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A Comprehensive Approach to Brain Tumor Classification in MRI: Unifying Classical Local Binary Patterns and Convolution Neural Networks

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Abstract: - Brain tumors, among the most perilous neurological disorders affecting the human nervous system, are categorized into glioma, meningioma, and Pituitary types. The proposed system combines Classical Local Binary Patterns (CLBP), Histogram of Oriented Gradients (HOG), and Convolutional Neural Networks (CNN) to extract texture information from MRI images. The methodology comprises three key steps: image pre-processing, feature extraction, and classification. By evaluating a publicly accessible brain tumor dataset, the proposed approach attains an impressive accuracy of 96%. The findings highlight the potential uses of the CLBP+CNN approach in clinical diagnosis and treatment planning, demonstrating the possibility of accurate and efficient brain tumor classification. The proposal introduces future extension methods like CLBPs (DLBP, ϴLBP), where the DLBP approach incorporates a 'D' parameter specifying the distance between neighboring pixels. The ϴLBP Method evaluates the pixel value by changing the 'ϴ' value, i.e., 15^0, 45^0, 90^0 and 120^0. The classification of tumors involved the application of various classification methods, namely ANN (Artificial Neural Networks), AlDE (Ant Lion Optimizer Differential Evolution), and LDA (Linear Discriminant Analysis). This classification is executed using feature extractions derived from CLBP (DLBP & ϴLBP) applied to MRI images within the dataset.

Keywords: Classical Local Binary Patterns (CLBP), Convolutional Neural Networks (CNN), Histogram of Oriented Gradients (HOG), Linear Discriminant Analysis.

I. INTRODUCTION

A brain tumor arises from the aberrant or malignant cells that grow linearly around or inside the brain. Gliomas are divided into primary and secondary tumors, depending on where they originated in the brain. The primary tumor may be benign or malignant if it does not spread to other body parts. The secondary tumors, however, are regarded as malignant. Benign tumors include meningiomas and gliomas, which are low-grade tumors. The brain in humans is in charge of all bodily functions. MRI images have been used to diagnose brain tumors, and these technologies have been crucial to the analysis [1]. Figure 1 shows the brain tumor image, a doctor can detect diseases and make decisions by classifying tumors on higher-resolution medical images. Deep Learning techniques based on learning to transfer brain magnetic resonance imaging (MRI) were used to classify all images. The three fundamental image classifiers are SVM, K-means, and KNN. Radiologists find that analyzing brain tumor images takes much time. [2]. LBP is the most critical and direct performance evaluation method because it is often used in image processing to enable pixels. The Regularized Extreme Learning Machine, or RELM, is a well-liked technique for recognizing and categorizing brain tumors because it provides fast training, very low complexity, and resists backpropagation. This technique uses tested photos once the input images are taken [3,4]. Input, output, and hidden layers are the components of this normalization rule-based technology that increases the intensity of MRI images. Early brain tumor detection and classification are crucial for saving lives and reducing the communication gap between medical professionals and patients. MRI images that have been pre-trained utilizing data sets are used to evaluate SVM and KNN models for brain tumor classification [5,6]. Convolution neural networks are another well-liked method for extracting features from photos to identify the skin. CNN is also the same as Deep Learning Neural Network, which is among the most significant image classifiers and is applied in numerous medical diagnosis applications, including skin issues, lung cancer, and chest and brain tumors.

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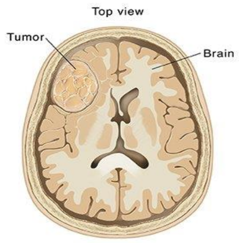

Figure 1: Brain Tumor Detection Image

The research methodologies utilized in this paper are categorized using a framework for classification and segmentation, which was gathered from various sources. Brain tumor approaches are divided into segmentation and classification methods according to the methodologies presented in the survey studies. Further details are provided regarding the research gaps and problems found in the current approaches for treating brain tumors. However, the characteristics taken out of the boundary zone are also covered.

II. LITERATURE REVIEW

This section summarizes the key discoveries and provides an overview of the current applications of multiple deep-learning algorithms for brain tumor segmentation by researchers. Neme, Shubhangi, and colleagues designed the enduring cyclic unpaired encoder-decoder network, combining residual and mirroring ideas (Rescue Net). The authors identified that preparing huge amounts of labeled data for deep network training is a time-consuming and difficult automatic brain tumor analysis operation. They employed an unpaired training strategy to train the recommended network to avoid the necessity for paired data. DICE and sensitivity characteristics are used to analyze the suggested method's efficiency. Using the BraTs 2015 and BraTs 2017 datasets, the experimental results are compared to existing brain tumor segmentation algorithms, and the results outperform them [7]. R. Cristin et al. [8] modeled a CNN classifier for automatic tumor segmentation using MR images. Gliomas were the most aggressive and most common tumor that led to death with the highest grade. Planning the treatment strategy was the key component to increasing human life. MRI was the highly significant method used to access the tumor region, but the data generated by the MRI prevented performing manual segmentation at a reasonable time. However, the brain tumor's large structural and spatial variability made the segmentation process more complex. It also used the intensity normalization and data augmentation model to achieve tumor segmentation in the MRI image. The detection rate of this model was meager. H. H. Sultan et al. [9] introduced a Deep CNN classifier to segment the brain tumor automatically. It used the inception module and the patch-based model to extract the co-centric phases with different sizes by training the network classifier. Here, the linear nexus architecture is modeled using the recent network classifiers, like non-linear activation, inception module, batch normalization, and dropout. Due to the dropout regularization with the data scarcity, the overfitting problem was reduced. Deep CNN used the normalized images and allocated the output label to the patch of the central pixel. The small false positive values situated around the tumor edges were removed using the morphological operators. It used the two-phase weighted training approach to deal with data imbalance issues. It considered both the contextual and local information to predict the output labels. This method probably took five to ten minutes to segment the brain tumor. N. M. Dipu et al. [10] introduced a Deep Convolutional Symmetric NN (DCSNN) for segmenting the brain tumor effectively. Glioma tumors have a high mortality rate, and surgery is the only way to perform the treatment planning. MRI helped access the glioma and make the successful treatment in the clinical strategy. The major key role in the treatment and diagnosis planning was accurately segmenting the glioma tumor. The structural and spatial variability between the brain tumors brings complex issues in automatically segmenting the MR images. This method provides better function mapping and enhances the feature quality of the brain images. DCNN requires prior knowledge of tumor segmentation as most images were usually in left-right asymmetry. DCSNN used the concept of DCNN and the symmetry model by including the symmetric masks at several layers. It used the Siamese-based model for extracting the abundant features by adding the loss functions at different layers to identify the exact tumor region based on the similarity metric. P. Afshar et al. [11] The RF classifier combined the redundancy features and classified the voxel of MRI images into various tumor parts and brain tissues. The segmentation model was evaluated through the BRATS dataset. Moreover, the contextual information from the background image, spatial information, and the texture features of the image were also extracted effectively. This method minimized the feature redundancy and enhanced the accuracy of classification. M. Gurbină et al. [12] utilized the cascade U-net for sequentially segmenting the tumor sub-regions. Moreover, the cascaded training model was adopted to enhance the segmentation performance for small glioma tumor regions with the transfer knowledge. Accurate tumor segmentation using MRI images was active research in the medical analysis system as it offered doctors reliable and meaningful quantitative data in monitoring and diagnosing neurological diseases. The deep learning-based method was designed to build the image patches successfully. Here, the up-skip connection was introduced between the tumor cells' decoding and encoding path of the tumor cells to increase the information flow. However, the segmentation map slices were automatically generated using the patch-wise model. N. Çınar et al. [13] trained the CRF and CNN based on image patches and generated the sagittal, coronal, and axial views. Here, the image patches were sampled using a training dataset, and the image patches belong to the same class, which was selected as the training patches that further helped to solve the data imbalance problem. The image slices were combined to perform the brain segmentation through the voting-based fusion model. The intensity normalization was used to normalize the MRI by subtracting the largest frequency gray value and dividing the robust deviation. The segmentation results were post-processed to remove the small connected regions and verify the false labels using a thresholding strategy. The intensity values effectively characterized the brain tissues with the MRI scan. It achieved enhanced performance with the BRATS dataset. S. Arora et al. [14] introduced a tumor segmentation technique for low-grade tumors using MRI. The quadrature filters using monogenic signal locally estimated the phase-based detection method. It used the intensity-invariant function for detecting the edge regions of brain tumors. The region-based factor was locally designed with the tumor segmentation model to strengthen the detection rate and increase the likelihood of segmentation of the tumor region of interest. The intensity of the local images was modeled by considering the Gaussian probability distribution function. Integrating the local phase details of the tumor overcomes the intensity changes and low contrast with ROI. The monogenic quadrature filter was used to estimate the localization of brain tumors. In addition, with this model, the overlap, precision, accuracy, specificity, and sensitivity rendered better results for the brain image slices. However, the performance of the segmentation process for synthetic tumors was abysmal. Thejaswini P. Bhat et al. [15] introduced a glioma detection approach using brain MRI images based on morphological and texture features. This model effectively detects the tumor by assisting the radiologists and suggesting the clinician detect the presence of a tumor. The ensemble classifier and the texture fusion features performed different classification levels based on the pulse sequences to detect the glioma tumor. Initially, at the first stage, the exact location of the tumor in the brain was analyzed by the brain tentorium, which was categorized into infratentorial and supratentorial levels. The tumor type can be effectively identified with the characteristic features, like solidity, perimeter, area, orientation, and morphological features. This method effectively performed well without the usage of manual interpretation and intervention. The fusion of morphological and texture features enhanced the performance of the detection rate. The tumor categorization was effectively and accurately performed based on different classification levels. However, it failed to enhance the performance of detection for high-grade tumors. M. Nazir et al. [17] introduced a tumor segmentation model based on kernel sparse and texture features using MRI images. At first, MRI was allowed to pre-process to eliminate the noise in the image, which increased the contrast and made the correct intensity. Here, the sparse coding was performed using the first and second orders of the statistical Eigenvector, which was retrieved from the original image with a patch of 3*3 voxels. The non-linear features were effectively extracted using dictionary learning, which further helped to model two dictionaries for pathological and healthy tissues. The voxels were coded using a kernel-based clustering approach, and the target pixels were classified using a linear discrimination model. It used the flood-fill function to enhance the quality of image segmentation. This method has better capacity with less computation cost, attained better segmentation accuracy, effectively solves the data imbalance problem, and evenly distributes the data. This method failed to use the multimodal sources for segmenting the tumor tissues. Y. Bhanothu et al. [18] modeled a Gray Level Co-occurrence Matrix-Based Cellular Automaton (GLCM-CA) for tumor classification. This model introduced two frameworks to enhance image transformation: tumor segmentation and classification. MRI was the highly preferred technique to perform the classification scheme more accurately. Due to the characteristic features of ambiguous tumor regions, segmentation makes it more complex in medical imaging systems. The key role of GLCM-CA was to transform the original MRI to the target-based feature image. However, it effectively enhanced the features of the tumor concerning the background area of segmentation. The tumor cut algorithm was highly preferred to achieve effective tumor segmentation, but the tumor cut model faces many issues in the robustness of seed growing. It also used the weighted distance model to improve the tumor cut accuracy. It attained better performance using the BraTs dataset with the evaluation of dice quantitative measure. The testing and training dataset revealed the experimental results using 55 real images. H. Ucuzal et al. [19] introduced an automatic tumor segmentation model using fuzzy c-means and the greedy snake approach. It effectively identified the ROI by eliminating the non-tumor region through a two-level morphological reconstruction model, like erosion and dilation. To segment the glioma tumor automatically using MRI was a complex task in the medical area as the tumor occurs at different parts of the brain with varying intensity, size, and shape. The reconstructed image was the threshold to form the mask, which was eroded to increase the segmentation accuracy using the greedy snake approach. The initial contour was developed with the mask boundary, and the greedy model was used to estimate the new tumor boundaries. The estimated boundaries were highly accurate at regions with sharp edges and less accurate at regions with ramp edges. The optimization for the inaccurate boundaries was performed using the fuzzy means algorithm for determining the accurate segmentation results. Finally, the region with the large perimeter was selected to remove the inaccurate regions in the brain image. This research experimented with the enhanced contrasted image set with the specificity, dice score, and sensitivity for various tumor categories, like pituitary, glioma, and meningioma tumors. However, it attained better performance for segmentation accuracy but poor results compared to the ground truth values. S. K. Baranwal et al. [20] introduced a multi-phase model to integrate domain and data knowledge into multi-sequence segmentation. However, accurate tumor segmentation was a critical task in the clinical sector of medical imaging systems. MRI provides complete information about the visual object or pathological tissues from the image. The radiologists combined the patient's multi-sequence images to verify the extension, diagnosis, and location of objects. K. N. Guy-Fernand et al. [21] introduced an efficient model named probabilistic NN for tumor classification as brain tumor was a major disease that causes death among people. The human survival rate may also increase when a tumor is detected early. The CAD algorithms were designed to increase tumors' classification and detection accuracy. This method involved three phases to perform tumor classification: wavelet decomposition, feature extraction, and classification. At first, the wavelet transform was used to decompose the image into various levels of detailed and approximate coefficients to generate the gray level-based co-occurrence matrix. The texture features, like contrast, homogeneity, entropy, correlation, and energy were effectively extracted from the computed matrix. The result obtained from the feature extraction phase was further used to perform tumor classification. This model was applied in the real MR images and the accuracy obtained using the probabilistic model was 100%. This method revealed outstanding results in tumor classification using MR images. F. P. Polly et al. [22] developed a fully automatic model named U-net-based deep CNN classifier for tumor segmentation and detection. However, determining the tumor context in the brain tumor evaluation and treatment strategy poses a major challenge in tumor segmentation. Here, the tumor segmentation was carried out using MRI images, as MRI was the most significant diagnostic tool used to perform the tumor classification and segmentation without ionizing the radiation. The BRATS dataset revealed the experimental result, which contains low-grade and high-grade glioma patients. This method offered both robust and efficient segmentation than the manual ground truth. M. R. Ismael et al. [23] The gray-level co-occurrence matrix was designed to specify the texture space features to achieve tumor segmentation. Moreover, the effectiveness of the tumor segmentation model was tested with two real datasets, which contain 600 images for about 55 patient's information. However, different categories of images existed, such as diffused tumors, synthetic images, and heterogeneous and homogeneous images. This model attained the results of tumor segmentation based on complex content heterogeneous and uniform intensity variation using a T1-weighted benchmark dataset. In this method, no over-segmentation issues existed in the presence of diffused and weak edges. Also, it had no pre-convergence issues in the presence of saddle points and false edges. It effectively segmented the irregular and complex tumor shape and size with accurate concavity. It automatically assigned the parameter for segmentation and facilitated less human intervention.

III. METHODS

A. Data Set

Based on previous studies, the data sets are provided by [24-27]. The dataset consists of 3265 images, the brain MRI images are composed of four tumor categories for case meningioma, glioma, and pituitary and no tumors. The dataset is divided into training and testing. The training images are composed of 822 meningiomas, 827 gliomas, 827 pituitary, and 395 no-tumor brain tumor type images, and the testing images are composed of 115 meningiomas, 100 gliomas, 74 pituitary, and 105 no-tumor brain tumor type images. For the classification of brain tumors, Kaggle. Figure 2 show the sample images of three different types of brain tumors. Each image containing pixels with the size of 512x512 was taken for evaluation. The proposed approach contains 2D MRI images.

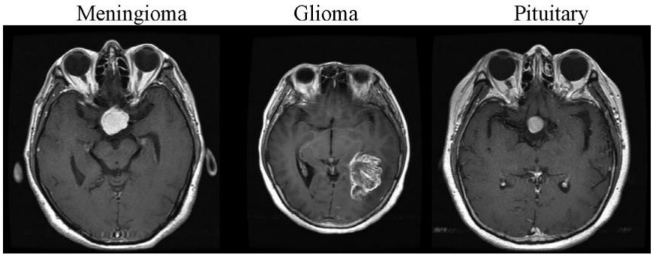

Figure 2: Sample images of three different types of brain tumors

The proposed framework for brain tumor classification encompasses four key stages. Initial tumor pre-processing involves applying the Histogram of Oriented Gradients (HOG) approach to eliminate unwanted noise and skull stripping to remove extraneous elements in the MRI images. Subsequently, the MRI images undergo segmentation in the second step, employing various Classical Local Binary Patterns (CLBP) for feature extraction, including DLBP and LBP techniques. The efficacy of these techniques is then systematically compared with existing algorithms to identify the optimal methodology for tumor classification. The culmination of the framework resides in the final classification step, where the selected methodology, along with pertinent datasets, is employed for tumor or no-tumor classification on the MRI images. Figure 3. Show the categorization systems proposed flow diagram. This holistic strategy endeavors to improve the precision and effectiveness of brain tumor classification by employing thorough pre-processing, sophisticated feature extraction, and efficient classification methods.

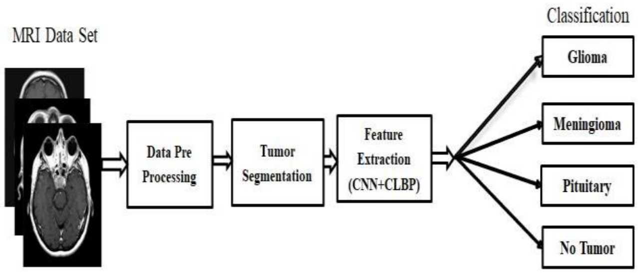

Figure 3: Brain tumor categorization system's proposed flow diagram.

B. Segmentation

Brain tumor imaging using techniques such as MRI and CT generates a significantly large number of images. Brain MRI scan consists of several slices across the 3D anatomical view for single image, manual segmentation of brain tumors from MRI is a challenging and time-consuming task. In addition, the artifacts introduced in the imaging process result in low-quality images that make the interpretation easier. As a result, the manual brain MRI segment is susceptible to inter and intra-observable variability. Different automatic brain tumor segmentation techniques have been proposed to alleviate these challenges and help radiologists. The brain tumor segmentation techniques provide objective, reproducible segmentation close to the manual results. Automated brain tumor segmentation can alleviate the difficulties of manually analyzing brain tumors. It will speed up the brain image analysis process, improve diagnosis outcomes, and make it easy to follow up on the disease by evaluating tumor progression.

C. Classical Local Binary Pattern

One prominent feature extraction method in computer vision and image processing is the classical local binary pattern (LBP), which has practical applications in medical image analysis, especially in brain tumor classification. The traditional LBP approach creates a binary code that contains the texture information of an image by comparing each pixel in the picture to its neighbors within a predetermined radius. The process of assessing the grey values of the center pixel yields this binary code against its neighbors, assigning a 1 if the neighbor's grey value is greater than or equal to the central pixel and a 0 if it is less. This comparative process is iteratively applied to all pixels in the image, resulting in a comprehensive representation of the image's texture.

In the context of brain tumor classification, classical LBP is useful in extracting texture features from magnetic resonance images (MRI) of the brain. These traits that have been retrieved are valuable inputs for machine learning algorithms that help classify different forms of brain tumors. The local texture patterns in brain MRIs are expertly captured by the LBP features, which aid in differentiating various types of brain tumors. Several research works have demonstrated excellent classification accuracy rates for brain tumors by utilizing traditional LBP characteristics with machine-learning methods like RF classifiers and SVM. The active exploration of classical LBP in brain tumor classification signifies a dynamic area of research with ongoing relevance, which is expected to continue playing a pivotal role in advancing medical image analysis techniques.

D. Distance Based Local Binary Pattern (DLBP)

Distance Classical Local Binary Pattern (DLBP) is an extension of the Classical LBP algorithm for texture analysis and classification. DLBP extracts features from images and is especially useful in applications with essential texture information. The DLBP algorithm is similar to Classical LBP but incorporates a distance function between neighboring pixels to generate more robust and discriminative features. In DLBP, the neighboring pixels are considered to be circularly arranged around the central pixel. The distance function is used to calculate the distance between each pair of neighboring pixels and then to adjust the weighting of the LBP code; these results in more robust features that can better distinguish between different textures.

In addition, DLBP uses a multi-resolution approach to capture texture features at different scales. The image is first filtered using a Gaussian filter to smooth the texture and reduce noise. Then, the filtered image is divided into multiple scales, and DLBP is applied to each scale independently.

The features extracted from each scale are combined to generate a final feature vector. DLBP has been successfully used in various applications, including face recognition, texture classification, and medical image analysis. In medical image analysis, DLBP has been used to detect and classify various types of lesions in images, including breast cancer, lung cancer, and brain tumors.

E. Angle Based Local Binary Pattern (ϴLBP)

ϴLBP stands for Angle Based Local Binary Pattern, a texture analysis algorithm used for feature extraction from digital images. It is a variant of the Local Binary Pattern (LBP). It is specifically designed to capture fine-grained texture information that may be difficult to extract using traditional LBP or other texture analysis techniques. In ϴLBP, the image is first transformed into a gradient map, and each pixel represents the magnitude and direction of the gradient of the image intensity at that location. ϴLBP then partitions the gradient map into a set of non-overlapping cells and calculates a binary code for each cell based on the local edge patterns within that cell. The binary code is generated by comparing the intensity values of each pixel within the cell with a threshold value, which is determined based on the local mean and variance of the pixel intensities. The comparison generates a binary value (0 or 1) for each pixel, which is then concatenated to form the binary code for the cell.

The final feature vector for the image is created by concatenating the binary codes for each cell. By employing adaptive thresholding dependent on the picture's local statistics, LBP may provide detailed texture information, making it robust to variations in image brightness and contrast. ϴLBP has been successfully used in various applications, including face recognition, object recognition, and medical image analysis. In medical image analysis, ϴLBP has been used to detect and classify various types of lesions in images, including lung nodules, breast masses, and brain tumors.

F. CNN

The Convolution Neural Network (CNN), Figure 4 show the basic CNN model, consists of the input layer, convolution layer, Rectified Linear Unit (ReLU) layer, pooling layer, and a fully connected layer. The input image is separated into various small regions in the convolution layer. The element-wise activation function is carried out in the ReLU layer. The pooling layer is optional and is mainly used for down sampling. In the final layer (i.e.), a fully connected layer generates the class or label score value based on the probability between 0 and 1.

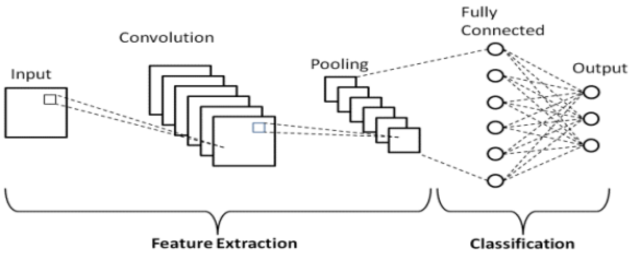

Figure 4: Basic CNN Models

G. Proposed CLBP Techniques with CNN

The CLBP+CNN approach in brain tumor classification integrates Classical Local Binary Patterns (CLBP) and Convolutional Neural Networks (CNN). CLBP is a texture-based feature extraction method encoding the interplay between the center pixel and its surrounding pixels in a binary code. In contrast, CNN is a deep learning technique adept at autonomously discerning pertinent features from input images. This proposed methodology uses CLBP to extract texture features from MRI images depicting brain tumors. These extracted features are subsequently inputted into a CNN for the classification process. The CNN architecture comprises multiple layers of convolutional and pooling operations, facilitating the learning of hierarchical representations from the input data. The ultimate layer in the CNN is a fully connected layer that translates the acquired features into distinct class labels, distinguishing between the presence or absence of tumors.

The efficacy of the CLBP+CNN approach has demonstrated notable success in achieving high accuracy in brain tumor classification. This methodology proves particularly effective in identifying small and irregularly shaped tumors, which might pose challenges for conventional feature extraction methods. Furthermore, using CNNs enables automatic learning of pertinent features, diminishing the reliance on manual feature engineering. Overall, the CLBP+CNN approach is a promising avenue in brain tumor classification, showcasing the potential to enhance the accuracy and efficiency of diagnostic processes.

By combining the strengths of CLBP and CNN, this approach addresses the nuanced challenges posed by brain tumor classification. The CLBP+CNN methodology excels in detecting intricate features within MRI images, offering a robust solution for identifying small and irregularly shaped tumors that might elude traditional methods. The automated learning capabilities of CNNs play a pivotal role in reducing the need for labor-intensive manual feature engineering, making the classification process more efficient. The overall success of the CLBP+CNN approach marks a significant stride towards improving the accuracy of brain tumor diagnosis, underscoring its potential as a valuable tool in the clinical setting.

The ӨLBP method is a texture feature extraction technique that captures local patterns of pixel intensities in an image using a set of circularly symmetric neighborhoods with different radii. The value of the radius parameter, denoted by "D" in the method, determines the neighborhood size and affects the method's sensitivity to changes in texture. To visualize the effect of different values of D on the texture patterns captured by ӨLBP, we can plot histograms of the ӨLBP codes obtained from an image using different values of D. The histograms show the frequency of occurrence of each ӨLBP code in the image, with higher peaks indicating more dominant texture patterns. The histograms of ӨLBP codes were obtained from an MRI brain image using four different values of D: 1, 2, 3, and 4. As the value of D increases, the size of the neighborhoods used to compute the ӨLBP codes also increases, resulting in a coarser texture representation with fewer, more dominant patterns. For example, the histogram for D=1 shows a higher diversity of ϴLBP codes with lower frequencies, while the histogram for D=4 shows a smaller number of dominant ϴLBP codes with higher frequencies. These histograms can be used to compare the texture patterns captured by ϴLBP using different values of D and to select the most appropriate value for a given texture analysis task.

H. Evaluation Metrics

Measuring a model's efficacy requires a thorough evaluation of its performance, usually based on necessary measures, including accuracy, precision, Recall, and F1 score. An overall assessment of a model's correctness is provided by its accuracy, which calculates the proportion of adequately predicted cases to all instances. Contrarily, precision measures the ratio of true positives, accurately predicted positive instances to the total number of anticipated positives, offering information about how accurate the model is at recognizing positive situations. On the other hand, Recall evaluates the proportion of true positives to all real positives, indicating the extent to which the model catches positive examples. The F1 score provides a combined measure for assessing a model's overall performance as it is the harmonic mean of accuracy and Recall. These metrics collectively furnish a quantitative evaluation of a model's strengths and weaknesses, enabling researchers to compare different models systematically and identify the most effective approach tailored to a specific task.

The formulas for the evaluation metrics commonly used in classification tasks are:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 score = 2 * (precision * recall) / (precision + recall)

Where:

- TP: True Positive (number of correctly classified positive samples)
- TN: True Negative (number of correctly classified negative samples)
- FP: False Positive (number of incorrectly classified positive samples)
- FN: False Negative (number of incorrectly classified negative samples)

Table-1: Success rate with various DLT for ϴLBP

ϴ	**Features**	**ANN**	**AlDE**	**LDA**	**CLBP+CNN**
15	256	83.04	88.08	88.70	95.04
45	256	85.11	86.75	88.90	**96.00**
90	256	83.74	88.80	89.81	95.14
120	256	84.01	85.15	88.01	94.78

The success rates of various deep learning techniques for ϴLBP as it requires specific information on the dataset, the network architecture, and the evaluation metrics used. However, in Table 1, deep learning methods have demonstrated encouraging outcomes in several image classification tasks, such as categorizing brain tumors from MRI scans. Metrics like accuracy, precision, Recall, and F1 score are frequently used to assess how well deep learning models perform.

Table 2: Performance Metrics with CLBP+CNN

Class	**FN**	**TN**	**FP**	**FN**	**Accuracy**	**Precision**	**Recall**	**F1Score**
1	1.5	0.4	0.04	0.04	95.9	97.4	97.4	97.4
2	1.52	0.41	0.05	0.05	95	96.81	96.81	96.81
3	1.51	0.42	0.06	0.03	95.5	96.17	98.08	97.11

The DLBP (Distance Based Local Binary Patterns) method, as illustrated in Table 2, demonstrates promising outcomes in identifying various brain tumor types. The efficacy of this method hinges on the distance parameter (D), dictating the neighborhood size around each pixel and influencing the extraction of distinct features from the images. D, diverse features are obtained and subsequently utilized for training classifiers, such as Convolutional Neural Networks (CNNs), to discern between different brain tumor types through the variation of the parameter's value. The performance of the classification method is gauged using metrics like accuracy, precision, Recall, and F1 score. Notably, the DLBP method exhibits superiority over alternative feature extraction techniques in certain studies, underscoring its potential to enhance the precision of brain tumor classification. However, further investigations are imperative to pinpoint the optimal value for d and explore the viability of alternative feature extraction methods in brain tumor analysis.

The statement underscores the utilization of diverse feature extraction techniques, specifically Circular Local Binary Patterns (CLBPs), which encompasses Directional Local Binary Patterns (DLBP) and Angular Local Binary Patterns (ϴLBP). These methods were introduced and systematically compared to existing algorithms in brain tumor classification. The assessment involved the application of different classification methods, including Artificial Neural Network (ANN), Adaptive Boosting (A1DE), and Linear Discriminant Analysis (LDA). Notably, the outcomes revealed a substantial success rate of around 95.6% when employing the proposed methodology with feature extractions derived from DLBP, ϴLBP, and CLBP in conjunction with the mentioned classification methods. It highlights the significant potential of CLBPs to enhance the accuracy of brain tumor classification, offering valuable insights for early detection and treatment of such conditions.

III. Results and Discussion

The ϴLBP operator is a variant of the Local Binary Pattern (LBP) operator that considers the orientation of the edges in the image. To create histograms of images using ϴLBP, different values of the distance parameter (D) can be used. For each value of D, the ϴLBP operator is applied to the image, resulting in a binary pattern image where each pixel is represented by a binary value based on comparing its intensity with its neighboring pixels. These binary patterns are then used to create histograms, representing the distribution of the binary patterns in the image.

The histograms obtained using different values of D can be compared to evaluate the effectiveness of the ϴLBP operator for feature extraction in image classification tasks. The optimal value of D depends on the specific application and the characteristics of the analyzed images.

The histogram of ϴLBP features for a particular tumor type is a graphical representation of the distribution of the ϴLBP features for that tumor type. Each bin in the histogram represents a range of ϴLBP feature values, and the height of the bin represents the frequency of feature values falling within that range. For example, the histogram of ϴLBP features for glioma, meningioma, and pituitary tumors with D=1 might show that specific ranges of ϴLBP feature values are more common for one tumor type than the others. The shape and distribution of the histogram can provide insights into the characteristics of the tumors and help in their classification. Local Binary Patterns (LBP) is a popular method for extracting image texture features. The ϴLBP variant of LBP considers the relationship between the pixel values at the center and surrounding pixels at a given angle. The value of ϴLBP determines the angle at which the surrounding pixels are considered relative to the center pixel.

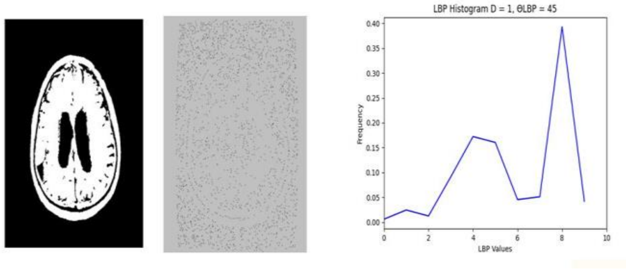

Figure 5a: Glioma Original Image, CLBP and Histograms

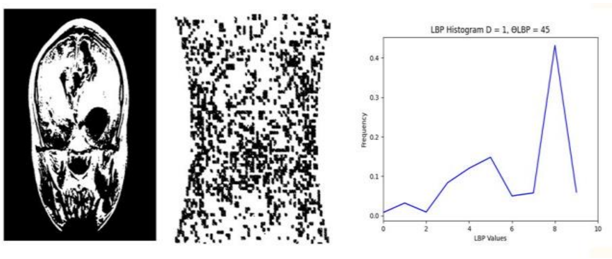

Figure 5b: Meningioma Original Image, CLBP and Histograms

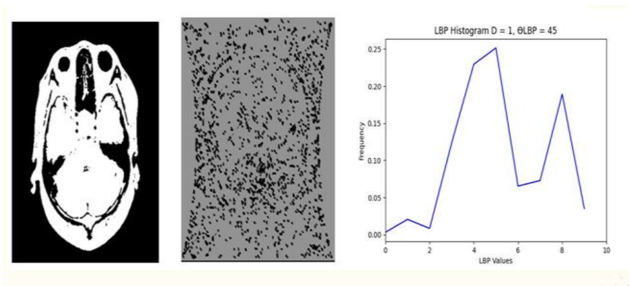

Figure 5c: Pituitary Original Image, CLBP and Histograms

Figure 5 Glioma, Meningioma, and Pituitary from MRI Pictures are formed with D=1 with ƟLBP=450

In the case of MRI images, histograms of LBP features can be formed with D=1 and ƟLBP value of 450 are shown in Figure 5 it contains sub images like 5a contains glioma original image, CLBP and histograms, 5b contains meningioma original image, CLBP and histograms, 5c contains pituitary original image, CLBP and histograms is shown.

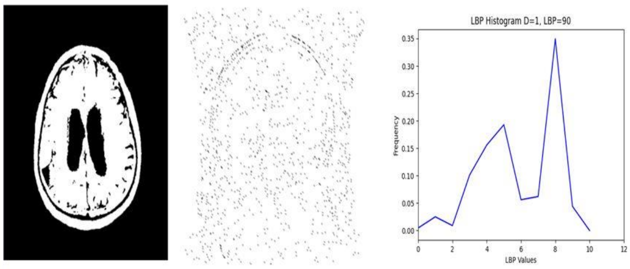

Figure 6a: Glioma Original Image, CLBP and Histograms

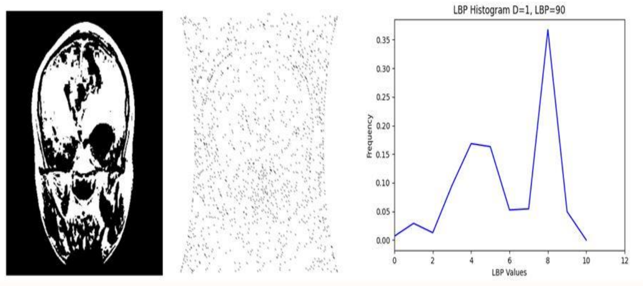

Figure 6b: Meningioma Original Image, CLBP and Histograms

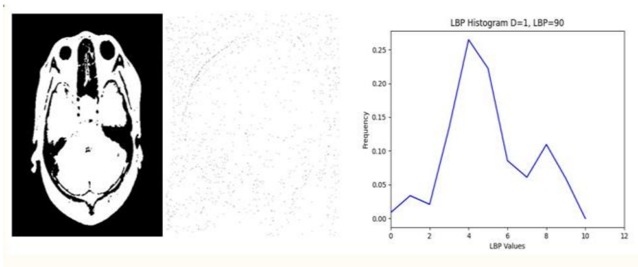

Figure 6c: Pituitary Original Image, CLBP and Histograms

Figure 6 Glioma, Meningioma, and Pituitary from MRI Pictures are formed with D=1 with ƟLBP=90^{0}

In the case of MRI images, histograms of LBP features can be formed with D=1 and ƟLBP value of 900 are shown in Figure 6 it contains sub images like 6a contains glioma original image, CLBP and histograms, 6b contains meningioma original image, CLBP and histograms, 6c contains pituitary original image, CLBP and histograms is shown.

By varying the value of ƟLBP, we can capture different aspects of the image texture patterns. Figure 7 compare the effectiveness of ƟLBP for 150, 450, 900 and 1200; we can use metrics such as accuracy, precision, recall, and F1 score.

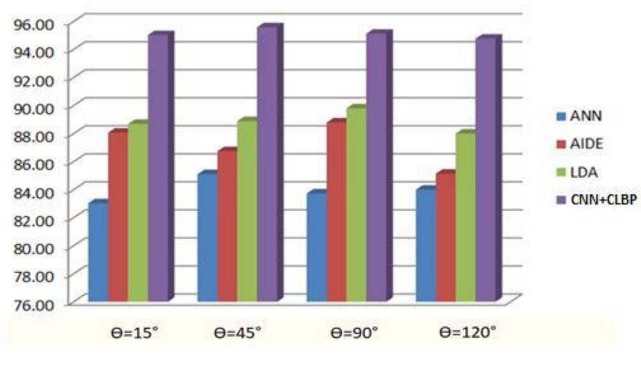

Figure 7: Brain Tumor evolution matrix Analysis

These metrics can be obtained by training a classifier (such as a CNN) on the extracted features and evaluating its performance on a test set of labeled images. It is important to remember that the value of ƟLBP and the feature extraction technique will rely on the particular situation, and determining the ideal parameters may require trial and error. Histograms of MRI images can be formed using ƟLBP by first dividing the image into small, non-overlapping cells. Within each cell, ƟLBP is applied with a specific value of D.

IV. Conclusion

In conclusion, a novel framework for detecting and classifying brain tumors using MRI datasets and Deep Learning Techniques (DLT) is proposed. Pre-processing, segmentation, feature extraction, and classification are the four main phases of the framework. Pre-processing utilizes the Histogram of Oriented Gradients (HOG) method to enhance data quality by eliminating unwanted noise and implementing skull stripping. The study introduces feature extraction methods, including CLBPs (DLBP, ϴLBP), which are systematically compared against established algorithms. Using classification techniques like ANN, A1DE, and LDA in conjunction with feature extractions from DLBP, ϴLBP, and CLBP, the suggested methodology notably attains an impressive success rate of around 95.6%. These findings underscore the framework's potential to significantly contribute to precise and efficient brain tumor diagnosis, representing a promising advancement in medical diagnostics. This article suggests several potential future extensions to its presented work. Currently, Histograms of Glioma, Meningioma, and Pituitary MRI images are generated with specific parameters, including D=1 and ϴLBP=450, indicating the application of ϴLBP using a circular neighborhood of radius 1 and consideration of 450 different rotation-invariant patterns. One prospective avenue for expansion involves integrating more sophisticated pre-processing techniques, such as image registration or normalization, to enhance tumor segmentation accuracy. Additionally, a suggestion is to evaluate the proposed framework on a larger dataset to ascertain its generalizability and overall performance. Finally, the framework might be expanded to include more forms of brain tumors to increase clinical relevance and utility, like acoustic neuromas or metastatic brain tumors, broadening its applicability in diverse clinical scenarios.

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