Analysis and development of brain tumor prediction model using deep neural network

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Abstract: The human brain consists of billions of living organisms and is very difficult to decipher because of its complexity. Brain tumors can be deadly, significantly impacting the quality of life and changing everything for patients and their loved ones. In today's world, brain tumors are a leading cause of death in both children and adults. A high death percentage is caused due to the invasive properties of tumors. But it is inspiring that the survival rate might increase if the diagnosis is performed at the early stage [9]. Accurate detection of the brain tumor at an early stage can prolong the chance of survival of an infected patient [4]. Magnetic Resonance Imaging (MRI) is the most popular imaging technique used today for detecting brain tumors. Deep Neural Network techniques plays an important role in detecting brain tumors. This manuscript offers a brief analysis of studies conducted by various authors in the field of BT categorization and diagnosis from MRI images using Deep Neural Network (DNN). This paper also suggests a method for classifying and identifying brain tumors based on MRI pictures and supporting text using DNN and DWT.

Keywords: - MRI (Magnetic Resonance Imaging), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Image Processing, Image segmentation, DWT (Discrete Wavelet Transformation)

1. Introduction

A Brain Tumor (BT) is an unusual growth of brain cells. A wide variety of BT is found in different parts of the body [1]. It is possible for tumors to begin in the brain or to spread from malignancies in other regions of the body into the brain. Swelling headaches, impaired vision, and balance issues are among the most common symptoms of brain tumors [2].

Surgery, radiation therapy, and chemotherapy are all options for treating human BT. The human brain consists of billions of living organisms and is very difficult to decipher because of its complexity. In today's world, brain tumors are a leading cause of death in both children and adults. Approximately 2,50,000 people worldwide are diagnosed each year with primary brain tumors, which account for less than 2% of all malignancies [3].

Medical pictures are segmented, classified, and optimized using deep learning-based algorithms. Segmenting photos entails classifying them using pixel-to-pixel approaches. A basic Convolutional Neural Network (CNN) is used to predict the center of each patch of medical pictures. A key part of picture identification and prediction is the use of a CNN [4].

A BT is the deadliest cancer of the nervous system, and it can be fatal or severely affect one's health. Glioma, a kind of primary BT has the highest sickness-to-fatality ratio. Magnetic Resonance Imaging (MRI) is one of the best commonly utilized medical imaging sensory systems for BTs and has revolutionized glioma diagnosis and therapy. Patients must have an early diagnosis and detection of BTs. Two kinds of BTs were introduced named malignant and benign. Tumors are defined as benign or malignant centered on the presence or absence of cancer cells [5].

BT is a malignant expansion of the central spine or tissue that can impair brain function. Furthermore, to be successful, tumor detection techniques must be extremely fast and exact. This can be done only using MRI, and by segmenting challenging medical images with MRI segmentation, ambiguity is minimized. Figure 1 depicts the different MRI classifications [6].

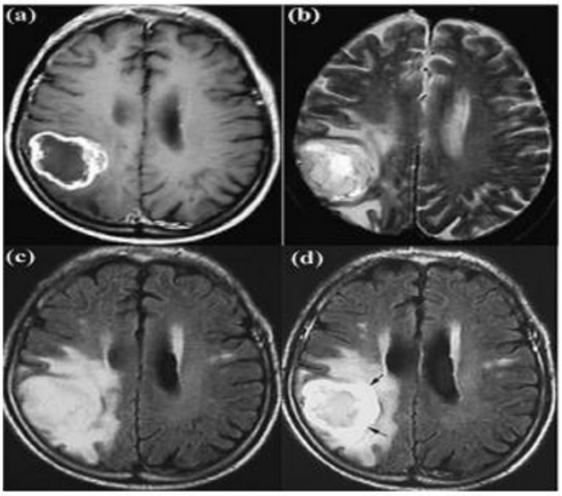

Figure 1: a) T1-Weighted MRI b) T2-Weighted MRI c) Flair d) Flair with Contrast Improvement [6]

In evaluating the structure of the tumors, Computed Tomography (CT) and MRI could be performed. In comes to brain imaging, MRI provides a more detailed view of the brain's architecture than CT scans, which use radiation that could be harmful to the patient's health. MRI creates detailed images of tissues and organs by using radio waves and magnetic fields [7].

In clinical brain anatomy research, MRI has become a crucial technique as the general clear separation of soft tissue, sharp contrast, and high resolution a valid diagnosis might well be established [8]. In diagnosing pathology, examining evolution, and determining the best surgical treatment or alternatives, MRI must be subdivided between healthy and sick tissues. It could be difficult to precisely determine the boundaries of various tissue sections with inconsistent automation, and automated volumetric MRI signal analysis is a viable solution to this problem. A tumor in the body represents unregulated cancer cell growth in the brain, it represents unrestrained neuronal proliferation. Benign tumors are similar in form but do not comprise active cancer cells, while malignant (heterogeneous) tumors have active cancer cells [9][10].

2. Literature of Review

This section contains contributions of various authors in the field of identification and classification of BT MRI images using CNN and Deep Neural Network (DNN).

Nayak et al., (2022) [11] explained that if MRI data is combined technologies, BT risk is determined more quickly and precisely than ever before. This aids in the delivery of treatment to patients. The performance of a collection of Artificial Neural Networks (ANN) employed in the detection of BT is evaluated using several criteria. Convolutional neural network parameters, which are used in the brain MRI dataset to identify any region of a tumor, utilize new and improved optimization approaches.

Santos et al., (2022) [12] described that the scientific community defines a BT as the expansion of irregular brain cells, some of which eventually develop into cancer. To identify malignancies in the brain, nuclear MRI has long been used. Tissue development in the brain that is out of control is detected using MRI imaging. Machine Learning and Deep Learning algorithms have been used in various studies to identify BT. BT probability is calculated quicker and more accurately using these methods, which are applied to MRI data.

Bayoumi et al., (2021) [13] stated that the outcome of a patient suffering from BT is improved if it can be discovered and treated as early as possible. It is very difficult to manually evaluate MRI pictures because of the sheer volume of data generated in the clinic daily. The most successful change has been tested on five CNNs, each of which had five different modifications done to it. In most BT datasets, there are just a few photos available to train the deep learning approach. Deep Learning utilizing MRIs reveals crucial BT indications.

Deepak et al., (2021) [14] stated that the human brain computer-aided diagnosis method is heavily reliant on automated tumor characterization. A significant difficulty in differentiating brain malignancies into meningioma, pituitary, and glioma tumors using MRI imaging. It comes to tackling photo classification challenges, the rise of Machine Learning and Deep learning procedures has generated favorable outcomes. However, the small size of medical image databases limits the categorization of medical images. The medical images were to be categorized using a pattern of CNN and Support Vector Machine (SVM) features. Extensive testing of the suggested technique on several MRI datasets for the brain to validate its advantages. The training data was restricted, and the SVM classifier outperformed the SoftMax classifier for CNN features. CNN-SVM classification requires fewer computations and memory than transfer learning-based categorization.

Irmak et al., (2021) [15] explained that biopsy samples are still used for the diagnosis and categorization of BT nowadays. These drawbacks highlight the need of developing a deep learning-based system for multi-classifying BT that is automated. To solve three separate categorization problems, CNN models have been developed for each. Five forms of brain tumors were classified by the second CNN model with an accuracy rate of 92.66%.

Jadhav et al., (2020) [16] explained that image processing is becoming one of the most sought-after and lucrative occupations. A brain tumor is an abnormal growth of cells that may occur anywhere in the body. Tumors are classified into two types: non-malignant and cancerous. Doctors used to manually diagnose early-stage tumors, but this procedure is time-consuming and can produce inaccurate results. MRI segmentation of BTs using CNN.

Researchers can utilize a variety of ways for segmenting and classifying BTs to find them. There are several techniques for detecting BTs, but it focuses on the benefits and cons of each. Instead, consider employing a CNN-based classifier. The accuracy of the taught and tested data can be compared using this classifier.

Amin et al., (2020) [17] stated that the BT is a grouping of the aberrant cells that increases the human death rate. Thus, to include structural and textural information for the identification of BTs, four MRI systems pulse sequences which are T1C, T1, T2, and Flair were merged in a fusion procedure. A single MRI sequence is not as informative as a Discrete Wavelet Transform (DWT) and Daubechies Wavelet Kernel (DWK) fusion method. Following the merging procedure, a Partial Differential Diffusion Filter (PDDF) is used to eliminate any residual noise. A large-scale thresholding technique is adopted to segment the tumor area which is subsequently input into the suggested CNN model to discriminate between tumor and non-neoplastic areas. The proposed technique is evaluated using five publicly accessible datasets such as Brain Tumor Image Segmentation Benchmark (BRATS) 2012, BRATS 2013, BRATS 2015, BRATS 2018, and BRATS 2013 Leader board. Images that have been fused outperform those that have been stitched together individually on benchmark datasets.

Kumar et al., (2020) [18] explained that to determine the tumor's stage, a tumor classification and segmentation technique must be used to make a distinction between tumorous and non-tumorous cells. Segmenting MRI data is tough because of the vast variety of image sizes and the sheer amount of data. It provides a novel deep understanding mechanism called Dolphin Echolocation centered Sine Cosine Algorithm (Dolphin-SCA) based Deep CNN to enhance classification accuracy and efficiency. On the input MRI images, the first round of pre-processing is conducted, followed by a segmentation phase. Dolphin-SCA is used to train the Deep CNN for BT categorization with an accuracy of 0.963 percent. The useful findings were obtained using MRI images from the Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) database.

Ahmed et al., (2020) [19] explained that when it comes to soft tissue planning, MRI is often the imaging modality of preference. It depicts an automated diagnosis strategy based on MRI image classification. The two key processes in the given technique are feature extraction and classification. Utilizing DWT-implemented MRI image qualities such as rotation invariant texture characteristics designed on Gabor filtering was created, as well as inverse and forward textural properties, and it analyses the significance of every single attribute in the division. The classifier employs a Feed Forward Back Propagation Artificial Neural Network in the grouping phase. A Neural Network (NN)-centered binary classifier could then teach to repeatedly assess whether the image depicts a disordered, sick, or healthy brain. For the clinical Brain MRI database, the suggested technique obtained 94.3 percent accuracy, 97.50 percent sensitivity, and 82.86 percent specificity. Compared to other modern methodologies, the algorithm shown here is robust and successful.

Özyurt et al., (2019) [20] explained that BT categorization is a challenging topic in the realm of medical image handling. It necessitates the use of a Hybrid approach, which includes the Neutrosophy CNN (NS-CNN). The main goal of the author is to discriminate benign and malignant tumor regions from brain pictures. MRI images were segmented utilizing Neuromorphic Set–Expert Maximum Fuzzy-Sure Entropy (NS-EMFSE) in the first phase. As categories, the properties of the segmented brain pictures obtained by CNN, SVM, and KNN classifiers were utilized. A five-fold cross-validation test was utilized to analyze the experimental data on eighty benign and 80 malignant tumors. According to the data, the CNN features beat a variety of classifiers. CNN features outperformed SVM because recommended model results supported production statistics with an ordinary accomplishment proportion of 95.62 percent.

In [21] authors Manmet et.al (2019) have developed an automated technique for malignant brain tumor classification utilizing the HAARLET transform and a probabilistic neural network. In addition to the HAARLET transform, data preprocessing employs threshold-based segmentation and binarization. The training data set's feature extraction produces twelve features for each of the training images, which are then utilized to train a probabilistic neural network. The developed approach has been proven to have a classification accuracy of 96.3 percent [21].

Table 1 shows the summary of the literature review based on Brain Tumor MRI images using DWT and DNN below:

Author	**Techniques**	**Outcomes**
Nayak et al., (2022) [11]	ANN	Convolutional neural network parameters, which are used in the brain MRI dataset to identify any region of a tumor, utilize new and improved optimization approaches.
Santos et al., (2022) [12]	Machine Learning and Deep Learning	BT probability is calculated quicker and more accurately using these methods, which are applied to MRI data.
Bayoumi et al., (2021) [13]	CNN	The most successful change has been tested on five CNNs, each of which had five different modifications done to it.
Deepak et al., (2021) [14]	Machine Learning	CNN-SVM categorization requires fewer computations and memory than transfer learning-based categorization.
Irmak et al., (2021) [15]	CNN	Five forms of brain tumors were classified by the second CNN model with an accuracy rate of 92.66%.
Rakshita et al., (2020) [16]	DWT	The developed approach has a success rate of 91.6 percent.
Amin et al., (2020) [17]	CNN	Images that have been fused outperform those that have been stitched together

		individually on benchmark datasets.
Kumar et al., (2020) [18]	Dolphin-SCA	With an accuracy of 0.963 percent, useful findings were obtained using MRI images from the BRATS database.
Ahmed et al., (2020) [19]	FP-ANN	Compared to other modern methodologies, the algorithm shown here is robust and successful.
Özyurt et.al., (2019) [20]	NS-CNN	CNN features outperformed SVM because recommended model results supported production statistics with an average achievement proportion of 95.62 percent.
Manmet et.al., (2019) [21]	HAARLET transform and a probabilistic neural network	The developed approach has been proven to have a classification accuracy of 96.3 percent

Table 1: Summary of literature review based on brain tumor MRI images

3. Research Gap

- BTs classification is a tough challenge in medical image processing.
- Detecting the tumor's growth direction is a critical issue in medicine.
- Finding infectious spots in MRI images of BTs takes a long moment and a great deal of effort.
- The storage and transmission bandwidth needs to increase because of the huge quantity of images produced by MRI.

4. Problem Formulation

A tumor is a grouping of aberrant cells. It has the unintended consequence of raising human death rates. A patient's long-term survival is increased when a tumor is detected in its early stages. DNN was used to create an automated technique for categorizing malignant BTs. Some of the techniques employed in this approach include grayscale conversion, label propagation for image segmentation, and MRI image feature extraction. Furthermore, in this work, the associated text is also utilized to increase the correctness of the model. The model is trained using a DNN. Compared to existing approaches, the suggested strategy has the potential to enhance classification accuracy.

5. Research Objectives

- To detect the direction of the tumor cells projection in the brain.
- To optimize the feature extraction of MRI images using the neural network.
- To increase the accuracy of image segmentation through label propagation and grayscale conversion approach.
- To enhance the performance of the model with the state-of-the-art literature.

6. Research Methodology

This section explains the proposed methodology for the classification and grouping of BT, and MRI pictures using DWT as well as DNN. In the proposed work given dataset https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 can be used at the time of implementation.

6.1 Technique used

Several techniques are used to classify and identify MRI images of BTs which are discussed below:

6.1.1 DWT

The DWT will be used to generate image banding. The use of the wavelet transform simplifies image analysis and feature extraction DNN [22]. Wavelet transformations are an excellent feature extraction approach because enable images to be analyzed at different resolutions. Although this method has a vast stockpile, it is more expensive to execute on a computer. The wavelet is utilized as a sophisticated mathematical method to obtain the wavelet coefficient from MR images [23].

An image in DWT is represented as a succession of wavelet functions at different sizes and locations. It creates a few images that depict the breakdown process. Any wavelet decomposition of an image produces two waveforms: one for the image's high-frequency features and the other for its low-frequency smoothness. The utility h(n) and g(n) indicate the measurements of the high-pass and low-pass filters individually, in a two-level DWT decomposition of an image (n). As a result, each level includes four sub-band images i.e., Low-Level (LL), Low-High (LH), High-High (HH), and High-Level (HL). The LL sub band represents the estimated elements of the text, although the LH, HL, and HH substitute groups reflect the detailed component [24].

DWT 3-level decomposition, as used before to extract 32 x 32=1024 features from each MRI image. This quantity is minimal in contrast to the sum of characteristic records created by CNN complexity streams; however, Principal Components Analysis (PCA) was used to estimate the initial returned includes with smaller-dimensional feature vectors [25]. Figure 2 shows the two-level DNN decomposition of an image.

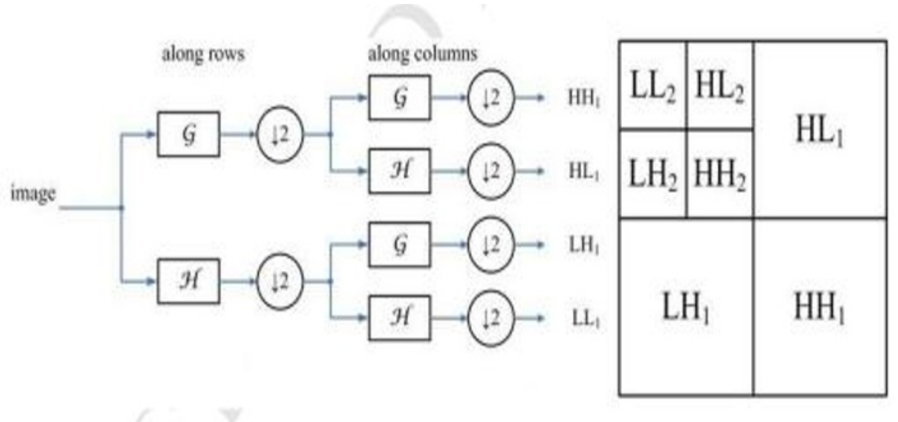

Figure 2: DWT decomposition of an image [24]

A wavelet was utilized to examine the frequency spectrum of an image where DWT is a powerful feature extraction tool. These images were used to extract wavelet coefficients from MR scans of the brain. A wavelet is used to localize the frequency information of the signal function, making it helpful for signal classification. Image text features could be better represented utilizing both low-level (LL) and high-level (HL) spatial frequency components recovered from images using the 2D DNN. The various frequency components were analyzed with a resolution appropriate to their scale and displayed as frequency components as shown below:

$$\text{DWT p(s)}= di.j = \sum p(s)\, h * \text{I}\ (\text{s} - 2\text{ij}) \quad (1)$$

$$\text{DWT p(s)}= bi.j = \sum p(s)\, g * \text{I}\ (\text{s} - 2\text{ij}) \quad (2)$$

The utility h(s) and g(s) in the calculation are high-level-forward along with low-pass screen quantities, individually, while factors i and j indicate riffle measurement and conversion considerations. The quantities $di.j$ belongs to the element point in signal $p(s)$ matching rippling work, whereas $bi.j$ refers to the valued elements in the indicator [26].

6.1.2 Deep Neural Network (DNN)

DNNs have been extensively employed for tackling complicated problems in a variety of disciplines, including computer vision, voice processing, and robotics, and DNNs produce spectacular results on increased cloud servers. Due to connection and latency restrictions, as well as confidentiality considerations, it is nevertheless anticipated to work effectively when utilized locally on smartphones [27].

DNN modeling for both sources of energy and resource-constrained devices has proliferated. DNN models for resource-constrained-end devices have so far received little interest in recent years, necessitating considerable research efforts. There are several DNN models, as well as hardware & software requirements for creation, resource limits imposed by computing equipment, and optimization strategies necessary for the effective processing of DNNs [28].

Each training and testing data set is represented by a distinct input neuron. Different inputs are present as a character in the data collection, which is a mathematical equivalence. A structure like this one allows convergence with an ideal classifier as the combined training set size rises, and it includes training models that can be added or withdrawn without needing major retraining. It is an excellent classifier and Figure 3 depicts a typical DNN model.

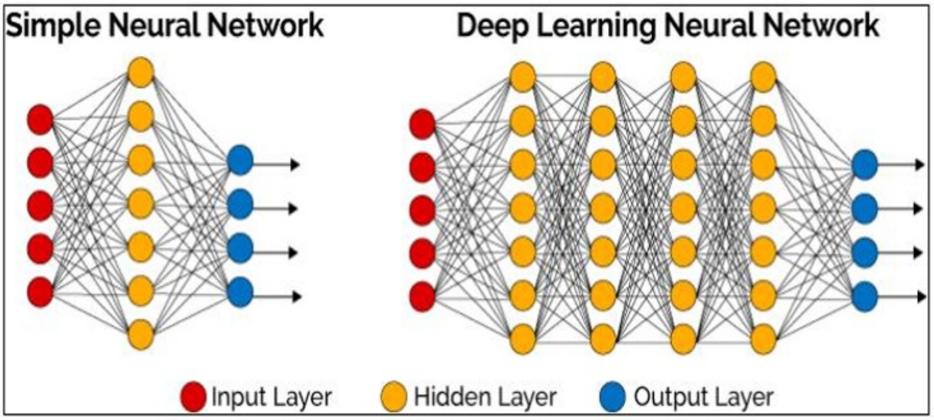

Figure 3: Architecture of DNN [28]

The four tiers of the DNN network are detailed in the following paragraphs [29]:

Input Layer: Each indication is represented by a single neuron. In categorizing information, neurons are connected in N1 groups, where N specifies the number of classifications. The input neuron is stated to normalize the range of inputs by subtracting the median value. From this point, it is expected that these features will be retained in each buried layer neuron.

Hidden Layer: In this array, each sample in the training dataset is represented by a single neuron. Neurons hold the objective and indication values for each instance. The x vector of the input layer is revealed, the hidden neurons calculate the experiment's Euclidean distance from the neuron's mid-point and then apply the Radial Basis Function (RBF) kernel function consuming the sigma value. The resultant is subsequently received by neurons in the summation layer.

Summation Layer: For every single class of tangible criteria, a single pattern neuron is available. Weight values generated by hidden neurons are transmitted to pattern neurons associated with the kind of hidden neurons by storing them with the target class for each training group. Following that, the values for each representation class are incorporated in the pattern neurons hence, these values represent the weighted votes for the classification. In preparation, the layer operates a dot product method (Z) on both input vector $X = (x_1, x_2, \dots, x_n)$ and weight vector $W = (w_1, w_2, \dots, w_n)$ such that Z = X.W. Subsequently, the non-linear activation function is triggered using Z as shown in the equation.

$$f(X) = exp\,\frac{(w_i - x)^t - (w_i - x)}{2\sigma^2} \tag{3}$$

Where, σ = smoothing parameter that is set in the initial step of the training.

Output Layer: This layer forecasts the target audience by comparing the eight votes in favor of each objective group obtained in the pattern layer.

6.1.3 Grayscale Conversion

For many years, color photographs have been grayscale converted for both practical and aesthetic reasons, such as presenting color illustrations on black and white monitors and printers. Color to grayscale conversion is a decline in color space from 3 to 1 dimension. The brightness data is paired with a functional mapping approach centered on the natural color sequence. Therefore, it cannot be tailored to certain texts. This can be accomplished by using either local contrast among pixels or global color contrast to choosing the best mapping. These methods generate grayscale images that are optimized for color and contrast rendering.

However, when utilizing such optimization methodologies, the brightness ordering of the pixels is lost, which is undesirable in the preprocessing step of document analysis systems [30]. Figure 4 depicts the original and standard image of the grayscale.

Figure 4: Original Image and Standard Grayscale [30]

6.1.4 Label Propagation for Image Segmentation

Label propagation refers to a class of semi-supervised approaches. Data similarity can be used to detect previously unknown data, allowing us to identify completely undiscovered data that had originally been labeled [31]. The procedure of label propagation picture division is the procedure of separating an image interested in components to find certain features or details. It is one of the most difficult pictures processing tasks. It is still a long way from being able to fully automate segmentation. Many automated procedures are medical-specific and hence only helpful in that field [32].

An image can be segmented into several homogeneous connected sections using low-level visual cues and a similarity criterion to extract one or more things of concern to the user from the chaotic backdrop setting. Contours or semantic regions are related to certain real-world entities or circumstances that are required for more complex image processing. Picture breakdown is a necessary stage in the picture processing as well as evaluation procedure, as well as a fundamental difficulty in computer vision [33]. Figure 5 shows the procedure of label propagation below:

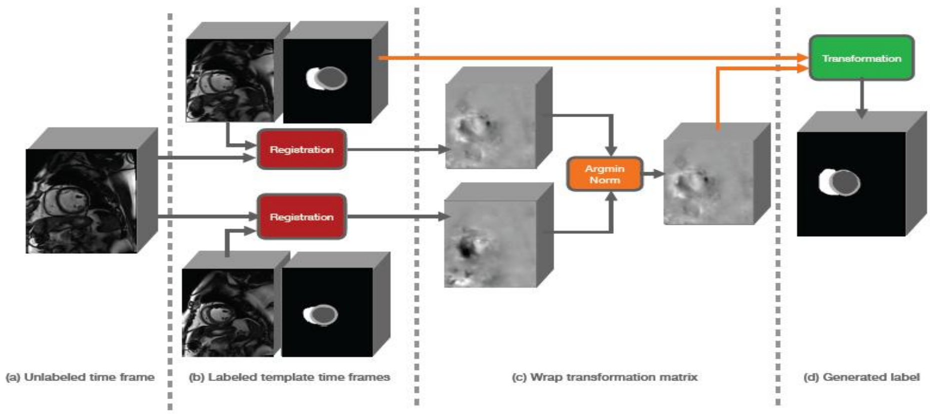

Figure 5: The Procedure of Label Propagation [33]

7. Proposed Methodology

This approach employs a variety of techniques to discover and categorize BTs based on MRI images and accompanying text. The next stage was to do text preprocessing/passing with a term similarity computation. Following that, images were processed using several approaches such as grayscale conversion, median filter DWT, and label propagation. Following that, a similarity matrix is produced, and weights are given to the abnormal tissues, organs, and tumors. Following that, DNN was utilized to train the system. The result was then utilized to categorize tumor tissue damage, as well as to adjust the pattern to suit feature pretense. Figure 6 shows the intended methodology, and their steps are shown below:

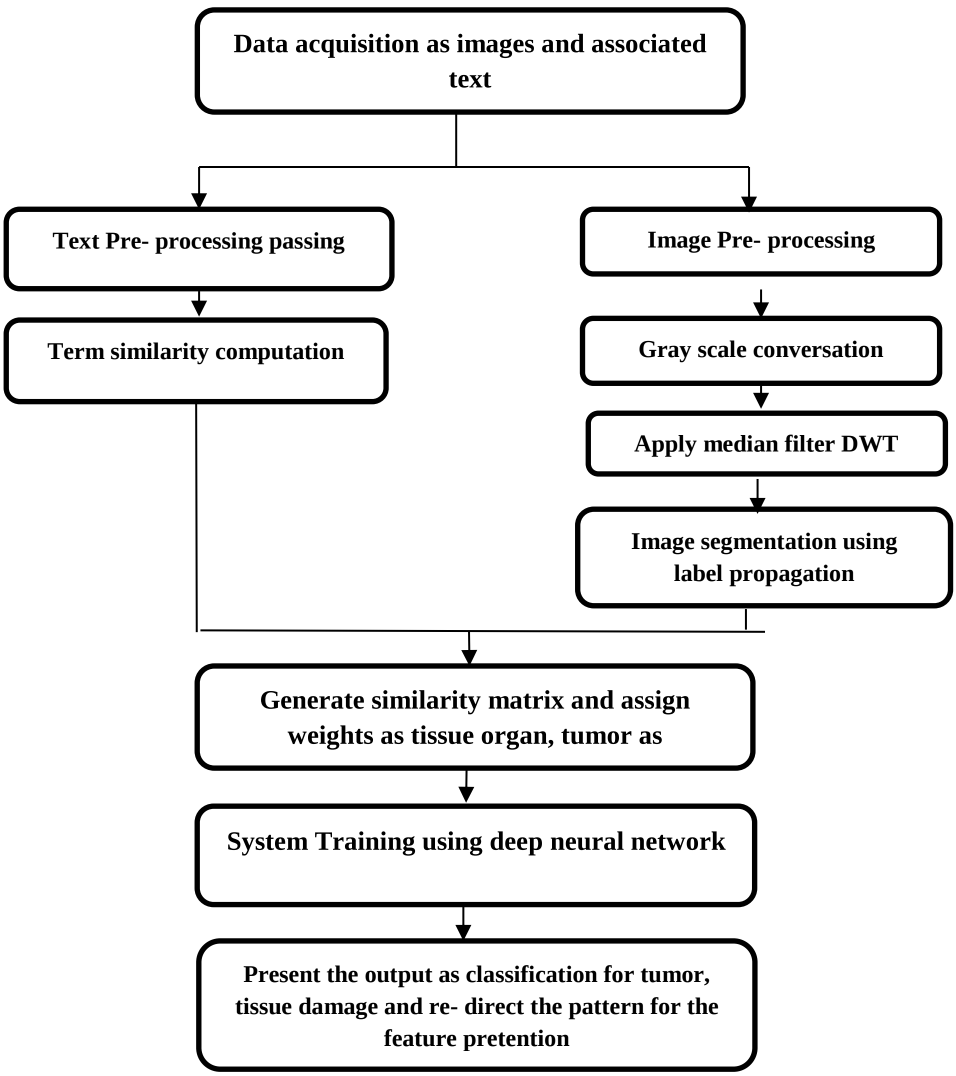

Figure 6: Proposed Methodology

Step 1: In this step, the data is acquired based on the images and their related texts. This data is used for the further processing of the methodology.

Step 2: In this step, the preprocessing of the text data is performed. Various steps of text pre-processing like tokenization, stop word removal, etc. are performed over the text data. To save feature space and future computational costs, remove usual break words (e.g., "a," "an," "are," etc.), words with a low frequency (less than 50), and unwanted keywords and phrases from the report text at this stage.

Based on the above text pre-processing, the term similarity score is computed and stored for the next phase.

Step 3: In this step, the pre-processing of the image data is performed. Various pre-processing techniques like grayscale conversion and DNN are performed. A grayscale conversion technique was used to convert color photographs to black and white.

After grayscale conversion, the DNN median filter was employed to eliminate the impulse noise coefficients from the residual coefficients. Image segmentation was used to uncover certain qualities or information in a photograph.

Step 4: After segmenting pictures, generate a similarity matrix using text pretreatment and image preparation. Tissues in the similarity matrix were assigned weights, and tumors were labeled as anomalies.

Step 5: Basis on the above output the training of the model is done using the DNN.

Step 6: Finally, based on the above training the output of the classification is presented as tumors, tissue damage, and re-directing the pattern for the feature existing results.

8. Expected Outcomes

- To enhance the state of art in the current work after considering the reviewed literature.
- To perform deep learning techniques for detecting BTs in MRI images.
- To analyze performance matrix parameters with comparison to the existing results.

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