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SIMULATION OF DEEP LEARNING BASED CLASSIFICATION FOR IDENTIFICATION OF BRAIN TUMOR DETECTION TO PROVIDE BETTER PERFORMANCE

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Abstract
Edge extraction with Deep learning mechanisms has been applied to improve performance during brain tumor detection, according to recent research. Some research has focused on brain tumor detection and deep learning, but performance remains a significant problem. Time was saved by incorporating edge detection into the already existing deep learning method for detecting brain tumors. Additionally, the time it takes to identify a tumor using a pre-trained network is cut in half. The MRI pictures have been trained using deep learning. The human brain seems to be like a wall clock, at least according to a dataset used to train deep neural networks. If tumors take the shape of a dish, their diagnosis is made easier. In this paper, we explore how DL and reinforcement learning may be used to identify brain cancers. Current research in the area has been reviewed, including its characteristics and method of operation. There have been discussions on the challenges of detecting brain tumors given the current research limitations. This assessment will serve as a springboard for further investigation. Edge detection has been shown to be necessary in order to boost the system's efficiency. Detection of edges and its extraction has thus been introduced, along with the functioning process and many kinds. Finally, the research's future directions have been clarified. As with artificial intelligence, the use of ML is rapidly growing in the areas of classification and forecasting. DL algorithms are often used in the diagnosis of brain tumors. Recent studies on detecting brain tumors have either low sensitivity or high error rates, which is a major concern. This study reviews the literature on the topic of brain tumor detection and discusses the methods, tools, and technologies currently in use. In addition to discussing new research, this study also addresses problems with existing research, such as poor performance and inaccurate results. At the moment, scientists are trying to figure out how to spot brain tumors. Edge detector processing has been used to MRI scans of the brain to boost efficiency and precision. The investigation includes the use of images, the identification of edges, deep learning, and healthcare. The proposed method would reduce the need for costly and time-consuming surgery for diagnosing brain tumors. A close eye will be kept on how well the neural network makes predictions as it functions. The purpose of the suggested research is to develop a more reliable prediction model by combining various compression and edge detection processes with deep learning mechanisms. After the brain MRI dataset was trained, the confusion measures were computed to evaluate the reliability of the test findings.
Keywords: MRI, PSNR, SSIM, Edge detection.

I. Introduction

ML, along with AI, is seeing explosive growth in its application to problems of categorization and prediction. The diagnosis of brain tumors is a common use of DL algorithms. Recent studies on detecting brain tumors have either low sensitivity or high error rates, which is a major concern. This study reviews the literature on the topic of brain tumor detection and discusses the methods, tools, and technologies currently in use. In addition to discussing new research, this study also addresses problems with existing research, such as poor performance and inaccurate results [2]. At the moment, scientists are trying to figure out how to spot brain tumors. Edge detector processing has been used to MRI scans of the brain to boost efficiency and precision. The investigation includes the use of images, the identification of edges, deep learning, and healthcare. The proposed method would reduce the need for costly and time-consuming surgery for diagnosing brain tumors. A close eye will be kept on how well the neural network makes predictions as it functions. The purpose of the suggested research is to develop a more reliable prediction model by combining various compression

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and edge detection processes with deep learning mechanisms. After the brain MRI dataset was trained, the confusion measures were computed to evaluate the reliability of the test findings [3].
Brain tumors, as defined by medical specialists, are masses or growths of aberrant cells in the brain. Brain tumors may be further classified into various different categories. Malignant brain tumours are cancerous, whereas benign ones are not. (the benign kind). Metastatic brain tumors, also known as secondary brain cancers, are malignancies that began in another part of body, in contrast, begin in the brain. The pace at which a brain tumor grows might be anything from very slow to very fast. A brain tumor's influence on your neurological system is defined not only by its location, but also by its growth rate. The kind of brain tumor you have, as well as its size and where it is located, will determine your treatment choices [4].
Everyone's brain is said to have several different functions. Information processing occurs in the brain, which stores, retrieves, and evaluates information [9]. A peculiar growth pattern might be seen. Two types of brain cells may exist. After the development of a single brain cell, all other units in the body transition to this phase as well. It's feasible that unchecked brain cell growth might result in both negative and positive outcomes. They respond by going in opposite direction of your body's normal cell migration. It has been shown that the cells may persist in damaging other areas as well. The human mind can only take in so much information. The heavier a person's head feels, the larger their brain is. As a result of brain damage, a person may experience heaviness in their head. Scanning methods of varying sophistication are used to detect and diagnose cancers in their earliest stages [5]. Medical practitioners employ MRI findings for early diagnosis. Tissue evaluation is essential for the separation and interpretation of digital images when a computerized programmed is needed for analysis. Imaging investigations give information that might be of use to medical experts in establishing whether or not the tumor is a primary brain tumor or whether or not cancer has spread to brain from another section of body [6]. During imaging tests, still photographs of the inside of the body could be shown on the screen. The following are some of the considerations that your doctor could take into account when choosing a diagnostic test for you:

- The probable kind of tumor
- The probable kind of tumor
- Your signs and symptoms
- Your age and overall health
- The findings of previous medical tests
- Your own age and general health

The majority of brain tumors are first discovered after the development of symptoms. In most cases, an internist or neurologist is the one to make the first diagnosis of a brain tumor. A physician who focuses their practice on the care of adults is called an internist. A neurologist is a kind of medical specialist that specialises in diagnosing and treating conditions that affect brain & central nervous system. In addition to doing a physical exam on patient & obtaining a full medical history from them, the doctor may also prescribe the tests that are outlined in the following paragraphs. These examinations are performed to determine whether or not a brain tumor exists, and occasionally also its classification and severity [7].

II. Problem statement

However, there have been a number of studies in this sector, but they have a number of flaws. Performance, storage capacity, and accuracy are all issues. The training of a DNN takes a long time & a lot of resources. A method that improves training speed while also improving feature detection performance is required. To boost performance when learning and detecting patterns, canny edge detection must be included. There has been a great deal of study in this field, but all of the solutions have their drawbacks. There is a lot riding on this, including speed, storage, and precision. To train, a DNN needs a substantial amount of time & data. A method that improves training velocity & FD accuracy is required. Learnability and pattern recognition depend on accurate detection of edges.

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Several research have been conducted in this area, however they all suffer from the same drawbacks. There are problems with speed, storage space, and precision. It is time-consuming and resource-intensive to train a DNN. We need a technique that can simultaneously enhance feature detection performance and training speed. Knowledgeable edge detection is essential for improving performance in pattern recognition and pattern learning.

Moreover, CBIR has been incorporated into the diagnostic procedures of several studies for brain tumors that have been conducted in the fields of engineering and medicine. However, these investigations are being hampered by the high storage and processing requirements of big pictures, which are causing a significant backlog. When making a call, having pictures that have been compressed and edges that have been recognised might be helpful. According to the findings, the amount of time spent deliberating increases significantly with the size of the image. The removal of a picture's unnecessary components necessitates the use of several IP methods, such as cropping, ED, & others. On the other hand, the system might arrive at the incorrect conclusion if the visual data it is relying on is either faulty or no longer current. Therefore, it is very necessary to enhance the image quality during CBIR operations.

III. Proposed work

The research uses images, edge detection, deep learning, and healthcare. The recommended method would save space and time in the search for brain tumors. During neural network operations, prediction performance and accuracy will be evaluated. Training on the brain MRI dataset would be carried out, and then the accuracy of test results generated after calculating the confusion measures would be evaluated.

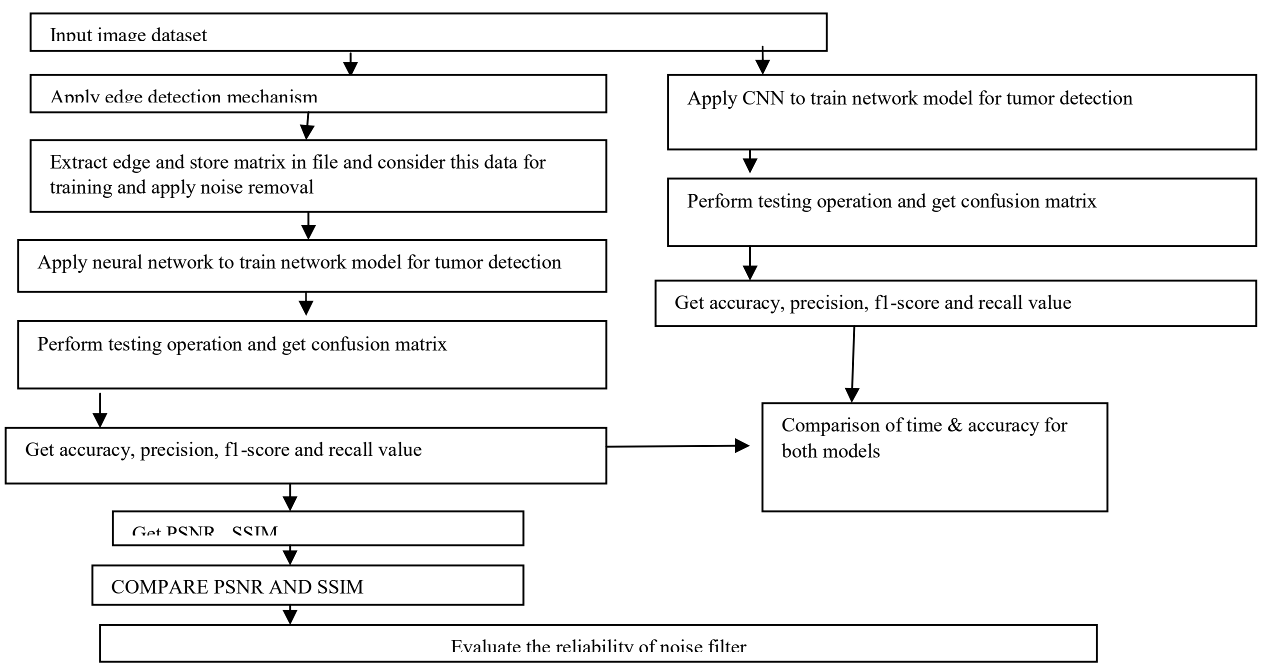

Figure 1: Flow chart of implementation of Proposed Work

Previous models' performance and accuracy are compared to the proposed model. The research described here used two MRI scans of human brains as a starting point. Images of one individual with a tumor, and another without one, are shown.

The work shown here will be completed in several stages. Initially images are captured and the images preprocessing is performed then classification using CNN model. Training and testing to get precision, accuracy, f1 score, recall value. Finally, performance and accuracy comparisons between past and future projects Images of a tumor and one without it are shown in the following model.

1. **PSNR**

PSNR is ratio between strongest possible signal value & strongest potential distortion from noise.

$$PSNR = 20\log_{10}(\frac{MAX_f}{\sqrt{MSE}})$$

2. **MSE**

Statistics error is quantified using MSE. It is calculating the mean squared discrepancy between actual value and forecasted value. In an ideal model, the MSE would be 0.

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

Legend,

- f reflect matrix information from source picture
- g shows our damaged image's matrix data
- m numbers of rows of picture pixels, and i is the index of a certain row
- n indicates the image's width in columns of pixels, and j is the column index for that width.
- MAX_f is the peak signals strength of the first picture we have verified to be excellent.

3. **SSIM Algorithm**

The SSIM index is calculated using many different window sizes from a single picture. The separation between two N×N-square windows x and y is given by:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)\left((\sigma_x^2 + \sigma_y^2 + C_2)\right)}$$

Where

- μ_x pixel sample mean of x;
- μ_y pixel sample mean of y;
- σ_x^2 variance of x;
- σ_y^2 variance of y;
- σ_{xy} covariance of x & y;

Divide by a weak denominator using the two-variable formula C1, C2.

4. **Median Filter**

The basic concept behind median filter is to iteratively go through the signal and replace each item with the median of the entries around it. The "window" is the pattern of neighbors that is slid across the whole signal one entry at a time. In one dimension, the most natural window would be the few entries immediately before and after the signal, but in two or more dimensions, the window would have to include all entries within a certain radial or elliptical area.

$$Median = (x_1, x_2, x_3, \dots, x_n)$$

on demonstrate, we'll apply a median filter with window size of 3 & one entry before & after each entry on following 1D signal:

x = (2, 3, 80, 6, 2, 3)

5. **Gaussian Filtering**

Image noise and details may be obliterated using Gaussian filtering. To simplify, the Gaussian function in one dimension is:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{x^2}{2\sigma^2}}$$

In where denotes the sample's standard deviation. It is assumed that the mean of the distribution is zero.

6. Confusion matrix and Accuracy Parameters

The nature of the business issue being addressed should frequently guide the selection of a performance indicator. Suppose you have a dataset containing 100 instances and you have classified each one using your model. A table called a confusion matrix may be used to plot the projected classification against the actual classification.

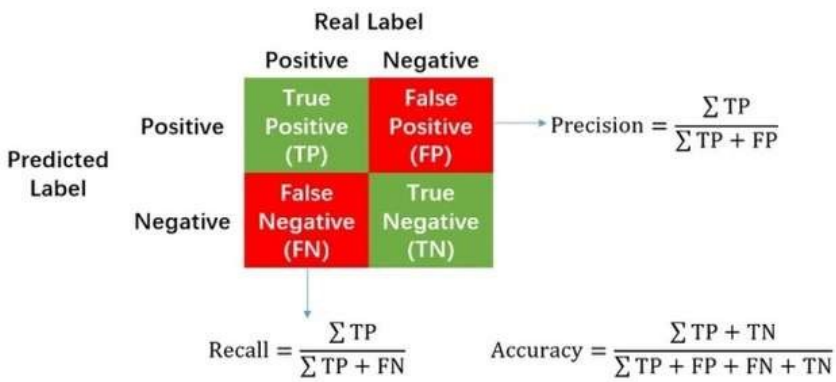

Figure 2: Confusion matrix and Accuracy Parameters

Accuracy

Accuracy is a good heuristic for gauging the quality of a model's training and its potential future performance. However, it does not provide specifics on how to apply it to the issue at hand.

$$Accuracy = \frac{\sum TP + TN}{\sum TP + TN + FP + FN}$$

When there is a large disparity across classes, performance metrics that rely heavily on accuracy tend to suffer. Apply the aforementioned confusion matrix to the dataset. Assume that the negatives represent legitimate purchases and the positives represent fraudulent ones. If you want to know how often you're right across all subject areas, accuracy will tell you.

Precision

When the cost of a false positive is large, accuracy is beneficial. Let's pretend, therefore, that finding skin cancer is the issue. There will be several further examinations and pressure. After being inundated with false alarms, people responsible for monitoring the data will eventually learn to disregard them when the false positive rate is high.

$$Precision = \frac{\sum TP}{\sum TP + FP}$$

Recall

A false negative has devastating consequences. If you make a mistake, we will all die. The thing you're seeking to prevent might have a devastating effect when false negatives occur often. A false negative is when you go into the woods and ignore the rustle of leaves and end up being devoured by a bear. You wouldn't want to keep a model that accidentally allowed in nuclear weapons. You should get rid of your model if chipmunks are keeping you up at night.

$$Recall = \frac{\sum TP}{\sum TP + FN}$$

F1 Score

F1 is overall measure of accuracy that mixes precision and recall, in the same strange way that adding and multiplying essentially mix two components to produce a new dish completely. To restate, high Fscore indicates that you are able to effectively identify significant hazards while ignoring false alarms. A perfect Fscore of 1 means model worked perfectly, whereas score of 0 means it didn't work at all.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

ANN Algorithm for deep learning

1. Assign Rndm weights to all linkages to start algorithm
2. With input and linkage (Hidden node), Calculate rate of activation linkage
3. With rate of activation linkage and linkages to output, get rate of activation output
4. Find output error rate and recalibrate all linkage between input and output node.
5. With output weight and output error found, cascade down error to linkage.
6. Recalibrate weights between linkage and input node
7. Repeat process till convergence criterion is met.
8. With final linkage weights score rate of activation output nodes.

Hybrid algorithm

Step 1 Get brain tumor images sci(i)
Step 2 Apply Resize image and set dimension and get Resci(i)
Step 3 Apply compression mechanism
Step 4 Apply edge detection (canny Edge Detection)
Step 5 Noise detection from image using Adaptive Noise Detector
Step 6 Noise filtering using Median filter

$$\boldsymbol{Median = (x_1, x_2, x_3, \ldots, x_n)}$$

Step 7 Evaluating PSNR

$$PSNR = 20\log_{10}(\frac{MAX_f}{\sqrt{MSE}})$$

Step 8 Find SSIM

$$SSIM(x1, y1) = \frac{(2\mu_{x1}\mu_{y1} + C_1)(2\sigma_{x1y1} + C_2)}{(\mu_{x1}^2 + \mu_{y1}^2 + C_1)\left((\sigma_{x1}^2 + \sigma_{y1}^2 + C_2)\right)}$$

Step 9 Find MSE

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j) - g(i,j)\|^2$$

Step 10 Training using CNN model using ResUNet++
Step 11 Get accuracy, recall, precision and f1-score after testing

Accuracy

$$Accuracy = \frac{\sum TP + TN}{\sum TP + TN + FP + FN}$$

Precision

$$Precision = \frac{\sum TP}{\sum TP + FP}$$

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Recall

$$Recall = \frac{\sum TP}{\sum TP + FN}$$

F1 Score

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

IV. Result and discussion

Simulation of amount of time consumed during the detection of brain tumors using normal images and edge detected images. To ensure that the proposed model is of sufficient quality, a comparison of MSE, PSNR, and SSIM has been carried out. In conclusion, a simulation of a deep learning-based classification has been carried out in order to present recall value, precision, accuracy, and F1-score. This was done in order to guarantee that the proposed model is reliable.

4.1 Simulation of Time consumption

Image analysis, boundary detection, deep learning, and medical treatment are all used in this study. Using the suggested technique might reduce the time and effort required to find brain tumors. The efficiency and precision of the neural network's predictions will be measured while it operates. Incorporating a number of different compression and edge detection techniques, as well as deep learning procedures, is part of the proposed study. After training on the brain MRI dataset, the confusion measures would be calculated and used to the test results to determine the reliability of the produced predictions. The suggested model is evaluated against the performance and precision of existing models. Two magnetic resonance imaging (MRI) scans of human brains formed the basis of the study reported here. Pictures of a tumor patient and a healthy person are shown.

These images represent the first of four phases necessary to finish the work exhibited here. Whereas step one involves obtaining the photos and doing preliminary processing, and step two involves utilising an artificial neural network to classify them. Training and testing is made to improve precision, accuracy, f1 score, and recall value is the third stage. Stage 4 analyses how current and future initiatives measure up in terms of performance and precision. The next photographs show a healthy body next to one with a tumor.

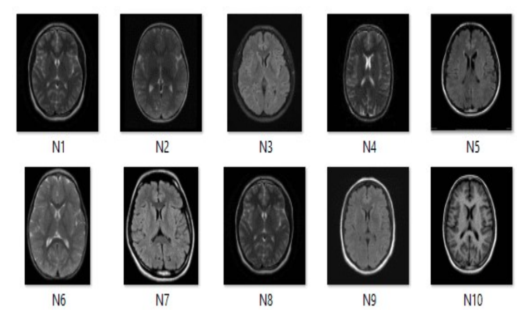

Figure 3: Brain MRI without tumor

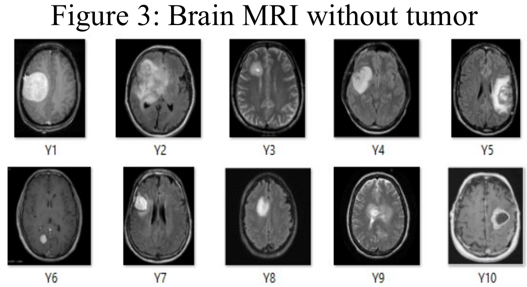

Figure 4: Brain MRI having tumor

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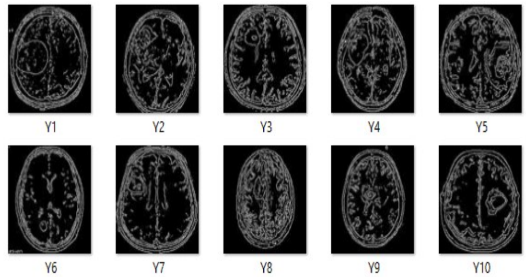


Figure 5: Edge based brain MRI with tumor

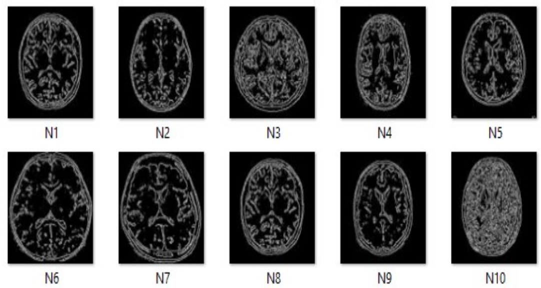


Figure 6: Edge based Brain MRI without tumor

The matching score is calculated using a neural network's ability to classify data. Work presented here employs ANN after the completion of edge detection and feature extraction. For this, we used an ANN classifier. It is also taken into account how long it takes to complete the sorting procedure. The following charts compare the processing time and accuracy of an ANN algorithm applied directly to an MRI Brain sample with that of an ANN algorithm applied to an MRI Brain sample with edges discovered. It is at this stage that the classifier is utilized to assign a grade.

Table 1: Comparison of Time consumption

Image	Without edge detection	With edge detection
1000	10.06672448	9.425674
2000	20.15156397	16.28081
3000	30.0842658	24.19699
4000	40.22673276	37.97994
5000	50.08549547	44.08487
6000	60.22573844	52.97552
7000	70.03956228	57.96528
8000	80.01685718	68.83811
9000	90.01284519	75.75832
10000	100.0934779	88.15598
11000	110.0064773	96.64592
12000	120.2458161	108.8863
13000	130.0942547	121.3851
14000	140.239385	135.8399
15000	150.1003632	147.7926
16000	160.1875875	139.7708
17000	170.0057091	147.875
18000	180.1215338	168.6432

Time's results for both a conventional brain MRI & an edge-based brain MRI are shown in Figure 7.

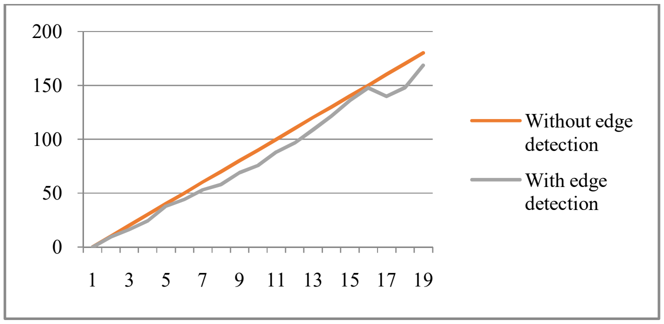


Figure 7: Time comparison

4.2 Simulation result for quality enhancement

Different noise removal filters have been applied over images and PSNR and SSIM has been calculated. Following figure is showing output after noise removal.

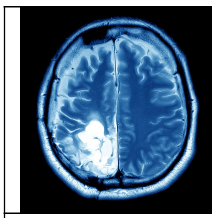
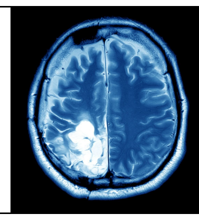
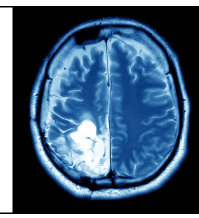
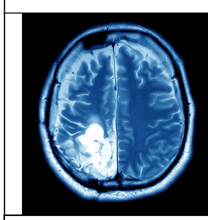
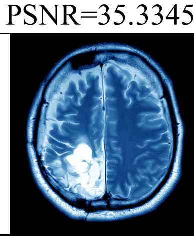
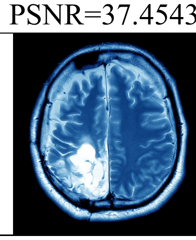
		
Normal image	Bilateral PSNR=35.33453	Blur PSNR=37.45435
		
Median PSNR=35.45533	Guassian PSNR=37.1000018986	Anisotropic PSNR=34.9604009

Figure 8: PSNR after filtering Image

Calculation of PSNR and SSIM has been performed in order to compare the filters

Table 2: Comparison of PSNR and SSIM

Filter	PSNR	SSIM
Bilateral	35.33453	0.82376
Guassian	37.1000018986	0.89607
Median	35.45533	0.85736
Blur	37.45435	0.85332
Anisotropic	34.9604009	0.88307

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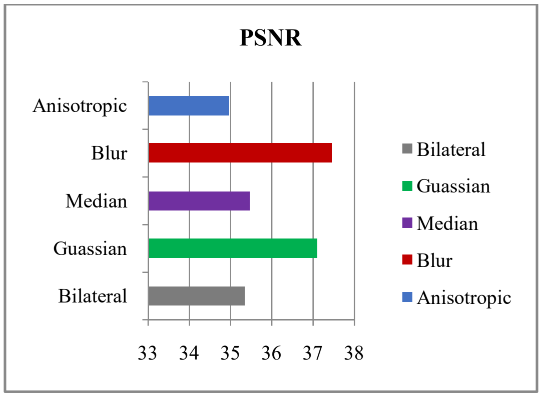

Figure 9: Comparison of PSNR

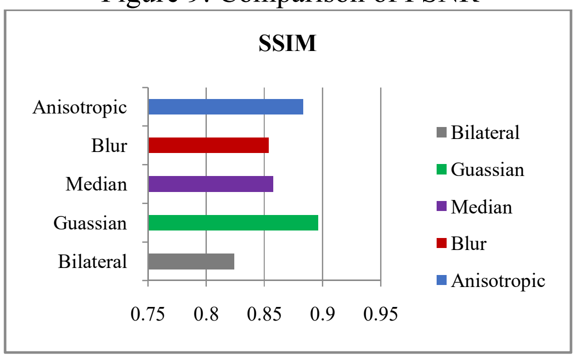

Figure 10: Comparison of SSIM

4.3 Simulation of DL for classification

Table 3: Confusion matrix of unfiltered dataset

	Brain tumor detected	Brain tumor not detected
Brain tumor detected	8866	1134
Brain tumor not detected	1129	8871

Results
TP: 17737
Overall Accuracy: 88.69%

Table 4: Accuracy of Unfiltered dataset

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	9995	10000	88.69%	0.89	0.89	0.89
2	10005	10000	88.69%	0.89	0.89	0.89

Table 5: Confusion matrix of filtered dataset

	Brain tumor detected	Brain tumor not detected
Brain tumor detected	8903	1097
Brain tumor not detected	1089	8911

Results
TP: 17814
Overall Accuracy: 89.07%

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Table 6: Accuracy of Unfiltered dataset

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	9992	10000	89.07%	0.90	0.91	0.91
2	10008	10000	89.07%	0.91	0.90	0.91

4.4 Comparison of Accuracy Parameter

1. Accuracy

Table 7: Comparison of Accuracy

Class	Unfiltered Dataset	Filtered Dataset
1	88.69%	89.07%
2	88.69%	89.07%

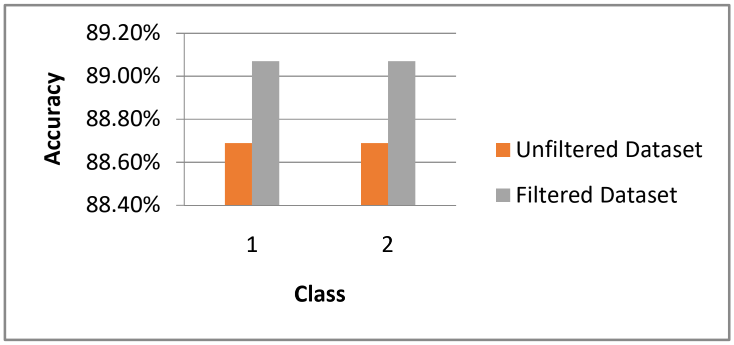

Figure 11: Comparison of Accuracy

2. Precision

Table 8: Comparison of Precision

Class	Unfiltered Dataset	Filtered Dataset
1	0.89	0.90
2	0.89	0.91

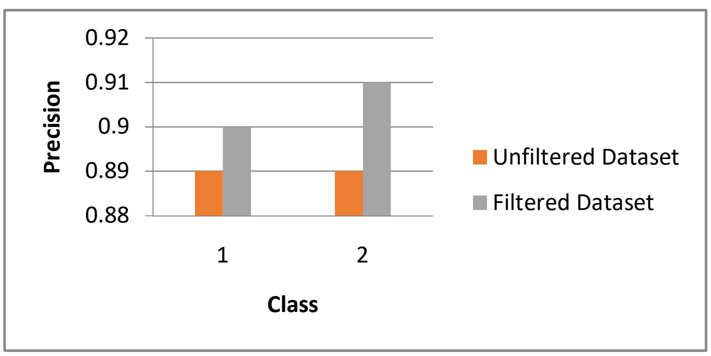

Figure 12: Comparison of Precision

3. Recall

Table 9: Comparison of Recall

Class	Unfiltered Dataset	Filtered Dataset
1	0.89	0.91
2	0.89	0.90

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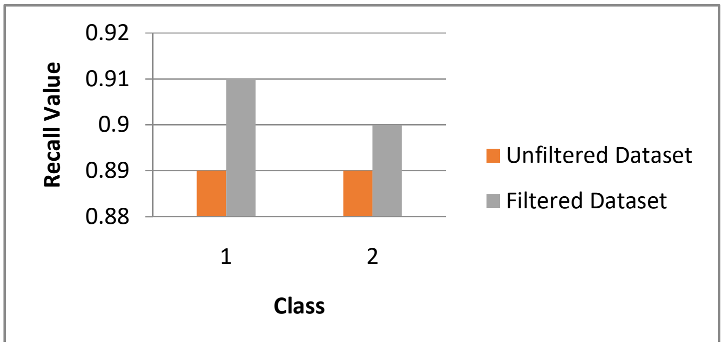

Figure 13: Comparison of Recall

4. F1 Score

Table 10: Comparison of F1 Score

Class	Unfiltered Dataset	Filtered Dataset
1	0.89	0.91
2	0.89	0.91

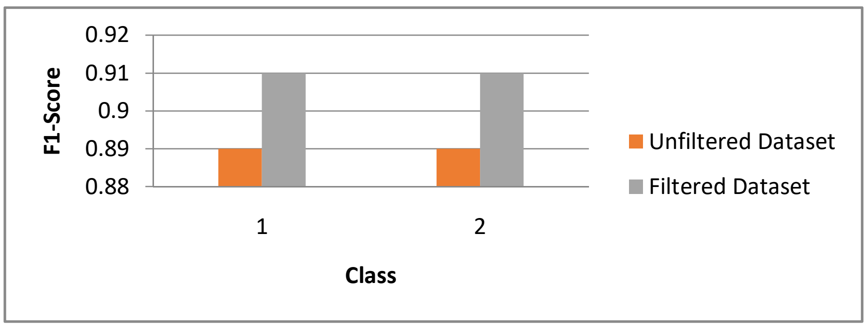

Figure 14: Comparison of F1 Score

V. Conclusion

Recent studies have shown that using deep learning algorithms has helped enhance diagnostic procedure for detecting brain tumors. While there has been discussion of using deep learning to detect brain tumors, more work has to be done. Adding edge detection to a preexisting deep learning technique for tumor diagnosis in the brain has improved accuracy. Furthermore, by using a pre-trained network, tumor detection time may be cut in half. The term "content-based imaging" refers to a kind of imaging technology used to locate and retrieve digital pictures based on their content, or shape. In this study, we review some recent publications dealing with CBIR. Simulation results during quality enhancement shows that Guassian filter is providing better PSNR and SSIM. Proposed work is providing better performance after integration of edge detection mechanism. Accuracy during brain tumor detection is also improved.

VI. Future Scope

The MRI pictures have been trained using deep learning. A dataset generated by DL reveals that the brain has a spherical shape, similar to a wall clock. If a tumor takes the form of a dish, doctors may have an easier time detecting it. This article describes the use of DL & RL to identify brain tumors. The most current research results, in addition to the characteristics and operation of the field, have been dissected. With the current state of knowledge, diagnosing a brain tumor is a huge problem. This evaluation is sufficient as a springboard for further exploration. ED has been shown to be essential for boosting the system's efficiency. The technique of operation and many forms of edge detection and extraction have thus been detailed. Directions for the study's future progress have been determined. In light of the present state of research, the difficulties in identifying brain cancers have been discussed. The results of this evaluation will be used to direct future research.Proof that edge detection is essential for optimal system performance. Thus, edge detection and extraction have been shown, together with their operational procedure and various forms. We now have a better idea of where this study is going in the future. After preprocessing the quality of brain image is enhanced and such image could be trained and tested using CNN model in future work. Research is to enhance diagnostic precision of brain tumours.

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