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Design of Intelligent Technique for Abnormality Detection in MRI Brain Images

Farha Anjum Mansoori, Agya Mishra

Abstract: This paper presents an intelligent technique particularly for MRI brain images. This introduces a clever method designed specifically for MRI brain pictures. To determine the abnormality in the brain images is processed using intelligent hybrid method of convolution neural networks and curvelet transform. 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 how well model- and parameter-based analysis performs. The topic of minimum batch accuracy and validation accuracy, which are then contrasted with the current method, comes to a conclusion in the paper. This concept is suited to ongoing MRI image analysis activities. In this paper, previous paper has also be reviewed and their method is investigated.

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

I. INTRODUCTION

Medical imaging describes a variety of procedures that can be utilised as minimally invasive ways to view within the body. Medical imaging includes several image modalities and procedures to image the human body for treatment and diagnostic purposes, and as a result, medical imaging plays a crucial and important part in determining what steps should be taken to improve people's health. A Bain 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 have a negative impact on 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 may be accomplished using two different CNN methods: feed forward classification and back propagation learning, and curvelet transform is used to extract the features of an MRI brain picture. The CNN network, which consists of the convolution classification layer, the fully connected layer, and the 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 by, is a machine learning technique where we reuse a pre-trained model as the model's starting point for the new assignment. 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

In the table below, there is a qualitative comparison for the identification of diseases using biomedical images. The results of the following table show that several illness detection techniques have been used. Here previous research work on the brain image MRI testing has been done and 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 images ckassification and detection of abnormalities in mri brain images [1]	CNN, K-MEANSALGORITHM	Accuracy mini batch loss	Brain tumor	High accuracy during 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 tumor detection [3]	CNN	Accuracy 93% loss value 0.23264	Brain tumor	More convolutional layer increase the accuracy	More time for training
4	Brain tumor detection using convolutional neural network [4]	Cnn, fcm, svm	Accuracy is 97% high	Brain tumor	Complexity is low	
5	Mri-based tumor image detection using cnn based deep learning method [5]	Cnn deep learning	Accuracy 99%	Brain tumor		
6	Classification of brain tumor types by deep learning with 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 tumor in MRI images utilizing transfer learning in xception model [7]	CADe xception model	High accuracy	Brain tumor		
8	Segmentation and detection of tumor in MRI images using CNN and SVM classification [8].	CNN,SVM	Mean-2.438 SD-1.0122	Brain tumor	Best technique for efficient class of data	Complex and force ranges

III. CONCEPT/ METHODS

A. Classification

The convolutional neural network processed the classification of MRI brain images can done by the convolutional neural network, and this can be perform by the two phases of CNN, which is the training and the testing of images. The convolutional neural network consists of 25 layers in alexnet out of which we can use last 3 layers in this study paper. The last three layers are as classification output layer, the fully connected layer and the last is softmax layer. In this method we can take the input images and passed through the filters and get the classified output with the different channel. For the image classification we can use 3 colored channel for RGB image and filter can be dependent on the channels. CNN is a powerful image processing, computing method that use deep learning. The CNN based brain tumor classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as cancer and non-cancer brain image… etc. In the training phase, pre-processing, feature exaction and classification with Loss function is performed 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 Gabor filter and wavelet transform's drawbacks are addressed by the curvelet 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 different Computer Vision methods in addition to CNNs. A small number matrix, referred as 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.

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

IV. PROPOSED MODEL

The suggested model system is displayed in figure 1 above. MRI scans from the Kaggle.com input image dataset are the proposed system. These pictures were divided into two groups: malignant and unimportant. 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 used for this. 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 how different variables relate to one another. 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 like artificial neural networks and reinforcement learning models, can be used with this technique. The block diagram of the proposed model is shown below.

Figure 1. Block Diagram of The Proposed Model

Flow chart of the proposed model is shown below:

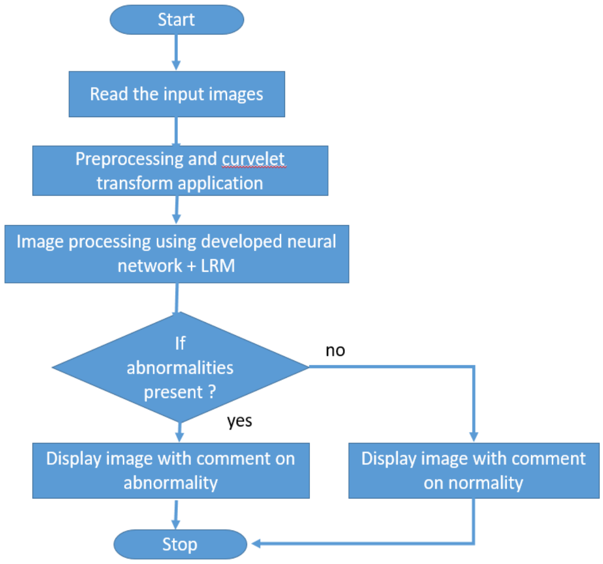

Figure 2. Flow Chart of the Proposed Model

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 includes 251 photos divided into two categories, yes and no, which each comprise 98 brain MRI images that are not malignant and 154 images that are. the sample images of data set is shown in figure 3.

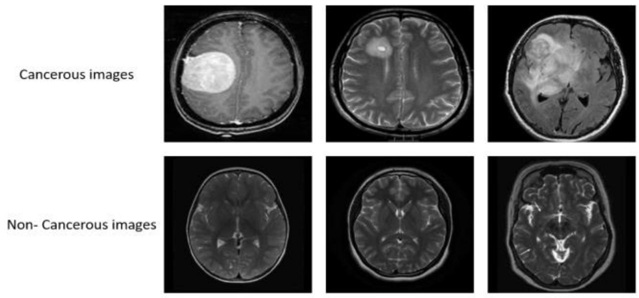

Figure 3. Training Dataset

B. Pre-processing

In order to improve the image quality, we try to analyse the image while using noise reduction and image enhancement algorithms. Pre-processing is intended to improve the image data by suppressing unintentional distortions or enhancing additional 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 use the wrapping method because it is faster than USFFT and as a result, wrapping based FDCT is widely used. In general, 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 $\in$[$0,2\pi$]is the orientation and k $\in$ R is the location.

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

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

D. Classification using CNN

The several layers of a convolutional neural network classify MRI brain pictures. Convolutional layer, Softmax layer, and completely connected layer. Feature extraction was followed by classification using the logistic regression approach, which is the softmax layer of CNN.

E. Efficiency Check

The performance analysis section can be used to check the efficiency from 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 accuracy, 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.

Analysis result of trained neural network is shown in figure 3, Performance analysis of the trained neural network is shown below.

Figure 4. Analysis of Trained Neural Network

```
Training on single CPU.
Initializing input data normalization.
|==========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      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 turn these numbers into probabilities. The softmax layer will have two inputs and two outputs, which are 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.

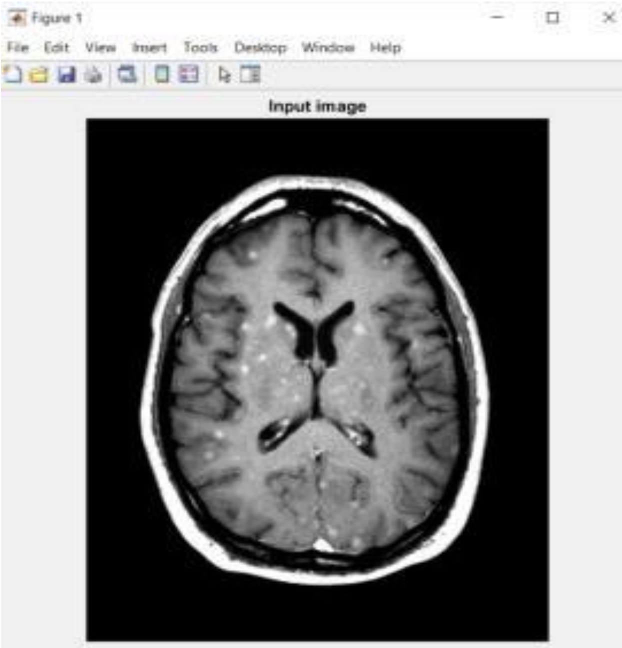

Figure 6. Input Image

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 FFT of a curvelet (shaded wedge) at scale 4 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. In order to avoid using redundant information during the feature extraction step, the number of scales represents resolution, which is necessary to choose the important sub bands. Figures 2, 3, and 4 illustrate the extracted curvelet feature from the MRI brain image in various scales. As seen in figure 5, the final image with feature enhancements can also be displayed alongside the original image.

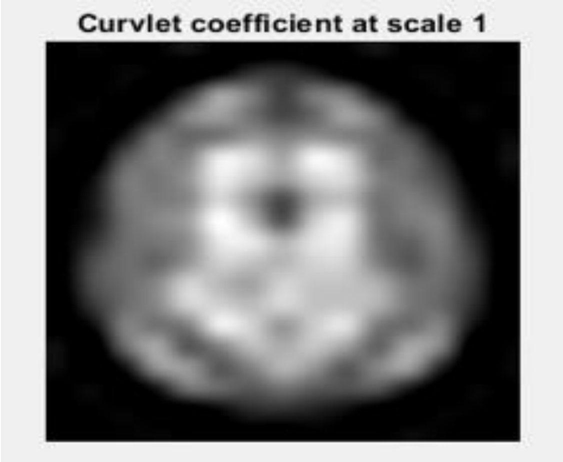

Figure 7. Curvelet Coefficient Image at Scale 1

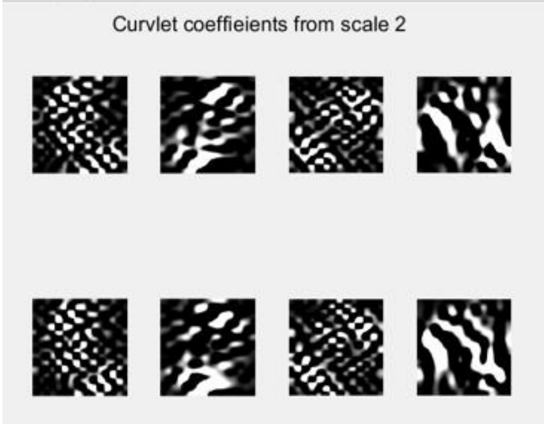

Figure 8. Curvelet Coefficient from Scale 2

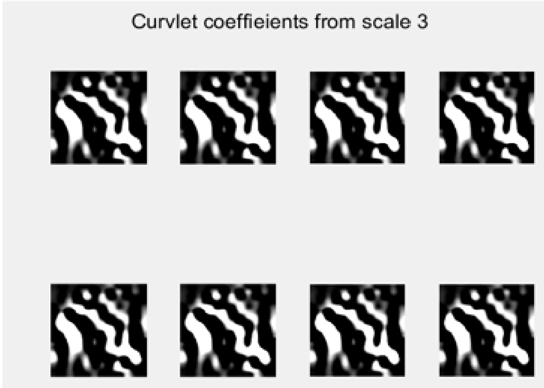

Figure 9. Curvelet Coefficient from Scale 3

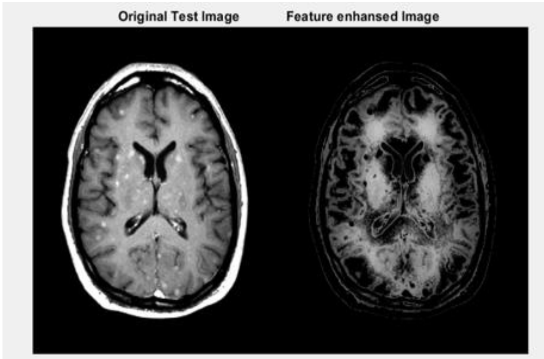

Figure 10. Feature Enhanced Image

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3. Disease Identification

This component determines whether an image has a sickness or not by assigning a minimal probability value, as seen in figure 8. The test and trial method approach can be used to demonstrate that this input MRI image is non-cancerous since the threshold value of the image is less than the score of the test image, that is, less than 0.5 (score0.5). 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, which indicates that 82.9% of the time, it is y2. If y1 is malignant and y2 is not

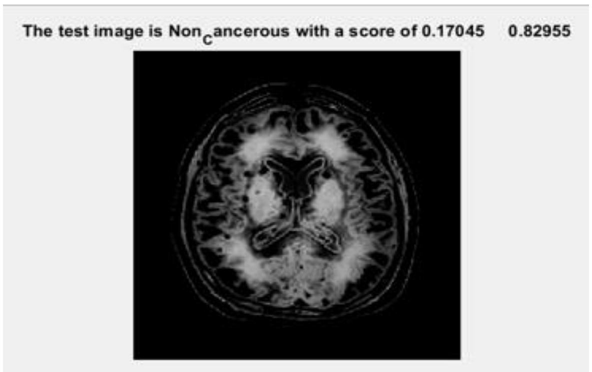

Figure 11. Tested/ Output Image

4. Performance Analysis

The variation in iteration and accuracy can be used to determine the accuracy factor in this part, and the variation in learning rate and accuracy is displayed in the following figures 9 through 10 and a plot between them. Table 2. shows the 100% mini batch accuracy with the minimum loss with increasing in iterations.

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

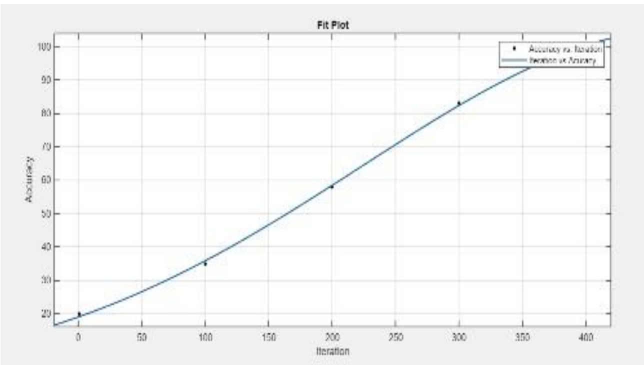

Figure 12. Variation of Iteration vs. Accuracy Plot

The above graph shows the increasing in iterations the accuracy will be change and gives good result in maximum iterations. The Table 3 shows the maximum accuracy with the changing in learning rate.

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%

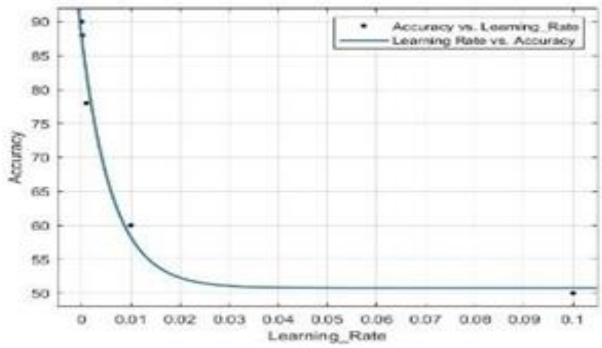

Figure 13. Variation of Learning Rate vs. Accuracy Plot

B. Case Study 2.

1. Input Image

The input image is taken from the dimensions of 630*630 from the dataset as shown in figure 11.

Figure 14. Input Image for Case Study 2

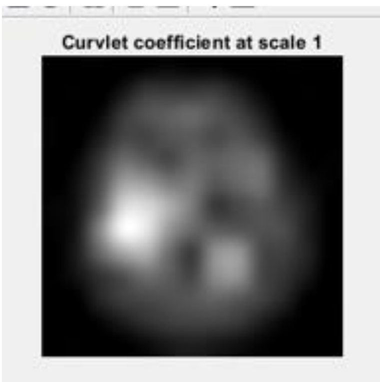

Figure 15. Curvelet Coefficient Image at Scale 1

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2. Curvelet Image

Curvelet is an extension of 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 sh0ow the feature enhanced image as shown in figure 7. this can be done by the three scale of curvelet coefficient, as shown in figure 4,5,6.

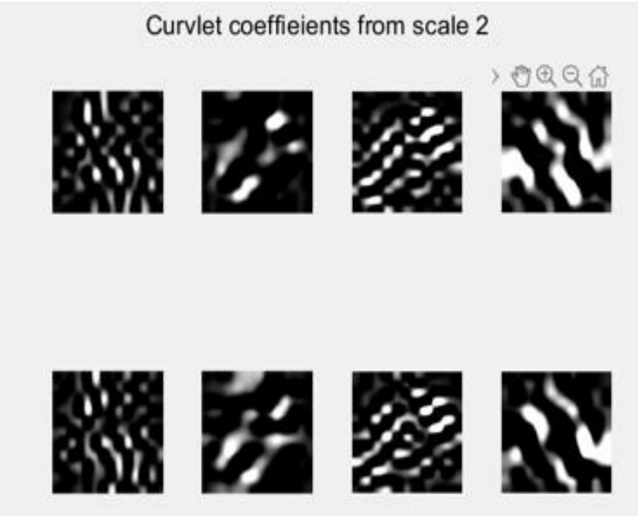

Figure 16. Curvelet Coefficient Image at Scale 2

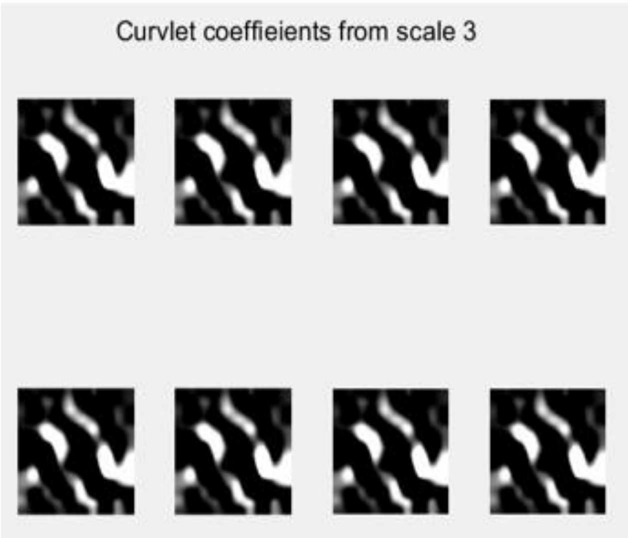

Figure 17. Curvelet Coefficient Image at Scale 3

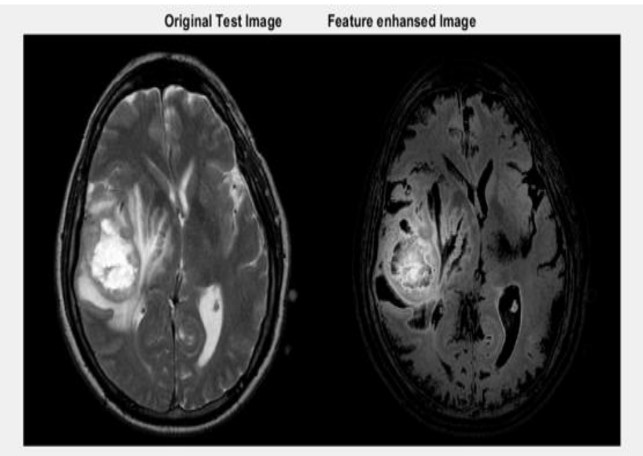

Figure 18. Feature Enhanced Image

3. Disease Identification

This component determines whether an image has a sickness or not by assigning a minimal probability value, as seen in figure 8. cancerous, with a maximum score of probability value as shown in figure 12. This can be shown in result by the test and trial method and as per research that the threshold value of image is more than the score of test image i.e., greater than 0.5 (score≥0.5) therefore this input MRI image is cancerous. since, it is a classification problem we will convert these numbers into probabilities by using softmax layer for 2 input there will be 2 outputs of softmax layer it is activation layer.

$$P(y_i) = e_{\sum} k^{e^{y}} {}_{e}{}^{i}{}_{y_i} \quad (8)$$

Let the output of fully connected layer is y_1 and y_2

The classification layer just predict the output according to the probability, if probability is (>0.5) it will choose y_2 or else y_1 . Therefore in case study 2 the tested image is y_1 with score 0.91854 and 0.081456,

It means 91.8% it is y_1

Where, y_1 is cancerous

y_2 is non-cancerous

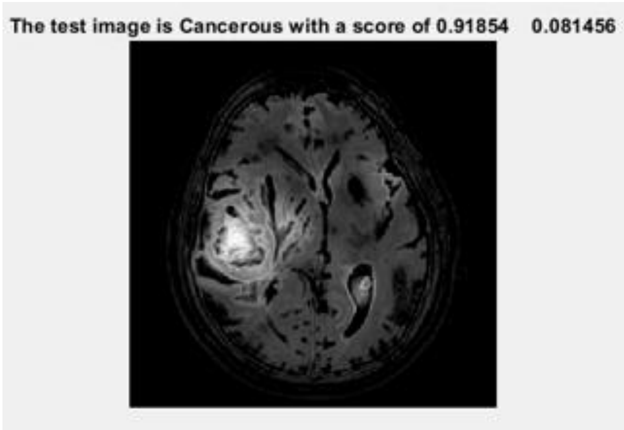

Figure 19. Tested or Output Image

4. Performance Analysis

In this section we can calculate the accuracy factor by the varation in iteration and accuracy and in next the variation of learning rate and accuracy as shown by table and plot between them, respectively in the following figure 13, figure 14 and Table 4, table 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 the 100% mini batch accuracy with the minimum loss with increasing in iterations.

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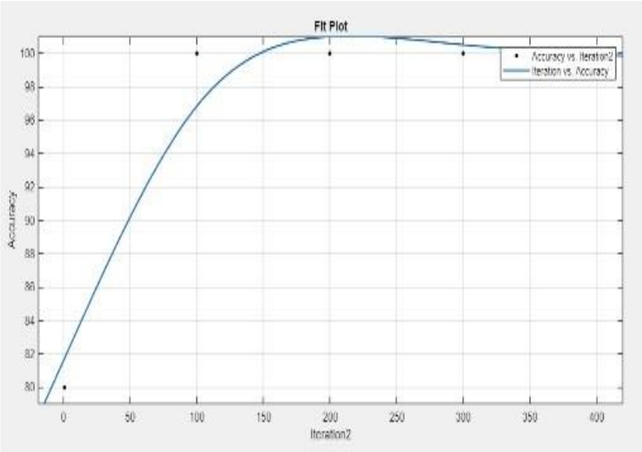

Figure 20. Iteration vs Accuracy Plot

The above graph shows the increasing in iterations the accuracy will be change and gives good result in maximum iterations. The Table 5. shows the maximum accuracy with the changing in learning rate.

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%

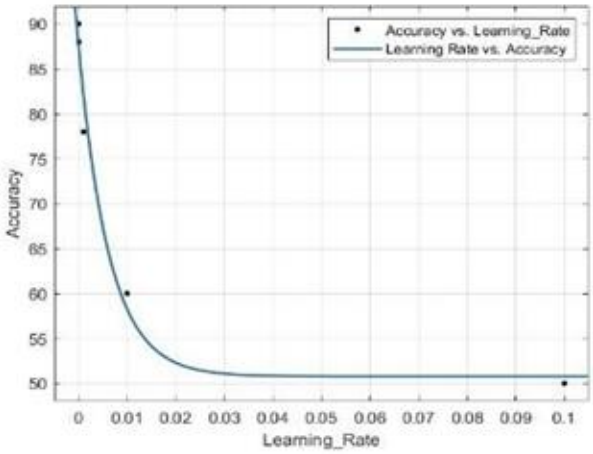

Figure 21. Variation of Learning Rate vs. Accuracy.

VI. COMPARISON TABLE

In this section, the proposed CNN and curvelet algorithm is compared with the existing CNN and k-means algorithm. Table 5 compares the epoch and mini batch loss and shows that the result obtained from the proposed algorithm is better as compared to 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 put into practise successfully. 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 suggested algorithm outperforms existing algorithms and is quite good in detecting cancer in MRI brain pictures, according to the experimental results and comparison with them. According to the data, this provides 100% accuracy with a low loss factor.

DECLARATION

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