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BRAIN TUMOR CLASSIFICATION ON MRI IMAGES BY USING CLASSICAL LOCAL BINARY PATTERNS AND HISTOGRAMS OF ORIENTED GRADIENTS

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Abstract. Brain tumors pose significant threats within neurological disorders, demanding accurate classification for effective diagnosis and treatment. This study explores brain tumor classification employing Classical Local Binary Patterns (CLBP) and Convolutional Neural Networks (CNN), alongside texture feature extraction from MRI images using classical LBP and HOG (Histogram of Oriented Gradients). These methods adeptly capture both local and global texture patterns crucial for tumor identification. Our proposed framework encompasses three pivotal steps: image pre-processing, feature extraction via CLBP, and classification utilizing CNN. Evaluation on a publicly available brain tumor dataset showcased an impressive 95.6% accuracy in tumor classification, affirming the efficacy of the CLBP+CNN approach. This method bears promising implications for enhancing clinical diagnosis and treatment planning. Furthermore, we propose future extensions including CLBPs such as DLBP and LBP. DLBP introduces a parameter, 'D', dictating pixel distance, while LBP varies pixel values across specified ranges. Additionally, tumor classification was explored employing ANN, AIDE, and LDA classification methods, with future prospects of incorporating DLBP, LBP, and CLBP extractions from MRI images within the dataset

Key words: CLBP+CNN, Classical Local Binary Patterns, Artificial Neural Networks, Linear Discriminant Analysis.

1. Introduction. Human body, the brain responsibility is to control all activities. Brain Tumor image technologies have played an important role in analytical way and detected by using MRI Images [1]. Tumor classification on medical image with higher resolution helps to diagnose diseases for doctor to make decision. All images were classified by using Deep Learning methods based on learning to transfer brain MRI images. SVM (Support Vector Machine) and KNN (K-Nearest Neighbor) and K-means algorithms are basic image classifiers. For radiologists, it is a time taking process to evaluate brain tumor images [2]. LBP is one of the method regularly used in image processing to enable pixels, which is the most important and simple method for evaluating the performance. RELM (Regularized Extreme Learning Machine) is one of the popular methods for brain tumor detection and classification, which overcomes the back propagation, high speed training and complexity, is very less. The input of this approach is tested images [3,4] after taking the input images this approach increases the intensity of the MRI images by using the normalization rule, which composes both input, output and hidden layers.

Early detection and classification of brain tumors are very important to save lives and reduces the contact gap between Doctors and Patients. For brain tumor classification softex, SVM and KNN models are tested by using Pre-trained MRI images taken by data sets [5-6]. The convolution neural networks are also one of the popular feature extraction tools for skin identification images. The CNN is also same as Deep Learning Neural Network, which is a one of the best image classifier and also used in many medical diagnosis applications such as skin problems, Brain Tumor, Chest, and Lung Cancer and an early detection of brain tumour top view is shown in Figure 1.1.

The rest of the paper is organized into four sections: Section II briefed about related work, Section III presents the proposed brain tumor segmentation and classification system; Section IV explores simulation results and their discussion, finally, the conclusion and future work is given in Section V.

2. Related Work. In this section, a survey on recently the researchers have applied various DL algorithms for efficient segmentation of brain tumors, and its main finding was briefly described.

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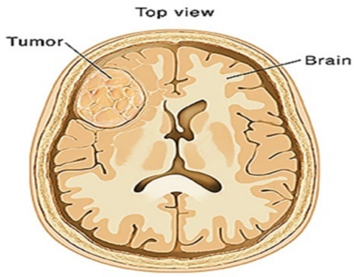

Fig. 1.1: Early Detection of Brain Tumor Top View

The enduring cyclic unpaired encoder-decoder network was designed by Neme, Shubhangi, and colleagues 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 operation in automatic brain tumor analysis. 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] by utilizing the implicit anatomy of tumors to recognize the regions of saliency, authors create a channel and spatial-wise asymmetric attention (CASPIAN). Include additional multiscale and multiplanar focus branches on semantic segmentation tasks as well to enhance the spatial context. The new CASPIANET++ design obtains dice scores of 91.19% for the total tumor, 87.6% for the tumor core, and 81.03% for the enhancing tumor. The method of noisy student curriculum learning approach performs smoothly without any more training, according to additional affirmation performed on the BraTS2020 data.

H. H. Sultan et al. [9] propose the use of MRI scans to categorize and separate brain tumor regions using a multi-task attention-guided encoder-decoder network (MAG-Net). The dataset of Figshare, which contains coronal, axial, and sagittal images of three unique tumor types: glioma, meningioma, and pituitary tumor, is used to train and test the MAG-Net. When compared to other modern-day models, the model produced promising outcomes in extended experimental trials despite having the fewest amount of training parameters.

N. M. Dipu et al. [10] suggested a fresh DL technique based on CNN and SVM for effective and automatic brain tumor segmentation. Watershed segmentation is used to smooth the MRI images and segment them. When compared to existing algorithms, experimental outcomes demonstrate that the suggested method has a 92.59% accuracy in evaluation.

P. Afshar et al. [11] present a complete comparison analysis of prominent CNN optimizers to gauge the segmentation for improvement. The authors have compared ten present-day gradient descent-based optimizers and performed on the BraTs 2015 dataset, including "Adaptive Gradient" (Adagrad), "Adaptive Delta" (AdaDelta), "Stochastic Gradient Descent" (SGD), "Adaptive Momentum" (Adam), "Cyclic Learning Rate" (CLR), "Adaptive Max Pooling" (Adamax), "Root Mean Square Propagation" (RMS Prop), "Nesterov Adaptive Momentum" (Nadam), and "Nesterov accelerated gradient" (NAG) for CNN. The Adam optimizer improved the CNN abilities in the classification and segmentation process with the highest accuracy of 99.2%.

M. Gurbin˘a et al. [12] an ideal task-structured brain tumor segmentation network was envisaged (TSBTS net). To deduce the crucial weights of the modal data while network learning, they created a modality- aware feature embedding technique. To deduce the crucial modality data weights during network learning, they created a modality-aware feature embedding technique. Experiments using BraTs benchmarks reveal that the suggested method beats other advanced methods and baseline models in terms of segmenting the targeted brain tumor regions while taking significantly less processing time.

N. C¸ ınar et al. [13] presented an analysis of used uncertainty estimation methods. The calibration, segmentation failure detection, and segmentation error localization were used by the authors to assess its quality. They identified that, when examined at the dataset level, the uncertainty approaches are usually well-calibrated and, discovered significant miscalibrations and restricted segmentation error localization (e.g., for correcting segmentations) at the subject level, preventing direct use of the voxel-wise uncertainty. Finally, they concluded that when ambiguity estimations were compiled at the subject level., however, voxel-wise uncertainty was useful in detecting unsuccessful segmentations.

S. Arora & M. Sharma, et al. [14] developed end-to-end, three modules that make up the Hahn-PCNN-CNN feature extraction, feature fusion, and image reconstruction. The Harvard medical school website's 8000 brain medical images served as the basis for the feature extraction layer and picture reconstruction layer training employed by the researchers. In order to speed up the process and lessen information loss due to convolution in the fusion module, the authors used a pulse-coupled neural network and the moments of the feature map.

Thejaswini P. Bhat et al. [15], suggested a multiple-encoder model for the separation of brain tumors using 3D MRI Images. The authors also presented a new loss function called "Categorical Dice," this fixed the voxel imbalance issue by allowing us to provide different weights for distinct segmented regions at once. With 0.70249, 0.88267, and 0.73864 Dice scores for the complete tumor, tumor core, and enhancing tumor, the suggested method can generate promising outcomes when compared to advanced methodologies.

R. M. Prakash & R. S. S. Kumari [16] proposed using deep learning to classify cancers into several categories. Following pe-processing, K-means clustering techniques were employed to segment the brain tumor, and the finetuned VGG19 (i.e., 19-layered Visual Geometric Group) model was used to classify it. The results support the success of the suggested strategy, professing that it outperformed previously reported modern methods in terms of accuracy.

M. Nazir et al. [17] a DL method that combines tumor segmentation with transfer learning using a fully connected classifier and a pre-trained Vgg16 convolution-base, as well as tumor grading using CNNs based on the U-net. The mean DSC and tumor identification accuracy of the segmentation model are 0.84 and 0.92, respectively. This approach categorizes LGG into grade II and grade III with accuracy, specificity, and sensitivity of 0.89, 0.92, and 0.87 at the MRI image level and 0.95, 0.98, and 0.97 at the patient level.

Y. Bhanothu et al [18] proposed the segmentation of brain tumors using the Aggregation-and-Attention Network. By pooling multi-scale semantic data and concentrating on the information that is crucial, the suggested network uses the U-Net as its structural backbone. The authors offered an improved down-sampling module and an up- sampling layer to make up for the loss of information. Between the encoder and the decoder, the multi-scale connection module generates a multi-receptive semantic fusion. Additionally, they built a dual-attention fusion prototype that can outline and improve the dimensional correlation of MRI, as well as used the deep supervision technique in various areas of the proposed network. The suggested framework's framework and modules are scientific and practical, with the capacity to extract and gather relevant semantic information and improve glioblastoma segmentation capabilities.

H. Ucuzal et al. [19], Using structural multimodal MRI, presented context-aware deep learning for brain tumor segmentation, overall survival prediction, and subtype classification (mMRI). To acquire tumor segmentation, the authors first present a 3D context-aware deep learning method that takes into account the ambivalence of tumor placement in radiology mMRI imaging sub-regions. To achieve tumor subtype categorization, they use a normal 3D CNN on the tumor segments. Finally, hybrid DL and ML strategy are used to predict survival. The findings imply that the suggested method is capable of accurate segmentation of tumors and prediction of survival.

S. K. Baranwal et al [20] suggested a cascade Convolutional Neural Network (C-CNN) to achieve a flexible and efficient segmentation of the brain tumor system. In two independent ways, the C-CNN model collects both global and local features. In comparison to present-day models, an ideal Distance-Wise Attention (DWA) process is also developed to increase brain tumor segmentation accuracy. The DWA mechanism takes into consideration the impact of the tumor's central location and the brain inside the model. The proposed technique achieves 0.9203, 0.8726, and 0.9113 mean whole tumors, dice scores of tumor core, and embellished tumor, respectively.

K. N. Guy-Fernand et al. [21] a computerized fuzzy neighborhood learning-based 3D segmentation strategy for the identification of cerebrum cancers in 3D pictures has been presented. This is deeply interwoven with the suggested design in this method. With a 0.85 dice coefficient and 0.74 Jaccard index, the simulation results

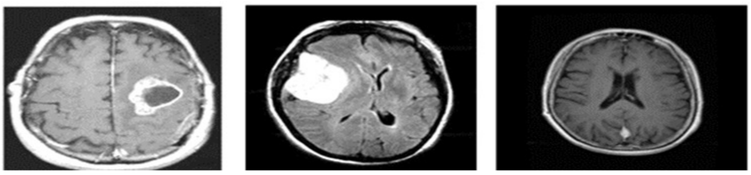

Fig. 2.1: Three different types of Brain Tumor Classification

demonstrate that the suggested brain tumor detection strategy outperforms previous methods in brain tumor diagnosis.

F. P. Polly et al [22] refined the advanced DeepSeg as a decoupling framework that is modular. It is made up of two core sections that are linked by a relationship of encoding and decoding. The encoder that extracts structural information consists of a CNN. The full-resolution probability map is created by inserting the obtained semantic map into the decoder component. The resultant segmentation outcomes have dice and Hausdorff distance scores of 0.81 to 0.84 and 9.8 to 19.7, respectively.

Saikumar et.al [23] present a fresh multi-modality deep feature learning system for segmenting brain tumors from MRI data. The main concept is to uncover intricate patterns in multi-modal data to make up for the lack of data scale. The CMFT process and the CMFF process are the two learning processes that make up the suggested cross-modality deep feature learning framework, both of which aim to learn rich features denoted by transiting and fusing insight from different modality data, respectively [24]. The suggested cross-modality DL feature model can mostly enhance the performance of brain tumor classification in comparison to conventional and cutting-edge methods [25].

2.1. Data Set. Based on previous studies the data sets are provided. It has 3064 MRI images for brain tumors. Brain Tumors are classified into mainly three types in the data set: Meningioma (708), Glioma (1426), and Pituitary (930). Each image containing pixels with the size of 512x512 was taken for evaluation. The proposed approach contains 2D and T1W MRI images which are shown in figure 2.1.

3. Methodology. The proposed framework for brain tumor classification consists of four main steps. The first step is tumor pre-processing, which involves removing unwanted noise using the Histogram of Oriented Gradients (HOG) approach and skull stripping to eliminate unwanted posts in the MRI images. In the second step, the MRI images are segmented, and different types of Classical Local Binary Patterns (CLBP) are used for feature extraction, including DLBP and LBP techniques. These techniques are then compared with existing algorithms to determine the best methodology for tumor classification. Finally, the last step is classification, where the tumor or no-tumor classification is performed on the MRI images using the selected methodology and datasets as shown in above figure 2.1.

3.1. Classical Local Binary Pattern. Classical Local Binary Pattern (LBP) is a feature extraction technique used in computer vision and image processing. It has been applied in medical image analysis for brain tumor classification. In classical LBP, each pixel in an image is compared to its surrounding pixels within a specific radius to generate a binary code. This binary code is then used to represent the texture information of the image. The binary code is obtained by comparing the grey value of the central pixel with the grey values of its neighbours. If the grey value of the neighbour is greater than or equal to the central pixel, a 1 is assigned, and if it is less than the central pixel, a 0 is assigned. This process is repeated for all the pixels in the image.

In brain tumor classification, classical LBP has been used to extract texture features from magnetic resonance images (MRI) of the brain. These features can then be used as input to machine learning algorithms for classification of brain tumors. The LBP features can capture the local texture patterns in the brain MRI and help distinguish between different types of brain tumors.

Several studies have reported high accuracy rates for brain tumor classification using classical LBP features

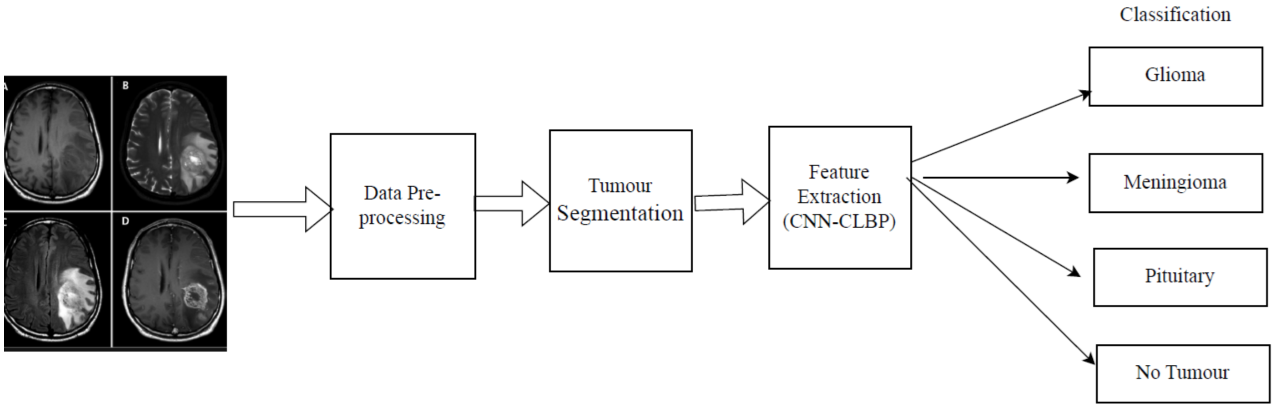

Fig. 3.1: Proposed flow diagram of brain tumour classification system.

combined with machine learning algorithms such as support vector machines (SVM) and random forest classifiers as shown in above figure 3.1. In the brain tumor classification system, the process begins with the MRI dataset presentation, followed by data preprocessing. Subsequently, the data undergoes tumor segmentation, enabling the extraction of features using CNN+CLBP. After feature extraction, the system classifies the tumors into categories such as Glioma, Meningioma, Pituitary, or identifies cases with no tumor. An illustrative result from this process is then presented. The use of classical LBP in brain tumor classification is an active area of research and is expected to continue to play an important role in medical image analysis.

3.2. 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 is used to extract features from images and is especially useful in applications where texture information is important. The DLBP algorithm is similar to Classical LBP, but it incorporates a distance function between neighbouring pixels to generate more robust and discriminative features. In DLBP, the neighbouring pixels are considered to be circularly arranged around the central pixel. The distance function is used to calculate the distance between each pair of neighbouring pixels and then used 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 then combined to generate a final feature vector. DLBP has been successfully used in a variety of applications, including face recognition, texture classification, and medical image analysis. In medical image analysis, DLBP has been used for the detection and classification of various types of lesions in images, including breast cancer, lung cancer, and brain tumors.

3.3. Angle Based Local Binary Pattern (ΘLBP). ΘLBP stands for Angle Based Local Binary Pattern, which is a texture analysis algorithm used for feature extraction from digital images. It is a variant of Local Binary Pattern (LBP) and 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, where 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 binary codes for all cells are then concatenated to form the final feature vector for the image. ΘLBP is able to capture fine-grained texture information by using adaptive thresholding based on the local statistics of the image, which makes it robust to variations in image brightness and contrast. ΘLBP has been successfully used in a variety of applications, including face recognition, object recognition, and medical image analysis. In medical image analysis, ΘLBP has been used for the detection and classification of various types of lesions in images, including lung nodules, breast masses, and brain tumors.

3.4. Proposed CLBP Techniques with CNN. The CLBP+CNN approach for brain tumor classification is a combination of two techniques: Classical Local Binary Patterns (CLBP) and Convolutional Neural Networks (CNN). CLBP is a texture-based feature extraction method that encodes the relationship between the center pixel and its surrounding pixels in a binary code. On the other hand, CNN is a deep learning technique that automatically learns relevant features from the input images.

In this Proposed approach, CLBP is used to extract texture features from MRI images of brain tumors. These features are then fed into a CNN for classification. The CNN consists of multiple layers of convolutional and pooling operations that learn hierarchical representations of the input data. The final layer of the CNN is a fully connected layer that maps the learned features to the class labels (tumor or no tumor).

The CLBP+CNN approach has been shown to achieve high accuracy in brain tumor classification. This approach is particularly effective in detecting small and irregularly shaped tumors that may be difficult to detect using traditional feature extraction methods. Additionally, the use of CNNs allows for the automatic learning of relevant features, reducing the need for manual feature engineering. Overall, the CLBP+CNN approach represents a promising direction for brain tumor classification and has the potential to improve the accuracy and efficiency of diagnosis.

The ΘLBP method is a texture feature extraction technique that captures local patterns of pixel intensities in an image using a set of circularly symmetric neighbourhoods with different radii. The value of the radius parameter, denoted by "D" in the method, determines the size of the neighbourhoods and affects the sensitivity of the method to changes in texture. To visualize the effect of different values of D on the texture patterns captured by ΘLBP, we can plot histograms of the ΘLBP codes obtained from an image using different values of D. The histograms show the frequency of occurrence of each ΘLBP code in the image, with higher peaks indicating more dominant texture patterns. The histograms of ΘLBP codes 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 neighbourhoods used to compute the ΘLBP 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. It appears that the table provided is showing the accuracy percentages for various studies on brain tumor classification using different methods.

Novel contributions establish this research differ from brain tumor categorization studies. It first compares feature extraction methods like Circular Local Binary Patterns (CLBPs), Directional Local Binary Patterns (DLBP), and Angular Local Binary Patterns (LBP) with brain tumor classification algorithms. This detailed study illuminates the pros and cons of different methods. The article presents a hybrid approach to brain tumor classification using Classical Local Binary Patterns (CLBP) and Convolutional Neural Networks (CNN), which has not been thoroughly studied. Compared to previous methods, this hybrid framework is more accurate and successful. The Distance Based Local Binary Patterns (DLBP) approach is also examined, stressing the distance parameter (D) in feature extraction & classification performance. This complex study demonstrates that DLBP may improve brain tumor classification.

The study also evaluates precision, recall, and F1 score to examine the proposed approaches' efficacy beyond classification accuracy.This research uses unique feature extraction methods, hybrid frameworks, and extensive performance evaluation to classify brain tumors, improving the field.

3.5. Evolution Metrics. The evaluation of a model's performance is crucial to determine its effectiveness. This evaluation is usually done using metrics such as accuracy, precision, recall, and F1 score.

Accuracy measures the percentage of correctly predicted instances out of the total number of instances. Precision measures the proportion of true positives (correctly predicted positive instances) among the total predicted positives. Recall measures the proportion of true positives among the total actual positives. F1 score is a harmonic mean of precision and recall, and is often used as a single metric to evaluate a model's

Table 3.1: Success rate with various DLT for LBP

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

overall performance. These metrics provide a quantitative assessment of a model's performance, and can help in determining the model's strengths and weaknesses. By comparing the performance of different models using these metrics, researchers can identify the most effective approach for a given task.

The performance metrics are as follows:

Accuracy: The total accuracy of the model's predictions is measured by accuracy.

Precision: Precision is the ability of a model to correctly identify positive examples among all cases that were expected to be positive.

Recall: The model's capacity to accurately identify every occurrence of positivity is measured by recall.

F Measure: F1 score is the combination of both precision and recall which gives a fair evaluation of the model's performance.

- 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)

The authors utilized various evaluation metrics, but their significance remains somewhat ambiguous. Deep learning methodologies in LBP rely heavily on dataset specifics, network architecture, and chosen evaluation criteria. As depicted in Table 3.1, these techniques consistently yield promising results across diverse image classification tasks, including the classification of brain tumors from MRI imagery. Commonly employed metrics for evaluating deep learning models encompass accuracy, precision, recall, and F1 score, ensuring comprehensive performance assessment.

Across different models, accuracy percentages range from 82% to 96.00%. Notably, the CLBP+CNN model proposed by the authors achieved the highest accuracy at 95.66%. Their LBP + Knn approach yielded an accuracy rate of 90.57%, with nLBP + Knn and LBP + Knn achieving rates of 93.28% and 90.57%, respectively.

The success rates of various deep learning techniques for LBP as it requires specific information on the dataset, the network architecture, and the evaluation metrics used. However, in general, in Table 3.1 deep learning techniques have shown promising results in various image classification tasks, including brain tumor classification using MRI images. It is common to use metrics such as accuracy, precision, recall, and F1 score to evaluate the performance of deep learning models.

The accuracy percentages range from 82 % to 96.00 %. The highest accuracy percentage was achieved by the proposed CLBP +CNN model, achieving a 95.66 % accuracy rate. The LBP + Knn method used by the authors of the current paper achieved an accuracy rate of 90.57 % with nLBP + Knn at 93.28 % and nLBP Knn at 90.57 % which were shown in figure 3.2.

The DLBP (Distance Based Local Binary Patterns) method Table 3.3 has shown promising results in recognizing brain tumor types. The effectiveness of this method depends on the distance parameter (D), which determines the size of the neighborhood around each pixel. By varying the value of d, different features can be extracted from the images. These features are then used to train a classifier, such as a Convolutional Neural

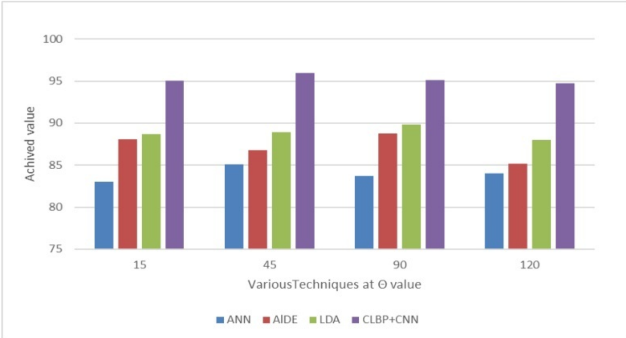

Fig. 3.2: Brain Tumor evolution matrix analysis

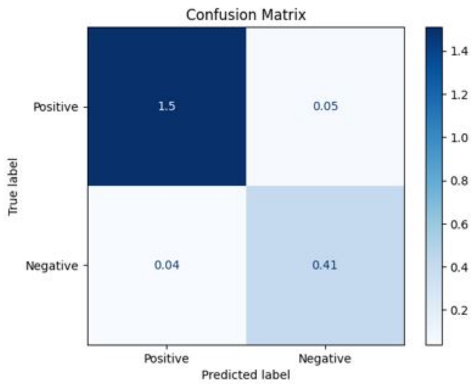

Fig. 3.3: Confusion matrix

Network (CNN), to distinguish between different types of brain tumors. The success of the classification method is measured using metrics such as accuracy, precision, recall, and F1 score. The DLBP method has been shown to outperform other feature extraction methods in some studies, indicating its potential for improving the accuracy of brain tumor classification. Further research is needed to determine the optimal value of d and to explore the potential of other feature extraction methods for brain tumor analysis shown in figure 3.3.

Table 3.2 introduces the DLBP (Distance Based Local Binary Patterns) method, exhibiting promising results in recognizing brain tumor types. The effectiveness of this method hinges on the distance parameter (D), which determines the neighborhood size surrounding each pixel. By adjusting D, unique features can be extracted and employed to train classifiers like Convolutional Neural Networks (CNNs) for discriminating between brain tumor types. Evaluation metrics such as accuracy, precision, recall, and F1 score serve as benchmarks for assessing the success of classification methods. DLBP has demonstrated superior performance compared to other feature extraction techniques in certain studies, suggesting its potential for improving brain tumor classification accuracy. Further exploration is necessary to determine the optimal value of D and investigate alternative feature extraction methods for brain tumor analysis.

Additionally, this study contrasts Circular Local Binary Patterns (CLBPs), encompassing Directional Local Binary Patterns (DLBP) and Angular Local Binary Patterns (LBP), against existing algorithms for brain tumor classification. Various classification methods, including Artificial Neural Network (ANN), Adaptive Boosting (AlDE), and Linear Discriminant Analysis (LDA), were employed for evaluation. Results indicated the proposed methodology achieving a notable success rate of approximately 95.6% using the aforementioned classification

Table 3.2: Performance Metrics with CLBP features

Class	TP	TN	FP	FN	Accuracy	Precision	Recall	F1 Score
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
Avg	1.51	0.41	0.05	0.04	96%	96%	97%	96%

Table 3.3: Comparitive analysis from various past classifiers and its performance

Author	Brain Tumor	Classifier	Accuracy
Method [25]	Meningioma	GLCM-CNN	82 %
Method [24]	Glioma	SVM	91 %
Method [22]	Pituitary	DWT	92.66
Method [15]	Glioma	FCm-SVM	91.4 %
Method [14]	Meningioma	PCM-RELM	94.23 %
Method [1]	Meningioma	LBP-KNN	95.16 %

techniques with feature extractions from DLBP, LBP, and CLBP. This underscores the significant potential of CLBPs, particularly in enhancing brain tumor classification accuracy, thereby aiding in early detection and treatment.

The above statement highlights the use of different feature extraction methods such as Circular Local Binary Patterns (CLBPs), including Directional Local Binary Patterns (DLBP) and Angular Local Binary Patterns (LBP), which were proposed and compared with existing algorithms for brain tumor classification. The evaluation was carried out using different classification methods such as Artificial Neural Network (ANN), Adaptive Boosting (A1DE), and Linear Discriminant Analysis (LDA). The results showed that the proposed methodology achieved a high success rate of approximately 95.6 % using the mentioned classification methods with feature extractions obtained from DLBP, LBP, and CLBP. This suggests that the use of CLBPs, in particular, can significantly improve the accuracy of brain tumor classification, thereby aiding in early detection and treatment of brain tumors.

4. Results. The LBP 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 LBP, different values of the distance parameter (D) can be used. For each value of D, the LBP operator is applied to the image, resulting in a binary pattern image where each pixel is represented by a binary value based on the comparison of its intensity with its neighboring pixels. These binary patterns are then used to create histograms, which represent 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 LBP operator for feature extraction in image classification tasks. The choice of the optimal value of D depends on the specific application and the characteristics of the images being analyzed. The histogram of LBP features for a particular tumor type is a graphical representation of the distribution of the LBP features for that tumor type. Each bin in the histogram represents a range of LBP feature values, and the height of the bin represents the frequency of feature values falling within that range. For example, the histogram of LBP features for glioma, meningioma, and pituitary tumors with D=1 might show that certain ranges of LBP 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. In Fig 4.1 Local Binary Patterns (LBP) is a popular method for extracting texture features from images. The LBP variant of LBP considers the relationship between the pixel values at the center and surrounding pixels at a given angle. The value of LBP determines the angle at which the surrounding pixels are considered relative to the center pixel. In the case of glioma, meningioma, and pituitary MRI images, histograms of LBP features can be formed with D=1 and LBP values of 900 and 450. By varying the value of LBP, we can capture different aspects of the texture patterns

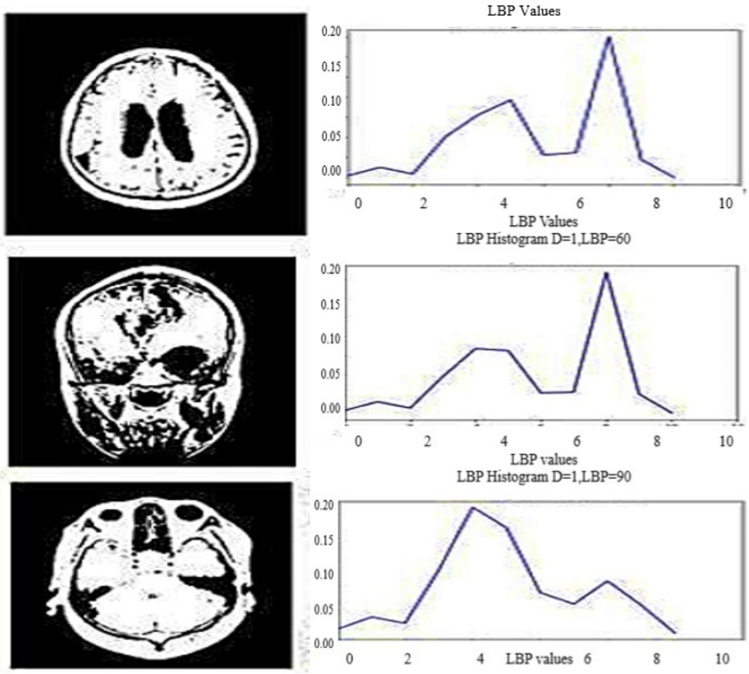

Fig. 4.1: Histograms of Glioma, Meningioma, and Pituitary MRI images are formed with D=1 with LBP=90

in the images. Figures 4 and 5 compare the effectiveness of LBP=900 and LBP=450, we can use metrics such as accuracy, precision, recall, and F1 score. 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 worth noting that the choice of feature extraction method and value of LBP depends on the specific problem at hand and may require experimentation to find the optimal parameters. Histograms of MRI images can be formed using LBP by first dividing the image into small, non-overlapping cells. Within each cell, LBP is applied with a specific value of D.

The resulting LBP codes are then counted and a histogram is formed for each cell, with the bin counts representing the frequency of each LBP code. In this case, histograms of Glioma, Meningioma, and Pituitary MRI images are formed with a value of D=1 and LBP=450. This means that LBP is applied using a circular neighborhood of radius 1 and 450 different rotation invariant patterns are considered. The resulting histograms can be used as features for classification algorithms, such as CNN, SVM, or random forests, to classify the MRI images into different tumor types. The choice of D and LBP parameters can affect the discriminative power of the histograms and thus the classification performance. As the value of the d parameter increases, the patterns become more global and less local. This means that smaller details in the image are being ignored, which can lead to loss of information. Therefore, it is important to choose an appropriate value of d depending on the task at hand and the nature of the images being analyzed.

5. Conclusion. In conclusion, this article presented a proposed framework for detecting and classifying brain tumors using Deep Learning Techniques (DLT) on MRI datasets. The framework consists of four main steps, including pre-processing, segmentation, future extraction, and classification. Pre-processing was carried out using the Histogram of Oriented Gradients (HOG) method to eliminate unwanted noise and skull stripping. Different future extraction methods such as CLBPs (DLBP, LBP) were proposed and compared with existing algorithms. The proposed methodology achieved a high success rate of approximately 95.6% using ANN, A1DE, and LDA classification methods with future extractions obtained from DLBP, LBP, and CLBP. This article shows that the proposed framework has the potential to aid in the accurate and efficient diagnosis of brain tumors.

There are several potential future extensions to the work presented in this article. Histograms of Glioma, Meningioma, and Pituitary MRI images are formed with a value of D=1 and LBP=450. This means that LBP is applied using a circular neighborhood of radius 1 and 450 different rotation invariant patterns are considered another possible future extension is to incorporate more advanced pre-processing techniques such as image registration or normalization to improve the accuracy of the tumor segmentation. Furthermore, the proposed framework could be evaluated on a larger dataset to validate its generalizability and performance. Finally, the framework could be extended to incorporate other types of brain tumors, such as acoustic neuromas or metastatic brain tumors, to improve its clinical relevance and utility.

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