Brain Tumor Detection from MRI Images

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Abstract

Brain tumor detection is a very important aspect in the medical field. Diversity in brain tumor including shape, color, texture, position makes it hard for early MRI detection and characterization using magnetic resonance (MR) Images. In addition, MR images are more vulnerable to noise and other environmental disturbances. While manual MRI detection is possible, tumor diversity makes it slow and relies heavily on expert experience. This study presents a novel approach for detection and classification of brain tumor from MR images. The primary objective of this study is to develop a novel algorithm that accurately detects and classifies brain tumors, enabling clinicians to assess the severity of the disease. In this paper we propose two tumor detection methodologies, one based on traditional image processing and classical machine learning, and other based on deep learning. In both the approaches, we harnessed the advantage of DWT(Discrete Wavelet Transform), whereas in traditional approach, we employed combination of feature selection techniques like GLCM and LBP before performing classification using classifiers like Random Forest, kNN and AdaBoost. In deep learning approach we harnessed the potential of ResNet101 for classification after certian modifications.

1. Introduction

1.1. Background and Motivation

Brain tumor is a serious health disease, which can be cancerous and fatal. According to the International Association of Cancer Registries (IARC), approximately 30,000 individuals are afflicted by brain tumors annually, with a staggering 24,000 losing their lives to this condition. The timely detection of brain tumors is crucial as it can halt their progression in the initial stages, thereby potentially saving lives.

The importance of brain tumor detection is highlighted by the BraTS challenge, an annual competition that pushes the boundaries of detection methods. This, along with the surge in research publications, reflects the ongoing effort to improve brain tumor detection accuracy. Magnetic Resonance Image(MRI) being the most sensitive imaging test, Computed Tomography(CT) and Positron Emission Tomography(PET) are other Medical imaging technologies used for brain tumor detection.MRI's sharp contrast images makes it best for brain tumor detection.

Various approaches, including image processing, traditional machine learning, and deep learning methodologies, are widely used for brain tumor detection. These methods leverage advanced techniques to enhance accuracy in detection and classifying brain tumors.

1.2. Objective

This paper aims to investigate the potential of various image processing, traditional machine learning, and deep learning methodologies for enhancing brain tumor detection accuracy. By leveraging these techniques, we hope to contribute to improved patient outcomes through more accurate diagnoses.

2. Problem Statement

Brain Tumor detection faces a formidable challenge in medical diagnosis due to their heterogeneous nature and the susceptibility of magnetic resonance (MR) images to environmental factors and noise. Hence, detecting brain tumors is a challenging task due to the complex anatomy of the brain and the similarity between tumor and non-tumor tissues in MRI images. Despite advances in imaging technology, early detection and accurate localization of brain tumors remain elusive.

Our primary aim is to comprehensively examine some of the popular methodologies adopted in the process of brain tumor detection and classification with a focus on understanding existing techniques, identifying their pros and cons and their applicability. Subsequently, we aim to explore the potential for using advanced image processing techniques to improve the accuracy of segmentation to achieve better classification results. Specifically, our interest lies in binary classification tasks applied to MR images, where the classes are ”Tumor” or ”Non-Tumorous”. Our performance metrics include - Accuracy, Precision, Recall, F1 score.

3. Literature Review

3.1. Overview of Classical Brain Tumor Detection Techniques

In their paper titled ”Image Processing Techniques for Brain Tumor Detection: A Review” [1], Vipin Y. Borole, Sunil S. Nimbhore, and Dr. Seema S. Kawthekar focus on various image preprocessing methods for brain tumor detection. They emphasize techniques like de-noising, image enhancement, and edge detection for preprocessing, along with image thresholding, segmentation, and morphological methods for post-processing

In their paper ”MRI Image Processing Method on Brain Tumors: A Review,”[2] Tomasila et al. provide a succinct overview of existing methodologies for brain tumor detection and classification. They highlight diverse approaches, combining segmentation, feature extraction, and classification methods. Common preprocessing includes brightness adjustment, noise reduction, and thresholding. Segmentation methods like Otsu’s thresholding, edge detection, and region growing are emphasized. Feature extraction involves discrete wavelet transform and Gray-Level Co-occurrence Matrix.

In their paper [4], Sravanthi and Swetha propose a sequential method for brain tumor detection. It involves MRI image input, pre-processing, feature extraction, and segmentation. Challenges like noise and low contrast are addressed through pre-processing, including geometric correction. Feature extraction identifies relevant characteristics for tumor classification, while segmentation employs techniques like support vector machines (SVM) and self-organizing maps. SVM, noted for high generalization performance, particularly in extensive function spaces, is highlighted. Visual outputs include grayscale images, filtered images, bounding boxes, and tumor outlines.

The paper ”Brain Tumor MRI Identification and Classification Using DWT, PCA, and KSVM”[7] presents a novel approach for brain tumor MRI identification and classification using Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Kernel Support Vector Machine (KSVM) . The method involves three stages: wavelet decomposition, texture extraction using Gray-Level Co-Occurrence Matrix (GLCM), and classification using KSVM. The authors evaluated the performance of the system on a dataset of 160 MR images, achieving a classification accuracy of over 98% using the GRB kernel . The authors also evaluated the performance of the proposed DWT-PCA-KSVM approach on the same dataset. The results show that the GRB kernel KSVM achieves the highest classification accuracy of over 99

3.2. Deep Learning in Medical Imaging

Aryan Sagar Methil in his research paper ”Brain Tumor Detection using Deep Learning and Image Processing”[4] introduces the integration of deep learning in conjunction with image processing techniques for brain tumor detection. Image augmentation techniques, including rotation and horizontal flip, are applied. Transfer learning with ResNet101v2 as the base model is utilized for classification, fine-tuning for tumor and non-tumor images

The research paper ”Effective detection and classification of brain tumor using discrete wavelet transform”[5] by M. Ajay Kumar, Sree Kamya, K.Kiranmai, S.Pragathi proposes a Wavelet-based Convolutional Neural Network (WCNN) approach that combines the strengths of DWT and Convolutional Neural Networks (CNNs) for effective brain tumor detection and classification The key aspects of the proposed methodology are:

- Wavelet decomposition of the input MRI image to extract discriminative features.
- Feeding the wavelet-based features directly into a CNN classifier, without the need for image segmentation.
- Comparing the performance of the WCNN approach with a traditional SVM classifier using the same wavelet-based features.
- Experimental results on the Figshare (Cheng) brain tumor dataset demonstrate that the proposed WCNN method achieves an impressive accuracy of 99.3%, outperforming the SVM classifier.

3.3. Traditional Feature Extraction Methods

In the paper ”Performance evaluation of feature extraction techniques in MR-Brain image classification system” [3] by Mohammed Khalila, Habib Ayada, Abdellah Adib, presents a MR-Brain image classification system that employs three feature extraction techniques - Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), and Histogram of Oriented Gradient (HOG) - to classify MR brain images as normal or abnormal. They evaluated the performance metrics of the three feature extraction techniques namely: GLCM, LBP and HOG. The feature vectors obtained from each technique are passed through a k-Nearest Neighbor (k-NN) classifier, and the resulting dissimilarity measures are combined using various fusion operators to improve classification accuracy.

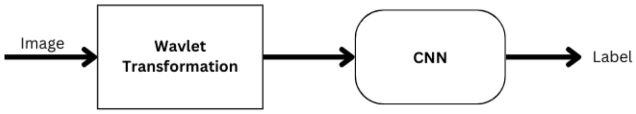

Figure 1. Model architecture

4. Methodology

4.1. Deep Learning Approach

In this approach we used combination of traditional image processing technique and deep learning technique. In image processing we used wavelets to generate feature map of the image and then deep learning CNN model to classify the image. You can see the model architecture in a fig 1.

4.1.1 Preprocessing

- **Histogram flattening:** In preprocessing stage we applied histogram flattening as it improves contrast which in turn enhances details of the image.
- **Open operation:** After histogram flattening we applied Open operation which is combination of erosion and dilation. It helps in noise removal.
- **Data augmentation:** After above 2 operations we did augmentation which helps in generalization and robustness of model. Some data augmentation techniques which we used are rotation, flip, translate, shear, scaling.
- **Resizing:** CNN models take 224×224 size arr as input so we need each channel to be of size 224×224. As we know that wavelets output are half of the size of real image so to make output of size 224 we need to resize the original image to 448×448.

4.1.2 Feature Extraction

For feature extraction we used Haar wavelets. The advantage of haar wavelet feature is that it contain localized information which is very important in images. Also it is effective in edge detection which can be useful in our case as we are searching for tumor in image. One more reason of choosing haar wavelet is that it reduces the feature map(output) size compared to original image which helps in less complex training of the classification model. In this stage we generated the 4 components Approximation (LL), Horizontal Detail (HL), Vertical, Detail (LH) and Diagonal Detail (HH) from the preprocessed image. Then we stacked these 4 feature map to make 3D array with 4 channels.

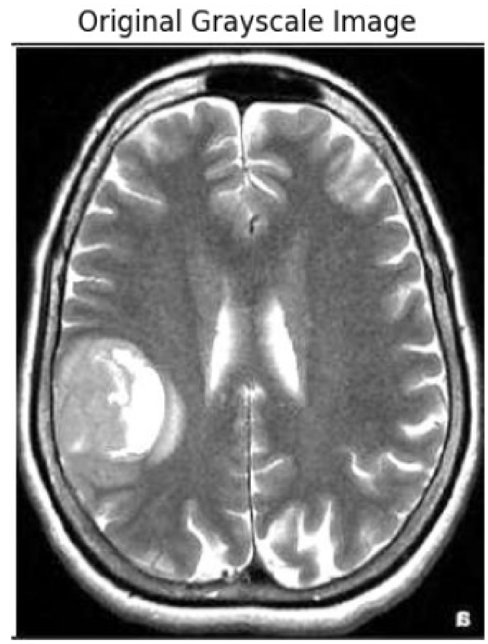

Figure 2. Original image

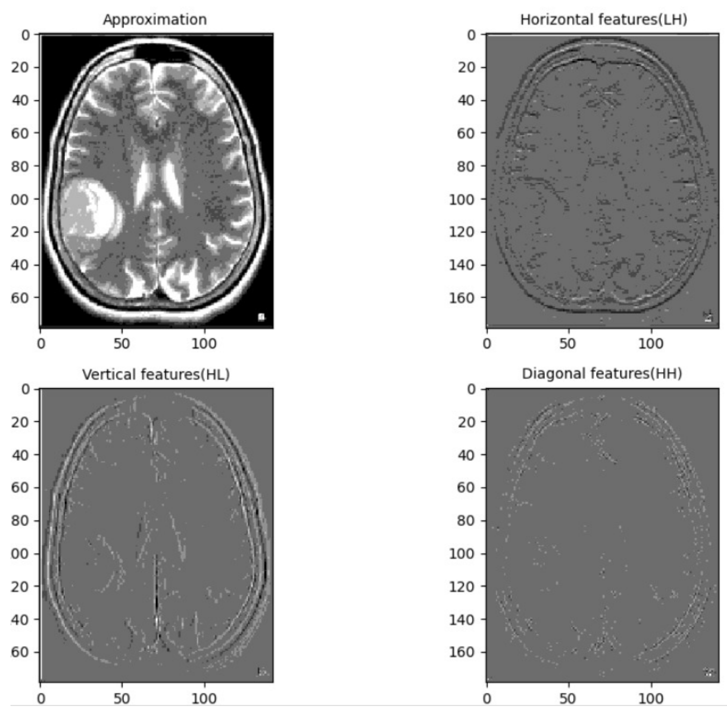

Figure 3. Wavelet components

4.1.3 Classification

As a classification model we choose RenNet101 as it is state-of-the-art model and proved effective in transfer learning.

Modification in model

- We are getting $4 \times 224 \times 224$ feature map after feature extraction as we mentioned above but default resnet model take 3 channels as input so we have modified resnet first convolution layer.
- Secondly we are predicting 'YES' and 'NO' as output so we changed the predictor head size to 2.

Since our dataset was not equally distributed over classes so it can result in biased model. To solve this we assign weights which gives higher weightage to minority class samples during training to penalize misclassifications.

4.2. Traditional Feature Extraction Approach

In this approach we have used traditional image processing and machine learning techniques for tumor detection.

4.2.1 Preprocessing

In the preprocessing stage, we aims to improve the quality of the MRI images for further processing.

- **Noise reduction**: We employed filtering techniques like median filter for the reduction of noise and artifacts for further processing and analysis.

- **Contrast enhancement**: Techniques like histogram equalization are employed for improving contrast for better feature extraction.

4.2.2 Feature Extraction

In this stage we aim to capture useful and informative characteristics from the preprocessed MRI image. Following techniques have been harnessed for the extraction of features.

- **Discrete Wavelet Transform (DWT)**: A very effective feature extracting technique, which decomposes the image into different frequency sub-bands, by which it captures both the spatial and the frequency information.

$$\begin{aligned}\mathrm{DDWT}_{j,k} &= \sum_{n=0}^{N-1} h[n] \cdot x[2n-k] + \sum_{n=0}^{N-1} g[n] \cdot x[2n-k] \\ &= \sum_{n=0}^{N-1} h[n] \cdot x[2n-k] \\ &+ \sum_{n=0}^{N-1} (-1)^n g[N-1-n] \cdot x[2n-k]\end{aligned} \tag{1}$$

Where the above notations denote:

– $DDWT_{j,k}$ represents the DDWT coefficient at scale j and position k

– h[n] is low-pass filter coefficients of the db-5 wavelet

– g[n] is high-pass filter coefficients of the db-5 wavelet

– x[n] represents the input signal.

– N is the length of the filters.

- **Gray Level Co-occurrence Matrix (GLCM)**: A very useful textural feature extraction algorithm, which analyzes the spatial relationships between pixels of specific gray levels. Out of many features GLCM provides, we have consider the following most important features:

1. *Contrast*: The contrast has calculated the variations in gray-level co-occurrence matrix and is explained in the equation below:

$$Contrast = \sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} (i-j)^2 p(i,j) \tag{2}$$

In this and all following equations we define:

– (i, j) are the coordinates of a particular pixel, with i denoting the row position and j denoting the column position.

– p is the probability occurrence matrix for the image window

– N_g indicates the number of Rows or Columns of the image window

– is the standard deviation of GLCM.

– μ is the mean of GLCM.

2. *Dissimilarity*: A metric similar to Contrast, defined by below equation:

$$\sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} |i-j| p(i,j) \tag{3}$$

3. *Homogeneity*: A metric measuring the smoothness of the gray scale image, which is inversely related to contrast, given by the below equation:

$$\sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} \frac{1}{1+(i-j)^2} p(i,j) \tag{4}$$

4. *Energy*: Defined as the sum of all pixels squared in the GLCM, indicating the uniformity measure.

$$\sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} [p(i,j)]^2 \tag{5}$$

5. *Correlation*: Defines the gray level linear correlation between pixels, given by:

$$\sum_{i=1}^{N_g-1} \sum_{j=1}^{N_g-1} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{6}$$

- Local Binary Pattern (LBP):The Local Binary Pattern (LBP) operator extracts texture information from an image by comparing the intensity of a central pixel with its neighboring pixels within a defined circular region. It assigns binary labels based on whether the neighbor's intensity is greater or less than the central pixel's intensity, generating a unique code for each pixel. This operator computes a binary code for each pixel by comparing its intensity with its neighbors in a circular region, thereby extracting texture information from the image. Below is the formula for LBP:

$$LBP(i_c, j_c) = \sum_{p=0}^{P-1} s(p) \cdot 2^p \tag{7}$$

where $s(p)$ is defined as:

$$s(p) = \begin{cases} 1 & \text{if } I(p) \geq I(i_c, j_c) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

Here we define the terms as follows:

  - (i_c, j_c) denotes the current pixel for which we are computing the binary code.
  - $I(p)$ represents the intensity of the p-th neighbor of the pixel (i_c, j_c)
  - $I(i_c, j_c)$ represents the intensity of the central pixel.
  - P denotes the number of sampling points in the circular neighborhood.
  - R denotes the radius of the circular neighborhood.

In this stage, we first used DWT($level = 1$), for extracting the features of the processed image. We employed DWT using db-5 wavelet, a special wavelet function in the Daubechies family, which maintains good balance between smoothness and vanishing moments. By using this, we obtained Approximation (LL), Horizontal Detail (HL), Vertical, Detail (LH) and Diagonal Detail (HH) sub -bands of the processed image. We then extracted 5 most relevant GLCM features(for 2 distance values and 4 angle values) for each of these sub-bands and the processed image, consisting of $5 \times 48 = 240$ features.

Now we applied Local Binary Pattern(LBP) operator on each of the 4 sub-bands(LL,LH,HL,HH) and the processed image, by which we can gain more useful features in regards to the image. By using all these feature extraction techniques, we achieved a total of $240 + 5 \times 18 = 240 + 90 = 330$ (where 240 is from 4 sub-bands and processed image and 90 is achieved by applying LBP operator on these 4 sub-bands and processed image).

We now aim to reduce these features, for further steps in the brain tumor detection.

4.2.3 Feature Reduction

After obtaining 240 and 90 features from GLCM and LBP on sub-bands and processed image, we now have in total of 330 features for each image. Since this is a very large number of features, we need to reduce these features, which helps us in combating the curse of dimensionality and help use generalize the model's ability .

In this phase we employed PCA for reducing the features, which potentially improves classification performance and computational efficiency.

- **Principal Component Analysis (PCA)**: Helps in identifying and focusing on a fewer number of principal components, that captures the most variance in the feature space, helping in dimensionality reduction. Here using PCA we have reduced the features we extracted earlier, i.e 330 to almost 20 principal components, which helps us in training computation and classification.

4.2.4 Classification

In this phase we employed various classical machine learning classifiers, for tumor detection.

- **Random Forest**: An ensemble learning method, consisting of decision trees which employed for classification here.
- **k-Nearest Neighbors (kNN)**: A supervised learning model, which classifies data points, based on its k nearest neighbors.
- **AdaBoost**: A classification model which considers ensemble of multiple weak learners to make a strong classifier.

Following the feature reduction phase using Principal Component Analysis (PCA), each of the aforementioned classifiers was applied to the resulting principal components. The performance of these classifiers will be presented in the Results section.

5. Experimental Setup

5.1. Dataset Description

For our research on brain tumor detection, we utilized two distinct datasets to ensure comprehensive analysis and validation.

5.1.1 Dataset 1: Br35H :: Brain Tumor Detection 2020

The first dataset, Br35H :: Brain Tumor Detection 2020, was obtained from Kaggle, a widely recognized platform for datasets and machine learning competitions. This dataset comprises a total of 3000 Brain MRI Images, divided into two folders:

- **Yes**: This folder contains 1500 Brain MRI Images depicting tumorous conditions.

- **No**: This folder contains 1500 Brain MRI Images representing non-tumorous conditions.

To ensure a robust evaluation, we split this dataset into training and testing subsets in an 80:20 ratio.

5.1.2 Dataset 2: Brain Tumor MRI Dataset

The second dataset, Brain Tumor MRI Dataset, is a composite collection sourced from multiple repositories, including figshare, SARTAJ dataset, and Br35H. This dataset is more expansive, comprising a total of 7023 images of human brain MRI scans.

The images in this dataset are classified into four distinct categories: glioma, meningioma, no tumor, and pituitary. Although the dataset was classified into four categories, we adapted it for binary classification by considering only the presence or absence of tumors. Therefore, we restructured the dataset into two classes: ”Yes,” indicating the presence of a tumor, and ”No,” indicating the absence of a tumor.

We used this dataset in our deep learning model as it has significant number of images(around 7000), which allowed the deep learning model to learn the minute details of the MRI-image.

5.2. Evaluation Metrics

In evaluating model performance, four key metrics are commonly used: accuracy, precision, recall, and F1 score.

- **Accuracy**:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number of Samples}}$$

- **Precision**:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- **Recall**:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **F1 Score**:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy measures the percentage of correctly classified data points but may be misleading at certain scenarios(imbalanced classes). While precision quantifies the proportion of true positive predictions among all positive predictions, highlighting the importance of minimizing false positives(FP). On the other hand, Recall measures the proportion of true positives correctly identified by the model, and F1 score provides a balanced assessment by considering the harmonic mean of precision and recall.

5.3. Hyperparameter Tuning:

To optimize the performance of our classification models, we employed hyperparameter tuning techniques. Specifically, we utilized the Grid Search method to fine-tune the parameters of the Random Forest classifier.

Grid Search: Grid Search is a systematic approach to hyperparameter tuning that involves defining a grid of hyperparameter values and exhaustively searching through the grid to find the optimal combination. Grid search techniques, particularly with the **Random Forest classifier** using sklearn’s **GridSearchCV**, were employed to optimize model performance for brain tumor detection. By systematically exploring a predefined hyperparameter space and evaluating combinations of parameters, the most effective settings were identified to enhance classification accuracy

6. Results

6.1. Deep Learning Approach

Figure 4. **With histogram flattening**

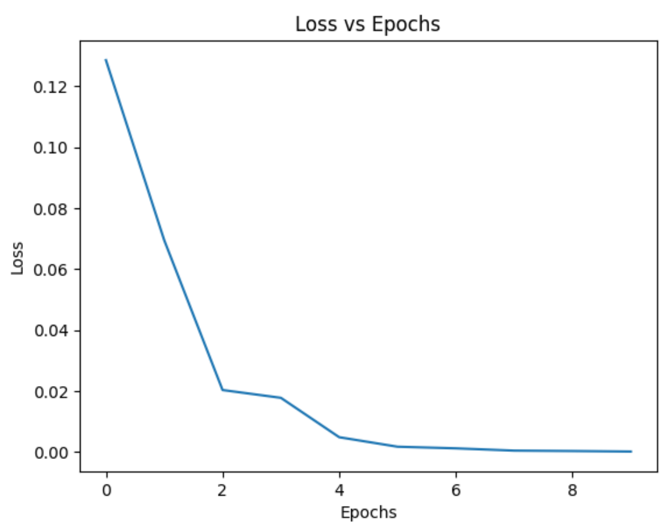

Figure 5. Graph of Training Loss

With histogram flattening and open-operation

	Recall	Precision	F1-Score	Accuracy (%)
Train	1.0	1.0	1.0	100.0
Test	1.0	0.9978	0.9989	99.847

When comparing the model with and without histogram flattening, it’s evident that applying this technique leads to a marginal improvement in precision on the test set (99.78% with histogram flattening versus 99.66% without).

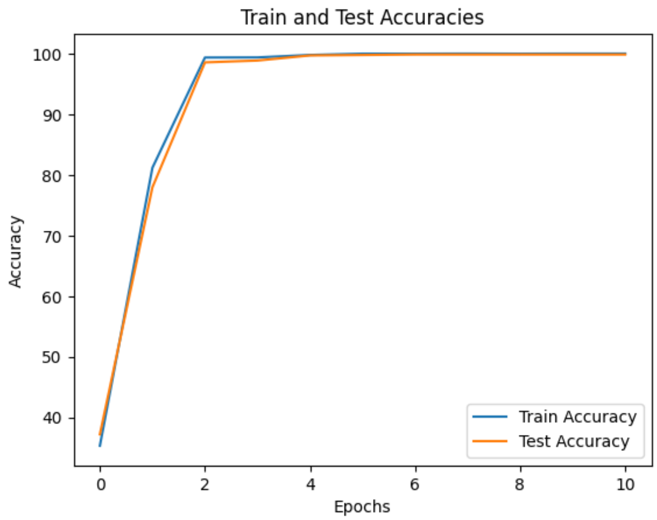

Figure 6. Graph of Accuracy vs Epoch

Without histogram flattening and open-operation

	Recall	Precision	F1-Score	Accuracy (%)
Train	1.0	1.0	1.0	100.0
Test	1.0	0.9966	0.9983	99.771

Histogram flattening likely aids in enhancing the model's ability to discriminate between classes, resulting in slightly better performance metrics, particularly in precision.

6.2. Traditional Methods

6.2.1 Classifier: KNN

KNN: GLCM Features

	Recall	Precision	F1-Score	Accuracy (%)
Train	0.9383	0.9393	0.9383	93.83
Test	0.8850	0.8876	0.8850	88.50

KNN: GLCM+LBP Features

	Recall	Precision	F1-Score	Accuracy (%)
Train	0.9858	0.9858	0.9858	98.58
Test	0.9750	0.9750	0.9750	97.50

6.2.2 Classifier: Random Forest

Random Forest: GLCM Features only

	Recall	Precision	F1-Score	Accuracy (%)
Train	1.000	1.0000	1.0000	100.00
Test	0.955	0.9551	0.9550	95.50

Random Forest: GLCM+LBP Features

	Recall	Precision	F1-Score	Accuracy (%)
Train	1.0000	1.0000	1.0000	100.00
Test	0.9950	0.9950	0.9950	99.50

6.2.3 Classifier: AdaBoost

AdaBoost: GLCM Features only

	Recall	Precision	F1-Score	Accuracy (%)
Train	0.8404	0.8413	0.8403	84.04
Test	0.7700	0.7746	0.7698	77.00

AdaBoost: GLCM+LBP Features

	Recall	Precision	F1-Score	Accuracy (%)
Train	1.0000	1.0000	1.0000	100.00
Test	0.9783	0.9783	0.9783	97.83

When comparing the classifier after adding the LBP feature along with GLCM, there is a significant increase in accuracy for all classifiers.

7. Key Insights

7.1. Importance of Traditional Image Preprocessing Techniques even for CNN-Based Classification:

Despite the advancements in deep learning, traditional image preprocessing techniques remain indispensable, even for CNN-based classification. Preprocessing steps such as denoising, contrast enhancement, and image normalization can improve the robustness and efficiency of CNN models. Effective preprocessing ensures that CNNs can focus on learning high-level features and patterns, leading to improved classification accuracy and generalization.

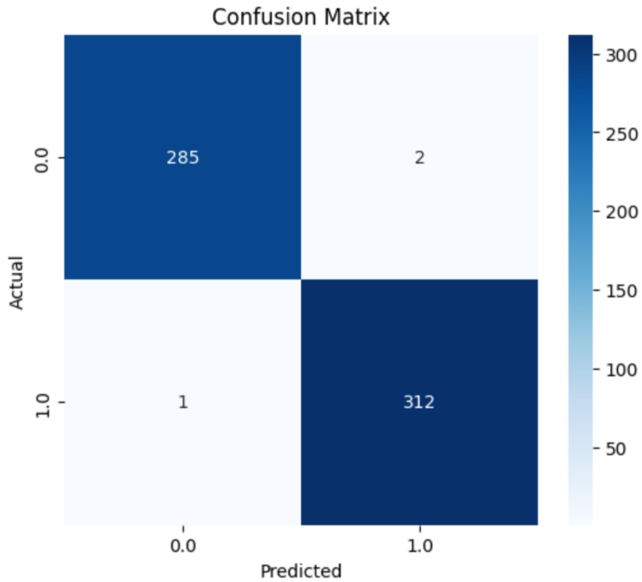

Figure 7. Confusion Matrix for Random Forest with GLCM+LBP features

7.2. Advantages of Deep Learning over Classical Machine Learning Classification Algorithms:

Deep learning offers several advantages over classical machine learning algorithms, driving the shift towards its adoption. Deep learning models, particularly CNNs, have demonstrated superior performance in handling large-scale, high-dimensional image data. However, it was observed that it requires a large amount of data to train on. The inherent ability of deep learning models to automatically learn hierarchical features from raw data obviates the need for manual feature engineering, leading to better and efficient results.

7.3. Challenges in Preprocessing:

While preprocessing techniques play a crucial role in enhancing image quality and feature extraction, their applicability may vary across different types of images. Certain preprocessing techniques may not be universally effective and may exhibit limitations when applied to specific distribution of images. As MRI images of brain tumor are diverse in nature, it is important to experiment and find the suitability of preprocessing techniques depending on the image distribution we have.

7.4. Importance of Feature Extraction on Accuracy:

Several paper have employed techniques like GLCM, LBP, HOG for extracting features. These techniques provide valuable information related to the image. With GLCM used in most instances of feature extraction, follwed by LBP and HOG. In our approach, we employed these important feature extraction technique. In our traditional approach, we employed two routlines, first we directly extracted GLCM features obtained from DWT sub-bands of our processed image. Later in second routline, we applied LBP technique on GLCM features obtained from DWT sub-bands of our processed image. The significance of these techniques can be seen, in the improvement of accuracy while employing LBP, outperforming the first routline.

8. Strengths and Limitations

8.1. Strengths

8.1.1 Deep Learning Approach

- **High Accuracy:** Deep learning models can achieve high accuracy in brain tumor tasks.
- **Robustness:** These models learn complex patterns in MRI images.
- **End-to-End Learning:** This approach offers automatic feature extraction, eliminating the need for manual feature engineering.

8.1.2 Traditional Method

- **Interpretability:** Traditional methods like GLCM, HOG, and LBP provide interpretable features that are easy to understand for classification tasks.
- **Simplicity:** This method is easy to implement and computationally efficient.

8.2. Limitations

8.2.1 Deep Learning Approach

- **Data Dependency:** This method depends on labeled datasets for efficient training, which may not be available with MRI images.
- **Computational Resources:** This method highly depends on computation, which includes GPU and time-consuming procedures.

8.2.2 Traditional Method

- **Limited Discriminative Power:** This method may lack the discriminative power of deep learning to learn complex patterns in MRI images.
- **Manual Feature Engineering:** Manual feature and selection in traditional methods is time-consuming.

9. Future Directions

9.1. Review of Recent Research Papers:

Delve into recent research papers and studies focusing on advancements in MRI-based brain tumor classification.

Identify novel techniques, methodologies, and insights that can potentially enhance the current approach.

9.2. Experimentation with Different Deep Learning architectures:

Explore various CNN architectures beyond Resnet101 and even explore different Neural network architectures such as recurrent neural networks (RNNs) or transformer-based models, to check their unique capabilities. This is because we found research papers using these architectures for the classfication task as well recently. Evaluate the performance of these architectures in MRI-based brain tumor classification tasks.

Explore advanced data augmentation for the dataset and find the best transfer learning strategy from pre-trained models.

9.3. Model Interpretability and Explainability:

Develop techniques for improving interpretability, Integration of attention mechanism and saliency mapping techniques (importance of input feature influencing the model output) may help. This is because model interpretability is important in such medical field.

9.4. Exploring combinations of different feature extraction techniques and classification algorithms:

Exploring different traditional methods like GLCM, HOG, LBP, and DWT and some other machine learning algorithms of classification such as SVM, kNN, RF, and deep learning classifiers like CNNs promises optimization to improved diagnostic performance. We can also try combination of different feature extraction methods and experiment

10. Conclusion

The importance of traditional image preprocessing techniques like denoising and enhancement for improving classification accuracy before the classification stage has been highlighted by numerous studies. Nevertheless, despite their prevalence, a significant shift towards deep learning approaches is evident.

Traditional methods offer interpretable results and lower computational demands but struggle with complex tumor shapes and intensity variations, leading to lower accuracy. Deep learning approaches, on the other hand, achieve higher accuracy with sufficient data, but often lack interpretability, a critical aspect in medical decision-making.

In this paper we aimed to make use of the best of both worlds and combine classical and deep learning strategies. Our work explored the potential of combining traditional and deep learning approaches for brain tumor detection.

In conclusion, by harnessing the best in both the traditional image processing techniques like DWT and deep learning paradigms, we achieved oustanding results in brain tumor detection. This advancement has the potential to significantly benefit patient care and diagnosis, ultimately leading to better health outcomes.

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