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# Brain Tumor MRI Segmentation Using Hidden Layer Convolutional Neural Networks and Discrete Wavelet Transform Technique With KSVM

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**Abstract:** Early and precise discovery of brain tumors in MRI data is serious for effective analysis and therapy planning. This study presents an automated methodology combining Discrete Wavelet Transform (DWT) with Convolutional Neural Networks (CNNs) for tumor localization, discovery, and cataloguing. The proposed system integrates advanced image processing techniques through a pre-processing, feature removal using a 2D - DWT combined with Grey Level Co-occurrence Matrix (GLCM), and classification with Hidden layer Convolutional Neural Networks (HL-CNNs). This hybrid approach addresses challenges such as noise in MRI scans, enabling accurate differentiation between tumorous and non-tumorous MRIs and further classifying tumors as benign or malignant. The system demonstrates robust performance, achieving high diagnostic accuracy and reliability when tested on Magnetic Resonance Images (MRI) from the Harvard Dataset. By automating the screening process, this methodology highlights the potential of DWT and HL- CNNs to advance brain tumor characterization, offering significant improvements over conventional manual methods.

***Keywords: 2D-DWT, Hidden layer-CNN, Grey Level Co-occurrence Matrix (GLCM), Magnetic Resonance Images (MRI)***

## INTRODUCTION

The furthermost significant organ in the human body is the brain. It is typically thought of as the center of the human body's power. The brain controls closely all of the body's essential functions. Feelings, program, intellect, dialog, memory, intelligences, thought, physical activity, sense of taste, creativity, and other functions are thought to be controlled by the brain. [1] Therefore, any accident or damage to this essential organ will interfere with the body's normal processes and lead to an irregular routine. Therefore, it is essential to give this priceless organ the best care possible. These days, brain tumors are the most prevalent and potentially fatal of the many issues that can affect the brain. Approximately 11,000 people obtain a brain tumor diagnosis every year [2]. An abnormal lump of flesh with unchecked cell growth and multiplication is called a brain tumor [3]. There are about Brain tumors can be classified into 130 diverse varieties based on their originating cell type, location within the brain, and growth and spread rate [2]. However, the broad categorization divides them into two core sets: primary and secondary. Primary brain tumors originate within the brain itself, On the other hand, a secondary brain tumor usually spreads to the brain through a bloodstream after starting in another body part, like the lungs. The typical features of above two types brain tumors are shown in Figure 1.

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**Brain Tumors**

A preliminary brain tumor grows in brain cells or inside the brain itself. Cancer cells are often transmitted to other places in the central nervous system (spine or brain) via primary brain tumors. Metastatic brain tumors, which is also called as secondary brain tumors, while secondary brain tumors develop when cancer cells migrate from another part of the body to the brain. In adults, secondary tumors occur more than three times as frequently as primary brain tumors. Both types can be further categorized as either benign or malignant. Figure 1.1 illustrates three forms of malignant tumors: pituitary, meningioma, and lymphoma.

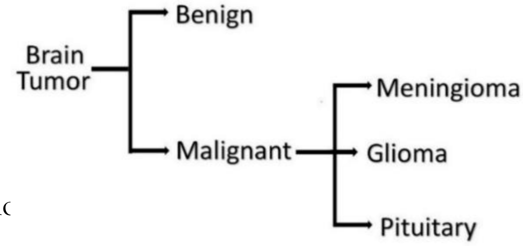


Figure 1: Brain Tumc

**Benign Tumor**

A self-limiting solid neoplasm, or benign tumor, does not invade nearby tissues or metastasize. These tumors have well-defined boundaries, grow slowly, and are often detected through CT or MRI scans. While they lack malignant features, their size and location in the brain can cause symptoms similar to malignant tumors, posing risks by compressing brain tissues and structures.

**Malignant Tumor**

Cancer cells that multiply and invade nearby brain tissues are known as malignant brain tumors. Despite being uncommon, they may recur after treatment and spread to other body parts. Because of their aggressive nature, these tumors, which are categorized as grade 3 or 4, lack clear boundaries and present significant, frequently fatal risks.

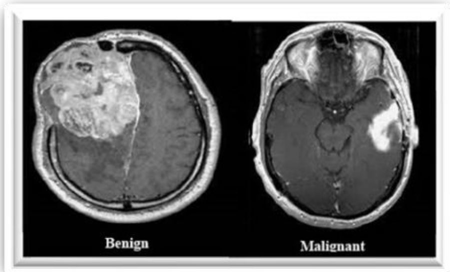


Figure 2: Benign and Malignant Tumors.

**Magnetic Resonance Imaging (MRI)**

MRI is a non-invasive imaging technology that produces finite 3D cross-sectional pictures. It is used to diagnose and identify illnesses, as well as to better monitor therapy outcomes. MRI employs magnetic and radio frequency fields to acquire images of bodily tissues. It includes a powerful magnet to create a strong magnetic field around the patient, causing photons to align with the same field. Protons are activated when the current is pulsed, and photons spin out of equilibrium, allowing MRI pictures to be acquired. To get a brighter picture, the protons are realigned quickly.

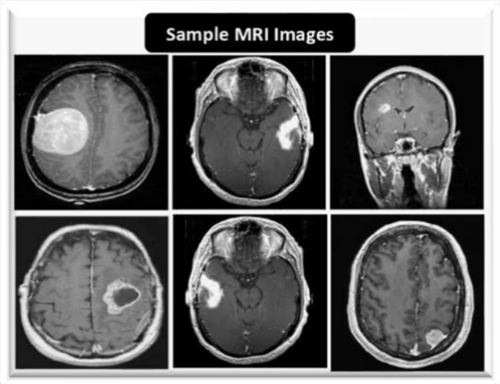


Figure. 3: MRI brain tumor sample pictures.

**Related Works**

This research investigates several techniques for using MRI images to segment and categorize brain tumors. It highlights the role of image processing techniques in detecting and distinguishing benign and malignant tumors based on their shape, size, and location. It highlights how crucial it is to increase the precision of tumor classification and diagnosis. Kumar and et.al. using MATLAB, 2022 assessed several brain tumor subdivision algorithms on the BRATS 2018 dataset. CNN had the best accuracy (91.39%) and the fastest reaction time (2.519 seconds). Their research emphasizes CNN's potential for embedded hardware applications as well as its superiority for medical image dissection.[1] Qiu, Xiaojing et.al. (2021) [11] have used deep learning techniques to address the task of medical picture segmentation by treating it as a problem of representing features and optimizing parameters. To tackle the problem of feature data loss during up-sampling and down-sampling in medical image segmentation, a new multilayer feature fusion network has been developed. Experimental tests on publicly available datasets show that this proposed method significantly improves segmentation accuracy. This research was conducted by Rituparna Sarma et al. (2021) [10]. The study offers a thorough scrutiny of current segmentation methods. and proposes modifications to create new segmentation methods that address the limitations of existing picture segmentation methods. A. Ramesh. Et.al (2021) examined a number of medical image segmentation methods, such as the cutting-edge Lattice Boltzmann Method (LBM), pointing out unsolved issues in the field. The study highlights LBM's capacity to model images effectively and with high quality, indicating that it is a promising area for further investigation.[9] A. Bousselham. and so on. (2019) [14] showed that brain tumor segmentation in MRI images can be enhanced by thermal information that is modeled using the Pennes bioheat equation and examined using the Canny edge sensor. Their approach suggested temperature-based tumor delineation as a useful improvement for MRI diagnostics, outperforming Chan-Vese-based level set segmentation. Saman, Sangeeta, et.al. (2018)[18] examined various approaches for segmenting MR brain images, with an emphasis on gliomas and tumors, ranging from simple thresholding to sophisticated deep learning methods like CNNs. In addition to highlighting current trends, the study makes recommendations for ways to standardize MRI-based brain tumor detection in clinical settings. Deepa et al. (2016) [23] This study provides a summary of current studies conducted on the identification and separation of brain tumors. This text describes the many techniques used by The study has shown that automating brain tumor recognition and segmentation from MRI scans is a highly active research area. Devendra et al. (2016) [24] investigated numerous randomness functions for tumor

segmentation and recognition in MRI images. The edge values, which influence the segmentation results, are determined by the specific entropy function used.
[3] Khairandish and associates. (2022) suggested a CNN-SVM hybrid model that outperformed models like RELM, DCNN, and kNN in classifying brain MRI images as benign or malignant, with a precision of 98 percent. The method improves precision and segmentation accuracy by fusing SVM's classification power with CNN's feature extraction capabilities. R. Remya et al. (2022) [6] presented an improved technique for detecting brain cancer in MRI scans by employing Otsu algorithms and fuzzy C-means (FCM) for noise filtering. With a 3.6 percent increase in the Jaccard coefficient and a 1.3 percent boost in the Dice coefficient for FCM, their method produced higher PSNR, SSIM, and enhanced segmentation accuracy. Varuna Shree N. et al. (2018) [17] presented a brain tumor detection technique that achieved almost 100% accuracy in MRI image analysis by combining GLCM feature extraction, DWT-based segmentation, and probabilistic neural network classification. T. Devi M. et al. (2018) [19] developed a method for classifying MRI brain scans, achieving 98% accuracy on a 90-image dataset. This method utilized DWT for feature extraction, PCA for dimensionality reduction, and KSVM with a Gaussian Radial Basis kernel. Smita A. Nagtode and colleagues (2017) [22] created an effective multistage image processing system for brain tumor classification.as benign, malignant, or metastatic by employing a probabilistic artificial neural network and the discrete wavelet transform for feature removal. B. Babu Shoban et al. (2017) [21] suggested a technique that combines grayscale and discrete wavelet transform. Bhavana Va et al. (2015) [25] improved MRI and PET image quality using Gaussian filters and merged images with DWT, achieving 80–90% accuracy on datasets with minimal color distortion and preservation of anatomical detail. Ajay Kumar et al. (2023) [1] They proposed a CAD technique combining DWT and CNN, achieving a 99.3% accuracy rate in classifying brain tumors in MRI. Arif et al. (2022) [2] developed a tumor segmentation method using BWT, GLCM, and a genetic algorithm, which improved performance metrics for MRI-based tumor identification.

Noor Mohammed Ghadia et al. (2022) [5] Used 2D-CWT, morphological operations and CNN for brain tumor segmentation on BraTS2019 set of information and achieved 97.37% accuracy and 97.43% F1 score. Meher et al. (2022) [7] Introducing an image fusion method with ATRE for military operations that outperforms traditional methods in visual and objective assessments. Kader I et al. (2021) [8] Proposed a DWAE model for MRI brain image classification that achieves 99.3% accuracy and low false positive/negative rates on a dataset of 2500 images. Javaria Amin et al. (2020) [12] Combined structure and texture data with DWT and CNN for tumor detection evaluated on five datasets with improved performance. Xia et al. (2020) [13] Introducing NSST-based medical image fusion with PAPCNN and CSR, which outperforms existing methods in feature and vision preservation.

**METHOD OF BRAIN TUMOR ANALYSIS**

The method outlined in this segment consists of collecting a dataset of MRI images, segmenting them using CNN and Two-Dimensional-DWT , extracting image features with Two-Dimensional-DWT , and then classifying the MRI images as either benign or

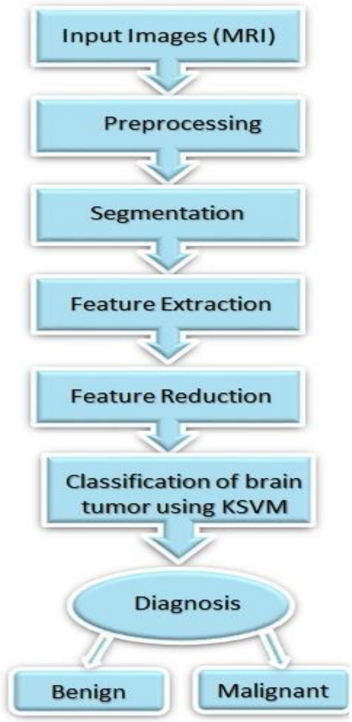


Figure 4: Proposed methodology of brain tumor malignant using HLCNN. Figure 4 illustrates the workflow diagram of the recommended methodology. The research project is implemented using MATLAB R2014a.The suggested approach for brain tumor analysis involves many essential processes in pre-processing and segmenting MR images. Collection of brain MRI images that contain both occurrences of infection and cases without infection. Pre-processing This step involves preparing the MRI images for further analysis using a variety of methods such as noise removal, intensity normalization, and image enhancement. Pre-processing enhances image quality and increases the visibility of tumor-related features.

The MRI images are segmented using HLCNN and Two-Dimensional-DWT . CNN is utilized for its capacity to get a piece of knowledge and extract characteristics from the pictures, whilst Two-Dimensional-DWT is employed to identify tumors and partition the image into distinct frequency bands for study. The characteristics of the segmented MRI images are obtained by the use of a Two-Dimensional-DWT . This procedure facilitates the retrieval of significant data from the photos, which may be used for categorization. The categorization of MR images as either benign or cancerous is accomplished using HLCNN after the process of segmented and feature extraction. HLCNNs have been utilized for their efficacy in image classification tasks, allowing for the discrimination between various kinds of tumors based on the collected characteristics. The suggested technique intends to enhance the analysis of brain malignancies in MRI pictures and reliably categorize them as benign or malignant.

**Algorithm of the proposed study**

Step 1: Gather Input brain MRI pictures that are infected or uninfected.
Step 2: Pre-processing and Separation of MR images.
Step 3: Apply the Two-Dimensional-DWT to detect tumors.
Step 4: The DWT divides the picture into various frequency bands. The 4 bands are LL, LH, HL, and HH.
Step 5: DWT is employed for tumor detection and extracting their specific features.
Step 6: Following segmentation, various parameters will be categorized.

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Step 7: To determine whether brain tumors are present in the MR image, a kernel-based SVM is used.
Step 8: A kernel-based SVM is used to test the precision of brain tumor recognition in the MR image.
Step 9: Convolutional Neural Networks categorize the image as either benign or malignant.
Step 10: In the end, the area of the detected tumor is computed. [9]

**Proposed Method**

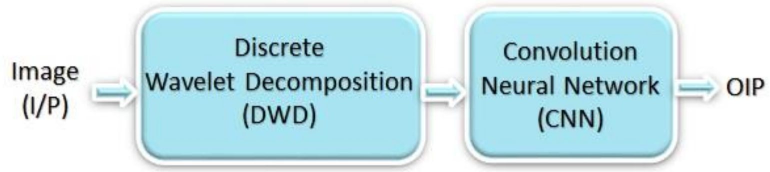


Figure 5: Block diagram of the suggested approach

**Segmentation Techniques**

It is the method of separating the image into equally special and jointly comprehensive segments that are even according to a predefined criterion. Separation in the context of brain tumors entails distinguishing between normal and aberrant brain tissues. Various methods used for segmentation include Thresholding methods, Region rising methods, Edge-based methods, Clustering methods, Watershed method, and Deformable model-based methods.

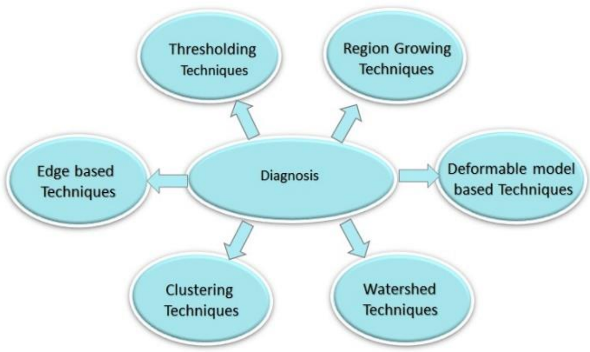


Figure 6: Segmentation Technique

**Various Algorithms Provide Distinct Benefits and Downsides**

| Sr. No | Algorithm | Description | Advantages | Limitations |
|---|---|---|---|---|
| 1 | Threshold-based | It is Uses the peaks in the image histogram to find specific threshold values. | The input image's history is not necessary. | Becomes challenging when there are large or flat valleys in the images. |
| 2 | Watershed | Based on the interpretation of topology. | As continuous boundaries are chosen, accurate and stable results are obtained | Calculating k values becomes challenging when a f ixed number of clusters is taken into account. |
| 3 | K-means clustering | Based on division into homogeneous clusters. based on the creation of uniform clusters. | In the case of small k values, it operates quickly. | The algorithm requires a certain number of clusters, and it is sensitive to both initialization and outliers. The |

| | | | | |
|---|---|---|---|---|
| | | | | K-means algorithm operates under the assumption that clusters are both spherical and of equal size. |
| 4 | Region-Based Segmentation | Based on a threshold value(s), divide the objects into different zones. | - Easy computations<br>- Quick operation<br>- This strategy works best with high-contrast objects and backgrounds. | Correct segmentation is difficult when grayscale pixel values overlap or there is no substantial grayscale difference. |
| 5 | Edge Detection Segmentation | Uses discontinuous local visual characteristics to detect edges and thereby define an object's border. | It is beneficial for photographs with higher contrast between objects. | This approach isn't suitable for images with too many edges and low contrast. |
| 6 | Segmentation based on Clustering | Splits the image's pixels into homogenous groups. | It performs admirably on tiny datasets and produces nice clusters. | - Too much computation time is costly.<br>-k-means uses distance. This method cannot cluster non-convex clusters. |

Table 1: Various algorithms provide distinct benefits and downsides

**Discrete Wavelet Transform (DWT)**

DWT is a signal-processing technique that breaks down data into components of differing frequencies, specifically low and high frequencies. DWT is extensively utilized in the analysis of medical images. for tasks like feature extraction, denoising, and compression. DWT is particularly effective in analyzing MRI images for brain tumor diagnosis, enhancing tumor representation and improving the accuracy of detection algorithms.

**2D Discrete Wavelets Transform (Two-Dimensional-DWT )**

The Two-Dimensional-DWT is a mathematical procedure that converts a two-dimensional transform a signal into a set of coefficients. representing numerous frequency mechanisms. In the context of magnetic resonance (MR) brain imaging, the Two-Dimensional-DWT breaks down the image into its estimated, vertical, horizontal, and diagonal components. The wavelet transform is effective for classification due to its ability to confine signals in both the time and frequency domains]. The decomposed sub-bands are present in a spatial domain that encompasses many degrees of resolution. The estimated sub-band consists of components with low frequencies. Whereas the final sub-band has diagonal edges and the corresponding sub-bands have edges oriented vertically and horizontally. The mother wavelet, or original wavelet, is the source from which the wavelet is generated. The coefficients for the low-pass and high-pass filters are represented by G(n) and H(n), respectively. A Two-Dimensional-DWT is created by utilizing digital filtering and down-sampling techniques. Figure 7 illustrates the diagram of the Two-Dimensional-DWT.

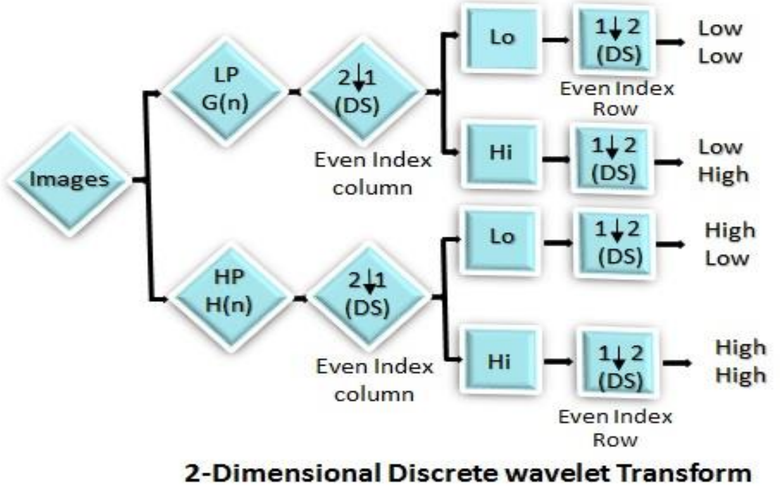


Figure 7: 2D Discrete wavelet transform (Two-Dimensional-DWT)

The two-dimensional discrete wavelet transform (Two-Dimensional-DWT) is applied separately to each dimension when processing 2D images. Figure 5.1 illustrates a simplified Two-Dimensional-DWT schematic. Each scale produces 4 sub-band images: LL, LH, HH, and HL. The LL sub-band is used in subsequent Two-Dimensional-DWT applications. The LL sub-band approximates the image, while LH, HL, and HH sub-bands represent more intricate details.

the more complex and fine-grained aspects. As the decomposition amount rose, the approximation component decreased in size and became coarser in texture. Wavelets provide a straightforward and precise hierarchical framework for analysing visual data. The methodology we used included performing level-3 decomposition employing DWT for feature extraction. The two-dimensional discrete wavelet transform (Two-Dimensional-DWT) typically utilizes a digital filter, which can lead to border distortion issues. When applying a mask to an image, it may extend beyond the image boundaries, necessitating the addition of extra pixels outside the image. To address this boundary value problem, our method implemented a symmetric padding approach. [28].

LL - offers an estimation by going through two LPFs simultaneously.

LH - The LH component refers to the horizontal features of the signal after it has been filtered by a high-pass filter that passes along the rows, after its passage through the LPH (Low Pass Filter).

HL- A high-level signal is sent via a high-pass filter and then a low-pass filter. Vertical attributes (column-wise high-pass filter).

HH – Simultaneously passing through two high-pass filters — Diagonal features refer to high-pass filters (HPF) scattered evenly across both rows and columns.

**Convolutional Neural Network (CNN)**

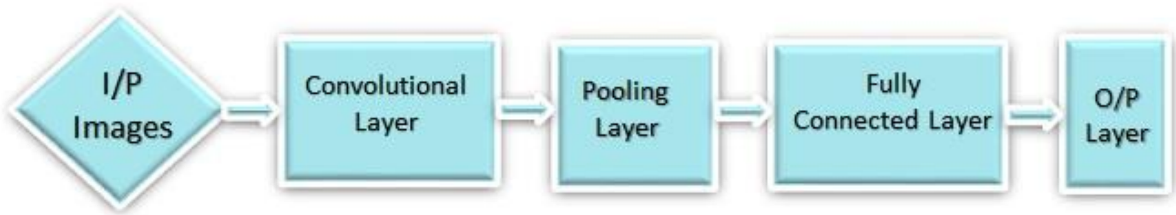

Figure 8: Block structure of Convolutional Neural Networks (CNNs)

**Convolutional Neural Networks (CNNs):** CNNs are a specialized form of neural networks engineered to process structured grid-like data, particularly images and videos. Drawing inspiration from the organization of the visual cortex, these networks have gained widespread adoption in tasks such as image classification, object detection, and facial recognition. CNN architecture consists of various layers, including convolutional, pooling, and fully connected layers. These layers work together to abstract features, reduce complexity, and perform classification tasks. Convolutional layers detect edges, patterns, and shapes, while pooling layers down sample feature maps.

sample feature maps, preserving important information and reducing computational burden. The final predictions in neural networks are generated by fully connected layers, which integrate features and employ activation functions. For classification tasks, these layers typically utilize functions such as ReLU and Softmax. In medical imaging, HLCNNs have shown exceptional performance in tasks such as brain tumor classification by extracting features and assigning them to categories such as benign or malignant. Techniques such as max pooling and image segmentation help refine feature learning and improve the accuracy of image processing. HLCNN architectures with layers for feature extraction, reasoning and decision-making have revolutionized applications such as automated driving, facial recognition and medical diagnostics.

1. **The Input Layer:** The input layer of a network of neural networks (CNNs) is the first stage when the pixel raw value of an input image is received. It serves as a three-dimensional representation of the image's height, breadth, and depth. The depth dimension represents several image methods, such as the blue, red, and green channels for color photos, or just one channel for grayscale pictures. This basic layer establishes the foundation for the later extraction of features and learning procedures.

**2. Convolutional Layers:** HLCNN's coevolutionary layers extract feature from input images such as edges, patterns, shapes, and use filters and kernels. These layers create feature maps that highlight significant patterns by advancing filters over the input and computing. products. Complex, hierarchical features can be learned by the network thanks to multiple convolutional layers. Backpropagation is used to modify the trainable weights of each filter during training. Complex spatial relationships in the data can be captured by the network due to the nonlinearity that ReLU activation introduces Pooling layers in CNNs function to decrease the dimensions of feature maps generated by convolutional layers. This technique reduces feature map size while retaining crucial information.

2. This helps the network handle differences in input data and also reduces the computational cost. Techniques like max pooling and average pooling are employed to preserve spatial hierarchy and extract key features. These pooling layers reduce the spatial dimensions of feature maps generated by convolutional layers through a down sampling process. This helps in maintaining the essential information while decreasing the overall size of the feature representations. Two commonly used pooling strategies are maximum pooling & average pooling. Max pooling preserves the highest value found inside each pooling window, while average pooling calculates the mean value. The pooling layer's goals are to lessen the network's computational complexity and increase the learned features' resistance to slight distortions or translations in the input data. Pooling layers help generate compact and abstract representations of input data by selectively retaining important information and discarding less relevant details.
3. **Fully Connected Layers:** In fully connected dense layers, every neuron has connections to all neurons in the adjacent layers, both above and below. They integrate features that were taken

from previous layers to enable more complex classification and reasoning. During training, these layers apply activation functions, compute weighted sums of inputs, and modify weights to increase prediction accuracy. In the latter stages of CNNs, fully connected layers are usually employed for tasks such as regression or classification

4. **The output layer:** A HL-CNN's output layer produces the network's final predictions. The system contains neural units equal to the number of categories in classification problems, with each unit producing a likelihood score for a specific category. These scores are often converted into class probabilities through the SoftMax function. The training process is guided by linking the output layer to a loss function, which measures the discrepancy between the predicted and actual labels. For classification tasks, cross-entropy is commonly used as this loss measure. When combined with convolutional, pooling, and fully connected layers, the output layer allows HLCNNs to preserve spatial information, extract features, and make precise predictions for tasks like object detection and image classification.

**Categorization of Brain Tumor Diagnosis Accuracy Measures.**

**RBF Accuracy** evaluates the effectiveness of classification systems that employ Radial Basis Function (RBF) networks to differentiate between tumor and non-tumor brain images. This evaluation involves analyzing various performance indicators, including sensitivity, precision, accuracy, and F1-score. RBF networks employ non-linear decision boundaries to enhance the accuracy of classification tasks.

**Linear Accuracy** examines classification models across linear decision boundaries ( such as SVM or logistic regression ) to distinguish between tumors and non - tumors , improving their performance through techniques such as hyperparameter tuning

Polygonal Accuracy investigates models that utilize polygonal, non-linear decision boundaries for brain tumor classification, employing metrics like sensitivity and accuracy to gauge the model's capability in distinguishing tumors from healthy tissues.

**Quadratic Accuracy** is a concept used to evaluate models that employ quadratic decision boundaries to differentiate between tumor and non-tumor tissues. This approach captures intricate relationships within the data by utilizing various performance indicators, including sensitivity, specificity, and F1-score, to assess the effectiveness of the model.

**The Distinctions between RBF Accuracy, Linear Accuracy, Polygonal Accuracy, and Quadratic Accuracy are as follows:**

| **Aspect** | **RBF Accuracy** | **Linear Accuracy** | **Polygonal Accuracy** | **Quadratic Accuracy** |
|---|---|---|---|---|
| Nature of Decision Boundaries | Nonlinear and flexible, defined by radial basis function networks | Linear, formed by linear classifiers like SVM or logistic regression | Represented by polygons, allowing for flexible shapes | Defined by quadratic functions or curves for nonlinear relationships |
| Complexity of Decision Boundaries | Can capture complex nonlinear relationships | Suitable for linearly separable classes, may struggle with nonlinear relationships | Provides flexibility, may not capture highly intricate boundaries | Offers a higher degree of flexibility compared to linear classifiers |
| Training and Optimization | Involves training parameters of | Optimizing parameters of | Training may involve | Involves optimizing parameters of |

| | | | | |
|---|---|---|---|---|
| | radial basis function networks, may require optimization techniques | linear classifiers using methods like gradient descent | determining polygonal decision boundaries based on data point distribution | models with quadratic decision boundaries |
| Applicability and Performance | Suitable for tasks with complex nonlinear relationships | Useful for linearly separable classes or simplicity. | Flexible in capturing different-shaped decision boundaries | Useful when data relationships are highly nonlinear |

Table 2: The distinctions between RBF Accuracy, Linear Accuracy, Polygonal Accuracy, and Quadratic Accuracy

**RESULT ANALYSIS**

During subsequent processing, the hidden layer convolution layer computed various parameters for both Benign and Malignant tumor types, as shown in tables 2 and 3. The parameters include Mean, Standard Deviation, Entropy (En), Skewness (Skew), Kurtosis (Kur), Energy Qualities (Eq), Contrast (Cont), Homogeneity (Homo) or Inverse Difference Moment (IDM), Correlation (Cor), and Coarseness (Coar).

**7.2 Textural Features of Benign Images**

| Images | Mean | Standard Deviation | Entropy | RMS | Variance | Smoothness |
|---|---|---|---|---|---|---|
| Image 1 | 0.00193932 | 0.0897940 | 3.65495 | 0.0898030 | 0.00798718 | 0.87828 |
| Image 2 | 0.00253275 | 0.089780 | 3.07567 | 0.0898030 | 0.00805625 | 0.904050 |

Table 3: Brain Image Textural Features of Benign Images

The key features of benign images are shown in Tables 3 and 4, which include mean, standard

| Images | Kurtosis | Skewness | IDM | Contrast | Correlation | Energy | Homogeneity |
|---|---|---|---|---|---|---|---|
| Image 1 | 5.81170 | 0.340780 | 1.0016 | 0.203283 | 0.112590 | 0.755390 | 0.933108 |
| Image 2 | 7.7973 | 0.577420 | 0.2603 | 0.25585 | 0.0895256 | 0.755694 | 0931416 |

deviation, entropy, skewness, kurtosis, energy qualities, contrast, homogeneity (or inverse difference moment), correlation, and coarseness. These values are provided for the segmented image.

**7.3 Textural Features of Malignant Images**

| Images | Mean | Standard Deviation | Entropy | RMS | Variance | Smoothness |
|---|---|---|---|---|---|---|
| Image 1 | 0.00630906 | 0.0895926 | 3.20516 | 0.0898028 | 0.00801768 | 0.959134 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Image 2 | 0.00425994 | 0.0897135 | 3.6047 | 0.0898026 | 0.00804976 | 0.940643 |

Table 5: Brain Image Textural Features of Malignant Images

| Images | Kurtosis | Skewness | IDM | Contrast | Correlation | Energy | Homogeneity |
|---|---|---|---|---|---|---|---|
| Image 1 | 12.2407 | 1.10482 | 1.2157 | 0.305894 | 0.142096 | 0.786233 | 0.937933 |
| Image 2 | 5.99722 | 0.521796 | 0.36997 | 0.227198 | 0.13259 | 0.743863 | 0.929017 |

Table 6: Brain Image Textural Features of Malignant Images

Tables 5 and 6 highlight significant features of malignant images. Like Tables 3 and 4, they display values for mean, standard deviation, entropy, energy qualities, skewness, kurtosis, contrast, homogeneity (or inverse difference moment), correlation, and coarseness. Separating benign from malignant tumors can be aided by applying image processing and machine learning to analyze quantitative image features from MRI scans. Among the important metrics are: Mean intensity: Greater values denote larger tumors, whereas lower values imply smaller ones. Higher standard deviations are indicative of tissue heterogeneity and are frequently associated with anomalies. Higher entropy values suggest aberrant structures and are indicative of complexity and irregularity. Skewness: A positive skewness indicates anomalies by implying that pixels with higher intensity predominate. Kurtosis: Elevated values indicate sharp intensity peaks that may indicate aberrant tissue composition. Enhanced contrast aids in defining the borders of tumors. Higher numbers indicate homogeneous tumor tissue. Distinct intensity patterns between the tumor and surrounding tissue are indicated by low correlation values. By describing texture, structure, and intensity together, these characteristics help with the diagnosis and characterization of brain tumors.

**Hidden Layer -CNN Based Classified Result**

This dissertation focuses on two types of MRI images: benign and malignant. Benign tumors differ from malignant ones, as the latter is indicative of cancer, characterized by its ability to invade surrounding tissues and spread to other parts of the body. In contrast, benign tumors do not have this invasive or metastatic potential. Although benign tumors generally have a favorable prognosis, they can still present significant risks if they compress vital structures such as blood vessels or nerves. Figure 9 illustrates a collection of non-malignant MRI images.

Malignant tumors consist of cancerous cells that grow uncontrollably. These cells have the ability to invade surrounding tissues and spread to distant parts of the body. In some cases, cells can break away from the original (primary) tumor and travel to other organs or bones, where they may continue to grow and form secondary tumors. This process is known as metastasis or secondary cancer. The secondary tumors retain the name of the primary cancer site. For example, when pancreatic cancer spreads to the liver, it is still referred to as pancreatic cancer. Figure 9 presents a collection of cancerous MRI images.

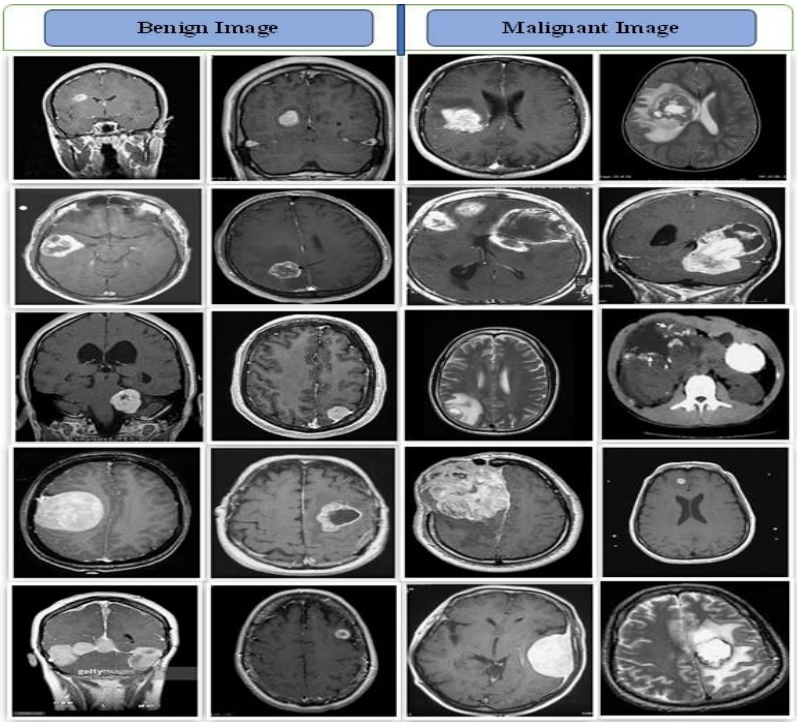


Figure 9: HL- CNN Based Classified Result

**Accuracy Results for Different Kernel Functions**

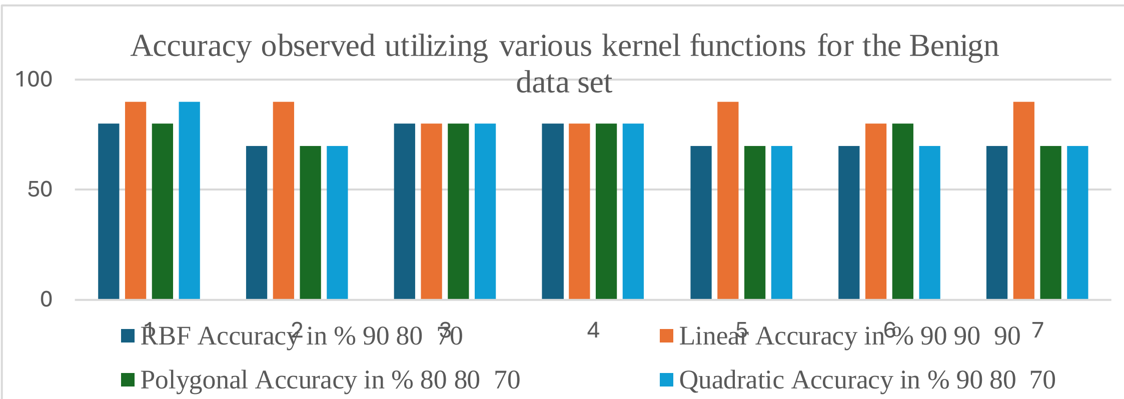


Figure 10: Using different kernel functions, accuracy was noted for the benign data set.

Figure 10 depicts the accuracy results for different kernel functions applied to benign datasets, demonstrating that the linear accuracy method performs effectively. The proposed approach is also applicable to multi-sequence MRI data, as the quality of such images can vary based on factors like the pulse sequence and contrast mechanisms used during image acquisition. Consequently, our method is capable of detecting brain cancers with a variety of patterns with relative ease. For segmentation, we employed the Support Vector Machine (SVM) technique, which successfully isolated the tumor location.

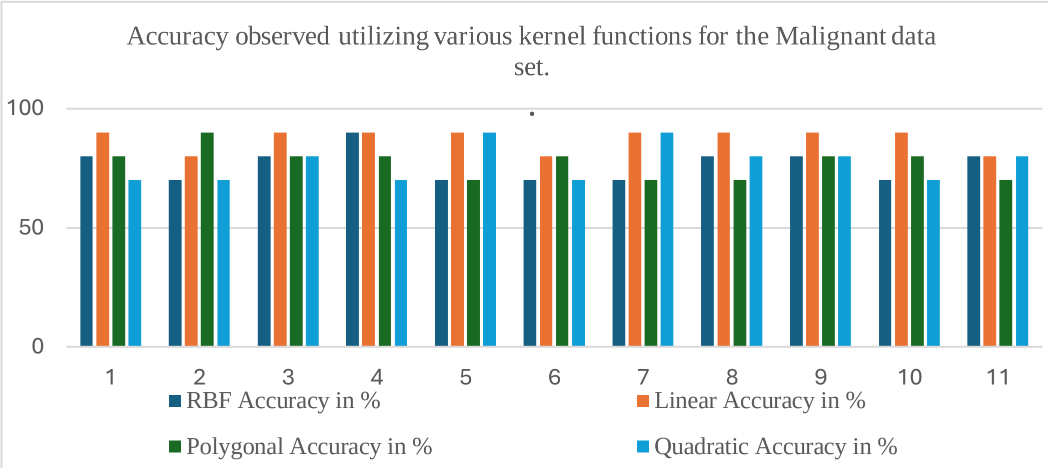


Figure 11: Using different kernel functions, accuracy was noted for the malignant data set
Figure 11. displays the accuracy results for different kernel algorithms when applied to the cancerous dataset.
The results demonstrate that the linear method achieved the highest accuracy, while the quadratic algorithm performed the poorest in terms of accuracy. These SVM kernel like (RBF, Linear, Polygonal, and Quadratic) extracted from brain tumor images and categorize them as tumor or non-tumor using a non-linear decision boundary.

## Conclusions and Future Work

This study evaluates the strengths and weaknesses of various brain tumor segmentation techniques, including manual, intensity-based, model-based, hybrid, and deep learning approaches. The application of image processing algorithms, particularly when used with MRI scans, has significantly advanced tumor detection, aiding in early diagnosis and treatment. The proposed method leverages MATLAB's graphical user interface (GUI) alongside image processing algorithms like Otsu's segmentation and Principal Component Analysis (PCA) for feature reduction to effectively identify and classify brain tumors. By combining techniques such as Support Vector Machine (SVM) with different kernels (linear, RBF, and polynomial) for classification and morphological operations for tumor localization, the method yields reliable results. Key features analyzed include mean, standard deviation, entropy, energy, contrast, and homogeneity. Preprocessing steps, including thresholding and noise reduction, enhance image quality and improve segmentation accuracy. Future research could focus on expanding data sets, incorporating hybrid models, and exploring advanced deep learning techniques. Our study highlights the transformative potential of integrating HL-CNN and DWT techniques for detecting brain tumors using MRI scans.This investigation exemplifies the growing adoption of computer-assisted technologies in healthcare, offering precise and efficient tools for diagnosing and classifying brain neoplasms. Ultimately, this approach enhances patient outcomes and healthcare decisions by leveraging deep learning and signal processing techniques to pave the way for a more accurate, efficient, and reliable diagnostic tool.

Future improvements will focus on exploring different neural network architectures, integrating additional imaging modalities such as PET or fMRI, and validating the approach in real-world clinical environments. It will also be essential to enhance the interpretability of algorithms for medical professionals and ensure their robustness to variations in MRI quality. By addressing these challenges, brain tumor detection methods will become more reliable and widely adopted, ultimately benefiting both patients and healthcare providers.

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