input data, μ_i is mean value.

3.2.2 Fuzzy C Means Clustering Algorithm

Grouping of objects/data such that substances in a group are more alike to each other than those in other groups. Is called clustering. Fuzzy C Means is a multiple clustering method.[15]. Fuzzy C-mean (derived from fuzzy logic) is a clustering technique, which calculates the measure of similarity of each observation to each cluster. Indirectly it

means that each observation belongs to one or more clusters at the same time, unlike traditional clustering algos in which each data point is a part of single cluster only

$$O(U, c_i) = \sum_{i=1}^k O_i = \sum_{i=1}^k \sum_{j=1}^n u_{ij}^m d_{ij}^2 \quad (3)$$

U_{ij} is membership value, d_{ij} is distance between j th data point and i th cluster.

3.3 Fusion Algorithms

3.3.1 Convolution Neural Networks (CNN)

Convolution Neural Networks are a type of neural networks. Are widely used for image recognition and classification purpose[16]. There are 3 classifications in CNN. They are Le Net, Alex Net, Google Net. CNN is mainly used to image classification [17]. We give the image as input, but the computer takes it in the form of array of pixels. The layers in CNN are convolution layer, maxpooling, Re LU and fully convolution layer [18].

$$\begin{aligned} (f * g)(t) &\stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)g(t - \tau) d\tau \\ &= \int_{-\infty}^{\infty} f(t - \tau)g(\tau) d\tau. \end{aligned} \quad (4)$$

3.3.2 Curvelet Transform (CVT)

CVT is more suitable than wavelet for the study of image edges, such as curve and line characteristics. It is known as the 2D transform. It is a discrete transform. CVT that is first formed in a continuous domain, and then diced to sampled data.

Two filter banks (FB) is used to construct CVT. Curvelet is a multiscale and multidirectional change capable to communicate to bend as an organization of super imposed elements of different lengths and widths [19]. It depends on multi scale ridge lets with a band pass sifting to isolate a picture into disjoint scales. The side length of the limiting windows is multiplied at each other dyadic sub band for keeping up the essential property of the Curvelet change.

3.3.3 Non-Subsampled Contourlet Transform (NSCT)

Non-Subsampled Contourlet Transform provides a multi-resolution and multi-directional analysis for 2D multiple scales, with flexible feature ratios which is a new allowance of wavelet transform. It is used for image enhancement purpose [20].

NSCT is a fully shift invariant version of contourlet transform. It allows for dissimilar and elastic number of instructions at each scale.

3.3.4 Multi-scale Weighted Gradient (MWGF)

The point of the leaning founded grouping is later to combination all the overbearing slope data from the information pictures and move it into the melded picture. It

depends on a "circuit then-break down" system, in which disposition channel is utilized to play out a superior component choice in the slope area, and after that exploit the traditional multi resolution technique to reproduce the intertwined picture [21]. The weighted inclination-based combination plan is proficient to distinguish the most essential nearby structures in the info pictures and reduce them into the interwove picture.

3.4 Segmentation Algorithms

3.4.1 Chan-Vese Model(C-V)

The Chan-Vese model is based on the functional Mumford-Shah for image segmentation and is commonly used in medical imaging, particularly for brain, heart and trachea segmentation.[22]

Chan-Vese model is based on energy minimization methods. In this method the segmentation is done as firstly loading a MRI image and then create initial mask by using dimensions of image and then convert image from 2D to grey image, then create a signed distance map from mask and the last step is to evolve curve's narrow band and interior and exterior means[23].

3.4.2 Level-Set Method (LSM)

Level-Set is a method that turn out to be broadly utilized for capturing interface development particularly when the interface experiences outrageous. Mathematically it is an implicit method for representing the contours of an active contour or deformable model [24]. Instead of explicitly tracking the points of a function we are interested in, it is represented implicitly within a higher dimensional function. This method uses partial differential equation and Hamilton Jacob method to solve image segmentation problem [25]. Level sets can be used to implement both contour evolution using image edges (edge-based) and those that use the region-based statistics. Many, many variations on this theme exist (I get about 18,000 results on Google Scholar for "level set" and "active contour". Three-dimensional level set segmentation is used as well, for example to segment organs from CT or MRI scans.

4. RESULTS & DISCUSSION

In the present paper we are going to explain which method either segmentation with fusion or segmentation without fusion gives more performance metrics and it depends on the output results.

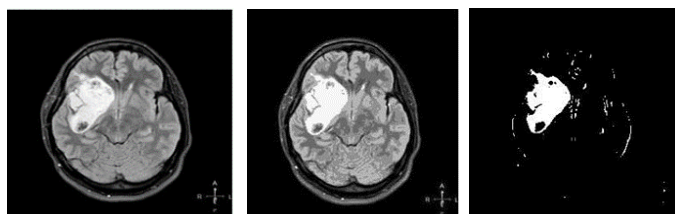


Figure 2: (a) MRI Image (b)K-Means(c)Fuzzy C-Means

The above Fig 2 shows that the input 2D image and second and third output images are outputs of clustering methods.

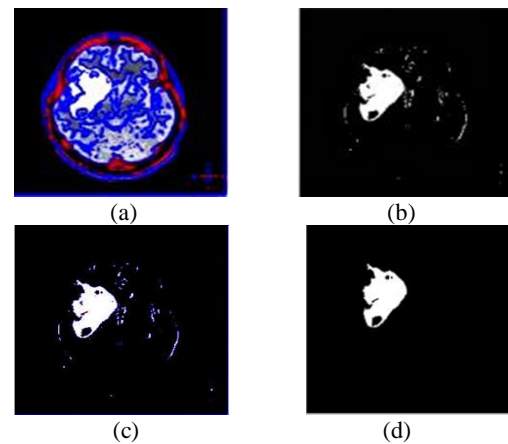


Figure 3: Segmentation without fusion (a), (b) Level Set of K-Means & Fuzzy C-Means (c), (d) Chan-Vese of both K-Means & Fuzzy C-Means respectively.

The above Fig 3 shows the output images of segmentation without using fusion methods, that includes Chan-Vese and Level Set techniques with clustering methods (K-Means & Fuzzy C-Means). And the below shows output images of segmentation with fusion which includes output images of all fusion techniques like CNN, CVT, NSCT, MWGF with Level-Set and Chan -Vese techniques.

| S. No | Fusion Method | Fused Image | Level-Set | Chan-Vese |
|-------|---------------|-------------|-----------|-----------|
| 1 | CNN | | | |
| 2 | CVT | | | |
| 3 | NSCT | | | |
| 4 | MWGF | | | |

Figure 4: Segmentation with fusion output images

Table1 1: Performance Metrics of Chan-Vese & Level-Set Segmentation Without Fusion.

| Method | Chan-Vese | | Level-Set | |
|--------|-----------|---------------|-----------|---------------|
| | K-Means | Fuzzy C-Means | K-Means | Fuzzy C-Means |
| PSNR | 22.24 | 26.05 | 20.65 | 21.58 |
| MSE | 2.01 | 1.14 | 4.19 | 3.02 |
| DC | 0.58 | 0.82 | 0.53 | 0.77 |
| SSIM | 0.91 | 0.98 | 0.88 | 0.96 |

Table 2: Performance Metrics of Chan-Vese Segmentation with Fusion Methods.

| S. No | Method | PSNR | MSE | DC | SSIM |
|-------|--------|-------|------|------|------|
| 1 | CNN | 35.34 | 2.61 | 1.05 | 0.95 |
| 2 | CVT | 33.98 | 3.42 | 0.81 | 0.89 |
| 3 | NSCT | 26.47 | 3.68 | 0.92 | 0.93 |
| 4 | MWGF | 34.95 | 2.89 | 0.97 | 0.89 |

Table 3: Performance Metrics of Level-Set Segmentation with Fusion Methods.

| S. No | Method | PSNR | MSE | DC | SSIM |
|-------|--------|-------|------|------|------|
| 1 | CNN | 41.23 | 0.67 | 1.02 | 0.98 |
| 2 | CVT | 39.08 | 0.65 | 0.95 | 0.96 |
| 3 | NSCT | 35.12 | 3.12 | 0.94 | 0.96 |
| 4 | MWGF | 40.17 | 2.51 | 0.98 | 0.97 |

5. CONCLUSION

The current study develops a novel method for image segmentation using Chan-Vese and level-set with fusion methods for better output. The image which was denoised using median filter and the processed image undergoes clustering techniques and then segmentation of clustered image is done processing by fusion methods. And the main goal of this work is to compare the performance metrics of two models which are segmentation with fusion and segmentation without image. By comparing the performance metrics image which was segmented by fusion methods gives more performance metrics. And the image which is processed by convolution neural network gives more performance metrics.

ACKNOWLEDGEMENT

We thankfully acknowledge management of KL University to provide each source and required facilities for completion of this work.

REFERENCES

1. A. Rajendran et.al. “A Survey on Brain Tumor Segmentation Techniques” Indian Journal of Public

Health Research and Development 10(2):1070 DOI: 10.5958/0976-5506.2019.00439.X,2019.

2. S. Cha “Update on Brain Tumor Imaging: From Anatomy to Physiology” American Journal of Neuroradiology , 27 (3) 475-487; March 2006

3. Aliİşın, aCemDirekoğlub, MelikeŞahcet.al. “Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods” Procedia Computer Science Volume 102, 2016, Pages 317-324
https://doi.org/10.1016/j.procs.2016.09.407

4. K. Rajesh Babu, P.V. Nagajaneyulu, K. Satya Prasad “Performance Analysis of Fusion Based Brain Tumour Detection Using Chan-Vese and Level Set Segmentation Algorithms”, 2019, International Journal of Recent Technology and Engineering, Volume-7 Issue-6, pp:2089-2095, ISSN: 2277-3878

5. Rajesh Babu K., Anishka Singal, Kandukuri Sahiti, Ch. V. S. Sai Jawahar., “Performance Analysis Of Brain Tumour Detection Using Optimization Based Fcm Technique On Mri Images”, 2019, International Journal Of Scientific & Technology Research , Vol:8, issue:11, pp:1717-1723, ISSN: 2277-8616.

6. Rajesh Babu K., K. Khanal Madhav Prasad, K. Rahul Krishna, M. Gowtham Samhith, P. Jameema Pushpitha, K. Kundana Gowri., “Effective Detection Of Brain Tumour On MRI Images Using Optimization Based Segmentation Techniques”, 2020, International Journal Of Scientific & Technology Research, Vol:9, issue:01, pp:1182-1185, ISSN:2277-8616.

7. Zawish, Muhammad & Siyal, Asad & Ahmed, Kainat & Khalil, Aiman & Memon, Sheeraz. (2018). Brain Tumor Segmentation in MRI images using Chan-Vese Technique in MATLAB. 1-6. 10.1109/ICECUBE.2018.8610987.

8. Rao, V. & Sharifi, Mona & Jaiswal, Ayush. (2015). Brain tumor segmentation with deep learning. MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS). 56-59.

9. Agn, Mikael, et al. "Brain tumor segmentation by a generative model with a prior on tumor shape." Proceeding of the Multimodal Brain Tumor Image Segmentation Challenge (2015): 1-4.

10. Alqazzaz, S., Sun, X., Yang, X. et al. Automated brain tumor segmentation on multi-modal MR image using SegNet. Comp. Visual Media 5, 209–219 (2019).
https://doi.org/10.1007/s41095-019-0139-y

11. Rao V., M. S. Sarabi, and A. Jaiswal. "Brain tumor segmentation with deep learning." MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS) (2015): 56-59.

12. B. Fischl, D. H. Salat, E. Busa, M. Albert, M. Dieterich, C. Haselgrove, A. van der Kouwe, R. Killiany, D. Kennedy, S. Klaveness, A. Montillo, N. Makris, B. Rosen, and A. M. Dale, "Whole Brain Segmentation: Automated Labeling of Neuroanatomical Structures in the Human Brain," Neuron, vol. 33, pp. 341-355, 2002.

13. R. A. Heckemann, J. V. Hajnal, P. Aljabar, D. Rueckert, and A. Hammers, "Automatic anatomical brain MRI segmentation combining label propagation and decision fusion," *Neuroimage*, vol. 33, pp. 115-126, 2006.
14. K. Rajesh Babu, P.V. Nagajanyulu and K. Satya Prasad "Performance Analysis for Efficient Brain Tumor Segmentation by using Clustering Algorithm" 2017, *Indian Journal of Science and Technology*, Vol:10, issue:111, pp:1-6, ISSN: 0974-6846, DOI: 10.17485/ijst/2017/v10i11/92979.
15. Rajesh Babu K., V.A.S.Chakravarthy, S.Sandeepreddy, G.Phani Kumar, M.Vamsi Kumar., "Automated Brain Tumour Detection In MRI Images Using Threshold Based FCM", 2019, *International Journal Of Scientific & Technology Research*, Vol:8, issue:12, pp:224-227, ISSN:2277-8616.
16. Anjali a. pure, neeshgupta and mehashrivastava, "an overview of different image fusion methods for medical applications", *IJSER*, ISSN: 2229-5518, vol.04, Issue 7, (2013).
17. Rajesh Babu K., U. Sai Deepthi, A. Sudha Madhuri, P. Sai Prasad., "Comparative Analysis Of Brain Tumour Detection Using Deep Learning Methods", 2019, *International Journal Of Scientific & Technology Research*, Vol:8, issue:12, pp:250-254, ISSN:2277-8616.
18. Yu Liu, Xun Chen et.al. "A Medical Image Fusion Method Based on Convolutional Neural Networks" *information Fusion*,2017.
19. Filippo nencini, andrea garzelli, et.al."remote sensing image fusion using the curvelet transform", Elsevier, ISSN:143-156, issue-2 may 2006.
20. Tianjie li, yuanyuan wang, et.al."Biological image fusion using a NSCT based variable-weight method", Elsevier, INSS:85-92, issue:3 April 2010. <https://doi.org/10.1016/j.inffus.2010.03.007>
21. Zhiqiang zhou, sulii, et.al. " multi scale weighted gradient-based fusion for multi-focus images", Elsevier, INSS:60-72, issue-7 January 2014.
22. Haiyongxu, gangyijiang, meiyu and ting luo, "a global and local active contour model based on dual algorithm for image segmentation", *CMA*, ISSN: 0898-1221, pp:1-18, (2017).
23. L. He, S. Osher, "Solving the Chan-Vese Model by a Multiphase Level Set Algorithm Based on the Topological Derivative," *Proceedings of SSVM'07*, vol. 4485/2007, pp. 777-788, 2007.
24. B. Sandberg, T.F. Chan, L.A. Vese, "A Level-Set and Gabor-Based Active Contour Algorithm for Segmenting Textured Images," *UCLA CAM Report 02-39*, 2002.
25. N.golestani, m.etehadtavakol and e.y.k.ng, "level set method for segmentation of infrared breast thermograms", *EXCLI*, ISSN: 1611-2156, pp: 241-251, (2014).
26. Inthiyaz, S., Madhav, B.T.P., Madhav, P.V.V. "Flower segmentation with level sets evolution controlled by colour, texture and shape features", *Cogent Engineering* 4(1)
27. Inthiyaz, S., Tulasi, S.K., Jayanthi, R.S.L., Sahitya, C., Jyothi, C." Design of bi-trigger sram using schmitt trigger for low power 13t cmos application", *International Journal of Scientific and Technology Research* 8(12), pp. 1466-1471.
28. Inthiyaz, S., Prasad, M.V.D., Usha Sri Lakshmi, R., Sri Sai, N.T.B., Kumar, P.P., Ahammad, S.H." Agriculture based plant leaf health assessment tool: A deep learning perspective", *International Journal of Emerging Trends in Engineering Research* 7(11), pp. 690-694. <https://doi.org/10.30534/ijeter/2019/457112019>
29. Ahammad, S.H., Rajesh, V., Venkatesh, K.N., Nagaraju, P., Rao, P.R., Inthiyaz, S." Liver segmentation using abdominal CT scanning to detect liver disease area", *International Journal of Emerging Trends in Engineering Research* 7(11), pp. 664-669. <https://doi.org/10.30534/ijeter/2019/417112019>
30. Prasad, M.V.D., Inthiyaz, S., Teja Kiran Kumar, M., Sharma, K.H.S., Manohar, M.G., Kumari, R., Ahammad, S.H." Human activity recognition using deep learning", *International Journal of Emerging Trends in Engineering Research* 7(11), pp. 536-541. <https://doi.org/10.30534/ijeter/2019/227112019>
31. Myla, S., Marella, S.T., Goud, A.S., Ahammad, S.H., Kumar, G.N.S., Inthiyaz, S. "Design decision taking system for student career selection for accurate academic system", *International Journal of Scientific and Technology Research* 8(9), pp. 2199-2206.
32. Inthiyaz, S., Madhav, B.T.P., Kishore, P.V.V." Flower image segmentation with PCA fused colored covariance and gabor texture features based level sets", *Ain Shams Engineering Journal* 9(4), pp. 3277-3291.
33. Inthiyaz, S., Madhav, B.T.P., Kishore Kumar, P.V.V." Flower image segmentation: A comparison between watershed, marker controlled watershed, and watershed edge wavelet fusion", *ARPN Journal of Engineering and Applied Sciences* 11(15), pp. 9382-9387
34. Siva Kumar, M., Noorbasha, F., Inthiyaz, S., Jameela, M., Sandhya, A., Imran, M., Tulasi, S.K." Low power carry look-ahead adder using transmission gate multiplexer", *International Journal of Emerging Trends in Engineering Research* 8(1), pp. 13-17 <https://doi.org/10.30534/ijeter/2020/03812020>
35. Inthiyaz, S., Ahammad, S.H., Sai Krishna, A., Bhargavi, V., Govardhan, D., Rajesh, V." YOLO (YOU ONLY LOOK ONCE) making object detection work in medical imaging on convolution detection system", *International Journal of Pharmaceutical Research* 12(2), pp. 312-326.
36. Kumar, S., Inthiyaz, S., Pavani, D., Naga Kishore, G., Harish, G.V., Navya Sri, S.V., Swathi, D., Tulasi, S.K." Implementation of recursive formulation for parallel self-timed adder using verlog logic", *International Journal of Emerging Trends in Engineering Research* 8(2), pp. 355-360. <https://doi.org/10.30534/ijeter/2020/19822020>

37. Siva Kumar, M., Inthiyaz, S., Aditya, M., Rupanjani, P., Aravind, B., Mukesh, M., Tulasi, S.K.” Implementation of GDI logic for power efficient SRAM cell with dynamic threshold voltage levels”, International Journal of Emerging Trends in Engineering Research 7(12), pp. 902-906.
<https://doi.org/10.30534/ijeter/2019/287122019>
38. Inthiyaz, S., Kishore, P.V.V., Madhav, B.T.P “Pre-informed level set for flower image segmentation”, Smart Innovation, Systems and Technologies 78, pp. 11-20
https://doi.org/10.1007/978-981-10-5547-8_2