Brain Tumor MRI Identification and Classification Using DWT, PCA, and KSVM

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Abstract

Background

Classification, segmentation, and the identification of the infection region in MRI images of brain tumors are labor-intensive and iterative processes. The optimum classification technique helps make the proper choice and delivers the best therapy. Despite several significant efforts and encouraging discoveries in this subject, precise segmentation and classification remain challenging tasks.

Method

In this study, we proposed a new method for the exact segmentation and classification of brain tumors from MR images. Initially, the tumor image is pre-processed and segmented by using the Threshold function for removing image noises. To minimize complexity and enhance performance used Discrete wavelet transformation (DWT) for getting the accurate in MR Images. Principal component analysis (PCA) are used to condense the feature vector dimensions of magnetic resonance images. Finally, for differentiate between benign and malignant tumor types, the Classification stage employs a pre-trained Support Vector Machine with several kernels, also known as a kernel support vector machine (KSVM).

Result

The efficacy of the suggested approach is also compared to that of other existing frameworks for segmentation and classification. Results demonstrated that developed approach is effective and quick, where as we obtained excellent accuracy and recognized the brain MR Images as normal and pathological tissues.

Introduction

A brain tumor may be a significant life-threatening condition for a human being. Brain tumor and its last stage is transformed into brain cancer, which leads to death. Survival rate may be raised if the tumor is found and diagnosed in the earlier stages. The identification of the tumor in MR images of the brain may be done via segmentation. Brain tumor may be benign or cancerous. Benign being noncancerous and is treated as a low-grade tumor. Malignant treated as a high-grade tumor. A Benign tumor is less damaging than malignant [1]. The benign tissue has cancer cells that are unrelated to the tumor and are physically equivalent. The malignant tumor contains active cancer cells that move across regions and has irregularly shaped features[2].

Normal MR image segmentation is time-consuming, challenging, and produces inconsistent results from expert to expert. This work uses the gray-level co-occurrence matrix (GLCM) for feature extraction to pinpoint the problem of segmenting the aberrant and normal tissues from MR images. The method of
feature extraction, which may identify the best traits to separate the tumors, is essential to the accurate categorization of malignancies [3, 4]. The feature extraction of tumor images uses the discrete wavelet transform (DWT). Wavelet has the ability to analyze pictures at various resolutions thanks to its multi-resolution analytic characteristic. Using imaging methods, segmentation is used to evaluate the part of the tumor that is affected. It is the process of dividing an object into component parts that share similar properties such as color, texture, contrast, and borders [5].

Principal Component Analysis (PCA) is used to decrease the size of the feature vector [6]. In order to extract the independent features from the high dimensional data, PCA is a crucial unsupervised technique. Due to its inherent property of lowering dimensionality, PCA is often used in domains such as face recognition, image processing, and engineering data extraction applications. Its primary goal is to reduce the computing cost of evaluating fresh data.

A productive area of current research [7] focuses on classifying brain tumors using supervised [4] and unsupervised [8, 9] methodologies. The foundation of supervised learning is the training and testing of data. All approaches provide decent results, but supervised methods especially SVM's perform better than unsupervised methods in terms of success classification rate or classification accuracy. SVM handles high-dimensional data and can classify both linear and nonlinear data. Direct geometric interpretation, higher accuracy, general mathematical tractability, and the avoidance of over fitting are the key benefits of SVM [6, 10–13]. It also needs a limited number of training samples. The nonlinear SVM extensions of linear SVMs were introduced in this work as SVMs with various kernels (KSVMs). The original SVMs' dot product form is eliminated in these KSVMs, drastically reducing the amount of dimension calculations.

This article describes a high-quality tumor classification approach in which individual magnetic resonance (MR) pixels are categorized as common genius tumors, non-cancerous tumor letters, and malignant tumor letters. There are three phases in the proposed method: (1) wavelet decomposition, (2) texture extraction, and (3) classification. The MR image was initially decomposed into unique steps with defined approximation coefficients using discrete wavelet processing with Daubechies' wavelet (db4), after which structural data such as forces were acquired. The suggested technique has been applied to real MR images, with a classification accuracy of over 98% utilizing probabilistic neural networks.

A preprint has previously been published [OMAR FARUQ et. al 2023]. A preprint of the paper is available in the Techrxiv [37].

**Literature Review**

The tumor affects around fourteen thousand individuals per year, as reported by the World Health Organization (WHO). The mortality rate rises year after year as a result of treatment failure. The most difficult problem analyzers have when utilizing manual techniques to diagnose and categorize malignancies. A study in [14] explains an automatic structure for identifying and categorizing cancers, that is a latest study area in science, per the survey published by Cancer.Net and the World Health Organization (WHO). As a result, a number of researchers are working to create a far more expense and
efficient computerized system for MRI scans, identification, as well as identification. The proposed method employs preprocessing techniques such as bias field correction, registration, and skull stripping. The textural characteristic enhances the accuracy of tumor region prediction. Discrete Wavelet Transform (DWT) is used to segment the detected picture, while PCA is used to extract features. This non-linear approach produced a simulation result that was 96.7% significant. Using the energy strategy, a research in [15] developed a machine learning approach for identifying brain tumor sites and segmenting the damaged regions. A random forest classification approach is also used, which has a 98% accuracy rate. The work in [16] used retraining and improvement approaches to improve classification and segmentation performance. In MRI, segmentation is used based on temperature mapping of tumor regions. The suggested model is used to detect small anomalies in brain tumor MR images from Pituitary, Glioma, Meningioma, and Malignant tumors, as well as no tumors. It makes use of both image processing and machine learning technologies. The model was trained to identify brain MR images using CNN (kaggle data sets) features and an ensembled classifier, and it achieved an accuracy of 95.547%.

The most difficult and promising area is the analysis and processing of MRI brain tumor images. Magnetic resonance imaging (MRI) is a sophisticated medical imaging method that produces high quality pictures of the human body’s internal organs. It is a critical step in determining the appropriate medication at the appropriate time for tumor infected individuals. Many techniques, such as fuzzy clustering means (FCM), support vector machine (SVM), artificial neural network (ANN), knowledge based techniques, and expectation maximization (EM) algorithm technique, have been proposed for classification of brain tumors in MR images. Bahadure et al. presented image analysis using BWT and SVM approaches for MRI-based brain tumor identification and classification. Using skull stripping, which removed all nonbrain tissues for detection, an accuracy of 95% was attained [17]. For the identification of tumor pictures, Joseph et al. [18] suggested segmentation of MRI brain images using the Kmeans clustering method in conjunction with morphological filtering. Alfonse and Salem [19] suggested automatic brain tumor categorization of MRI images using support vector machine. The accuracy of a classifier was increased by applying the fast Fourier transform for feature extraction and the minimum redundancy maximum relevance approach for feature reduction. The planned effort produced an accuracy of 98%. The brain MRI picture has two sections that must be separated in order to retrieve brain tumor locations. Yao et al. [20] suggested a technique that combined texture feature extraction with wavelet transform and SVM with an accuracy of 83% to handle and address protocols of diverse pictures and nonlinearity of actual data an effective classification based on contrast of improved MRI images. Kumar and Vijayakumar [10] suggested employing principal component analysis (PCA) and radial basis function kernel with SVM for brain tumor classification and segmentation. With this strategy, they achieved an accuracy of 94%. Sharma et al. [6] introduced an artificial neural network tool that served as both a classifier and a segmentation tool for the successful categorization of brain tumors from MRI images, and it obtained a 100% accuracy. Wang et al. [21] suggested using an active contour approach to tackle the issue of brain tumor image segmentation based on intensity homogeneities in MRI images. Sachdeva et al. [12] employed an artificial neural network and PCA-ANN for multiclass brain tumor MRI image classification and segmentation using a dataset of 428 MRI images and obtained an accuracy of
75–90%. Much effective segmentation with integrated feature extraction was not possible, and only a few features were retrieved, resulting in poor tumor identification and detection accuracy. The classifiers used to train the features are ineffective as well. We integrated DWT with the extraction of textural and GLCM features, followed by morphological procedures with 24 N in this research. T. N. R. Kumar and Varuna Shree 123 Springer Nature provided the content; terms of use apply. All rights are reserved. A probabilistic neural network may be used as a classifier [1]. The research focuses on extracting characteristics from the segmented area in order to identify and categorize normal and malignant tumor cells in medical brain MRI images for a big database. Our findings suggest that the suggested strategy makes it easier for clinical specialists to make decisions about diagnostic treatment screening.

Experiment, Results And Discussion

3.1 Image acquisition

The datasets were created from OASIS and, the ADNI to axial T2-weighted MR pictures and 256 albums. Higher contrast images are T2 and have the best visuals between the T1 and PET (positron emission tomography) modalities; we prefer the T2 model. The unnatural data set of brain MR picture consists of the below diseases: Alzheimer's disease, glioma, meningioma, visual agnosia, Pick's disease when Alzheimer's disease stays with it, Huntington's disease, & sarcoma. All disease specimens are shown in Fig. 1. Pick 20 random images for each brain category. The reason is that there is one category of the natural brain & seven categories of the unnatural brain in the dataset, and 160 pictures are chosen to create 20 natural & 140 unnatural brain pictures.

3.2 Pre-Processing

Five different levels are created by dividing the images of the MRI by the identical coefficients of the LL and HL bands. Such sub-bands have been attained from the disarranged wavelet; GLCM has been used to extract quantitative textural features such as strength, correlation, entropy, and homogeneity [22]. Filtering and denoising pictures are the initial stages of image pre-processing. Certain recovery approaches are used to eliminate generated noise that might enter a picture during capture, transfer, or compression, shown in Fig. 2. [23].

3.3 Segmentation of Image

Image segmentation is the procedure of splitting an image into distinct segments, each with comparable features in Fig. 3. depicts the many types of image segmentation [1, 23].

3.4 Feature Extraction

Five different levels are created by dividing the images of the MRI by the identical coefficients of the LL and HL bands. Such sub-bands have been attained from the disarranged wavelet; The GLCM has been used to extract quantitative textural characteristics such as strength, correlation, entropy, and uniformity
Filtering and denoising pictures are the initial stages of image pre-processing. Denoising is the technique of eliminating artificial noise from a picture before capturing, transmission, or compression utilizing specialized recovery algorithms [25]. Picture segmentation is the process of dividing an image into distinct segments, each with comparable features. As seen in Fig. 4, there are several forms of image segmentation [21, 24]. Feature extraction is the process of retrieving statistical data from an image that resembles color characteristics, texture, shape, and contrast [5]. We employed the DWT to extract wavelet coefficients and the GLCM to obtain applied math features. Feature extraction is the process of choosing subsets from the set of variables that demonstrate the behavior of the entire set. choosing the helpful variables and discarding the inapplicable ones.

Pictures 1 to 9 display various sub-band levels up to the decomposition stage of the 5th wavelet. As an input vector, the extracted form was used to train and evaluate the output of the PNN types. The characteristics of the statistical field are shown in Table 1 [25].

<table>
<thead>
<tr>
<th>Picture</th>
<th>Contrast</th>
<th>Correlation</th>
<th>Energy</th>
<th>Homogeneity</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Picture 1</td>
<td>0.386541</td>
<td>0.0805</td>
<td>0.81568</td>
<td>0.900</td>
<td>2.3224</td>
</tr>
<tr>
<td>Picture 2</td>
<td>0.360122</td>
<td>0.1725</td>
<td>0.81607</td>
<td>0.9474</td>
<td>0.2244</td>
</tr>
<tr>
<td>Picture 3</td>
<td>0.265017</td>
<td>0.1248</td>
<td>0.77808</td>
<td>0.9383</td>
<td>2.8746</td>
</tr>
<tr>
<td>Picture 4</td>
<td>0.315628</td>
<td>0.0928</td>
<td>0.79636</td>
<td>0.9404</td>
<td>2.6739</td>
</tr>
<tr>
<td>Picture 5</td>
<td>0.365406</td>
<td>0.1353</td>
<td>0.80855</td>
<td>0.9447</td>
<td>2.5116</td>
</tr>
<tr>
<td>Picture 6</td>
<td>0.285873</td>
<td>0.1143</td>
<td>0.75812</td>
<td>0.9315</td>
<td>2.8806</td>
</tr>
<tr>
<td>Picture 7</td>
<td>0.299221</td>
<td>0.1129</td>
<td>0.78455</td>
<td>0.9387</td>
<td>2.9101</td>
</tr>
<tr>
<td>Picture 8</td>
<td>0.267241</td>
<td>0.1246</td>
<td>0.77884</td>
<td>0.9367</td>
<td>2.9114</td>
</tr>
</tbody>
</table>

3.5 Image Classification

Image classification is the extraction of data classes from bitmap image having numerous bands. The real three types of classification are per pixel, per subpixel, and object. This study concentrated on pixel-scale image categorization [25, 26], which is classified into three categories.: The two most common approaches are supervised classifiers (manual) and unsupervised classifiers [27, 28], (calculated by the software), but analytical object based images are rare and the most recent technique, as mentioned above, and the analysis is fed with high resolution images. Figure 4 depicts the various types of object classification from different points of view.

The tests were performed with a 5.0GHz processor and 32 GB of RAM on the Intel i7 platform running Windows 10. Using the wavelet toolbox to develop the algorithm, Matlab’s 2018 bio statistical toolbox (Mathworks®c) was used. Install a free SVM toolbox, expand the SVM kernel, and use the classification of
the MR brain picture. On any software platform where Matlab is available, the programs can be run or checked. We tested four SVMs using the most recent Di® kernels. The SVM using a linear kernel is called K SVM [29, 30, 31].

<table>
<thead>
<tr>
<th>Approach from existing study</th>
<th>Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM + DWT</td>
<td>95</td>
</tr>
<tr>
<td>SVM + DWT with linear kernel</td>
<td>96</td>
</tr>
<tr>
<td>SVM + DWT with RBF based kernel</td>
<td>98</td>
</tr>
<tr>
<td>PCA + KNN + DWT</td>
<td>98</td>
</tr>
<tr>
<td>PCA + ANN + DWT</td>
<td>97</td>
</tr>
<tr>
<td>PCA + ACPSO + FNN + DWT</td>
<td>98.75</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Approach from this study</th>
<th>Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA + K SVM + DWT (LIN)</td>
<td>95.38%</td>
</tr>
<tr>
<td>PCA + K SVM + DWT (HPOL)</td>
<td>96.53%</td>
</tr>
<tr>
<td>PCA + K SVM + DWT (IPOL)</td>
<td>98.88%</td>
</tr>
<tr>
<td>PCA + K SVM + DWT (GRB)</td>
<td>99.61%</td>
</tr>
</tbody>
</table>

Table 2
Confusion matrix of our DWT + PCA + K SVM method
(Kernel pick out LIN, HPOL, IPOL)
Table 3
A comparison of the classification accuracy of eight different algorithms using the same MRI dataset and the same number of images.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Normal (T)</th>
<th>Abnormal (T)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIN</td>
<td>18</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>230</td>
</tr>
<tr>
<td>HpoL</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>232</td>
</tr>
<tr>
<td>IPOL</td>
<td>18</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>239</td>
</tr>
<tr>
<td>GRB</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>239</td>
</tr>
</tbody>
</table>

The results reveal that the proposed DWT + PCA + KSVM technique generates outstanding results both at the training and validation datasets. Sum up the overall classification performance of the LIN, HPOL, IPOL, and GRB kernels in Table 2. The GRB kernel SVM architecture which provides the best the kernel's compared to others three SVMs kernels [32]. Furthermore, we evaluated our technique to six successful techniques disclosed in the current papers employing the same MRI datasets and image count. Table 2 displays the results of the analysis. It demonstrates that our suggested DWT + PCA + KSVM system with the GRB kernel outperforms the other 8 approaches, obtaining the greatest classification performance at 99.38 percent. The next technique is the DWT + PCA + ACPSO + FNN method, which has a 98.75 percent accuracy. The fifth is our suggested DWT + PCA + KSVM IPOL kernel, which has a classification accuracy of 98.12% [28, 29].
Table 4
GLCM of LL and HL sub bands of tested images & statistic field.

<table>
<thead>
<tr>
<th>Pictures</th>
<th>Psnr</th>
<th>Mse</th>
<th>Area of Picture in pixel</th>
<th>Area of the tumor region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Picture 1</td>
<td>13.011</td>
<td>5.121</td>
<td>38,240</td>
<td>7598</td>
</tr>
<tr>
<td>Picture 2</td>
<td>12.82</td>
<td>2.116</td>
<td>66,824</td>
<td>9774</td>
</tr>
<tr>
<td>Picture 3</td>
<td>13.12</td>
<td>6.068</td>
<td>49,508</td>
<td>7532</td>
</tr>
<tr>
<td>Picture 4</td>
<td>14.86</td>
<td>5.77</td>
<td>49,388</td>
<td>8956</td>
</tr>
<tr>
<td>Picture 5</td>
<td>12.79</td>
<td>4.84</td>
<td>23,964</td>
<td>4465</td>
</tr>
<tr>
<td>Picture 6</td>
<td>12.82</td>
<td>6.79</td>
<td>49,429</td>
<td>3598</td>
</tr>
<tr>
<td>Picture 7</td>
<td>12.99</td>
<td>5.92</td>
<td>49,298</td>
<td>5979</td>
</tr>
<tr>
<td>Picture 8</td>
<td>13.004</td>
<td>6.35</td>
<td>34,040</td>
<td>12,932</td>
</tr>
</tbody>
</table>

Table 5
The declaration of the region and the success of the evaluation of tumors extraction location of trained image.

<table>
<thead>
<tr>
<th>Pictures</th>
<th>Con</th>
<th>Cor</th>
<th>Ene</th>
<th>Hom</th>
<th>Ent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Picture 1</td>
<td>0.2755</td>
<td>0.106333</td>
<td>0.72044</td>
<td>0.92139</td>
<td>3.3209</td>
</tr>
<tr>
<td>Picture 2</td>
<td>0.2611</td>
<td>0.129665</td>
<td>0.76435</td>
<td>0.93428</td>
<td>3.3830</td>
</tr>
<tr>
<td>Picture 3</td>
<td>0.2611</td>
<td>0.129665</td>
<td>0.76435</td>
<td>0.93428</td>
<td>3.2821</td>
</tr>
<tr>
<td>Picture 4</td>
<td>0.2929</td>
<td>0.156369</td>
<td>0.82164</td>
<td>0.94967</td>
<td>2.7610</td>
</tr>
<tr>
<td>Picture 5</td>
<td>0.2469</td>
<td>0.07749</td>
<td>0.74696</td>
<td>0.92848</td>
<td>3.3895</td>
</tr>
<tr>
<td>Picture 6</td>
<td>0.2416</td>
<td>0.177739</td>
<td>0.77415</td>
<td>0.9373</td>
<td>2.5186</td>
</tr>
<tr>
<td>Picture 7</td>
<td>0.2611</td>
<td>0.12966</td>
<td>0.76435</td>
<td>0.93428</td>
<td>3.2820</td>
</tr>
<tr>
<td>Picture 8</td>
<td>0.3053</td>
<td>0.09188</td>
<td>0.7674</td>
<td>0.9326</td>
<td>2.9181</td>
</tr>
</tbody>
</table>

The training data set objects were those for which the extracted features were classified using the PNN algorithm, whereas the test set was not trained and just statistical and textual characteristics were extracted. The correctness of the qualifying and verified image was determined by classifying malignant cells as either normal or abnormal [33, 34]. Figure 5 depicts the results of the identification of malignant and non-malignant tumor tissues.

The efficacy of an acceptable classification proportion to the actual number of form is referred to as prediction performance or “correct level” [29, 32]. The brain tumor classification procedure was applied to a variety of both normal and abnormal MR images, and the performance of the PNN predictor was modified using the equation shown below:
Calculation time is also an important factor in classifier evaluation. Since the SVM parameters stayed the same after training, the SVM training time was not taken into account. All 260 images were fed into the classifier. The time spent at each stage of the DI® event was plotted in Fig. 6, along with the associated computation time, average value, and reported computation time.

In this lesson, we also created a brand new DWT + PCA + KSVM technique to differentiate between authentic and artificial brain MRIs. We selected four different kernels for the LIN, HPOL, IPOL, and GRB [33, 34]. The study's findings show that the GRB kernel SVM outperformed the HPOL, IPOL, and GRB kernels as well as other well-known methods, achieving a classification performance of 99.38% on the 260 images from MR.

**Conclusion**

In this research, we used brain MRI images separated between healthy (unaffected) brain tissue and aberrant (infected) tumor tissue. Preprocessing is used to eliminate noise from images and smoothing them out. This also helps to increase the signal-to-noise ratio. As a result, we applied a discrete wavelet transformation, which breaks down the image and extracts the features from the GLCM, which was detected using structural procedures. PNN could be a classifier used to perceive tumors in brain MRI images. According to research findings, diagnosing a brain tumor yourself is both faster and more accurate than having it done by a medical professional. The greatest components also demonstrate that it performs better by increasing PSNR and MSE metrics. The suggested technique concluded with precise, quick brain tumor detection and tumor site localization. By recognizing and classifying normal and abnormal tumors in the brain, MR pictures have achieved almost 100 percent for the series of qualified data due to the extraction of the statistical features of the wavelet decomposition of LL and HL sub bands and 95 percent for the proven record. We conclude with the above findings that our mentioned technique clearly differentiates the tumor from normal and abnormal, which allows medical experts to make clear diagnostic decisions. We are encouraged by the research now available to investigate medical image technology. We believe we can develop a system that continuously increase better image processing results.

**Methodology**

The suggested method for the identification of brain tumors involves six major steps. Which is shown in Fig. 7:

- Extraction of features using DWT
- Extraction of textures using GLCM
- Selection of features using PCA
- Detection of tumors and K-means structural analysis
- Using PNN-RBF Network identification
5.1 Extraction of features using DWT

\[ w_{\psi} (a, b) = \int_{-\infty}^{\infty} f(x) * \psi_{ab} (t) \, dx \]

Where \( \psi_{a,b} (t) = \frac{1}{\sqrt{|a|}} \)

As a function vector, the proposed system makes use of the coefficients of the DWT. The wavelet is a powerful mathematical tool for extracting facets and determining the wave coefficient from images; we employed MR. Wavelets are twisted as well as resized variations of constant moment wavelets that have localized basic properties. Wavelets have the primary advantage of imparting localized frequency records about a signed variable, which is especially useful for ranking. A quintessential review of wavelet decomposition is delivered as below: \( (t) \) is a continuous wavelet transformation of the \( ax(t) \) signal with a squareintegrable characteristic, unlike a real value wavelet. An indispensable evaluation of wavelet decomposition is delivered as below: A continuous wavelet transformation of an \( ax (t) \) signal, a squareintegrable feature comparative to a real value wavelet \( (t) \), is defined as:

\[
WT_x(n) = \begin{cases} 
   d_{j,k} = \sum (x(n) h^* j (n - 2jk)) \\
   d_{j,k} = \sum (x(n) g^* j (n - 2jk)) 
\end{cases}
\]

Wavelets j and k are defined by translation and dilation from the mother's wavelet, wavelet, dilation factor, and b translation parameter (both of which are real, high quality numbers). Under some mild assumptions, the base wavelet responds to the limit of having zero meaning. The equation can be debunked by means of limiting j and k to a discrete lattice, which gives the discrete wavelet [12].

The technique that divides information into different wavelength elements and analyzes these elements with a precision proportional to their size is known as DWT:

\[ Ho_D - High \ Pass \ Filter, \ Lo_D - Low \ Pass \ Filter (3) \]

The Daubechies wavelet is thought to have the best quality for image utility based on literature analysis, and among the other wavelets, LH's overall performance was once better than the HL sub-band characteristics, shown in Fig. 8. The qualities were then extracted from the DWT sub bands LH and HL, and a five level decomposition of the Daubechies wavelet usage was determined in this approach.

5.2 Extraction of textures using GLCMs
Examination of the texture makes it easy to distinguish between regular and anomalous tissue. It even contrasts malignant tissue to regular tissue, which can be under the person's experience level. Texture evaluation is one of the uses of computer assisted pathology as a supplement to strategies for biopsy. This technique calculates a specific gray level frequency in a random photograph region and does not take the correlations between pixels into consideration. Using this strategy, the frequency is computed at a specific gray level in a random image region. It no longer takes into account pixel associations. The chance of detecting a pair of grey ranges at very vast distances and with intention throughout a full body is the base of statistical texture analysis in second order texture recording. Using the GLCM additionally acknowledged as the Gray Level Spatial Spatial Dependence Matrix (GLSDM), statistical aspects of the MR snapshots are obtained. Haralick's GLCM is a statistical technique for explaining the connection between pixels of a particular gray level. GLCM is a two dimensional histogram where \((i, j)\) is the variable and the prevalence frequency is \((I, J)\). It is an interval feature with \(d = 1\), perspective 45, 90, and 135, and greyscales \(I\) and \(J\) calculate the frequency with which a pixel has an intensity \(I\) that is about to positively outstrip and an orientation in relation to another pixel \(J\). The gray degree co-occurrence matrix and the statistical field elements such as contrast, interrelationship, and electricity are formed in this way. Homogeneity and entropy were obtained from the first five wavelet decomposition degrees of the LH and HL sub-bands [6].

### 5.3 Equation Selection of features using PCA

The element component analysis is the best way to do dimension reduction. In PCA, the linear data seeks the lower dimensional in such a way that the replicated data variance due to a set of data is preserved. Limiting the feature vector calculated from waves based on a combined feature vector component analysis using a feature reduction system to a variable chosen by the PCA will result in an effective classification algorithm using a monitoring method, shown in Fig. 9. The purpose of PCA is to diminish the complexity of the wavelet coefficient. It operates under a classification that is much more descriptive and precise.

### 5.4 Using the Probabilistic Neural Network (PNN) Classification

It is a neural feed forward network derived from a Bayesian network and Kernel Fisher's discriminatory analysis statistical algorithm [30]. D.F. implements it. Specht's operations were founded in early 1990s on a fourtiered, multilayered, feed forward network based on a PNN: in layer: 1. Input, 2. Pattern /Summation, 3. Output, 4. Hidden. PNN is regularly used in problems with classification. When an entry is present, the very first layer calculates the gap between the entry vector and the entry vectors of the layers. It generates a vector in which the factors indicate how close the center is to the center of the learning [35, 36]. Level 2 adds up the benefits of every input class and generates its internet output like a probability vector. Then, a real switch characteristic on 2D layer output selects the greatest of these chances and generates a 1 for that type and a 0 (obstructive identity). In Fig. 10, shown the architecture of PNN model.
Declarations

Consent for publication:

All authors approved to publish in the journal of BioMedical Engineering OnLine.

Availability of data and material:

Available Datasets in Kaggle repository (https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection). We are not able to reveal our unique code. However, we have used Matlab, and C to create our code, schematics, and simulations.

Conflicts of interest:

There are no conflicts of interest involving the authors.

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Authors' contributions:

In this study, we investigated various segmentation and classification techniques while processing image data via DWT, PCA, PNN, and KSVM. We have shown that our technique can distinguish the best results from others. OMAR FARUQ wrote the main manuscript, drafting, Implementation, data collection, prepared figures 3-6. Islam Md Jahidul wrote and processed code and simulation, prepared figures 7-10. Md. Sakib Ahmed, Md. Sajib Hossain generated ideas, collect findings, help to write codes, and prepared figures 1-2. All authors reviewed the manuscript.

References


**Figures**

![Figure 1](image)

**Figure 1**

MRI brain picture: (a) natural brain; (b) Glioma; (c) Meningioma; (d) Alzheimer's illness; (e) Alzheimer's illness with visual agnosia; (f) Pick's disease; (g) Sarcoma; (h) Huntington's illness.
Figure 2

Example of noisy image and reduction of noise.
Figure 3

Image segmentation types.
Figure 4

Different types of techniques for image recognition.
Figure 5

The categorization of training and tested datasets using probabilistic neural networks is compared.

Figure 6

Segmentation and Classifying of Tumor.
Figure 7

Six-stage image reference block diagram to output.

Figure 8

DWT Schematically
Figure 9

Block diagram for the extraction and reduction of the feature used

Figure 10

Architecture of PNN