Journal of Theoretical and Applied Information Technology
31st August 2024. Vol.102. No. 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EDGE ENHANCE SPARSE DEEP AUTO ENCODER MODEL FOR HIGH-ACCURACY BRAIN TUMOR DETECTION IN MRI IMAGES

SATYAVATI JAGA[1], K. RAMA DEVI[2]

[1]Research Scholar, Department of ECE, JNTU College of Engineering, Kakinada, Andhra Pradesh, India

[2]Assiatant Professor, Department of ECE, JNTU College of Engineering, Kakinada, Andhra Pradesh, India

E-mail: [1]satyavati_ece@cbit.ac.in, [2]kolisettyramadevi@gmail.com

ABSTRACT

Brain tumors are among the most lethal cancerous diseases, with their severity making them a leading cause of cancer-related deaths. The treatment of brain tumors depends on the tumor's type, location, and size. Solely relying on human inspection for accurate categorization can result in potentially dangerous situations. This manual diagnostic process can be enhanced and expedited through the use of an automated Computer Aided Diagnosis (CAD) system. This research embarks on a ground-breaking path, leveraging cutting-edge deep learning methods to revolutionize anomaly detection and classification of brain tumor in MRI images. The aim of this work is to address the crucial area of brain tumor detection by presenting a new and innovative methodology that surpasses the limitations of current techniques. Central to this investigation is the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) model, which introduces a network designed to detect and enhance edge saliency through deep learning (DL) techniques. The significance of the EES-DAE model is highlighted by its multidimensional approach, which greatly enhances the detection of brain tumors. The process starts with a pre-processing phase where a Wiener filter is applied to enhance the quality of brain MRI scans, providing a robust basis for further analysis. Next, a pixel normalization elimination step is performed to extract essential features while minimizing the effects of noise interference. Additionally, the intermediate stages of the methodology smoothly incorporate the 2D Discrete Cosine Transform (DCT) and entropy filters, orchestrating the precise extraction of complex features that greatly enhance the model's accuracy. The integration of the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) model with the capabilities of soft-max entropy classification marks the apex of this innovative journey. The BRATS MRI brain images are utilized to assess the effectiveness of the developed techniques. This seamless fusion of advanced techniques achieves a remarkable outcome: the detection of brain tumor regions with an impressive accuracy rate of 99.13%.

Keywords: *MRI, CAD System, EES-DAE Model, DL, 2D-DCT, CNN, Softmax, Preprocessing, Wiener Filter, Pixel Normalization Elimination, Feature Extraction.*

1. INTRODUCTION

The detection and classification of anomalies in medical images, particularly MRI Scans, is critical in the early diagnosis and treatment of diseases such as brain tumors [1-3]. DL techniques have shown remarkable success in image analysis tasks, prompting the search for improved enhanced approaches [4-5]. Deep learning approaches for anomaly detection and classification in MRI Scans are significant [6-8]. The ability to detect brain tumors accurately and early can have a significant impact on patient outcomes by allowing for timely intervention and treatment planning [9-11]. To improve detection accuracy, the Improved Deep Learning method known as Edge Enhance Sparse Deep Auto Encoder (EES-DAE) for brain tumor detection employs a multi-stage approach. Throughout the research, the MATLAB tool is used to implement and evaluate the proposed models. The BRATS MRI brain images is used to evaluate the efficacy of the developed methods.

The contribution of this research work is that it introduces improved enhanced deep learning approaches for anomaly detection and classification in MRI Scans, focusing on brain tumors in particular. The development of the Proposed method, Edge Enhance Sparse Deep Auto Encoder (EES-DAE) for detecting brain tumors demonstrates a multi-stage strategy that combines advanced techniques. The use of MATLAB as the implementation and evaluation tool, as well as the testing on the Kaggle database of brain (BRATS), demonstrates the practical applicability of the proposed models. This work highlights the development and implementation of a new methodology for brain tumor detection and classification using MRI images. It introduces the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) model, which focuses on enhancing edge saliency through deep learning techniques. This research work focuses on presence or absence of tumor in brain MRI images but not on classifying the tumor type and other properties of the tumor such as size and location of the tumor.

The section 1 introduction provides the necessary context and emphasises the significance of the research. It presents the Improved Enhanced CNN method for brain tumor detection. The second section provides a comprehensive review of the existing literature, with an emphasis on previous works pertaining to the detection and classification of anomalies in MRI Scans. It discusses the limitations and deficiencies of current approaches, laying the groundwork for the proposed enhanced deep learning models.

In section 3, the research methodology employed is described in depth. It describes the multi-stage approach used in the proposed Edge Enhance Sparse Deep Auto Encoder (EES-DAE) method for detecting brain tumors. In section 4, the experimental design and results are presented. The use of MATLAB and the BRATS MRI via Kaggle database of brain scans for testing the proposed model is discussed. Exhaustively explained are the obtained results and their significance in detecting and classifying brain tumor in MRI Scans.

Section 5 focuses on evaluating the performance of the developed model. It examines the accuracy rates of the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) model for detecting brain tumors. Other performance metrics, including sensitivity, specificity, and PSNR, are also taken into account. The concluding section summarises the key findings and contributions of the research to conclude the paper. It demonstrates the efficacy of Proposed deep learning approach in detecting and classifying brain tumor regions in MRI Scans. In addition, it discusses potential areas for future research and development, indicating opportunities for improving and refining the proposed model and methodology further.

2. LITERATURE REVIEW

A methodical application of "Erosion" with an Area of Interest (AOI) method is implemented to improve the effectiveness of skull stripping in MRIs following the identification of false backgrounds. Prior to using "Erosion," a fake background is found. After using the scan line approach to fill in the fake backdrop area, we were able to determine the boundary of the skull using dilation. As a result, the "Erosion" algorithm will only degrade the AOI, removing the skull without affecting the brain's other tissues. Subsequent research aims to achieve a symmetric method of skull stripping through the modification of certain current algorithms and the discovery of more effective and efficient methods. [13]

DL (Deep learning) models, with their inherent ability to independently learn complex shapes and images from big datasets, have exhibited capable outcomes. This is particularly noteworthy in the realm of medical imaging, where accurate identification and classification of anomalies in MRI scans hold paramount importance [14]. Berkeley wavelet transformation (BWT) based brain tumor segmentation is used to enhance performance and simplify the process of medical picture segmentation. Additionally, pertinent characteristics are retrieved from each segmented tissue in order to increase the support vector machine (SVM) based classifier's accuracy and quality rate. Based on tests using magnetic resonance brain imaging, the effectiveness and quality analysis of the suggested technique has been assessed and validated in terms of accuracy, sensitivity, specificity, and dice similarity index coefficient [15]. Many research endeavours have adopted deep learning methodologies for detecting and classifying anomalies in MRI scans, underscoring their superiority when compared to traditional ML algorithms [16]. An extensive survey of pertinent deep learning-based brain tumor segmentation techniques is offered. Advanced DL (Deep learning) models have proven their capacity to substantially improve diagnostic accuracy, thereby aiding radiologists in making more informed and precise decisions [17].

Deep learning models have emerged as leaders in medical image analysis, showcasing superior performance in various benchmarks [18-20]. Their ability to surpass traditional methods extends to minimizing false positives and negatives, potentially leading to enhanced patient outcomes.

These models leverage large-scale datasets and intricate neural network architectures, enabling them to capture nuanced details in MRI scans that conventional approaches may overlook. The survey may discuss trends in incorporating multimodal data, such as combining MRI with other imaging modalities, to enhance the accuracy of diagnostic tasks. In conclusion, surveys focusing on deep learning applications in MRI scan analysis, especially in areas like brain tumor segmentation, play a pivotal role in consolidating knowledge, identifying trends, and informing future research directions and clinical practices in the rapidly evolving field of medical imaging.

Convolutional neural networks (ConvNets) and recurrent networks are examples of deep learning architectures that have been constructed in the past and have been shown to be suitable for non-handcrafted complex feature extraction. In order to enhance the effectiveness of the ConvNet models even further, a multi-layer perceptron based on handmade features and ConvNet integration is presented in [21] as a cascaded ensembled network. The provided model mines texture and color moments as handcrafted features, as well as non-handcrafted image characteristics, using a convolutional neural network model.

The research carried out by Zhang, J., et al. in 2021 [22] canters on forecasting a process through machine learning. More specifically, it employs a SVM (Support Vector Machine) model to classify different types of tumors. The study emphasizes the application of SVM in tackling common challenges observed in medical contexts, particularly within the domain of brain tumor classification. Hasanah et al. employ a Support Vector Machine model for the classification of different types of tumors. SVMs are known for their effectiveness in binary and multiclass classification tasks. The average reported accuracy of 95.83% signifies a notable success in categorizing different tumor types, underscoring the effectiveness of the SVM model for the given task. The study suggests that careful consideration of sampling techniques is crucial for handling imbalanced data. Techniques like oversampling the minority class or under sampling the majority class may be employed. Another approach mentioned is the application of cost-sensitive learning strategies. This involves assigning different misclassification costs to different classes, emphasizing the importance of correct classification for the minority class. The reported high accuracy suggests that the SVM model developed by Hasanah et al. has potential generalizability and effectiveness in diverse datasets or real-world scenarios. In conclusion, Hasanah et al.'s work provides valuable insights into the use of SVMs for tumor classification, emphasizing the importance of addressing imbalanced datasets in medical applications. The reported high accuracy underscores the potential practical significance of the model developed in the study.

A technique for separating brain tumors from 2D magnetic resonance imaging (MRI) using the fuzzy C-Means clustering algorithm was presented in [23]. Conventional classifiers and convolutional neural networks came next. A real-time dataset with a variety of tumor sizes, locations, forms, and image intensities was used for the experimental investigation. Six classic classifiers—Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest—that were implemented in scikit-learn were used in the traditional classifier section. After that, since convolutional neural networks (CNNs) perform better than standard ones, we moved on to utilize Keras and Tensorflow to create CNNs. While acknowledging potential limitations, the reported high accuracy demonstrates the practical effectiveness of the proposed approach in the specific task at hand. The study opens avenues for further research to optimize and refine the integration of different feature types with CNNs in medical imaging applications.

The work by Khalil et al. in 2020 [24] introduces a new method, a system for segmenting 3D MR images of brain tumors with two-step dragonfly mechanism. While the system demonstrates high accuracy (98.20%), the study highlights several limitations that may impact its effectiveness, particularly in dealing with certain types of tumors and in real-time or resource-constrained environments. The proposed system utilizes a modified two-step dragonfly mechanism for the segmentation of 3D MR images. This suggests a unique approach to image segmentation involving two distinct steps. The system may face challenges when dealing with heterogeneous or irregularly shaped tumors. This issue suggests that complicated tumor boundaries may be difficult for the segmentation algorithms to accurately capture and characterise, perhaps resulting in under- or over-segmentation. The technology is said to have significant processing time and computing needs, particularly when working with huge volumes of 3D MR images. This limitation implies that the system may not be well-suited for real-time applications or environments with resource constraints. Despite the limitations mentioned, the system achieves a notable segmentation accuracy of 98.20%. This high accuracy is a positive aspect of the proposed approach, indicating its effectiveness under certain conditions. The effectiveness limitations noted in dealing with heterogeneous or irregularly shaped tumors suggest that the system may be more suitable for specific tumor types or conditions. Future research could focus on refining the segmentation algorithms to address the challenges associated with irregularly shaped or heterogeneous tumors. In conclusion, Khalil et al.'s system presents a unique approach to 3D MR image segmentation, achieving high accuracy but acknowledging limitations in dealing with certain tumor characteristics and resource-intensive processing. The study provides valuable insights for further research to address these limitations and optimize the system's performance in diverse clinical scenarios and real-time applications.

In 2019, Avsar E., et.al [25] employed a faster Region-based CNN, rooted in deep learning techniques, for the diagnosis of human brain tumors. However, this approach exhibits limitations and drawbacks in the context of diagnosing such tumors. The process of acquiring and annotating datasets for brain tumor diagnosis is time-consuming, expensive, and prone to inter-observer variability. Insufficient or biased training data may lead to overfitting, impacting the system's accuracy and generalization. Additionally, the interpretability of deep learning models remains an issue. Despite achieving impressive diagnostic performance, the interpretability of region based CNNs is challenging. Nevertheless, it's noteworthy that this system demonstrates a higher accuracy of 91.66%.

The Improved Enhanced algorithm is introduced to overcome the limitations identified in earlier approaches, employing a variety of techniques to improve the accuracy of brain tumor detection and classification. The deficiencies found in ConvNets, SVMs, texture-based and statistical features, and region-based CNNs are specifically addressed through the integration of advanced methodologies. Wiener Filter improves image quality by reducing noise and artifacts. Enhances the clarity of MRI images, providing a cleaner input for subsequent processing steps. Pixel Noise Normalization ensures consistent pixel intensities across images. Promotes greater consistency in pixel values, aiding in the standardization of input data. 2D Discrete Cosine Transform (2D DCT) facilitates the capture of local and global frequency information in images. Helps in extracting relevant frequency components, which can be valuable for image analysis. Entropy Filtering identifies relevant features by effectively removing extraneous data. Enhances the focus on critical image features, potentially improving the algorithm's ability to discriminate between tumor and non-tumor regions. Proposed Edge Enhance Sparse Deep Auto Encoder (EES-DAE) Model learns sparse features, reducing overfitting and enhancing generalization. Adds a sophisticated neural network model to the algorithm, allowing it to learn intricate patterns and spatial relationships more effectively. The Improved Enhanced algorithm is designed to overcome the limitations of previous approaches by combining these techniques. The goal is to increase the accuracy in detection and classification of brain tumor.

The integration of advanced image processing, frequency analysis, feature extraction, and deep learning components aims to create a more robust and versatile system for medical image analysis. The incorporation of the proposed EES-DAE model suggests a specific focus on addressing overfitting issues, potentially leading to more reliable and generalized results. By combining multiple techniques, the Improved Enhanced algorithm takes a holistic approach to address the limitations identified in previous methodologies, potentially leading to a more comprehensive solution for brain tumor detection. In summary, the Improved Enhanced algorithm aims to advance brain tumor detection and classification by addressing the shortcomings of previous methods, leveraging a combination of image enhancement, normalization, frequency analysis, feature extraction, and deep learning techniques. The proposed approach demonstrates a holistic strategy to enhance the accuracy and reliability of the medical imaging system.rks (ConvNets) in combination.

3. METHODOLOGY

The block diagram of the novel Improved proposed algorithm is depicted in Figure 1 (shown in page number 14) with Edge Enhance Sparse Deep Auto Encoder (EES-DAE) as the Deep Learning model for detecting and classifying brain tumors.

The algorithm is made up of several key components that work together to improve the detection and classification process's accuracy and reliability.

3.1 Algorithm of Edge Enhance Sparse Deep Auto Encoder (EES-DAE)

Step i. Image acquisition from medical database i.e BRATS database [12]

Step ii. Pre-processing using Gaussian Filter.
(a) Assuming the original image is denoted as I(x, y) and the noisy image as

$I_{noisy}(x,y)$, noise can be added using an additive model:

$$I_{noisy}(x,y) = I(x,y) + N(x,y) \quad (1)$$

Where N (x, y) represents the noise at each pixel location.

(b) Apply a Gaussian filter to the MRI images for noise reduction and smoothing.

The Gaussian filter operation is defined by the following equation:

$$G(x,y) = \left(\frac{1}{(2 * pi * sigma^2)}\right) * \exp\left(-\frac{(x^2+y^2)}{(2 * sigma^2)}\right) \quad (2)$$

Whereas sigma: The parameter controlling the amount of smoothing. Remember that the choice of "sigma" affects the degree of smoothing applied. Smaller values of "sigma" will preserve finer details but might not effectively remove strong noise, while larger values of "sigma" will provide more aggressive smoothing but might blur important details.
(c) To apply the Gaussian filter to the noisy image $I_{noisy}(x,y)$, you convolve the filter with the image:

$$I_{smoothed}(x,y) = I_{noisy}(x,y) * G(x,y) \quad (3)$$

where $I_{smoothed}(x,y)$ is the output image after applying the Gaussian filter.

Step iii. Deconvolution

(a) The Wiener deconvolution is used to restore an image that has been convolved with a known filter and affected by additive noise. The Wiener deconvolution can be formulated as follows:

Given the blurred and noisy image:

$$B(x,y) = I_{smoothed}(x,y) * H(x,y) + N(x,y) \quad (4)$$

Where B(x, y) is the observed blurred and noisy image.

$I_{smoothed}(x,y)$ is the output of the Gaussian filter (from the previous step).
H(x, y)is representedas the known blurring filter.
N(x, y)is represented as the known additive noise.
The Wiener deconvolution estimates the true underlying image I(x, y) as

$$I_{wiener}(x,y) = F^{\wedge}(x,y) * [H^{\wedge}(x,y) / ((|H(x,y)|^{\wedge}2 + K))] * B(x,y) \quad (5)$$

where:
- F^*(x, y) represents the complex conjugate form of the image in frequency domain.
- H^*(x, y) represents the complex conjugate form of the blurring filter.
- K is a regularization parameter that helps balance noise amplification and suppression.

(b) Next the Lucy-Richardson deconvolution is applied which is an iterative algorithm that aims to restore an image from a convolved and noisy observation. It can be expressed iteratively as:

$$I^{\wedge}_{iterative}(k+1)(x,y) = I^{\wedge}_{iterative}(k)(x,y) * \left|\frac{H(x,y)}{(I^{\wedge}_{iterative}(k) * H(x,y))}\right| * \left(\frac{I_{smoothed}(x,y)}{(H(x,y) * (I^{\wedge}_{iterative}(k) * I_{smoothed}(x,y)))}\right) \quad (6)$$

where:
- I^ iterative (k)(x, y) is the estimated image after k iterations.
- B (x, y) is the observed blurred and noisy image.
- H (x, y) is the blurring filter.
- I_ smoothed(x, y) is the Gaussian filter's output
- For the next stage the assumption is

where:
- I^iterative (k)(x, y) is the estimated image after k iterations.
- B(x, y) is the observed blurred and noisy image.
- H(x, y) is the blurring filter.
- Ismoothed(x, y) is the Gaussian filter's output

For the next stage the assumption is

$$I_{wiener}(x,y) = \hat{I}_{iterative}(k)(x,y) = P(i,j) \quad (7)$$

Step iv. Initiate the Pixel Normalization Elimination process
(a) Determine the pixel values' mean and standard deviation in P(i, j).

mean value: $\mu = \left(\frac{1}{(M\ N)}\right) \sum P(i,j)$ (8)

standard deviation:

$$\sigma^2 = \frac{1}{(MN)} \sum (P(i,j) - \mu)^2 \quad (9)$$

(b) Normalize the pixel values in P (i j) using the mean and standard deviation. For each pixel P (i,j), apply the normalization formula given by

$$P_{norm}(i,j) = \frac{(P(i,j) - \mu)}{\sigma} \quad (10)$$

The resulting image after pixel normalization is denoted as $P_{norm}(i,j)$.

Step v. Introduce the 2D – DCT as a Transformation process,

(a) It is applied to convert the spatial domain pixel values of an image to the frequency domain. The image's frequency components are represented by this transformation.

The 2D DCT of an image $P_{norm}(i, j)$

$$F(u,v) = \left(\frac{1}{\sqrt{M * N}}\right) * C(u) * C(v) * \Sigma\Sigma P_{norm}(i,j) * \cos\left[\frac{(2 * i + 1) * u * \pi}{(2 * M)}\right] * \cos\left[\frac{(2 * j + 1) * v * \pi}{(2 * N)}\right] \quad (11)$$

where:

- F (u, v) is the DCT coefficient
- M and N are the dimensions of the image.
- C(u) and C(v) are normalization constants ($C(0) = 1 / \sqrt{2}$, $C(u) = 1$ for $u > 0$).
- P_ norm(i, j) is the normalized pixel value at spatial indices (i, j).

Let us add assumption $C_{norm}(t,f) = F(u,v)$ Which represent DCT Coefficients for next stage

Step vi. Filtering the Transformed Image using Entropy Filtering

(a) Compute the entropy of each DCTT coefficient and is given by

$$H(t,f) = -|C_{norm}(t,f)|^2 \, log2(|C_{norm}(t,f)|^2) \quad (12)$$

(b) Compute the local entropy threshold and Filter the DCT coefficients and To obtain the filtered image in the pixel domain, the inverse DCT is applied to the filtered coefficients F(t, f) using the following formula:

$$P_{filtered}(i,j) = Re\left[\Sigma\left(F(t,f)\, K(i - t, j - f)\right)\right] \quad (13)$$

where Re [] denotes the real part of the complex value, and the summation is performed over all time-frequency points (t, f) and the resulting image after applying entropy filtering to the DCT coefficients is denoted as $P_{filtered}(i,j)$.

Step vii. Extraction of features and complexity features

(a) The mathematical equations for extracting specific features

Mean:

$$\mu = \left(\frac{1}{(M\ N)}\right) \Sigma P_{filtered}(i,j) \quad (14)$$

where M and N are the dimensions of the filtered image

Standard Deviation:

$$\sigma^2 = \frac{1}{(MN)} \Sigma\left(P_{filtered}(i,j) - \mu\right)^2 \quad (15)$$

Entropy:

$$Entropy = -\Sigma\left(P_{filtered}(i,j)\, log2\left(P_{filtered}(i,j)\right)\right) \quad (16)$$

here the summation is performed over all pixel values in the filtered image.

Correlation:

$$Corr. = \left(\frac{1}{M\ N\ \sigma_x \sigma_y}\right) \Sigma\left(\left(P_{filtered}(i,j) - \mu_x\right)\left(P_{filtered}(i,j) - \mu_y\right)\right) \quad (17)$$

where σ_x *and* σ_y are filtered image standard deviations and μ_x and $\mu_y$are the means of the filtered image.

Energy:

$$Energy = \Sigma\left(P_{filtered}(i,j)\right)^2 \quad (18)$$

where the summation is performed over all pixel values in the filtered image.

Step viii. Edge Enhance Sparse Deep Auto Encoder (EES-DAE) Algorithm:

1. Load the extracted specific features from the filtered image P_filtered (i,j) into matrix X.
2. Prepare the corresponding labels or targets matrix Y for the training samples.
3. Initialize the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) architecture, designed to enhance edges using a deep autoencoder with sparsity regularization.
4. Initialize the weights and biases of the EES-DAE model with random values or use a pre-trained model.
5. Perform forward propagation to obtain the encoded representations. The forward propagation equation can be written as:
   $$Z = f_L\left(f_{(L-1)}\left(\dots f_2\left(f_1(X\ W_1 + b_1)\right)\dots\right)\right) \quad (19)$$
   Here, Z represents the encoded representations, f_i denotes the i-th layer activation function, W_i denotes the weights of the i-th layer, and b_i denotes the biases of i-th layer. L signifies the number of layers in the EES-DAE.
6. Incorporate sparsity regularization by adding an L1 regularization term, thus
   $$Loss = MSE(Z,Y) + \lambda * \Sigma\|W_i\|_1 \quad (20)$$
   Where MSE (Mean Square Errors) denotes the mean squared error, λ represents the regularization parameter, and $\Sigma\|W_i\|_1$||_1 represents the sum of L1 norms of the weights across all layers.
7. To calculate the gradients of the weights and biases with respect to the loss function, use backpropagation.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

8. Utilizing an optimization algorithm and the obtained gradients, update the weights and biases. (e.g., gradient descent).
9. Repeat steps 5 to 8 for multiple epochs until convergence is achieved.
10. After training, the EES-DAE model can be utilized for image enhancement, particularly in edge enhancement applications.

Step ix. Carrying out Softmax Entropy Classification and Extraction process to detect the brain tumors based on trained dataset.

(a) Let Z be the matrix representing the predicted outputs for the test samples.
(b) Compare the predicted outputs Z with the ground truth labels or targets for the test samples to detect the Brain Tumor Region.

Step x. Performance evaluation for Accuracy, Specificity, Sensitivity and PSNR attributes

4. EXPERIMENTATION RESULTS

The initial brain MRI scan from the BRATS medical database is shown in Figure 2 to illustrate the algorithm's beginnings. This raw image is the basic beginning point of the algorithm. It includes noise, artifacts, and complex anatomical details that were included in the original scan, together with the raw data that was extracted from the patient's brain.

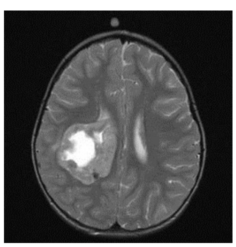


Figure 2: Input Brain Scan

A Gaussian filter is used as part of a transformative pre-processing step for the brain scan in Figure 3. This method skillfully smoothes the image and lowers noise. Consequently, the initial scan is improved, offering a more structured and transparent basis for the ensuing computational processes.

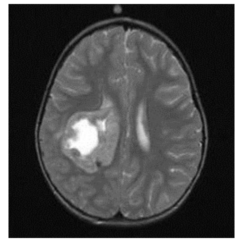


Figure 3: Pre-processed Image

A critical point at which noise reduction takes precedence is shown in Figure 4. The genuine essence of the underlying image is recovered using the Wiener deconvolution. By accounting for additive noise and reducing the impacts of noise by convolution with a known blurring filter, image clarity is increased and key brain scan structures are made to stand out.

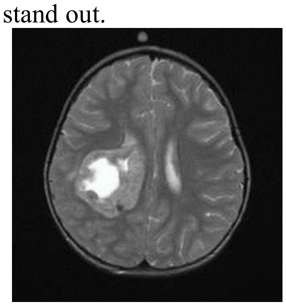


Figure 4: Pixel Noise Ratio Elimination

An important stage in the process is to filter the transformed image from the 2D Discrete Cosine Transform (DCT) for entropy, as shown in Figure 5. This intricate process removes coefficients that are below a predetermined threshold and calculates the entropy for every DCT coefficient. The filtered image is better represented of the complex structure of the brain since it highlights important features while reducing less important changes. The filtered image was reconstructed using inverse DCT.

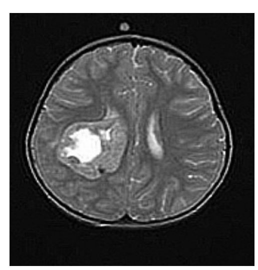
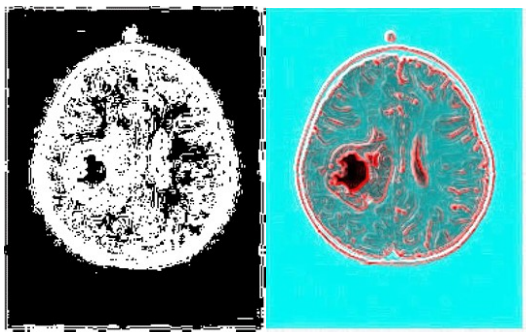


Figure 5: Entropy Filtered Image

The extraction of complexity features is examined in Figures 6(a) and (b). Sub-figure (a) includes properties that reveal details about the complexity and value distribution of pixels, such as

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

entropy, mean, and standard deviation. Sub-figure (b) introduces Correlation and Energy elements that clarify the correlations between pixels and the overall intensity of the signal. These features that were retrieved capture different facets of the image's attributes.



6(a) *6(b)*

Figure 6 (a) & (b): Complexity feature Extraction

Brain tumor region detection is highlighted in Figure 7, which shows the peak of the algorithm. After processing, enhancing, and extracting features, the image is applied to Edge Enhance Sparse Deep Auto Encoder (EES-DAE) and classified using Softmax entropy. Predicted outputs from test samples are compared to ground truth labels in this step. Potential tumor spots within the processed image can be identified thanks to the algorithm's use of Softmax entropy classification to give probabilities to classes. This classification uses picture enhancement and extracted attributes to reliably identify brain tumors.
.

Figure 7: Brain Tumor Detected region

120 BRATS MRI scans from a dataset comprising were used to evaluate the suggested model. 20% of the dataset (24 photos) were reserved for rigorous testing, which assessed the model's performance on fresh, never-before-seen data. Of these scans, 80% (96 images) were utilized to train the model. Additionally, Table 1 offers a thorough overview of the features like standard Deviation, Entropy, Mean, Variance, Smoothness, Contrast, Correlation and Energy, that were extracted with the help of the complexity feature extraction method. Using a subset of five carefully selected samples from the broader dataset, these properties were calculated. Due to its restricted scope, the model's performance on these particular samples can be thoroughly examined, offering important information on how well the model can identify minute characteristics in MRI scan images.

Table 1: Features Derived for MRI Brain Tumor Images

	Sample Brain Tumor Images				
Features Extracted	**Glioma**	**Meningioma**	**Pituitary**	**Metastasis**	**Astrocytoma**
Standard Deviation	0.0857	0.093	0.0897	0.09234	0.083
Entropy	0.00854	0.0079	0.00764	0.0071	0.0075
Mean	0.0036	0.0034	0.00423	0.00382	0.0047
Variance	2.4345	2.431	2.4245	2.424	2.479
Smoothness	0.9321	0.971	0.9324	0.931	0.931
Contrast	0.365	0.345	0.3712	0.345	0.352
Correlation	0.1865	0.1045	0.1091	0.1123	0.1201
Energy	0.8175	0.8129	0.8263	0.8157	0.8234

An MRI scan with a higher mean value could reveal a more intense or concentrated area, which might be indicative of a tumor. On the other hand, a higher standard deviation denotes more variance in pixel intensities, suggesting the coexistence of different tissue types inside the possible tumor location. On the other hand, higher entropy values show a wider range of pixel intensities, suggesting the existence of irregular or heterogeneous tissue structures that could be connected to tumorous growth. Moreover, larger variance values signify a larger degree of intensity variations, which may suggest the existence of particular tumor features or different tissue types.
The local consistency or regularity of the tumor region is referred to as smoothness. It displays the spatial distribution of pixel intensities. A greater smoothness rating suggests a more homogeneous and consistent appearance of the tumor region. Additionally, sharp fluctuations in pixel intensities, which are indicative of well-defined tumor borders,

Journal of Theoretical and Applied Information Technology
31st August 2024. Vol.102. No. 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

are present in higher contrast values. When correlation values are high, pixel intensities show a strong linear interdependence, suggesting the presence of particular texture patterns that could be connected to tumorous features. Lastly, elevated energy levels highlight the possible importance of the tumor by indicating a higher total intensity level inside the tumor location.

5. PERFORMANCE EVALUATION

One important parameter for evaluating the effectiveness of the created algorithm is the detection accuracy of brain tumors. It clarifies if the system can accurately recognize and categorize brain tumors in medical photos. The number of tumor regions accurately categorized relative to the total number of the areas investigated is used to calculate accuracy.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \qquad (21)$$

Here TP depicts the True Positive (identified Tumors), TN depicts True Negative, FP depicts False Positive whereas FN depicts False Negative (not identified)

The percentage of true negatives that the model correctly detected is known as specificity. It shows how well the model can categorise cases that are not tumors or cancers.

$$Specificity = \frac{TN}{(TN + FP)} \qquad (22)$$

Sensitivity, also known as the true positive rate or recall, is a crucial performance indicator in binary classification tasks, particularly in the medical diagnostics domain where cancer detection is concerned. This measurement relates to the model's ability to correctly identify positive cases in this specific setting, namely tumors or malignancies.

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

Peak Signal-to-Noise Ratio (PSNR) is a statistic that compares a compressed or reconstructed image to a reference (often the original) image to determine how good the reconstruction is. PSNR is used in the context of MRI (Magnetic Resonance Imaging) to evaluate the quality of pictures after they have been processed, such as by denoising, reconstruction, or compression methods, even though it is more frequently linked with general imaging or video compression.

The following formula can be used to get the Peak Signal-to-Noise Ratio (PSNR):

$$\mathrm{PSNR} = 10 \log 10 \left[\frac{(\max(I)^2)}{\mathrm{MSE}}\right] \qquad (24)$$

where MSE is the Mean Squared Error, given by:

$$MSE = \frac{1}{m * n} * \Sigma i = 1{:}m \; \Sigma j = 1{:}n \, [I(i,j) - D(i,j)]^2 \quad (25)$$

m and n denote the image dimensions.

5.1 Performance Evaluation of Brain Tumor detection

Table 2 presents a comprehensive comparison between the novel Edge Enhance Sparse Deep Auto Encoder (EES-DAE) proposed in this study and several existing techniques, including recurrent networks and ConvNets (CNN), Machine Learning, Texture-based and statistical features, a modified two-step dragonfly mechanism system, and a faster Region- based CNN. The focus of this comparison is on accuracy values, a crucial metric in assessing the effectiveness of these methods. The results of the analysis unmistakably highlight the advantage of the proposed Technique EES-DAE over the aforementioned methods in terms of accuracy.

Table 2: Evaluation of Accuracy Performance

S. No	Methodology implemented	Accuracy (%)
1	ConvNets	98.3
2	Machine Learning	95.83
3	Statistical features based on Texture	97.87
4	Improved two-step dragonfly mechanism model	98.20
5	Faster Region-based CNN	91.66
6	Proposed Technique (Edge Enhance Sparse Deep Auto Encoder (EES-DAE))	99.13

Considering the suggested approach that was previously discussed, the thorough analysis shown in Table 2 and the corresponding graphical representation in Figure 8 clearly show that the improved method performs better than developed techniques, especially in terms of accuracy, with an accuracy of 99.13%.

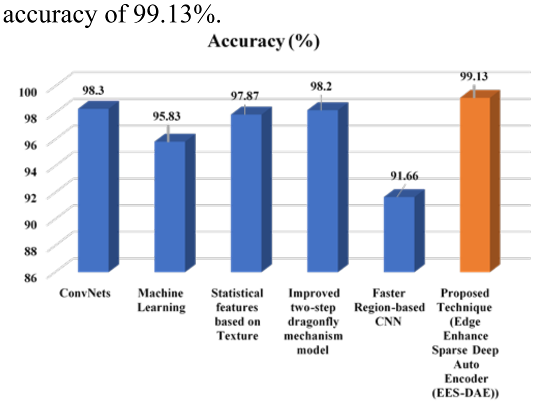


Figure 8: Comparison of Accuracy in Brain Tumor Detection

This remarkable result highlights the cooperative impact of the suggested approach's combination of improved features, skillful pre-processing techniques, and the customized algorithm utilized. The combined outcome represents a significant breakthrough in the field of brain tumor identification and categorization. Consequently, the suggested approach shows promise and makes a significant addition to the field of medical picture analysis.

Table 3: Evaluation of specificity and sensitivity in the detection of brain tumors

S. No	Techniques used	Specificity (%)	Sensitivity (%)
1	Improved Residual Network	76.13	83.5
2	Chronological Artificial Vultures Optimization (CAVO)	93.8	94.1
3	*i*-YOLOV5	98.78	95.77
4	Whale Harris Hawks optimization (WHHO) + Deep Convolution Neural network (DCNN)	79.1	97.4
5	Proposed Technique	99.43	99.3421

Table 3 offers a thorough assessment of specificity and sensitivity with regard to brain tumor identification. Evaluations are being conducted on the following methods: the Improved Residual Network [35], the Whale Harris Hawks Optimisation (WHHO) + Deep Convolution Neural Network (DCNN) [33], the Chronological Artificial Vultures Optimisation (CAVO) [36], and the proposed technique [34]. A tumor detection technique's effectiveness is mostly determined by its specificity and sensitivity metrics. While sensitivity gauges a method's capacity to identify real tumor instances, specificity assesses a method's capacity to accurately distinguish non-tumor cases. Improved performance overall is shown by elevated values for both criteria, which are Specificity 99.43% and Sensitivity 99.4321%.

By visualizing this comparative analysis, Figure 9 demonstrates the dynamics of specificity and sensitivity in brain tumor identification. This graphical depiction highlights the obvious superiority of the suggested method and offers an easy-to-use platform for direct comparisons between methodologies.

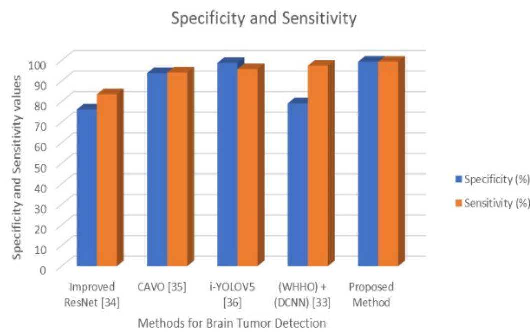


Figure 9: Comparison of Specificity and Sensitivity in Brain Tumor Detection

Table 4: Comparing PSNRs to Detect Brain Tumors

S. No	Methodology used	PSNR (dB)
1	Modified Residual Network	21.457
2	*i*-YOLOV5	27.28
3	Deep Convolutional Neural Networks	29.38
4	Machine Learning	24.2
5	Noise Learning Generative Adversarial Network	28.49
6	Proposed Method	50.0118

A thorough performance evaluation based on the peak signal-to-noise ratio (PSNR), a commonly used metric for evaluating the quality of reconstructed or denoised pictures, is given in Table 4 with regard to brain tumor identification. The PSNR values obtained using various techniques for brain tumor detection are presented in this table in a comparative manner.

In order to explore this assessment in more detail, Figure 10 becomes an essential illustration, focusing on the PSNR component in the context of brain tumor identification. This comparison figure carefully lines up the PSNR values obtained from several approaches, such as the suggested strategy and a few well-known methods. Among the noteworthy ones are the Noise Learning Generative Adversarial Network [32], Deep Convolutional Neural Networks [31], Machine Learning [22], i-YOLOV5 [36], and Improved Residual Network [34].

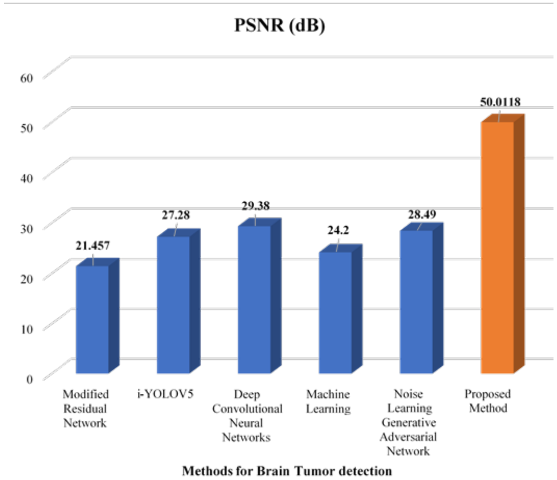


Figure 10: Comparison of PSNR in Brain Tumor Detection

The plot provides a visual representation of various approaches' PSNR performance and successfully captures their ability to improve image quality in the context of brain tumor identification. By comparing the suggested technique to its existing counterparts, this visual analysis highlights its advantages and demonstrates its capacity to produce better PSNR results of better value 50.018 dB, which in turn improves the overall quality of rebuilt or denoised brain tumor images.

6. CONCLUSION AND FUTURE SCOPE

The research contribution of this work lies in its development and implementation of a novel methodology for brain tumor detection and classification in MRI images, leveraging advanced deep learning techniques. This research introduces the Edge Enhance Sparse Deep Auto Encoder (EES-DAE) model, which is designed to enhance edge saliency and improve the accuracy of tumor detection. The innovative approach combines multiple steps: preprocessing with a Wiener filter to improve MRI image quality, pixel normalization to minimize noise, and feature extraction using 2D Discrete Cosine Transform (DCT) and entropy filters. This work advances the field by offering a comprehensive, multidimensional approach that surpasses the limitations of existing brain tumor detection methods. The journey has several stages, beginning with preprocessing, in which a Wiener filter is used to improve the quality of brain MRI scans. This foundation lays the groundwork for subsequent analysis. Following that, a pixel normalization elimination process extracts key features while simultaneously mitigating the impact of noise interference. In its intermediate stages, the methodology advances further, seamlessly incorporating the 2D Discrete Cosine Transform (DCT) and entropy filters. This meticulous integration extracts intricate features, significantly improving the model's accuracy.

The culmination of these techniques, integrated with soft-max entropy classification, results in a highly accurate detection system, achieving a 99.13% accuracy rate on the BRATS MRI brain image dataset. The accomplishments of the proposed methodology have significant implications for the field of medical image analysis. The model's specificity of 99.43%, sensitivity of 99.3421%, and PSNR of 50.0118 dB demonstrate its superiority over methods previously reported in the literature. These remarkable results not only highlight the possibility of early and accurate brain tumour detection, but also open the door to improved diagnostic precision.

The EES-DAE model's multidimensional approach, combined with cutting-edge techniques such as softmax entropy classification, provides a blueprint for future efforts to improve medical imaging techniques. The ability of this methodology to improve early diagnosis, prognosis, and treatment monitoring highlights its transformative impact on the healthcare landscape. This research work focuses on presence or absence of tumor in brain MRI images but not on classifying the tumor type and other properties of the tumor such as size and location of the tumor. In future the researchers can work on it. As technology and methodologies advance, this research paves the way for even more sophisticated and precise medical image analysis methodologies in the future.

REFERENCES:

[1] Medical Imaging in Cancer Care: Charting the Progress, US Oncology and National Electrical Manufacturers Association (2012)

[2] Mishra PK, Satapathy SC, Rout M (2021) Segmentation of MRI Brain Tumor Image using Optimization based Deep Convolutional Neural networks (DCNN). Open Comput Sci 11:380–390

[3] Parihar AS (2017) A Study on Brain Tumor Segmentation Using Convolution Neural Network. 2017 International Conference on Inventive Computing and Informatics (ICICI)

[4] Rammurthy D, Mahesh PK (2020) Whale Harris Hawks optimization based deep learning classifer for brain tumor detection

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

using MRI images. J King Saud Univ Comput Inf Sci 1–14.

[5] Reza, S.; Iftekharuddin, K.M. Improved brain tumor tissue segmentation using texture features. In Proceedings of the MICCAI BraTS (Brain Tumor Segmentation Challenge), Boston, MA, USA, 14 September 2014; pp. 27–30

[6] Ramtekkar PK, Pandey A, Pawar MK (2020) A proposed model for automation of detection and classifcation of brain tumor by deep learning. 2020 2nd International Conference on Data, Engineering and Applications (IDEA).

[7] Ramtekkar PK, Pandey A, Pawar MK (2023) Innovative brain tumor detection using optimized deep learning techniques. Int J Syst Assur Eng Manag 14:459–473

[8] Ruan, S.; Lebonvallet, S.; Merabet, A.; Constans, J.-M. Tumor segmentation from a multispectral MRI image by using support vector machine classification. In Proceedings of the 2007 4th IEEE International Symposium on Biomedical Imaging: From Nano to Macro, Arlington, VA, USA, 12–15 April 2007; pp. 1236–1239.

[9] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, et al. "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)", IEEE Transactions on Medical Imaging 34(10), 1993-2024 (2015) DOI: 10.1109/TMI.2014.2377694

[10] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J.S. Kirby, et al., "Advancing The Cancer Genome Atlas glioma MRI collections with expert segmentation labels and radiomic features", Nature Scientific Data, 4:170117 (2017). DOI: 10.1038/sdata.2017.117

[11] S. Bakas, M. Reyes, A. Jakab, S. Bauer, M. Rempfler, A. Crimi, et al., "Identifying the Best Machine Learning Algorithms for Brain Tumor Segmentation, Progression Assessment, and Overall Survival Prediction in the BRATS Challenge", arXiv preprint arXiv:1811.02629 (2018)

[12] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. Kirby, et al., "Segmentation Labels and Radiomic Features for the Pre-operative Scans of the TCGA- GBM collection", The Cancer Imaging Archive, 2017.

[13] S. Mohsin, S. Sajjad, Z. Malik, and A. H. Abdullah, "Efficient way of skull stripping in MRI to detect brain tumor by applying morphological operations, after detection of false background," International Journal of Information and Education Technology, vol. 2, no. 4, pp. 335–337, 2012.

[14] B. Willmore, R. J. Prenger, M. C. Wu, and J. L. Gallant, "The Berkeley wavelet transform: a biologically inspired orthogonal wavelet transform," Neural Computation, vol. 20, no. 6, pp. 1537– 1564, 2008.

[15] P. Remya Ravindran and K. P. Soman, "Berkeley wavelet transform based image watermarking," in Proceedings of the International Conference on Advances in Recent Technologies in Communication and Computing (ARTCom '09), pp. 357–359, IEEE, Kerala, India, October 2009.

[16] M. Alwan and E. M. Jamel, "Digital image watermarking using Arnold scrambling and Berkeley wavelet transform," AlKhwarizmi Engineering Journal, vol. 12, pp. 124–133, 2015.

[17] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Transactions on Systems, Man and Cybernetics, vol. 3, no. 6, pp. 610–621, 1973.

[18] J. Liu, M. Li, J.Wang, F.Wu, T. Liu, and Y. Pan, "A survey of MRIbased brain tumor segmentation methods," Tsinghua Science and Technology, vol. 19, no. 6, pp. 578–595, 2014.

[19] S. Bakas, H. Akbari, A. Sotiras, M. Bilello, M. Rozycki, J. Kirby, et al.,(opens in a new window) "Segmentation Labels and Radiomic Features for the Pre-operative Scans of the TCGA-LGG collection", The Cancer Imaging Archive, 2017.

[20] Pashaei A, Sajedi H, Jazayeri N. Brain tumor classification via convolutional neural network and extreme learning machines. In: 2018 8th international conference on computer and knowledge engineering (ICCKE). IEEE; 2018 Oct 25. p. 314–9.

[21] Sharma AK, Tiwari S, Aggarwal G,Goenka N, Kumar A, Chakrabarti P, Chakrabarti T, Gono R, Leonowicz Z, Jasiński M (2022) Dermatologist-Level Classification of Skin Cancer Using Cascaded Ensembling of Convolutional Neural Network and Handcrafted Features Based Deep Neural Network. IEEE Access. https://doi.org/10.1109/ACCESS.2022.3149824

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[22] Zhang, J., Zhou, H., Niu, Y., Lv, J., Chen, J., & Cheng, Y. (2021). CNN and multi-feature extraction based denoising of MRI Scans. Biomed. Signal Process. Control., 67, 102545.
[23] Hossain T, Shadmani Shishir F, Ashraf M, Abdullah Al Nasim MD, Muhammad Shah F (2019) Brain Tumor Detection Using Convolutional Neural Network, 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT-2019)
[24] Khalil, H.A.; Darwish, S.; Ibrahim, Y.M.; Hassan, O.F. 3D-MRI brain tumor detection model using modified version of level set segmentation based on dragonfly algorithm. Symmetry 2020, 12, 1256.
[25] Avsar E, Salcin K (2019) Detection and classification of brain tumors from MRI images using faster R-CNN. Tehnički Glasnik 13(4):337–342
[26] Naseer I, Akram S, Masood T, Jaffar A, Khan MA, Mosavi A. Performance analysis of state-of-the-art cnn architectures for luna16. Sensors. 2022;22(12):4426. doi: 10.3390/s22124426.
[27] Hussain S, Anwar SM, Majid M. Segmentation of glioma tumors in brain using deep convolutional neural network. Neurocomputing. 2018; 282:248–61.
[28] Khalid S, Khalil T, Nasreen S. A survey of feature selection and feature extraction techniques in machine learning. In: 2014 science and information conference. IEEE; 2014 Aug 27. p. 372–8.
[29] Tripathi PC, Bag S. Non-invasively grading of brain tumor through noise robust textural and intensity based features. In: Computational intelligence in pattern recognition. Springer; 2020. p. 531–9.
[30] Han S, Pool J, Tran J, Dally W. Learning both weights and connections for efcient neural network. Adv Neural Inf Process Syst. 2015;28:1135–43.
[31] Unal, M.O., Ertas, M., & Yildirim, I. (2020). An unsupervised reconstruction method for low-dose CT using deep generative regularization prior. Biomed. Signal Process. Control., 75, 103598.
[32] Y. Ma, B. Wei, P. Feng, P. He, X. Guo and G. Wang, "Low-Dose MRI Scan Denoising Using a Generative Adversarial Network With a Hybrid Loss Function for Noise Learning," in IEEE Access, vol. 8, pp. 67519-67529, 2020, doi: 10.1109/ACCESS.2020.2986388.
[33] Rammurthy D, Mahesh PK (2020) Whale Harris Hawks optimization based deep learning classifier for brain tumor detection using MRI images. J King Saud Univ Comput Inf Sci 1–14
[34] Aggarwal, M., Tiwari, A.K., Sarathi, M. et al. An early detection and segmentation of Brain Tumor using Deep Neural Network. BMC Med Inform Decis Mak 23, 78 (2023). https://doi.org/10.1186/s12911-023-02174-8
[35] Geetha M, Prasanna Lakshmi K, Sajeev Ram Arumugam & Sandhya N (2023) Conditional random field-recurrent neural network segmentation with optimized deep learning for brain tumour classification using magnetic resonance imaging, The Imaging Science Journal.
[36] Sivapathi Arunachalam & Gopalakrishnan Sethumathavan (2022) An effective tumor detection in MR brain images based on deep CNN approach: i-YOLOV5, Applied Artificial Intelligence.

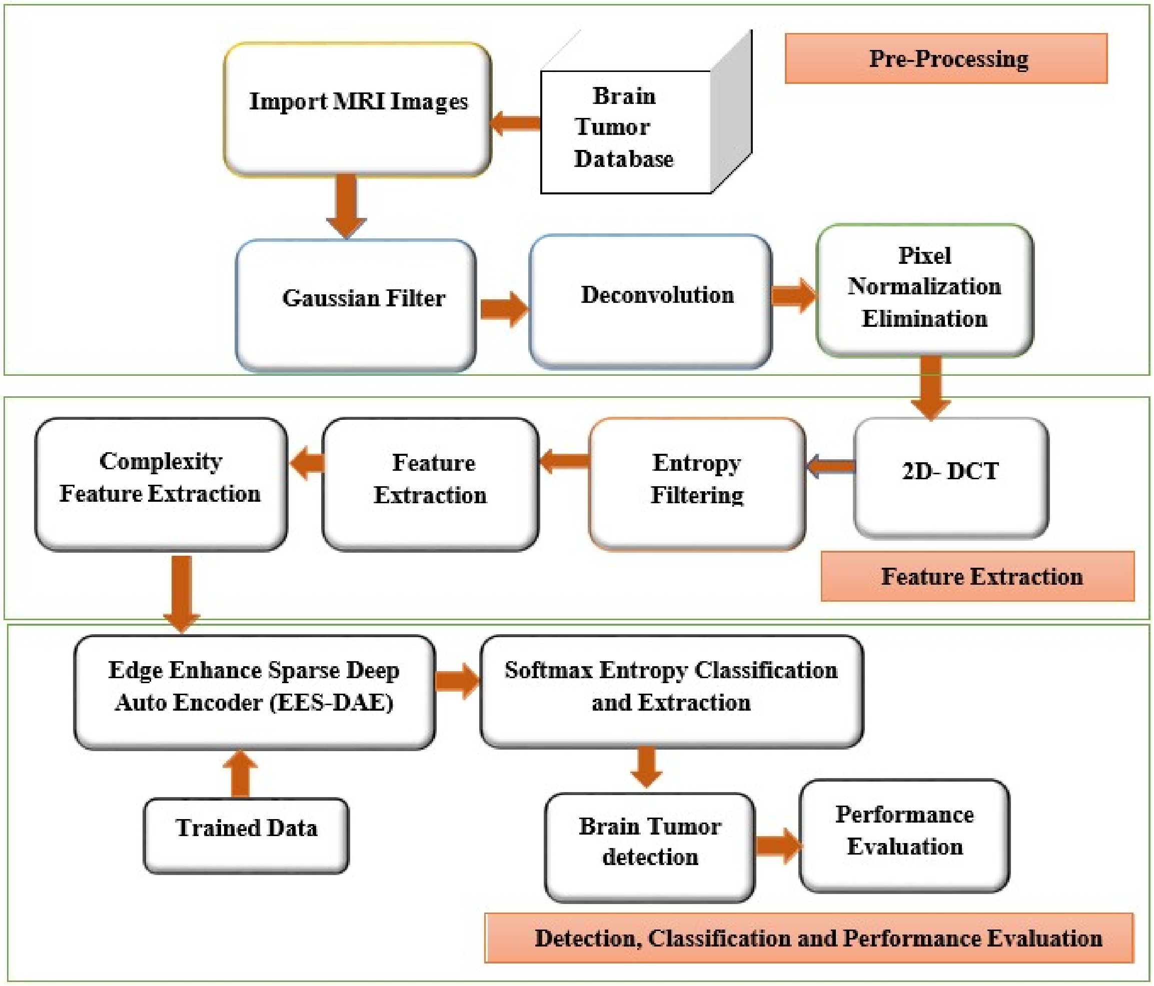


Figure 1: Proposed Brain Tumor Detection Method