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Design of an Intelligent Technique for Abnormality Detection in MRI Brain Images

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Abstract: This paper presents an intelligent technique, particularly for MRI brain images. This introduces a clever method designed explicitly for MRI brain images. To detect abnormalities in the brain images, an intelligent hybrid method combining convolutional neural networks and curvelet transform is employed. Feature extraction, the logistic regression method (LRM), and learning algorithms are all used in the proposed model. Additionally, the categorization system identifies cancerous or non-cancerous tumours in the images of the brain. Results from experiments demonstrate the effectiveness of model- and parameter-based analysis. The paper concludes by contrasting the topic of minimum batch accuracy and validation accuracy with the current method. This concept is suited to ongoing MRI image analysis activities. In this paper, a previous paper has also been reviewed, and its process is investigated.

Keywords: CNN, MRI Brain Image, Curvelet Transform, Brain Cancer, Transfer Learning, Logistic Regression Model.

I. INTRODUCTION

Medical imaging refers to a range of procedures that can be used as minimally invasive methods to visualise the inside of the body. Medical imaging encompasses various image modalities and techniques used to visualise the human body for treatment and diagnostic purposes. As a result, medical imaging plays a crucial role in determining the steps necessary to improve people's health. A brain tumour is an uncontrolled growth of cancer cells that are present in the brain. The brain serves as the body's primary control centre, and an increase in cells there can put pressure on the skull and hurt people's health, as can be seen in several works of literature.

The classification and segmentation of MRI images can be performed by the CNN network, demonstrating that CNN is a well-organized technique in the field of medical image processing.

In this paper, we investigate whether using CNN alone, rather than another method, can detect the presence of cancer in the provided MRI brain images. The deep learning method known as CNN [convolutional neural network] is used to classify images and address the issue of data complexity.

This can be accomplished using two different CNN methods: feed-forward classification and backpropagation learning. The curvelet transform is used to extract features from an MRI brain picture. The CNN network, which consists of a convolution classification layer, a fully connected layer, and a softmax layer as the final layer, can classify and segment MRI images. and from this network, statistical measures such as accuracy, precision, recall, f1 score, and specificity are calculated. The total number of images used in this study is 251, with a training-to-testing image dataset ratio of 7:3 for MRI brain scans. Two methods—(a) the unequally spaced fast Fourier transform (USFFT); and (b) a method based on wrapping—are used to create the curvelet transform, also known as the fast discrete curvelet transform (FDCT). Transfer learning, as defined, is a machine learning technique that reuses a pre-trained model as the starting point for a new task. The remaining portions of the essay are divided into four sections: the introduction, the idea and theory section, the proposed model, and the determination of abnormality by performance analysis of experimental findings.

II. LITERATURE REVIEW

The table below presents a qualitative comparison of disease identification methods using biomedical images. The results of the following table show that several illness detection techniques have been used. Previous research work on brain MRI testing has been conducted and is represented in Table 1.

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Table 1: Comparison Table of Previous Research Work

S. No.	TITLE	ALGORITHM	MEASURING PARAMETER	DISEASE	ADVANTAGE	LIMITATION
1	CNN-based image ckassification and detection of abnormalities in MRI brain images [1]	CNN, K-MEANS ALGORITHM	Accuracy mini batch loss	Brain tumor	High accuracy during the training process	Computationally expensive
2	Brain cancer detection using curvelet transform and neural network [2]	Ann, curvelet transform, fcm	Accuracy	Brain cancer	To detect the brain cancer	
3	Convolutional neural network for brain tumour detection [3]	CNN	Accuracy 93% loss value 0.23264	Brain tumor	More convolutional layers increase the accuracy	More time for training
4	Brain tumour detection using a convolutional neural network [4]	Cnn, fcm, svm	Accuracy is 97% high	Brain tumor	Complexity is low	
5	MRI-based tumour image detection using CNN-based deep learning method [5]	CNN deep learning	Accuracy 99%	Brain tumor		
6	Classification of brain tumour types by deep learning with a convolutional neural network on magnetic resonance images using a developed web-based interface [6]	CNN web-based software	Accuracy 96%	Brain tumor	Used as a clinical decision support system	
7	Preliminary assessment for the development of CADe system for brain tumour in MRI images utilizing transfer learning in Xception model [7]	CADe exception model	High accuracy	Brain tumor		
8	Segmentation and detection of tumours in MRI images using CNN and SVM classification [8].	CNN, SVM	Mean-2.438 SD-1.0122	Brain tumor	Best technique for efficient classification of data	Complex and force ranges

III. CONCEPT/ METHODS

A. Classification

The convolutional neural network can be used to classify MRI brain images, which can be performed through two phases of the CNN: training and testing. The convolutional neural network consists of 25 layers in AlexNet, out of which we can use the last three layers in this study paper. The last three layers are the classification output layer, the fully connected layer, and the softmax layer. In this method, we can take the input images and pass them through the filters to get a classified output with different channels. For image classification, we can use three coloured channels for RGB images, and the filter can be dependent on the channels. CNN is a powerful image processing and computing method that uses deep learning. The CNN-based brain tumour classification is divided into two phases: training and testing. The number of images is divided into different categories by using label names, such as cancer and non-cancer brain images. In the training phase, pre-processing, feature extraction and classification The loss function is used to make a prediction model.

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B. Feature Extraction

Curvelet Transform Feature Extraction. The scale, location, and orientation factors determine the frame elements of the multi-scale geometrical transform known as the curvelet transform. It exhibits a very high degree of directionality in addition to having the wavelet's time-frequency localization characteristics. The curvelet addresses the drawbacks of the Gabor filter and wavelet transform. To get complete coverage of the spectral domain and to gather more orientation data, the curvelet transform has been created. Since the curvelet transform encompasses the entire frequency spectrum, there is no information loss while using it. The initial method of the curvelet transform is the discrete ridgelet transform.

C. Convolution neural Network

Kernel convolution is a fundamental component of numerous computer vision methods, in addition to CNNs. A small number matrix, referred to as the kernel or filter, is used in the process to alter the image based on the values from the filter. The input image is represented by the letter f, and our kernel by the letter h in the following formula, which is used to generate subsequent feature map values. The rows and columns of the result matrix's indexes are denoted by the numbers m and n, respectively.

$$G[m,n] = (f * h)[m,n] = \sum_{j} \sum_{k} h[j,k] f[m-j, n-k] \quad (1)$$

IV. PROPOSED MODEL

The suggested model system is displayed in figure 1 above. The proposed system utilises MRI scans from the Kaggle.com input image dataset. These pictures were divided into two groups: malignant and benign. In comparison to the paper [1], we obtained a 100% accuracy validation and mini batch accuracy result using the suggested method with minimal loss and time. The LRM approach can be applied in this case. Based on some dependent variables, the machine learning classification process known as logistic regression is used to forecast the likelihood of a given class. The logistic regression algorithm examines the relationship between different variables. The sigmoid function, which transforms numerical values into an expression of probability between 0 and 1.0, is used to assign probabilities to discrete outcomes. With a cut-off of 0.5, we can separate the photos into two groups for this investigation. Everything with a 0.5 or above is thought to be malignant, whereas everything with a value of 0.5 is seen to be non-cancerous. The threshold value for this can be set. Transfer learning is a machine learning research issue that focuses on retaining knowledge obtained while resolving one problem and applying it to another that is unrelated but yet important. Many machine learning models, including deep learning models such as artificial neural networks and reinforcement learning models, can be utilised with this technique. The block diagram of the proposed model is shown below.

Figure 1. Block Diagram of The Proposed Model

A flow chart of the proposed model is shown below:

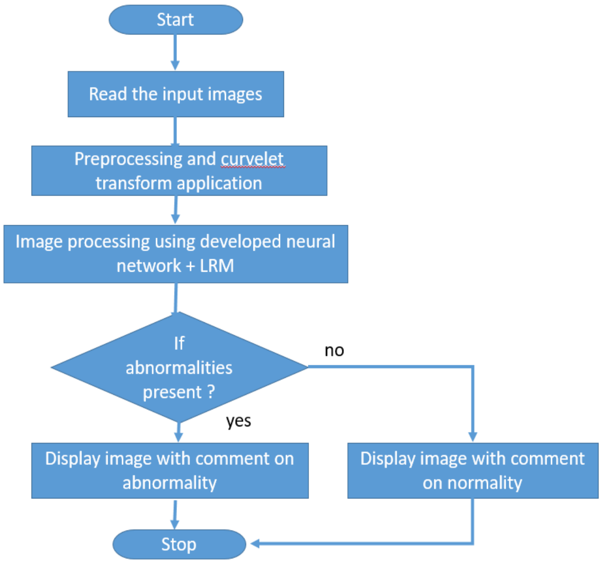

Figure 2. Flow Chart of the Proposed Model

A. Input Data

The dataset of brain MRI scans for brain tumour detection available at http://www.kaggle.com/datasets/brain-tumor-detection was used in the study. The collection comprises 251 photos, categorised into two groups: 'yes' and 'no'. Each category consists of 98 brain MRI images that are not malignant and 154 images that are. The sample images of the dataset are shown in Figure 3.

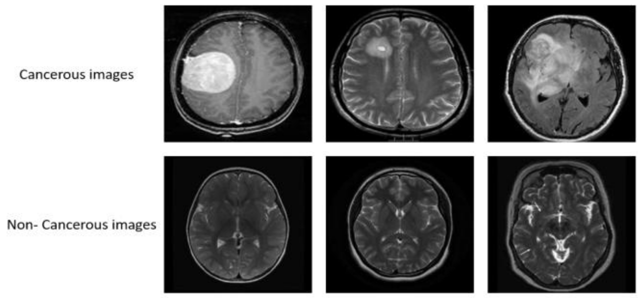

Figure 3. Training Dataset

B. Pre-processing

To improve image quality, we analyse the image using noise reduction and image enhancement algorithms. Pre-processing is designed to enhance the image data by eliminating unintentional distortions or amplifying essential elements that are crucial for subsequent processing.

C. Feature Extraction using Curvelet Transform

The discrete curvelet transform is very effective in representing curve-like edges in the introduction part of the proposed model, where feature extraction from images is carried out using the curvelet transform method. In this study, we employ the wrapping method because it is faster than the USFFT, and as a result, wrapping-based FDCT is widely used. In general, the discrete curvelet transform can be expressed by:

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$$C^D(j,l,k)=\sum_{0\le x<M,0\le y<N} g[x,y].\varphi^D{}_{j,l,k} \quad (2)$$

Where, g[x,y] , $0\le x<M$, $0\le y<N$ is the 2-D input image,

$C^D(j,\ l,\ k)$ are the discrete curvelet coefficients, , is the curvelet basis function. j is the scale, l ∈[0,2π]is the orientation and k ∈ R is the location.

Curvelet transform is usually implemented in the frequency domain. Therefore, the above equation can be written in the frequency domain as,

Curvelet transform=IFFT{FFT(curvelet)×FFT(image)} (3)

D. Classification using CNN

A convolutional neural network classifies MRI brain pictures through several layers: a convolutional layer, a Softmax layer, and a fully connected layer. Feature extraction was followed by classification using the logistic regression approach, which is equivalent to the softmax layer of a CNN.

E. Efficiency Check

The performance analysis section can be used to verify the efficiency of equation (4), which provides the accuracy factor in this part. when the experimental result section's analysis of the minibatch accuracy, minibatch loss, and validation accuracy (4). By calculating the percentages of sensitivity, specificity, and precision, the effectiveness of a classification algorithm is assessed. The corresponding definitions are as follows. [6] This is depicted in picture 3.

$$Accuracy = TP{+}TN//TP{+}FP{+}TN{+}FN \quad (4)$$

$$Sensitivity(recall) = TP/\ TP{+}FN \quad (5)$$

$$Speficity = TN/TN{+}FP \quad (6)$$

$$Precision\ (PPV) = TP\ /TP{+}FP \quad (7)$$

Where,

True Positive (TP): Correctly classified positive cases.
True Negative (TN): Correctly classified negative cases.
False Positive (FP): Wrongly classified negative cases.
False Negative (FN): Wrongly classified positive cases.

The analysis result of the trained neural network is shown in Figure 3. The performance analysis of the trained neural network is presented below.

ANALYSIS RESULT

	Name	Type	Activations	Learnable Prope...
1	data	Image Input	227(S) × 227(S) × 3(C) × 1(B)	-
2	conv1	Convolution	55(S) × 55(S) × 96(C) × 1(B)	Weig... 11 × 11 × 3... Bias 1 × 1 × 96
3	relu1	ReLU	55(S) × 55(S) × 96(C) × 1(B)	-
4	norm1	Cross Channel Nor...	55(S) × 55(S) × 96(C) × 1(B)	-
5	pool1	Max Pooling	27(S) × 27(S) × 96(C) × 1(B)	-
6	conv2	Grouped Convolution	27(S) × 27(S) × 256(C) × 1(B)	Wei... 5 × 5 × 48 ... Bias 1 × 1 × 128...
7	relu2	ReLU	27(S) × 27(S) × 256(C) × 1(B)	-
8	norm2	Cross Channel Nor...	27(S) × 27(S) × 256(C) × 1(B)	-
9	pool2	Max Pooling	13(S) × 13(S) × 256(C) × 1(B)	-
10	conv3	Convolution	13(S) × 13(S) × 384(C) × 1(B)	Wei... 3 × 3 × 256... Bias 1 × 1 × 384
11	relu3	ReLU	13(S) × 13(S) × 384(C) × 1(B)	-
12	conv4	Grouped Convolution	13(S) × 13(S) × 384(C) × 1(B)	Wei... 3 × 3 × 192 ... Bias 1 × 1 × 192 ...
13	relu4	ReLU	13(S) × 13(S) × 384(C) × 1(B)	-
14	conv5	Grouped Convolution	13(S) × 13(S) × 256(C) × 1(B)	Wei... 3 × 3 × 192 ... Bias 1 × 1 × 128 ...
15	relu5	ReLU	13(S) × 13(S) × 256(C) × 1(B)	-
16	pool5	Max Pooling	6(S) × 6(S) × 256(C) × 1(B)	-
17	fc6	Fully Connected	1(S) × 1(S) × 4096(C) × 1(B)	Weigh... 4096 × 92... Bias 4096 × 1

Figure 4. Analysis of Trained Neural Network

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:30:44	20.00%	56.86%	2.1273	0.8103	1.0000e-04
1	20	00:33:06	40.00%	80.39%	1.6346	0.5176	1.0000e-04
2	40	00:34:51	90.00%	90.20%	0.2332	0.3553	1.0000e-04
3	50	00:35:43	90.00%		0.3306		1.0000e-04
3	60	00:36:40	90.00%	88.24%	0.2632	0.4116	1.0000e-04
4	80	00:38:27	100.00%	86.27%	0.1459	0.4646	1.0000e-04
5	100	00:40:04	100.00%	90.20%	0.0800	0.4103	1.0000e-04
6	120	00:41:39	100.00%	86.27%	0.0755	0.5504	1.0000e-04
7	140	00:43:18	100.00%	92.16%	0.1189	0.4287	1.0000e-04
8	150	00:44:02	90.00%		0.1809		1.0000e-04
8	160	00:44:51	90.00%	90.20%	0.2498	0.3527	1.0000e-04
9	180	00:46:24	100.00%	90.20%	0.0226	0.3497	1.0000e-04
10	200	00:48:00	100.00%	90.20%	0.0150	0.3605	1.0000e-04

Training finished: Max epochs completed.

Figure 5. Performance Analysis of the Trained Neural Network

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F. Output Comment

In this section, a comment on the output image is given with a cancerous and non-cancerous scope. An output is shown in the figure below:

V. EXPERIMENTAL RESULTS

Two MRI input images are used for the experiment. The input image in example 1 is not cancerous and has a low likelihood of scoring, but the input image in case 2 is cancerous and has a high probability of scoring. It is a classification problem; thus, we will use the softmax layer to convert these numbers into probabilities. The softmax layer will have two inputs and two outputs, which are the outputs of the activation layer. The classification layer only makes predictions based on likelihood; if the probability is greater than 0.5, it will select either Y2 or Y1.

1. Input Image

The input image is taken from the dimensions of 227*227 from the dataset, as shown in Figure 6.

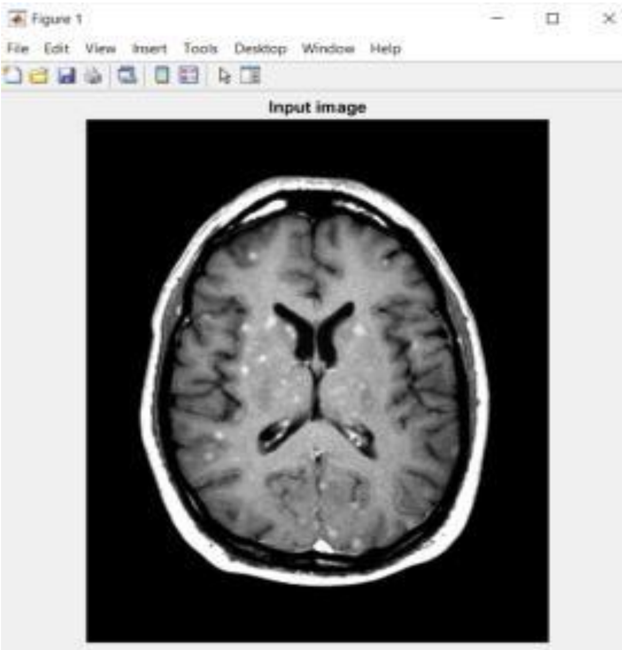

Figure 6. Input Image

2. Curvelet Images

To prevent any signal loss, these curvelets in the spatial domain are organised in various orientations (l) and scales (j), "coarser to finer," such that the whole FFT plane of the image is covered. Along with the FFT of a curvelet (shaded wedge) at scale four and orientation 5, there is a five-level curvelet digital tiling of an image. While other wedges provide comprehensive curvelet coefficients at scales j=2, 3, and 4, the centre square just provides approximation coefficients (at scale 1).

There are 16 different possible curvelet orientations at scale 2, 16 at scale 3, 32 at scale 4, and so on. To avoid using redundant information during the feature extraction step, the number of scales represents the resolution, which is necessary to select the essential sub-bands. Figures 2, 3, and 4 illustrate the extracted curvelet feature from the MRI brain image at various scales. As seen in figure 5, the final image with feature enhancements can also be displayed alongside the original image.

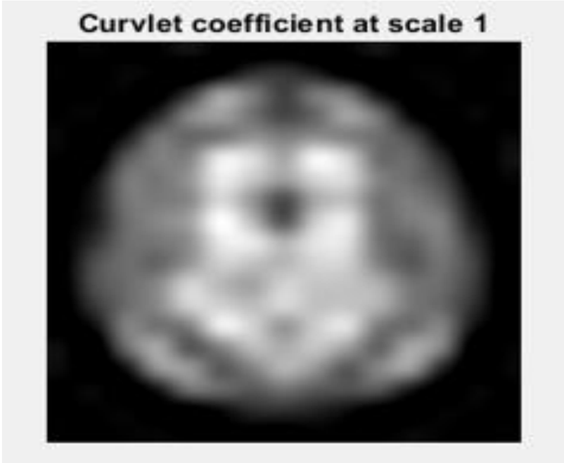

Figure 7. Curvelet Coefficient Image at Scale 1

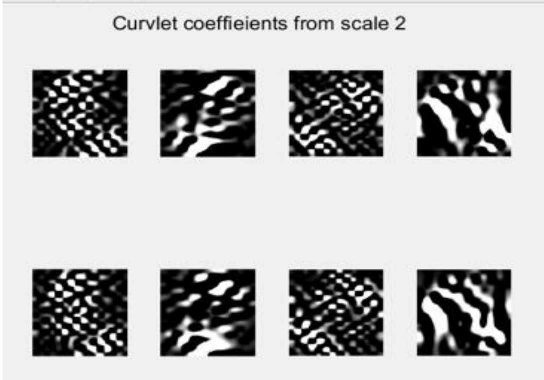

Figure 8. Curvelet Coefficient from Scale 2

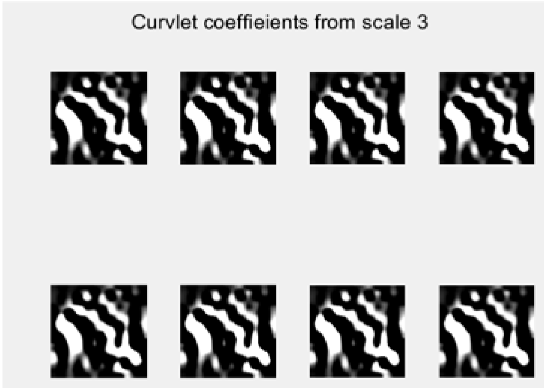

Figure 9. Curvelet Coefficient from Scale 3

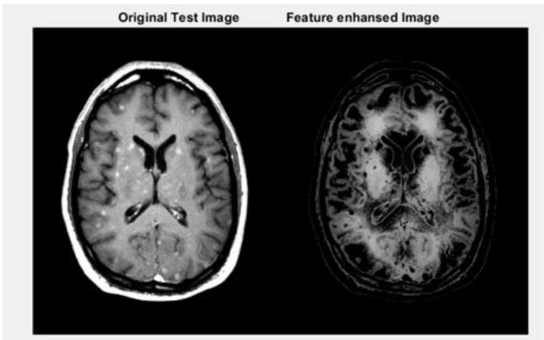

Figure 10. Feature Enhanced Image

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3. Disease Identification

This component determines whether an image contains a sickness or not by assigning a minimal probability value, as shown in Figure 8. The test and trial method approach can be used to demonstrate that this input MRI image is non-cancerous, as the threshold value of the image is less than the score of the test image, specifically less than 0.5 (the score is 0.5). Since it is a classification problem, we will use the softmax layer to turn these values into probabilities. Since there are two inputs, there will be two softmax layer outputs, which are activation layers.

$$P(y_i) = e_{\sum} k^{ey}{}_{e}{}^{i}{}_{yi} \quad (7)$$

Let y1 and y2 be the output of the completely connected layer. The classification layer simply forecasts the result based on the likelihood; if the probability is greater than 0.5, it will select either y2 or y1. In Case Study 1, the tested image is y2, with scores of 0.17045 and 0.82955, indicating that it is y2 82.9% of the time. If y1 is malignant and y2 is not

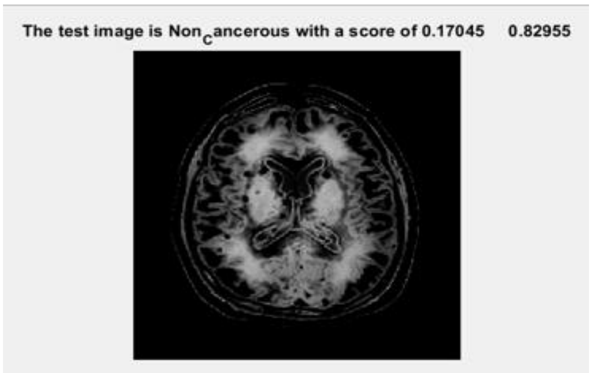

Figure 11. Tested/ Output Image

4. Performance Analysis

The variation in iteration and accuracy can be used to determine the accuracy factor in this part. The variation in learning rate and accuracy is displayed in Figures 9 through 10, along with a plot between them. Table 2 shows the 100% mini-batch accuracy with the minimum loss as the number of iterations increases.

Table 2. Variation of Iterations vs. Accuracy Table

S. No.	Iterations	Mini-batch accuracy	Validation accuracy	Mini batch loss
1	1	20.00%	64.71%	3.0788
2	100	35.00%	82.35%	1.1394
3	200	58.00%	82.35%	0.2176
4	300	83.00%	92.00%	0.4133
5	400	100.00%	92.16%	0.0486

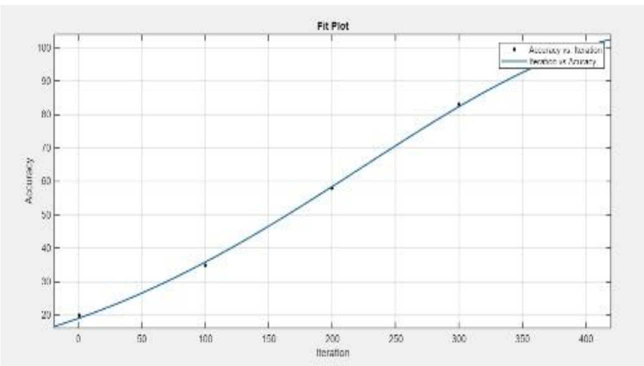

Figure 12. Variation of Iteration vs. Accuracy Plot

The above graph shows that accuracy increases with the number of iterations and yields a good result at the maximum number of iterations. Table 3 presents the maximum accuracy achieved with varying learning rates.

Table 3. variation of learning rate vs. accuracy table

S. No.	Learning Rate	Accuracy
1	0.1	50.78%
2	0.01	60.88%
3	0.001	78.43%
4	0.0001	88.20%
5	0.00001	90.24%

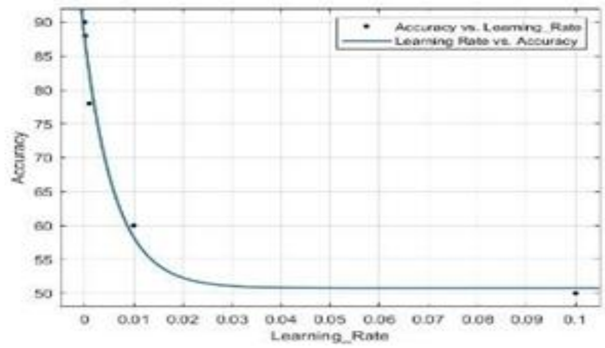

Figure 13. Variation of Learning Rate vs. Accuracy Plot

B. Case Study 2.

1. Input Image

The input image is taken from the dataset, with dimensions of 630x630, as shown in Figure 11.

Figure 14. Input Image for Case Study 2

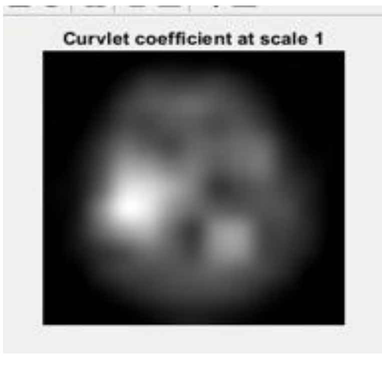

Figure 15. Curvelet Coefficient Image at Scale 1

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2. Curvelet Image

Curvelet is an extension of the wavelet concept. When the image is taken, the curvelets provide a representation that is considerably sparser than other wavelet transforms. By this curvelet transform algorithm, the input image is shown as a feature-enhanced image, as shown in Figure 7. This can be achieved by using the three scales of curvelet coefficients, as shown in Figures 4, 5, and 6.

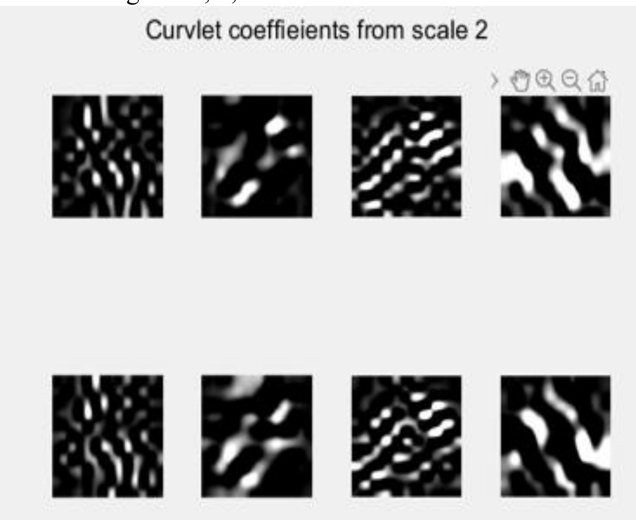

Figure 16. Curvelet Coefficient Image at Scale 2

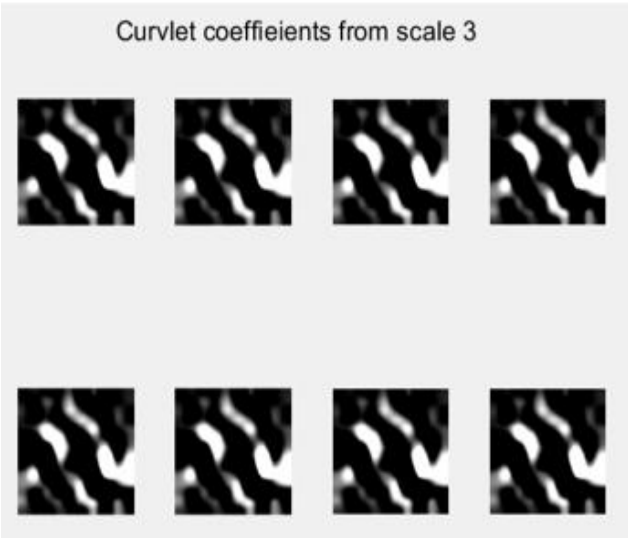

Figure 17. Curvelet Coefficient Image at Scale 3

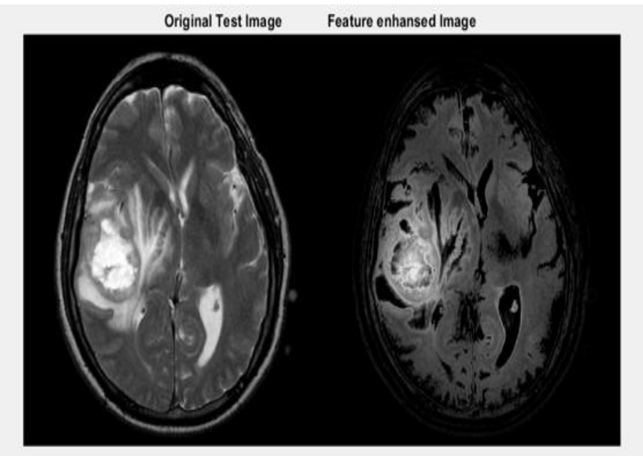

Figure 18. Feature Enhanced Image

3. Disease Identification

This component determines whether an image is cancerous or not by assigning a minimal probability value, as seen in Figure 8. The maximum score of the probability value is shown in Figure 12. This can be demonstrated by the test and trial method, as well as research, which shows that the threshold value of the image is greater than the score of the test image, i.e., it is greater than 0.5 (score ≥ 0.5). Therefore, this input MRI image is likely to be cancerous. Since it is a classification problem, we will convert these numbers into probabilities by using a softmax layer. For two inputs, there will be two outputs from the softmax layer, which is an activation layer.

$$P(y_i) = \frac{e^{y_i}}{\sum_k e^{y_k}} \quad (8)$$

Let the output of the fully connected layer be y_1 and y_2

The classification layer predicts the output according to the probability; if the probability is greater>0.5, it will choose y_2 or else y_1. Therefore, in case study 2, the tested image is y_1 with scores 0.91854 and 0.081456,

It means 91.8% it is y_1

Where, y_1 is cancerous

y_2 is non-cancerous

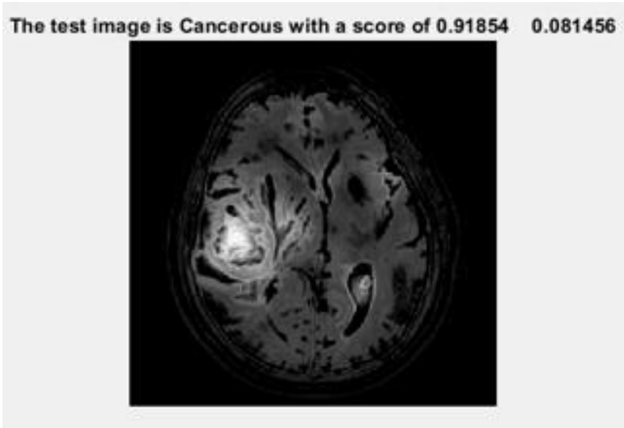

Figure 19. Tested or Output Image

4. Performance Analysis

In this section, we can calculate the accuracy factor by the variation in iteration and accuracy, and next, the variation of learning rate and accuracy as shown by the table and plot between them, respectively, in the following figure 13, and figure 14 and Tables 4 and 5.

Table 4. Variation of Iteration vs. Accuracy Table

S. No.	Iterations	Mini-batch accuracy	Validation accuracy	Mini batch loss
1.	1	80.00%	52.94%	0.7972
2.	100	100.00%	92.16%	0.0134
3.	200	100.00%	96.08%	0.1423
4.	300	100.00%	94.00%	0.0039
5.	400	100.00%	94.16%	0.0412

The above table shows 100% mini-batch accuracy with the minimum loss as the number of iterations increases.

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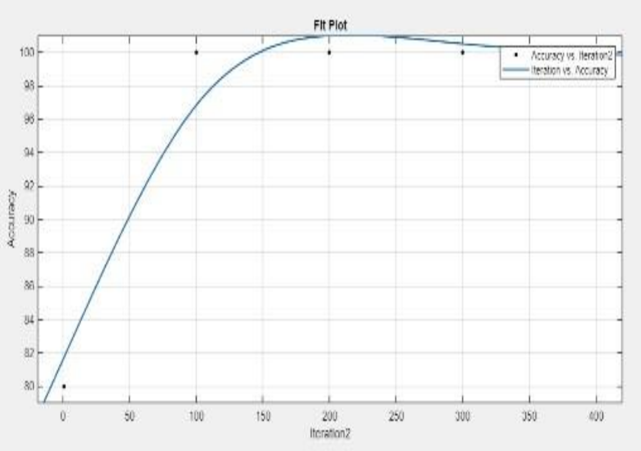

Figure 20. Iteration vs Accuracy Plot

The above graph shows that accuracy increases with the number of iterations and yields a good result at the maximum number of iterations. The Table 5. shows the maximum accuracy with varying learning rates.

Table 5. Learning Rate vs Accuracy

S. No.	Learning rate	Accuracy
1	0.1	50.78%
2	0.01	60.88%
3	0.001	78.43%
4	0.0001	88.20%
5	0.00001	90.24%

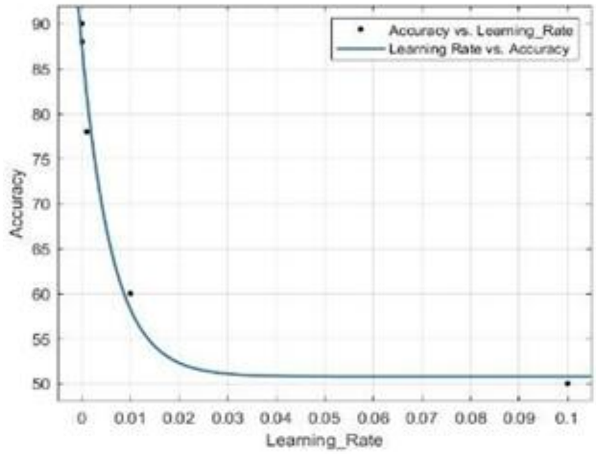

Figure 21. Variation of Learning Rate vs. Accuracy.

VI. COMPARISON TABLE

In this section, the proposed CNN and curvelet algorithm are compared with the existing CNN and k-means algorithm. Table 5 compares the epoch and mini-batch losses, showing that the result obtained from the proposed algorithm is better than that of the existing algorithm.

Table 6. Comparison Table with Existing Technique

S. No	Research work	Technique	Epoch	Mini-batch accuracy	Mini batch loss
1.	CNN-based image classification and detection of abnormalities in MRI brain images [1]	CNN+k-means algorithm	100	100	0.1088
2.	Proposed Model	CNN+curvelet transform	10	100	0.0412

VII. CONCLUSION

The suggested method has been successfully implemented. This study employs a transfer learning technique and a CNN and curvelet transform approach. The sickness can be located, and the outcome is available. The proposed algorithm outperforms existing algorithms and performs well in detecting cancer in MRI brain images, as indicated by the experimental results and comparisons. According to the data, this provides 100% accuracy with a low loss factor.

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