International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 2, Mar.-Apr. 2023 pp: 248-254 www.ijemh.com

"Braintumor Detection Using MRI Images"

Abhinav EB

Date of Submission: 14-04-2023 Date of Acceptance: 29-04-2023

ABSTRACT
Medical professionals can benefit from MRI (Magnetic Resonance Imaging) technology for the early diagnosis of brain tumour disease. However, using MRI pictures to diagnose brain tumour sickness is still manual, which is a drawback. The complexity of the human brain's structure made it a lengthy procedure. Patients may experience delays in receiving medical care and recovering as a result. It is envisaged that this research will provide knowledge on numerous image processing techniques that can be utilised as a foundation for MRI image processing. I'll examine a variety of approaches and strategies that have been utilised to identify brain cancers on MRI images.

I. INTRODUCTION

Because of the intricate structure of the brain, detecting brain tumours is an extremely difficult challenge [1]. Because they have so many varied characteristics, such as shape, size, and location, brain tumours are challenging to diagnose. Because early-stage brain tumour detection is extremely challenging, the type of treatment required varies [2].

Medical imaging aids in the possibility of non-invasive diagnosis. many forms of medical imaging Non-invasive techniques utilising MRI technology, including CT, ultrasonography, SPECT, PET, and X-rays Inside the MDS (Medical Diagnostic System) space, automatic The results of magnetic resonance imaging (MRI) are good. compared to computed tomography (CT) increased contrast between resonance images is provided. the body's various soft tissues [3]. MRI scans are a powerful magnetic field to identify components It produces radio frequency pulses and emits precise images of the inside organs, soft tissues, bones, and other bodily components. Brain tumours can be found using MRI technology. Brain tumours can be found with MRI by using the MRI images. picture enhancement and processing. The tools are used to enhance how medical image processing is done. To draw attention to features, contrast modification and peripheral techniques are used. Edge detection in MRI images, histograms, segmentation, and morphological processes all have a significant impact. brain tumour categorization and diagnostics play this role.

This article's primary goal is to investigate and consider various research projects. Methods for filtering and segmenting data, as well as brain algorithms that recognise different stages. For instance, MR imaging is used to find cancer regions in MRI images using pre-treatment, feature extraction, segmentation, post-processing, etc.
The fundamental framework for feature extraction in digital image processing is depicted in Figure 1

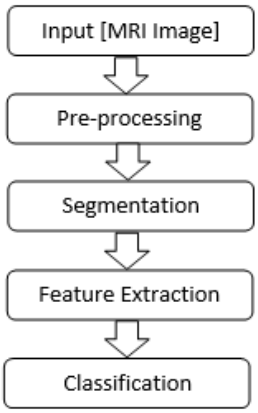


Fig -1

II. LITERATURE REVIEW

To detect brain tumours, strokes, and other forms of abnormalities in the human brain using MR imaging, numerous researchers have proposed numerous approaches and algorithms.

The cancer locations were identified in the high-resolution 3D MRI images using the U-Net Model, which reduced the resolution of the pictures to identify the features known as encoder paths, then up-sampled the images using the extracted features known as decoder paths. The topic of "3D MRI segmentation for the detection of brain tumour" has been covered by the authors in [20]. The BRATS2020 dataset is where they got their information. The images were divided into

categories such as no tumor, edema, necrotic/core, and enhancing tumour after pre-processing. The tumour-related characteristics were also retrieved and classed during training. The gathered data showed that the target area on the BRATS2020 dataset was segmented with 99% accuracy.

A fully automated method for segmenting brain tumours was given by Shivhare, Sharma, and Singh [21] by combining the parameter-free K-means clustering algorithm with mathematical morphological procedures like dilation and hole filling. The training dataset for Brats 2015 is used to test the suggested technique. The ground truth result included in the dataset is connected with the tumour segmented using the presented methodology. In accordance with the known ground truth, the resulting results showed a Dice Similarity Coefficient (DSC) of 75%.

Jagan [22] described a novel approach for segmenting tumours by pre-processing the image with an anisotropic filter. The FCM approach and the enhanced Expectation Maximisation (EM) approach are then used to do the initial segmentation. Then, a better segmentation is carried out using the provided methodology. The work of the suggested strategy is connected to the FCM clustering approach and improved EM approach in terms of segmentation accuracy. Segmentation accuracy for the suggested method, which outperformed FCM clustering and enhanced EM approaches, was 97.98% on average over a sample of 10 cases.

A segmentation method that Sompong and Wongthanavasu [23] proposed uses cellular automata and an enhanced tumour cut methodology. Using GLCM-based Cellular Automata, the suggested technique first transforms an image into the intended featured image. (GLCM-CA). The improved tumour cut approach is then used for segmentation. The suggested method is evaluated on the BraTS 2013 dataset for performance evaluation utilising the metrics of DC, sensitivity, specificity, and PPV. The proposed approach and the cutting-edge methods applied on the same dataset are associated. The suggested method outperforms cutting-edge methods.

Vishnuvarthanan et al. [24] provided an automated method based on clustering and optimisation approaches for segmenting the cancer and tissues. This approach employs a skull-stripped brain MRI picture as its input. An adaptive histogram equalisation method with a contrast limit is used to pre-process the reduced image of the skull. The Modified Fuzzy K-means (MFKM) method is utilised to do the clustering. Next, the appropriate threshold value is chosen using the Bacteria Foraging Optimisation (BFO) approach. The output of the MFKM technique is reevaluated using the established threshold value. The proposed approach interacts with the existing MFKM, Particle Swarm Optimisation (PSO) based FCM, and conventional FCM approaches. PSNR, MSE, sensitivity, and other performance indicators are utilised to assess the effectiveness of the suggested technique.

The classification of aberrant brain materials into benign and malignant was done by Rajeshwari G. Tayade et al. [25] using a combination of wavelet statistical features and co-occurrence wavelet texture features acquired from two level separate riffle processing. The system was designed to go through four stages: segmenting the area of interest, separating ripples, feature abstraction, feature selection, organization, and analysis. Tumor segmentation was done using the support vector machine. The neoplasm region was extracted from a second level distinct ripple remodel using a grouping of WST and WCT. The best texture alternatives from the pool of well-mined options were selected using a genetic algorithm.

The authors of Bahadure et al. [26] suggested strategies based on discrete wavelet transformation (DWT) using feature extraction techniques. If these feature extraction techniques are used, the crucial nuances of brain images are lost. SVM was recommended by Sandhya et al.'s [27] authors for cancer identification. The First Fourier Transform (FFT) was used to extract the features after segmentation, which was carried out using the adaptive threshold technique. Then, SVM was used for prediction. They could only extract 16 x 16 features each epoch from the 512 x 512 image. The system also required longer processing times.

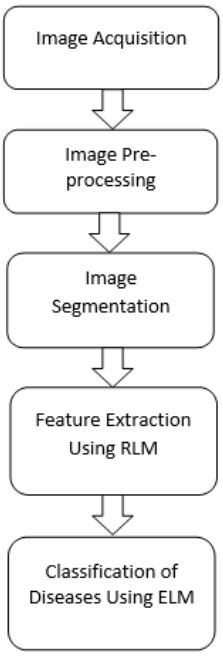
For the purpose of cancer segmentation in multi-modal MRI brain imaging, Soltaninejad et al. [28] introduced a 3Dsupervoxel-based segmentation technique. To categorise each supervoxel into one of the following three groups: tumour core, oedema, or healthy brain tissue, they retrieved several feature sets for each supervoxel, such as first order intensity statistical features and histograms of texton descriptor. Two clinical datasets, one from a local clinic with 11 patient images and the other from BRATS 2013 with 30 multimodal images, were used to test the approach.According to the experimental findings, the local clinical datasets have an average tumour detection sensitivity of 86%, a balanced error rate (BER) of 7%, and a Dice score of 0.84 for automatic tumour segmentation.

International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 2, Mar.-Apr. 2023 pp: 248-254 www.ijemh.com

The segmentation of the 3D MRI image using a Multi-Encoder Network (ME-Net) architecture with the new loss function "Categorical Dice" is said to be made simpler by Zhang et al. [29]. Additionally, they applied various weights for various segmented areas of the 3D MRI image in order to address the voxel imbalance issue. The multi-class segmentation problem's enhancing tumour area, however, cannot be adequately addressed by the segmentation results of this approach.

III. PROPOSED METHOD

Absolute accuracy is needed when a person's life is on the line, which is why automated brain tumour identification is crucial. Automated cancer detection in MR images is feasible by using machine learning techniques for feature extraction and classification. This study suggests a technique that might be displayed in figure 1 that can automatically detect cancers in MR images.



Overview of the Proposed Method in Fig 1

3.1 Image Acquisition: The MRI brain pictures are acquired and sent as input to the pre-processing stage because they enable medical professionals to produce detailed images of the brain that can aid in identifying the presence of a tumour and helping to assess its presence, location, size, and shape. Figure 2 displays several example MR scans of the brain.

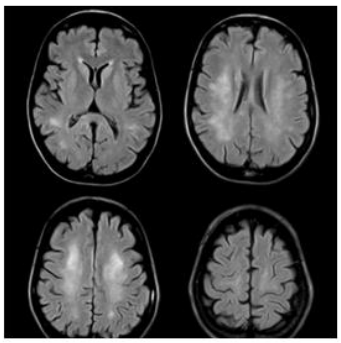


Fig 2. Samples of brain MR image

3.2 Pre-processing: A crucial stage in the analytic pipeline is the pre-processing of MRI data for brain tumour analysis. The major purpose of pre-processing is to remove any distortions or artefacts from the data and to enhance the image's quality for precise tumour segmentation and detection. The following steps are used to pre-process an MR image:

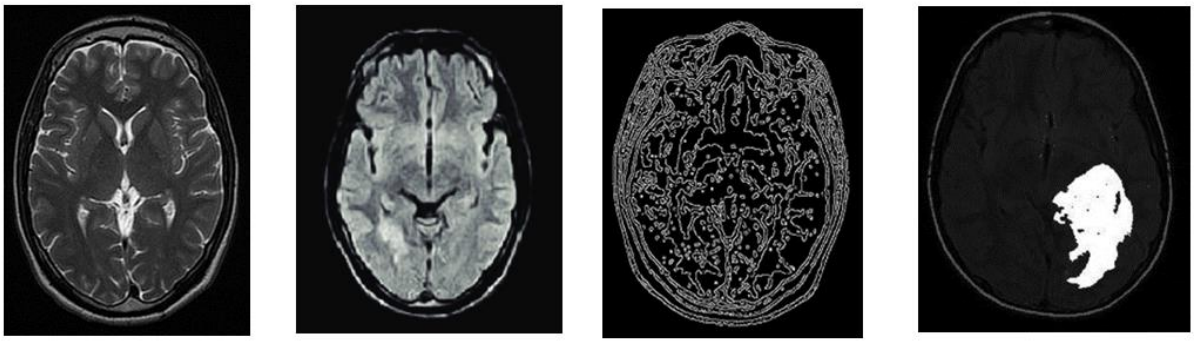
3.2.1 Region-Based: This technique groups together pixels that are associated with an item. The region that was discovered for segmentation should be sealed off. Due to the lack of edge pixels, there won't be any gaps in this region-based segmentation. The boundaries are determined for segmentation. Each stage considers and accounts for at least one pixel that is connected to the region. After identifying the change in colour and texture, the edge flow is converted into a vector. These edges are then located for further segmentation.

3.2.2 Edge-Based: Techniques for edge detection can also be applied to segment data. There are further approaches, such as Gradient, Robert, Canny, Sobel, and Laplacian. The border to segment is found using this technique. Edges are identified in order to locate the visual discontinuities. For classification, they use the fixed and flexible features of support vector machines.

3.3 Region Growing Segmentation: This straightforward and efficient technique divides an image into regions based on similarity in pixel values. Finding the area of the image that corresponds to the tumour is the objective in the case of brain tumour detection. Beginning with a seed pixel or set of pixels, region expanding segmentation works by incrementally adding nearby pixels to the region if they satisfy a set of similarity requirements. The similarity criterion may take into account intensity levels, texture characteristics, or other aspects of the images. Further analysis can be

International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 2, Mar.-Apr. 2023 pp: 248-254 www.ijemh.com

done on the segmented region to extract features like size, shape, and texture after the region has been expanded to include the entire tumour. The tumour depicted in figure 3 can then be classified and diagnosed using these features.



(a) Original Image (b) Filtered Image (c) Edge Detected Image (d) Segmented Image

Fig 3(a-d) Pre-processing operations on input brain image

3.4 Feature Extraction: Using the run-length matrix (RLM), one can examine textural features in pictures. The RLM, which is used to explain the spatial relationship between the pixels in a picture, is based on the idea of a grey-level co-occurrence matrix. Statistical data on texture features in an image, such as contrast, homogeneity, entropy, etc., can be extracted using the RLM approach. In order to characterise the distribution of runs of pixels with the same grey level value, the RLM approach creates a matrix of run-lengths and grey levels. The number of runs with pixels of grey level i and run length j is defined as a run-length matrix, or p(i; j), for a given image.Various texture features can then be derived from this run-length matrix.The equation for RLM method are as follows:

Image Discretization: Discretizing the image into a finite number of grey levels—typically 8, 16, or 256 grey levels—is the first step in the RLM approach. The following equation is used to accomplish this:

$I(i,j) = floor[(G(i,j) / Gmax) \times Ng]$

3.4.1 Run-Length Matrix Generation: After the image has been discretized, the RLM is created by counting the runs of pixels in a certain direction that have the same grey-level value. (usually horizontal, vertical, or diagonal). The RLM is a matrix with the dimensions Ng x Nr, where Ng is the number of discretized picture grey levels and Nr is the longest possible run length. The following equation is used to get the RLM:

RLM(i,j) = count of runs of length j and gray-level value i in the given direction

Calculation of Texture Features:

Once the RLM is generated, various texture features can be calculated from it. The most commonly used texture features are:

1)Contrast: Contrast is a measurement of the regional differences in the image's grayscale values.

Contrast = $\sum_{i=1}^{Ng}\sum_{j=1}^{Nr^2} RLM(i,j)$

2)Homogeneity: Measures the degree to which adjacent pixels in a picture are similar.

Homogeneity = $\sum_{i=1}^{Ng}\sum_{j=1}^{Nr} RLM(i,j)/(1+|i-j|)$

3)Entropy: evaluates how random or unpredictable the image's grey-level values are.

Entropy = $-\sum_{i=1}^{Ng}\sum_{j=1}^{Nr} RLM(i,j)\log(RLM(i,j))$

3.5 Extreme Learning Machine: A class of artificial neural network called the ELM has been used to detect brain tumours among other classification-related tasks. The equations for using an ELM classifier to detect brain tumours are as follows:

Assuming our dataset consists of n samples, each of which is represented by a binary label y(i) = -1, 1 indicating the existence or absence of a brain tumour and a d-dimensional feature vector x(i) = [x1(i), x2(i),..., xd(i)].

Step 1: Create the hidden layer's weight matrix W and bias vector b at random.

W = [w1, w2, ..., wm], where each w is a d-dimensional vector, and m is the number of hidden neurons.

b = [b1, b2, ..., bm], where each b is a scalar.

Step 2: Use the formula below to compute the H hidden layer output matrix:

$H = g(XW + b)$,

International Journal of Engineering, Management and Humanities (IJEMH)
Volume 4, Issue 2, Mar.-Apr. 2023 pp: 248-254 www.ijemh.com

where X is the n x d input data matrix, g is the activation function (e.g., sigmoid or ReLU), and the + sign denotes element-wise addition.
Step 3: Use the following equation to calculate the output weight matrix beta:
beta = pinv(H)*Y,
where Y is the n x 1 label vector and pinv(H) is the pseudo-inverse of H.
Step 4: Classify a new sample x as follows:
y = sign (g(xW + b) * beta),
where sign() is the sign function, which, depending on the sign of the argument, returns either -1 or 1.

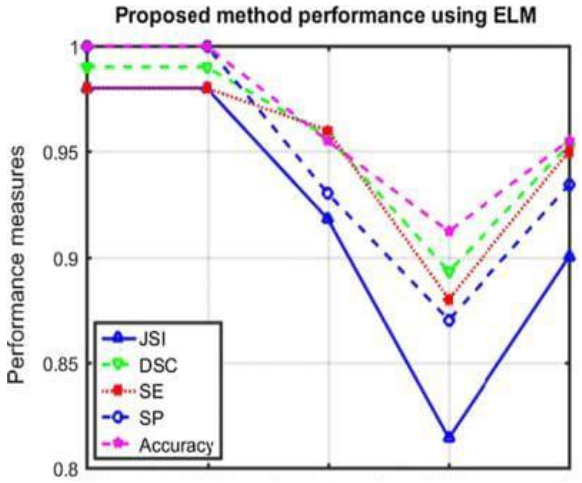
IV. Result

Table 1 analyses the dataset accuracy, the number of photos in the dataset, the true positive and true negative images, the false positive and false negative images, and the outcomes of the suggested approach. It indicates that there are 37, 36, and 33 true positive values for batches 1, 2, and 3, respectively. Additionally, for batches 1, 2, and 3, there are 1, 1, and 2, respectively, true negative values.

Dataset (No. of Images)	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy
Batch1 (40)	37	1	1	1	95%
Batch2 (40)	36	1	2	1	92.5%
Batch3 (40)	33	2	2	3	87.5%
Total = 120	106	4	5	5	**Average = 91.67%**

Table 1

It demonstrates that our suggested method correctly identified 38, 37, and 35 photographs from batches 1, 2, and 3, which each had 40 images. For batches 1, 2, and 3, our suggested strategy provides accuracy of 95%, 92.5%, and 87.5%, respectively. The images were pre-processed using region-based and edge-based techniques. And extracted a total of 10 features from the pre-processed images including shape, texture, size features. Run Length Matrix algorithm was used to select the most relevant features for classification. Applied Extreme Learning Machine classifier to classify whether the MRI brain images as tumor or normal. The performance is evaluated using accuracy, sensitivity and specificity of classification algorithms.



V. CONCLUSION

Finally, MRI is a reliable imaging method for spotting brain tumours. It offers clear images of the brain and can be used to determine a tumour's size, location, and kind. Advanced imaging methods like functional MRI and diffusion tensor imaging can also give more details on the tumour's effects on the surrounding tissues and brain function. But a conclusive diagnosis necessitates a mix of imaging and further procedures, such a biopsy. For good outcomes, brain tumours must be diagnosed and treated as soon as possible, and MRI is crucial to the diagnosis procedure.

REFERNCES

[1]. Deepak C. Dhanwani, Mahip M. Bartere, "Survey on various techniques of brain tumour detection from MRI images", IJCER, Vol.04, issue.1, Issn 2250-3005, January 2014, pg. 24-26.

[2]. Megha A joshi, D. H. Shah, "Survey of brain tumour detection techniques through MRI images", AIJRFANS, ISSN: 2328-3785, March-May 2015, pp.09

[3]. Poonam, JyotikaPruthi, "Review of image processing techniques for automatic detection of tumor in human brain", IJCSMC, Vol.2, Issue.11, November 2013, pg.117-122.

[4]. Manoj K Kowear and SourabhYadev, "Brain tumor detection and segmentation using histogram thresholding", International Journal of engineering and Advanced Technology, April 2012.

[5]. Rajesh C. patil, A.S. Bhalchandra, "Brain tumor extraction from MRI images Using MAT Lab", IJECSCSE, ISSN: 2277-9477, Volume 2, issue1.

[6]. Vinay Parmeshwarappa, Nandish S, "A segmented morphological approach to detect tumor in brain images", IJARCSSE, ISSN: 2277 128X, volume 4, issue 1, January 2014

[7]. M.Karuna, Ankita Joshi, "Automatic detection and severity analysis of brain tumors using gui in matlab" IJRET: International Journal of Research in Engineering and Technology, ISSN: 2319-1163,
Volume: 02 Issue: 10, Oct-2013

[8]. R. B. Dubey, M. Hanmandlu, ShantaramVasikarla, "Evaluation of three methods for MRI brain tumor segmentation", IEEE computer society, ITNG.2011.92

[9]. Rafel C. Gonzalez, Rechard E. Woods, "Digital Image Processing", Prentice-Hall, 3rd Edition, 2008

[10]. SenthilkumaranN ThimmiarajaJ," Histogram equalization for image enhancement using MRI brain images", IEEE CPS, WCCCT.2014.45

[11]. R. Preetha, G. R. Suresh, "Performance Analysis of Fuzzy C Means Algorithm in Automated Detection of Brain Tumor", IEEE CPS, WCCCT, 2014.

[12]. Amer Al-Badarnech, Hassan Najadat, Ali M. Alraziqi, "A Classifier to Detect Tumor Disease in MRI Brain Images", IEEE Computer Society, ASONAM. 2012,142

[13]. Usha Mittal, SanyamAnand, "Modified Watershed Segmentation with Denoising of Medical Images", IJIRSET, Vol. 2, Issue 4, April 2013.

[14]. Priyanka, balwinder Singh, "A review on Brain tumor detection using segmentation", IJCSMC, Vol. 2, Issue, pg. 48-54. 7, July 2013.

[15]. Ashraf A. Aly, Safaai Bin Deris, NazarZaki, "Research review for digital image Segmentation techniques", IJCSIT, Vol 3, No 5, Oct 2011
[16]. SwezinOo, Aung SoeKhaing, "Brain tumor detection and segmentation using watershed segmentation and morphological operation", IJRET, Volume 03, Issue 03, March 2014
[17]. Y.Ramadevi, T.Sridevi, B.Poornima, B.Kalyani, "segmentation and object recognition using edge detection techniques", IJCSIT), Vol 2, No 6, December 2010.
[18]. M. A. Balafar, A. R. Ramli, M. I. Saripan, S. Mashohor, "Review of brain MRI image segmentation methods", Springer Science Business Media, 22 January 2010
[19]. Mohammed Y. Kamil, "Brain Tumour Area Calculation in CT-scan image using Morphological Operations", IOSR Journal of Computer Engineering (IOSR-JCE) ISSN: 2278-8727, Volume 17, Issue 2, Ver.-V, PP 125-128, Mar – Apr. 2015.
[20]. "3D MRI Segmentation using U-Net Architecture for the detection of Brain Tumour" "SmartaSangur", Tamim Iqbal, Piyush Chandra Chandra", Swarup Kr Ghost", Anupam Ghosh a Sister Nivedita University, Kolkata 700156, India b Netaji Shubash Engineering College, Kolkata 700152, India
[21]. S. N. Shivhare, S. Sharma, and N. Singh. (2019) "An Efficient Brain Tumor Detection and Segmentation in MRI Using Parameter-Free Clustering," in M. Tanveer and R. B. Pachori (eds) Machine Intelligence and Signal Analysis. Advances in Intelligent Systems and Computing 748, Springer Singapore: 485–495.
[22]. A. Jagan. (2019) "A Contemporary Framework and Novel Method for Segmentation of Brain MRI," in Proceedings of the International Conference on ISMAC in Computational Vision and Bio-Engineering 2018 (ISMAC-CVB) 30: 739–747.
[23]. C. Sompong and S. Wongthanavasu. (2017) "An Efficient Brain Tumor Segmentation Based on Cellular Automata and Improved Tumor-cut Algorithm." Expert Systems with Applications 72: 231–244.
[24]. A. Vishnuvarthanan, M. P. Rajasekaran, V. Govindaraj, Y. Zhang, and A. Thiyagarajan. (2017) "An Automated Hybrid Approach Using Clustering and Nature Inspired Optimization Technique for Improved Tumor and Tissue Segmentation in Magnetic Resonance Brain Images." Applied Soft Computing 57: 399–426.
[25]. Rajeshwari G tayade,MichelCrucian , "Unsupervised And Semi-Supervised Clustering: A Brief Survey," InriaRocquencourt, B.P. 105 78153 Le ChesnayCedex, France.
[26]. Bahadure, N. B., Ray, A. K., &Thethi, H. P. (2017). Image analysis for MRI based brain tumor detection and feature extraction using biologically inspired BWT and SVM.International Journal of Biomedical Imaging, 2017.
[27]. Sandhya, G., Giri, K., & Savitri, S. (2017). A novel approach for the detection of tumor in MR images of the brain and its classification via independent component analysis and kernel support vector machine. Imagining in Medicine.
[28]. Soltaninejad, M., Yang, G., Lambrou, T., Allinson, N., Jones, T. L., Barrick, T. R.,Howe, F. A., & Ye, X. (2018). Supervised learning based multimodal MRI brain tumour segmentation using texture features from supervoxels. Computer Methods and Programs in Biomedicine, 157, 69–84.
[29]. Zhang, W., Yang, G., Huang, H., Yang, W., Xu, X., Liu, Y., & Lai, X. (2021). ME-net:Multi-encoder net framework for brain tumor segmentation. International Journal of Imaging Systems and Technology.
[30]. Amir Shahzad, Muhammad Sharif, Mudassar Raza, Khalid Hussai, " Enhanced Watershed Image Processing Segmentation " , Journal of Information & Communication Technology, Vol. 2, No. 1, 2009.
[31]. Komal Sharma "Brain Tumor Detection based on ML Algorithms",researchscholar,M.E-CSE CU,Gharuan Mohali, International journal of Computer Applications
[32]. "An Overview of the Research on Plant Leaves Disease detection using Image Processing Techniques "Ms. Kiran R. Gavhale1 , Prof. Ujwalla Gawande2 1 Department of Computer Technology, YeshwantraoChavan College of Engineering, Nagpur, Maharashtra, India. 2 Asst. Prof. Department of Computer Technology, YeshwantraoChavan College of Engineering, Nagpur, Maharashtra, India