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Article Title: Modified Convolutional Neural Networks for Efficient and Precise Brain Tumor Diagnosis in Clinical Application Use

Modified Convolutional Neural Networks for Efficient and Precise Brain Tumor Diagnosis in Clinical Application Use

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ABSTRACT

Brain tumor is the growth of abnormal brain cells, some of which have the potential to develop into cancer. For medical professionals, it is quite difficult to diagnose brain tumors early. They assess the Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans for finding the brain tumor. Searching through the vast number of MRI images by hand to find a brain tumor is now extremely time-consuming and inaccurate. Using basic imaging techniques to identify aberrant brain areas is challenging. This work uses image processing techniques to automatically detect and classify brain tumors. There are four primary steps in the methodology: The first step is image preprocessing, in which the Gaussian filter is used to enhance and filter the images. Second, the Global Thresholding approach for image segmentation. Third, the features of the image are extracted using the Local Binary Pattern (LBP). Fourth, the classification of brain cancers is done using the Modified Convolutional Neural Network (CNN).This classifier is implemented using the python software. The findings show that it offers greater accuracy and the results are then contrasted with those of earlier classification methods. This classification algorithm is executed with greater performances and detect the brain tumor in MRI images with more favorable results.

Keywords: Gaussian filter, Global Thresholding, Local Binary Pattern, Support Vector Machine

1 Introduction

Brain tumors are common around the world and can occur in young persons as well as in older adults. Brain tumors are a serious health risk and have detrimental effects on patients. Accurate and timely brain tumor diagnosis is essential for enabling successful treatment plans[1]. The field of medical imaging is at a turning point and is ready for revolutionary developments, especially when it comes to brain tumor analysis and prediction of the patient’s stability. The precision and effectiveness of the traditional methods for dividing, categorizing, and forecasting the hazards related to brain tumors have been limited. Recently, models based on machine learning have become increasingly effective instruments for analyzing medical images[2]. Glial cells produce gliomas, which are brain tumors. Researchers and scientists have been trying to create advanced procedures and strategies for detecting brain cancers. Although computer tomography (CT) and magnetic resonance imaging (MRI) are frequently used to detect anomalies in the location, size, or shape of brain structures, which help diagnose malignancies, doctors prefer MRI[3-4]. MRI is special because it forecast the results without relying on clinical or pathological information. However, doctors are increasingly using automated methods, mostly computer-aided medical image processing techniques, to help them diagnose brain cancers[5-7]. A brain's existence with the complexity of the brain's anatomy, tumors pose a significant barrier to healthcare. Therefore, it is essential to develop precise and trustworthy algorithms for the automated prediction of overall survival and segregated areas in patients with gliomas. These algorithms offer crucial guidance for prognostication, diagnosis, and planning therapy[8-9].

In order to forecast a patient's chances of surviving a brain tumor, machine learning methods are used to train models on pertinent variables[10]. Large volumes of medical imaging data, including MRI and CT scans, are analyzed using methods that is utilized in machine learning classification models to search for trends and abnormalities that indicate the existence of a tumor. Machine learning techniques not only improves the specificity of the identification process but also brings more efficiency by replacing human operations with computers, which lowers the chance of mistakes [11]. Brain cancers that are improved if an information bridge between the shallow and deep levels functions are properly separated using a machine learning system for brain tumor classification and long-term stability prediction (MRIs)[12-13]. Personalized treatment planning benefits from the implications of ML-related brain tumor grading. Additionally, it improves the course of the condition and lessens the strain on medical professionals. Classification techniques seek to enhance early diagnosis and treatment planning by utilizing machine learning and multimodal features, thereby improving patient care and results[14-15]. In order to identify medical images related to brain cancer, this study suggests an evolutionary brain tumor prediction system that makes use of a sophisticated machine learning model and a modified CNN classifier.

The following four steps are used to complete this work: To prepare the MRI images for segmentation, the brain MRI dataset is first gathered and preprocessed using the gaussian filter. The segmentation of brain tumors using the widely used global thresholding technique is then incorporated into the suggested framework. Using the Local Binary Pattern (LBP) feature extractor, Radiomics features are extracted from the segmented image. After applying the modified Convolutional Neural Network (CNN) classification technique, the selected features are used to classifying the brain tumors from the brain MRI dataset. Lastly, the classification approach is evaluated using evaluation criteria including accuracy, recall, and specificity. The outcomes are contrasted with the other methods that have been discussed in the literature, demonstrating the superiority of the suggested framework.

2 Related Works

Anindya Nag *et al.* (2024) [16] have presented a ten transfer learning methods, such as GoogLeNet and VGG-16, were thoroughly evaluated for the brain cancer classification. Explainable AI methods, particularly Local Interpretable Model-Agnostic Explanations

(LIME), were applied to guarantee transparency in image predictions. The outcomes show how well the suggested TumorGANet model performs, attaining the greatest accuracy. Its drawbacks include interpretability restrictions and the requirement for diverse, high-quality labeled data to guarantee generalizability and avoid overfitting.

Aarif Raza *et al.* (2024) [17] have proposed a method called GARU-Net and it is a system that integrates the deep residual network and U-Net model with attention guiding. The proposed architecture addresses the vanishing gradient problem by using the network that remains as an encoder and the decoder of the U-Net model. Additionally, the U-Net decoder side is amplified with an attention mechanism that de-emphasizes healthy tissues and highlights malignant tissues, leading to improved generalization and reduced computational resources. The proposed architecture has demonstrated with greater performance metrics and this work provides highest loss value while applying on huge datasets.

Abdullah A. Asiri *et al.* (2024) [18]have introduced a novel two-module computer method intended to increase the accuracy and speed of brain tumor identification. To normalize images and deal with issues like noise and changing low region contrast, neural networks, independent component analysis, and adaptive Wiener filtering are proposed. Support Vector Machines are used to segment and classify tumors and validate the findings of the first module. The sensitivity and specificity of the tumor classification were mediocre, and its robustness is low.

Saravanan Alagarsamy *et al.* (2023) [19] have developed an algorithm that uses the Interval Type-II fuzzy logic system (IT2FLS) algorithm and artificial bee colony operating principles to outline the tumor location, which has been surrounded by complex brain tissues. The oncologists' decisiveness is crucial to the success of any treatment regimens. The BRATS challenge datasets contain a variety of visual sequences that this model can handle with ease. This system is more difficult to work with the highest number of parameters.

Guanghui Yue *et al.* (2024) [20] have proposed a segmentation of multimodal brain tumors with a novel adaptive context aggregation network (ACANet). In order to investigate the complementary information of two input branches, an adaptive context aggregation (ACA) method combines the multiple data from their encoders. The prediction-aware decoding strategy (PDS) at the decoder helps the network focus more on error-prone regions by employing two temporal predictions to direct the network while absorbing the features of the encoder. Poor results on very small datasets and overfitting easily occur.

3 Proposed Work

This approach uses an automated, intelligent, and reliable technique for classifying and predicting brain tumors. This classification model completes its processing in four steps. The first step applies the gaussian filter for filtering the MRI images and to remove the noisy data from the images. Segmenting the brain images using the Global Thresholding is the second step. In this stage, the observed data is thoroughly analyzed to accurately delineate tumor size, location and shape variations. The brain imaging features are extracted using the feature

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extractor after segmentation. The Local Binary Pattern extractor extracts the features from the brain images. Following feature extraction, the fourth step classification accomplishes to predict the brain tumor from the images.

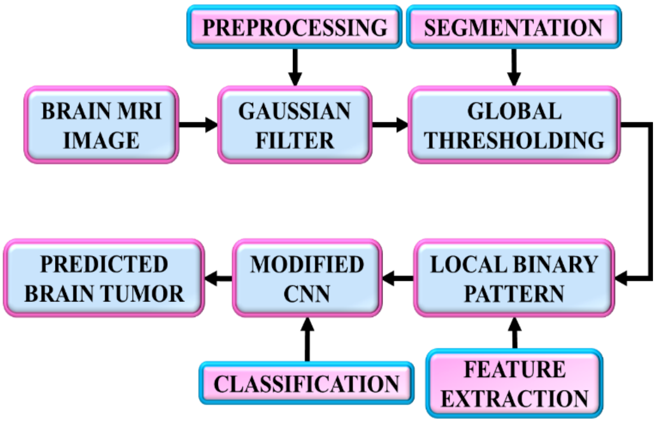

Figure 1: *Block diagram for the proposed system*

The brain image dataset's tumor and non-tumor images are classified using the modified CNN classifier. Additionally, to evaluate the model efficacy, a performance matrix portion calculates measures including accuracy, precision, F1-score, and recall value. This procedure is implemented in the Python platform for classifying the brain images with highest accuracy. The steps in the proposed work are shown in Figure 1.

3.1 Preprocessing By Gaussian Filter

The process of transforming unprocessed image data into a format that is accessible and usable is known as image preprocessing. It makes it possible to remove extraneous noises and improve particular attributes that are necessary for additional processing. Before supplying image data to classification algorithms, preprocessing is an essential first step. Furthermore, the low contrast, noise, and poor visual quality of these images make it difficult to locate and identify a tumor. Consequently, the Gaussian filter preprocessing approach is used to enhance the image, reduce noise, and increase visual quality. Noises of various kinds corrupt an image. Gaussian, impulsive, Poisson, and speckle noises are the frequently detected noises in images. The purpose of filters is to minimize the noise in images. The noise characteristics are used to determine which filter is best. The Gaussian filter eliminates Gaussian noise.

Gaussian filters are commonly employed in image processing to minimize noise and blur in images. A Gaussian filter is a linear filter with a Gaussian function-like impulse response. By convoluting the image with its function, the Gaussian filter will alter the image. When applying a Gaussian filter to an image, first specify the dimensions of the matrix that will be used to demize the image. Since the sizes are typically odd, the middle pixel is used to calculate the total results. Additionally, the matrix has the same number of rows and columns because it is symmetric. The Gaussian function, which is as follows, calculates the values inside the matrix:

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$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

Where, $x \rightarrow X$ coordinate value, $y \rightarrow Y$coordinate value, $\pi \rightarrow$ Mathematical Constant PI (value = 3.13), $\sigma \rightarrow$ Standard Deviation. Given the right parameters, the aforementioned equation (1) is used to calculate a gaussian matrix of any dimension. A two-dimensional 3x3 Gaussian matrix approximation with a standard deviation of 1 is shown in figure 2 as follows.

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

Figure 2: *3×3 gaussian matrix*

Although the Gaussian filter has an infinite dimension in theory, it is reduced to a conventional rectangular form for practical use. The output of the filter may contain errors as a result of this reduction. Filters of various sizes are used to fix those issues. It is possible to create a Gaussian mask with varying values and associated x and y coordinates. The purpose of the moving window is to obtain the pixel values as a mask. Thus, this filtering provides the best possible trade-off between inverse filtering and noise. Tumor segmentation and classification obtain from the preprocessed brain MRI image.

3.2 Segmentation by Global Thresholding

Image segmentation separates objects, boundaries, or structures within the image for more meaningful analysis. The thresholding-based algorithms are the best for segmenting images. Thresholding-based segmentation algorithms categorize every pixel in the image into either the background or clusters. All of the image pixels are classified using global thresholding. To approximate global thresholding, the mean and standard deviation of the image pixel intensity values have been incorporated. By maximizing the log conditional probability of the pixels given their respective classes, it is computed under the assumption that the pixels are statistically independent. The probability density of intensity values is described by computing that conditional probability using a population mixture model with various means and a shared variance.

Equation (3,4) provides an estimate of the global threshold. An intensity image is first taken. Next, local intensity variance of the intensity image is calculated at each pixel location. The resulted image is called variance image.

$$\text{Intensity Image } I(x,y), x = 0, \ldots, N-1, y = 0 \ldots, M-1 \tag{2}$$

$$\text{Variance Image } V(x,y), x = 0, \ldots, N-1, y = 0 \ldots, M-1 \tag{3}$$

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Values of discrete variance V in the meantime $[0, V_{max}]$will be assumed. A histogram $h(V)$ is used to show the intensity values in the variance image with the intensity values which are distributed.

$$V = 1, \dots, V_{max} \tag{4}$$

It indicates how frequently local variance of the variance image appeared. By normalizing the histogram of the local variance values, the local variance probability density function is calculated as follows:

$$p(V) = h(V)/(N.M) \tag{5}$$

Using a population mixing model to describe the probability density function $p(V)$ by adding two weighted conditional Gaussian probability density functions with means $m_1$and m_2,variances $\sigma1^2$ and $\sigma2^2$and weights c_1 and c_2. Where,

$$c_1 + c_2 = 1 \tag{6}$$

The following is the expression for the resulting likelihood function:

$$L(k) = N.\sum_{j=1}^{2} c_j(k).\left(c_j(k)\right) - \frac{N}{2}(2\pi) + \frac{N}{2}.\sum_{j=1}^{2} c_j(k).\sigma_j{}^2(k) - \frac{N}{2} \tag{7}$$

$$c_1(k) = \sum_{v=0}^{k} p(V) \tag{8}$$

$$c_2(k) = \sum_{V=k+1}^{V_{max}} p(V) \tag{9}$$

$$m_1(k) = \frac{1}{c_1(k)}\sum_{V=0}^{k} V.p(V) \tag{10}$$

$$m_2(k) = \frac{1}{c_2(k)}\sum_{V=k+1}^{V_{max}} V.p(V) \tag{11}$$

$$\sigma_1{}^2(k) = \frac{1}{c_1(k)}\sum_{V=0}^{k}(V - m_1)^2.p(V) \tag{12}$$

$$\sigma_2{}^2(k) = \frac{1}{c_2(k)}\sum_{V=k+1}^{V_{max}}(V - m_2)^2.p(V) \tag{13}$$

The value$k, k = 0 \dots, V_{max} - 1$, the maximised likelihood function by k is$L(k)$, is the global thresholdth_g. Following global thresholding, the segmented clusters are displayed. The resulting image will then be used as input for the subsequent image processing step.

3.3 Feature Extraction by Local Binary Pattern

The amount of redundant data in the data collection is decreased with the assist of feature extraction. To process a digital image or video, feature extraction algorithms look for properties like shape, edges, or motion. To extract characteristics from brain images, the Local Binary Pattern (LBP) method is suggested. The following enables the extraction of LBP features: (1) Computational simplicity to prevent complex arithmetic and to enable quick processing. (2) High discriminative power guarantees that just a small number of characteristics are required

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for accurate brain tumor identification, in turn enabling faster processing and training. (3) Because of the threshold method, it is more resilient to changes in illumination than many other basic features.

By comparing the gray value of the image pixel with the neighbor pixel, the LBP operator determines a local pattern for the pixel.

p = circular neighborhood sampling points which are equally spaced, R = radius, the center pixel binary pattern is described as:

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{14}$$

$$s(x) = \begin{Bmatrix} 1, & x \geq 1 \\ 0, & x < 0 \end{Bmatrix} \tag{15}$$

g_c = central pixel gray value, g_p=circular neighbourhood sampling point on p, $s(x)$ = function of binary values.

It suggests that rotation invariant uniform patterns by eliminating the weights and restricting the transition (0/1 or 1/0 changes) of the LBP code in order to reach the variance rotation. An invariant uniform pattern of the pixel rotation is described as follows:

$$LBP_{P,R}^{riu2} = \begin{Bmatrix} \sum_{p=0}^{P-1} s(g_p - g_c), & if U(LBP_{P,R}) \leq 2 \\ P+1, & otherwise \end{Bmatrix} \tag{16}$$

Where

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{P-1} - g_c)| \tag{17}$$

Equation (16) defines that the $LBP_{P,R}^{riu2}$operator has $P+2$ different output values. In brain image classification, the $LBP_{P,R}^{riu2}/VAR_{P,R}$ operator frequently performs better when combined with the local variant ($VAR_{P,R}$).

3.4 Classification by Modified Convolutional Neural Network (CNN)

Image classification is the process of classifying an image into one of several preset categories. The image classification stage uses an appropriate classification algorithm that compares image patterns with the target patterns to classify detected images into specified classes. For the purpose of classifying the brain MRI image dataset, a modified convolutional neural network (CNN) is suggested. A convolution layer and a pooling layer are added to a forward propagation neural network to create a convolutional neural network. In essence, the forward propagation neural network is the procedure by which an input value is sent to the neuron model for computation. The process that receives the output value after applying the activation function. In addition to updating the weights, it computed the input and output value errors. The convolutional neural network then learns and categorizes the input values. Figure 3 displays the representation of a single neuron.

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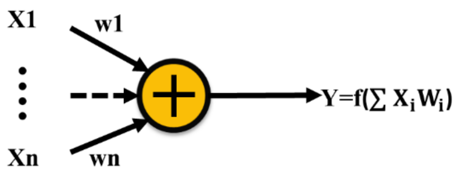

Figure 3: *Single neuron model*

In order to classify the glioma, meningioma, no-tumor, and pituitary brain images from the brain MRI dataset, this study created a modified CNN. In order to improve the classification accuracy unique to medical imaging issues, it built the architecture. The model starts with a 32-filter starting layer and moves through layers with 64, 128 and 256 filters, each having a 3 × 3 kernel size. The purpose of these layers is to gradually extract increasingly intricate information from brain imaging data. To maintain the model's effectiveness and focus on key components, such as max pooling stages that aid in reducing the amount of data that travels through the network and activation functions known as ReLUs (Rectified Linear Units). To complete decision-making process of the model, the data is flattened and sent through a sequence of dense layers with 128 and 64 neurons after processing via these layers. Furthermore, a dropout layer lessens the possibility of overfitting, making the model more trustworthy when examining fresh, untested brain images. A sigmoid function, which is ideal for classification jobs, is used to make the ultimate judgment about the identification of the brain tumor images. The CNN's decision-making layers facilitate the prediction of brain tumor images from the brain MRI dataset, which contains pituitary, glioma, meningioma, and no-tumor images. This transparency is essential for early brain tumor identification, particularly in the medical field. Figure 4 shows a modified CNN model's processing structure.

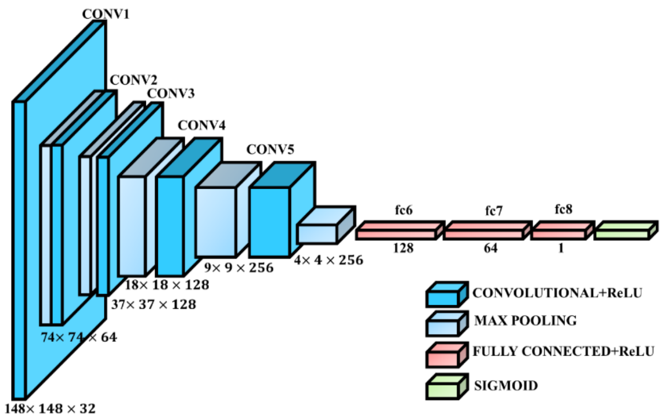

Figure 4: *Modified CNN structure*

After that, a CNN model specifically designed for tumor identification is defined and trained with predetermined hyperparameters. At training, the performance of the model was carefully assessed. The suggested customized CNN model stands out from other models like

VGG_SCNet by optimizing feature extraction and classification especially for brain tumor detection in MRI images when compared to pre-trained models. The suggested model outperformed deep and reliable than other classifier architectures in terms of accuracy and efficiency. Medical experts are more likely to trust the model as a result of its increased transparency, which offers clear insights into its decision-making process.

3.5 Predicted Performance Matrix

Several basic indicators, such as TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative), are considered in the experimental evaluation that follows. TP stands for attack flows that were correctly anticipated, TN for normal flows that were correctly predicted, FP for attack flows that were mistakenly predicted, and FN for normal flows that were incorrectly predicted.

S.No	Performaces Matrices	Definition	Formula
1	Accuracy	Accuracy is defined as the proportion of accurate estimations to total predictions.	$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$
2	Precision	It is the propotion of correctly predicted attacks to all attacks that were forecasted.	$Precision = \frac{TP}{TP + FP}$
3	Recall	Recall, is referred to as true positive rate, and it is the proportion of correctly predicted attacks to actual attacks.	$Recall = \frac{TP}{TP + FN}$
4	F1 Score	Precision and Recall are weighted averages that make up the F1 score.	$F1\ score = \frac{2.(Recall.Precision)}{Recall + Precision}$
5	AUC	The Area under the ROC Curve (AUC) shows Recall against False Positive Rate at different categorization criteria.	$FPR = \frac{FP}{FP + TN}$

The module makes predictions for the categorized datasets and assesses the confusion matrix, accuracy, recall, time, F1 score, and precision. At last, the classification technique's performance is attained.

4 Results and Discussions

Python software is used for this model's implementation. This study used 5327 brain MRI images as the training dataset and 1411 brain MRI images from various individuals as the

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testing dataset to assess the efficacy of the suggested approach. The collection also includes MRI scans of people who have benign or malignant brain tumors. The MRI image samples that were used for training and testing in this work are shown in Figure 5. Glioma, meningioma, non-tumor, and pituitary MRI images are among the images randomly selected from the brain MRI image dataset for the prediction procedure. The randomly chosen brain images for additional processing are displayed in Figure 6.

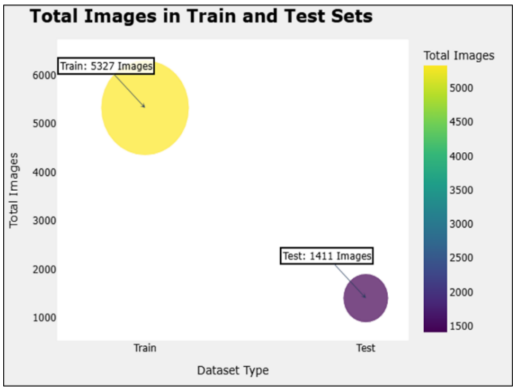

Figure 5: *Total images in train and test sets*

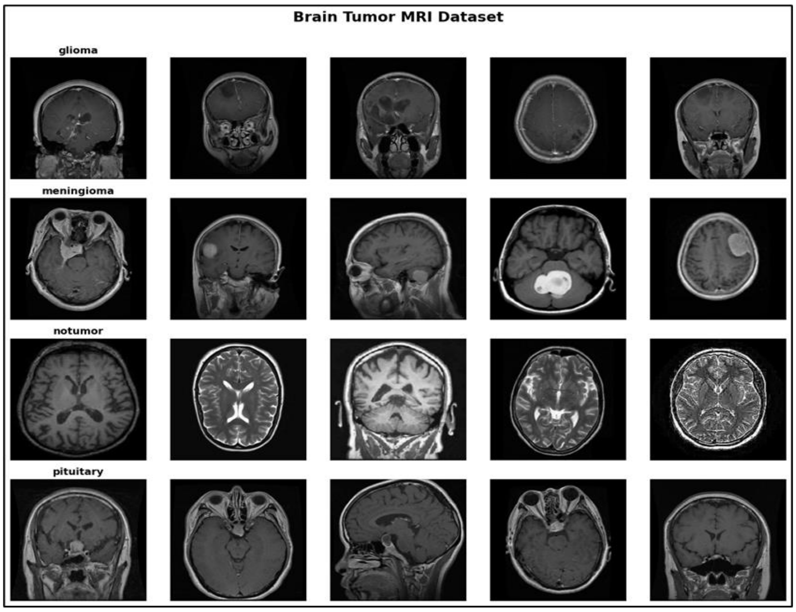

Figure 6: *Random images from train data*

Image resizing reduces the training time of a neural network and it increases the capacity of the brain MRI for further processing. Figure 7 illustrates the resized image of the given input brain image.

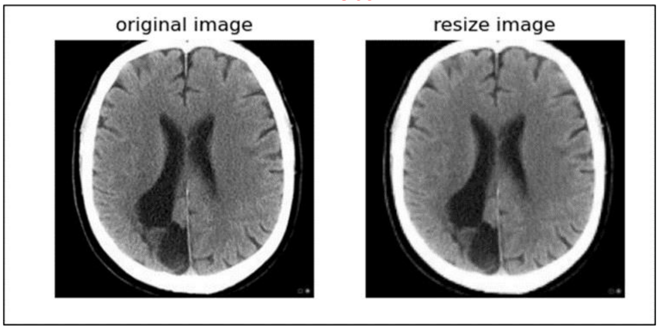

Figure 7: *Resize image*

The preprocessed and filtered image is seen in Figure 8. Preprocessing with a gaussian filter is used to shorten the training period of the brain image and speed up the inference of the model. This step serves two purposes: noise removal and image enhancement. It removed the noise from the brain image for segmentation.

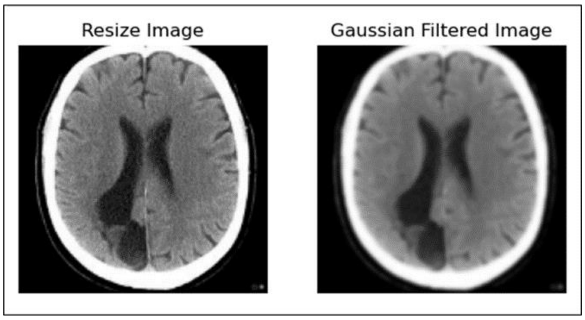

Figure 8: *Gaussian filtered image*

The global thresholding method is used in this approach to segment data. To distinguish tumor and non-neoplastic regions, it is necessary to normalize the intensity over the pixel range. An abdominal MRI image of a brain tumor segmented using masks and overlapped images is the end result. Figure 9 showcases the brain image which is segmented using the global thresholding technique.

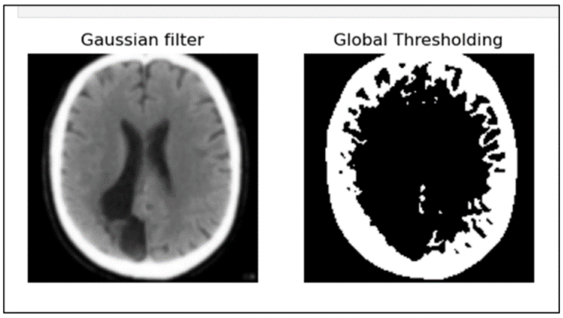

Figure 9: Segmented brain image using global thresholding

By applying a Local Binary Pattern to the segmented brain image, the radiomics features are extracted. Converting the raw brain image data into numerical characteristics that maintain the

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most important information of the brain MRI image. It guarantees that only a limited number of features are necessary for both brain tumor detection and classification. Using this method, the feature extracted image is displayed in Figure 10.

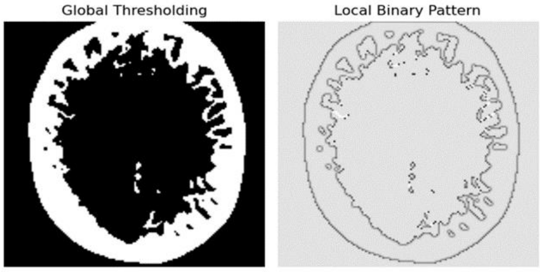

Figure 10: *Extracted the feature using Local Binary Pattern*

The loss is the discrepancy between the actual target value and the expected output of the model. A perfect prediction results in a loss value of zero, while imperfect predictions yield higher loss values. Accuracy is defined as the proportion of correctly classified data instances to all data instances. This proposed classification model provided the minimized low value and the highest accuracy of 94%. Figure 11 showcases the graphical representation of accuracy and loss at training and validation across different examples.

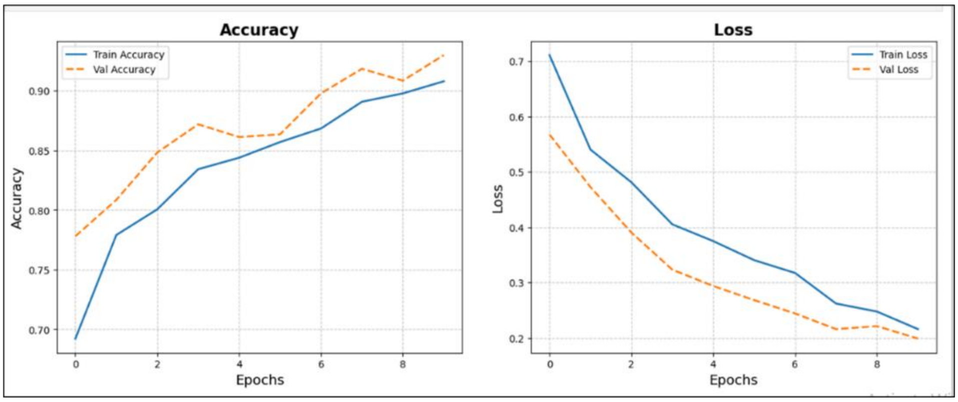

Figure 11: *Training & validation accuracy and loss*

A table that contrasts the number of expected class instances with the number of ground truth instances of a certain class is called a confusion matrix. This is commonly utilized to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. The confusion matrix for the proposed work with predicted and true labels are shows in figure 12.

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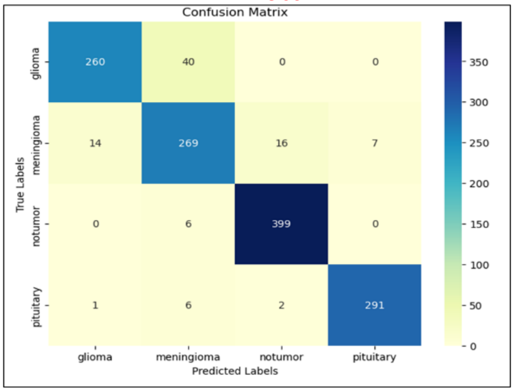

Figure 12: *Confusion matrix*

Figure 13: *Predicted brain MRI image*

Figure 13 displays the predicted output of the input brain MRI image. Using the suggested modified CNN model, the brain tumor is predicted with good accuracy, and pituitary is the predicted class.

Table 1: *Performance Matrices*

Class	Accuracy	Precision	Recall (Sensitivity)	Specificity
Glioma	93.7%	94.5%	86.7%	97.5%
Meningioma	93.7%	74.5%	88.0%	100%
Notumor	93.7%	95.7%	98.5%	100%
Pituitary	93.7%	97.8%	97.0%	99.7%

The performance matrix values for the predicted classifications of glioma, meningioma, no-tumor, and pituitary are shown in Table 1 and include accuracy, precision, recall, and specificity. The proposed model implemented with the accuracy of 93.7% and the precision value is 74.5% to 97.8% for each classes. Recall value is evaluated as 86.7% to 98.5% and the specificity is 97.5% to 100% for each classes.

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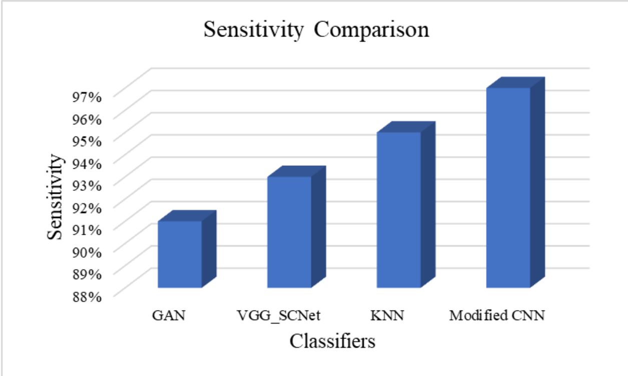

Figure 14: *Comparison graph for sensitivity*

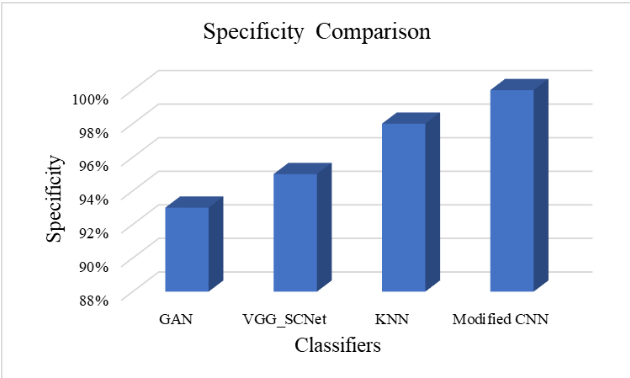

Figure 15: *Comparison graph for specificity*

Figure 14 and figure 15 shows the sensitivity and specificity of various classifiers in which the proposed classifier shows the highest specificity of 97 % and sensitivity of 100% than other conventional classifiers such as Generative Adversarial Network (GAN)[2], VGG Stacked Classifier Network (VGG_SCNet)[4] and k-Nearest Neighbor[5].

5 Conclusion

This work is suggested to use a modified CNN classifier with a global thresholding framework to classify brain cancers, including meningioma tumors, pituitary tumors, glioma tumors, and no-tumor. Pre-processing and segmentation play pivotal roles in enhancing the efficiency of tumor detection and classification when deploying the modified CNN classifier. Metrics such as specificity, accuracy, sensitivity, F1-score, and precision are used to assess the classification performance of the proposed work. Among the other methods, the modified CNN approach's confusion matrix showed the classifier's highest performance on the test set. This approach is successful in correctly identifying and categorizing brain tumors because it combines contrast enhancement techniques with a classification model. The suggested work performs better in terms of F1-score, accuracy, and precision. Notably, the detection rate achieves an impressive precision of 97%, specificity of 97%, and sensitivity of 99.8%. Modified CNN significantly improves overall prediction accuracy, achieving a peak accuracy of 94%. Future research will concentrate on better classifying tumor stages and estimating the brain tumor location, which will aid in early tumor discovery and may be helpful in prompt additional therapy.

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