CREATION OF AN INTELLIGENT MODEL FOR MRI IMAGE ABNORMALITY DETECTION

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ABSTRACT

This study introduces a clever method designed specifically for MRI brain pictures. Convolution neural networks and curvelet transform are used in an intelligent hybrid processing technique to identify abnormalities in brain pictures. Feature extraction, the logistic regression method (LRM), and learning algorithms are all used in the proposed model. Also, the categorization system identifies cancerous or non-cancerous tumours in the pictures 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.

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

I. INTRODUCTION

A brain tumour is an unchecked tumour development of cancer cells in the brain area of the body [1]. The brain is the main control centre of the body, and as we can see from a number of literary works, an increase in cells can cause pressure on the skull and adverse health effects. Moreover, there are other methods for finding brain tumours. using CNN as opposed to another strategy. In this study, we investigate if the massive CNN network can classify pictures on its own to find any cancer in the provided MRI brain scans. CNN network is capable of classifying and segmenting MRI images, proving that it is a well-organized method for processing medical pictures. The deep learning method known as CNN [convolutional neural network] is used to classify pictures and address the issue of data complexity. This may be accomplished using two different CNN methods: feed forward classification and back propagation learning [3], and curvelet transform technique 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 pictures 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 is a machine learning technique where we start a model on the new task using a previously trained model, according to [9]. 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. CONCEPT / THEORY

A. Classification

The categorization of MRI brain pictures may be carried out by the convolutional neural network, and this can be done by the two phases of CNN: the training and testing of images. Alexnet's convolutional neural network has 25 layers, of which we may use the final three for our study. The completely linked layer, the softmax layer, and the classification output layer make up the last three layers. With this technique, we may use the input photos to produce the filtered output using a variety of channels. We may utilise a three-colored channel RGB picture for image categorization, and the channels can influence the filter. CNN is an effective deep learning-based image processing and computation technology. The CNN-based categorization of brain tumours is split

into two stages, such as the training and testing phases. Using labels with names like "brain picture" and "cancer and non-cancer brain image," etc., the number of images is sorted into several categories. To create a prediction model, preprocessing, feature excision, and classification using the Loss function are carried out in the training phase.

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 comprehensive coverage of the spectral domain and to gather additional orientation data, the curvelet transform has been created. As the curvelet transform encompasses the whole frequency spectrum, there is no information loss while using it. The initial method of the curvelet transform is the discrete ridgelet transform
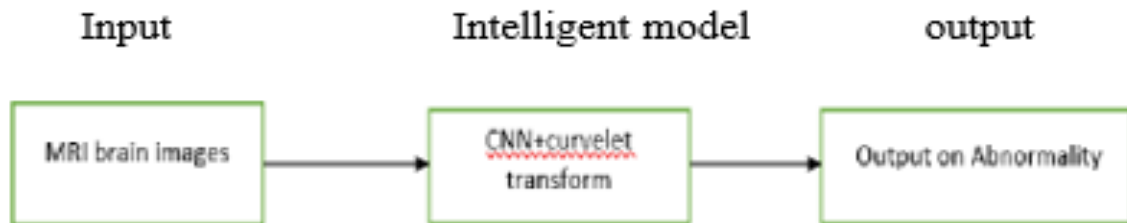

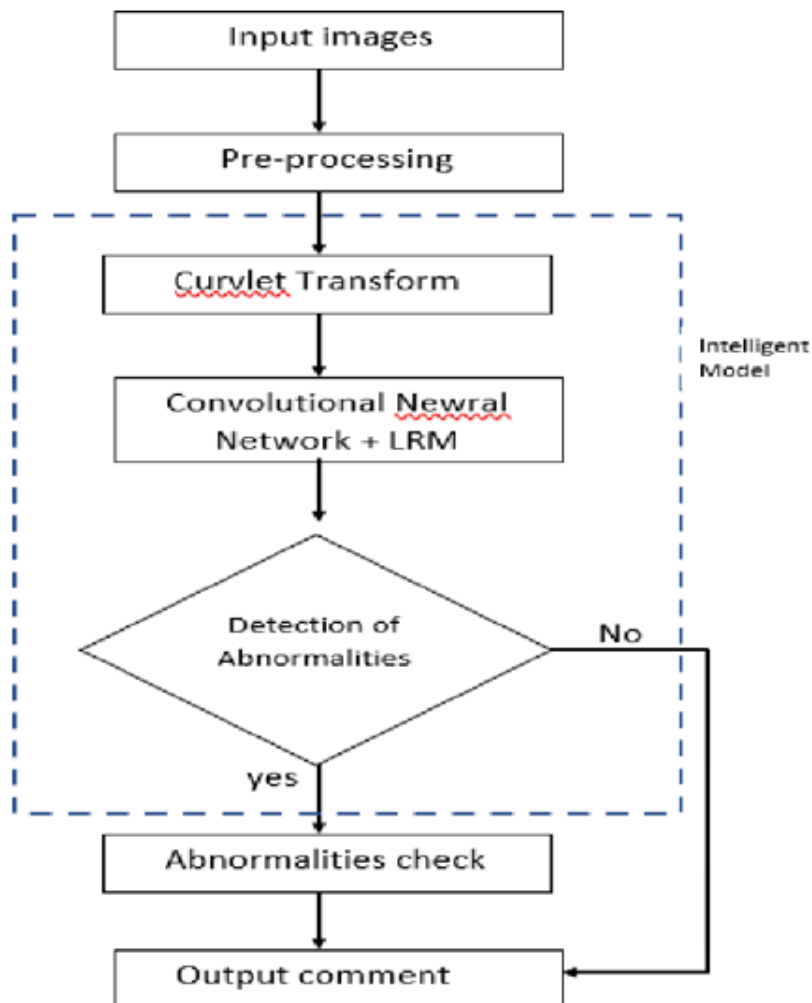**Figure 1:** Proposed model

III.   PROPOSED MODEL

Figure 2: Flow chart of 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 photos were divided into two categories. classifications of malignant and unimportant. In comparison to the publication [1], we obtained a 100% accuracy validation and small batch accuracy result using the suggested technique with little loss and time. The LRM approach can be used for this. Based on various 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 analyzes relationships between variables. It assigns probabilities to discrete outcomes using the Sigmoid function, which converts numerical results into an expression of probability between 0 and 1.0 . For this study, we can divide the images into two groups with a cut-off of 0.5. Everything above 0.5 is considered to belong to cancerous, and everything below is considered to belong to non-cancerous .this can be set the threshold value. Transfer learning is a research problem in machine learning that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem this technique is applicable to many machine learning models, including deep learning models like artificial neural networks and reinforcement model.

Classification

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.

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 picture data by suppressing unintentional distortions or enhancing additional elements that are crucial for subsequent processing.

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:

$$C^D(j,l,k) = \sum_{0 \le x < M, 0 \le y < N} g[x,y].\varphi^D_{j,l,k} \tag{1}$$

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

$C(j, l, k)$ 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)} (2)

Cassification using CNN

Classification of MRI brain images is done by the different layers of convolutional neural network. The Softmax layer ,fullyconnected layer and convolutional layer. After the feature extraction , classification had been done to adopt the classifierare logistic regression method it is the softmax layer of CNN.

Efficiency check

The performance analysis section may be used to assess the efficiency from equation (2), 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] Figure 3 can be used to display this..

$$Accuracy = TP+TN//TP+FP+TN+FN \tag{3}$$

$$Sensitivity(recall) = TP/TP+FN \tag{4}$$

$$Speficity = TN/TN + FP \qquad (5)$$

$$Precision \ (PPV) = TP \ / TP + FP \qquad (6)$$

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

Accuracy	Precision	Recall	F1_Score	Specificity
94.117 %	0.9677	0.9375	**0.9524**	0.9474

Figure 3: performance of proposed algorithm

Output Comment

In this section of paper if the image is detected non the abnormality in abnormality check box which can be cancerous the it will go to directly output commemt for the shown in experimental result.

IV. EXPERIMENTAL RESULTS

Two MRI input pictures are used for the experiment. The input picture in example 1 is not malignant 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. By using the experiment's accuracy and threshold value, the mri picture in rgb in both case studies is used to diagnose the illness. For testing and training purposes, data may be collected from the Kaggle.com dataset. This is demonstrated by the CNN network's training development, as illustrated in figure 3.
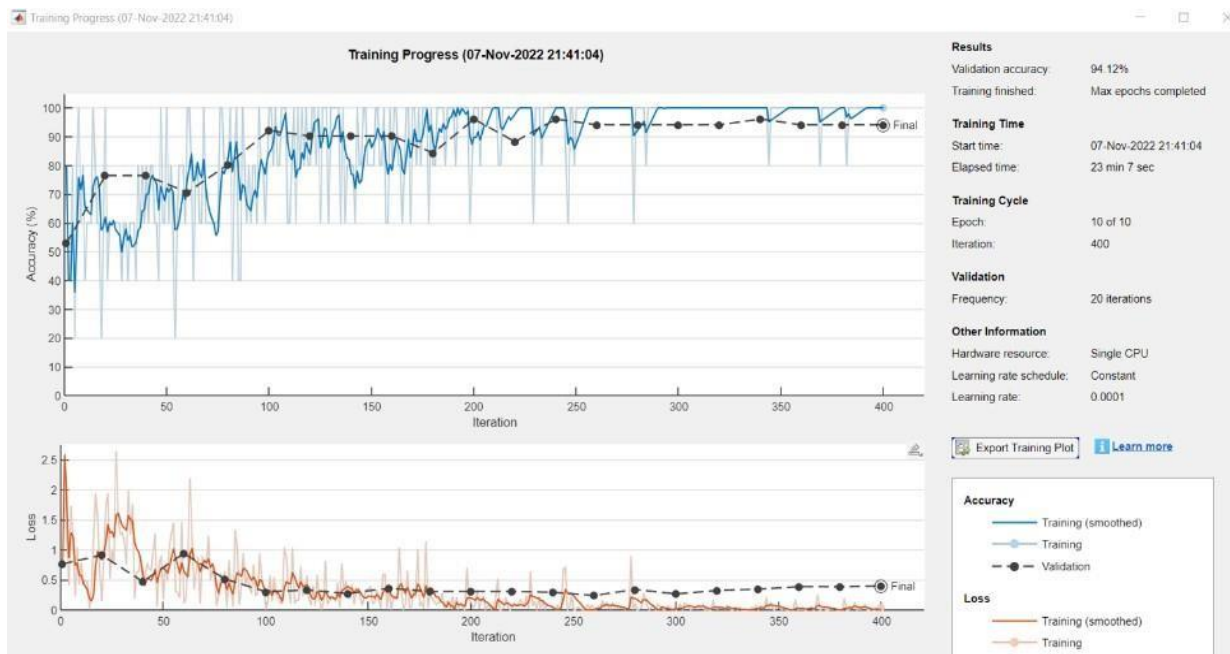

Figure 4: Training and learning plot of study case 1 and 2

CASE STUDY 1.

1. Input image

The input image is taken from the dimensions of 227*227 from the datasetas shown in figure 4.
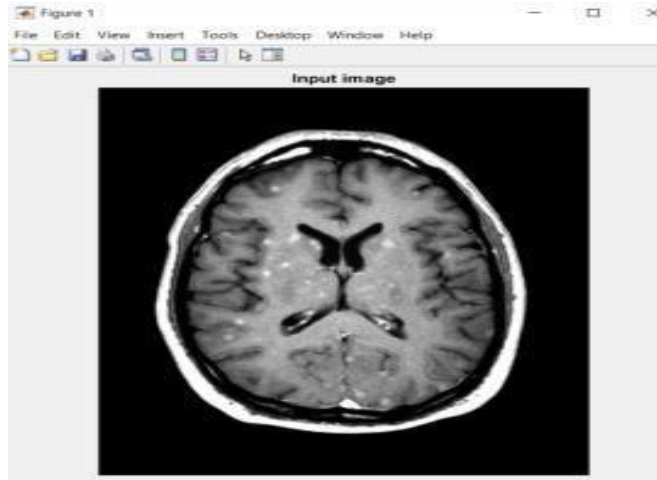
Figure 5: Input image

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 picture is covered. Together with FFT of a curvelet (shaded wedge) at scale 4 and orientation 5, there is a five level curvelet digital tiling of an image. Although other wedges provide comprehensive curvelet coefficients at scales j=2, 3, and 4, the centre square just provides approximation coefficients (at scale 1).

At scale 2, there are 16 possible curvelet orientations at scale 3 these are 16, at scale 4 these orientations are 32 and on....
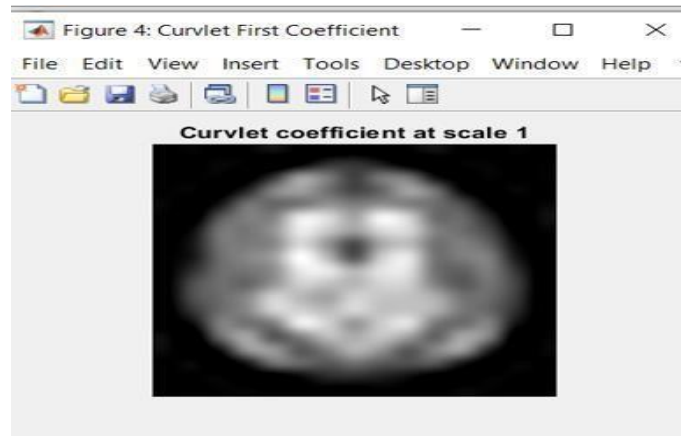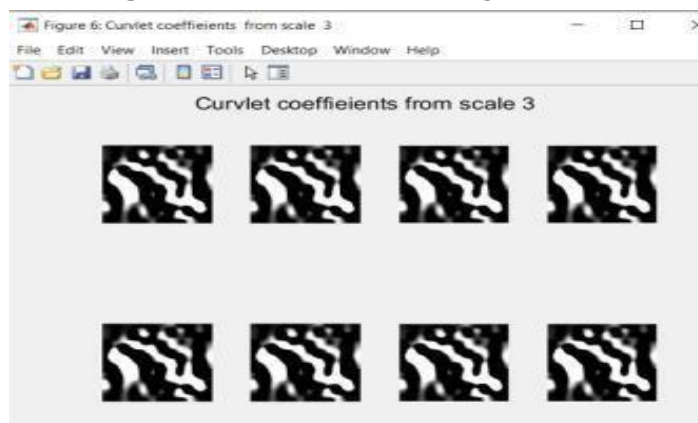

Figure 6: curvelet coefficient image at scale 1

Figure 7: curvelet coefficient image at scale 3
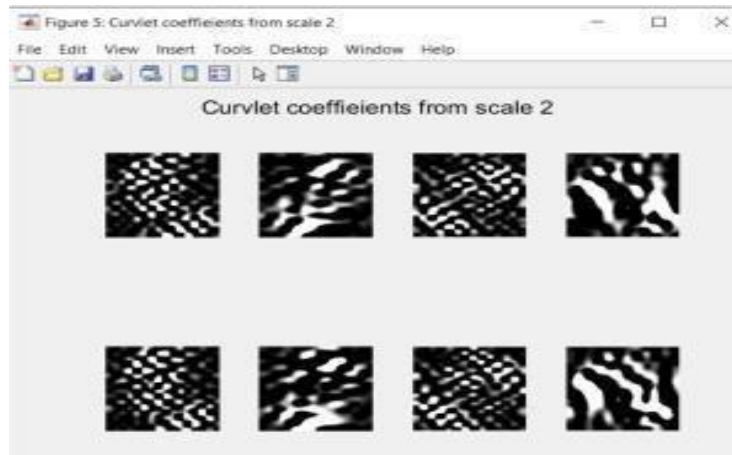
3. Disease Identification

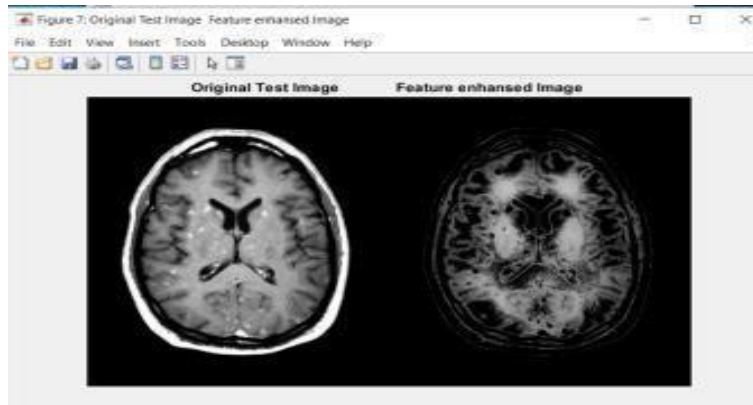**Figure 8:** Curvelet coefficient image at scale 2

Figure 9: feature enhanced image

This component determines whether a picture has a sickness or not by assigning a minimal probability value, as seen in figure 8. The test and trial method approach may 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). As it is a classification issue, 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.

$$P(y_i) = e \sum k \frac{e^{y_i}}{e^i} y_i \qquad (7)$$

Let the output of fully connected layer is $y1$ and $y2$

The classification layer just predict the output according to the probability, if probability is (>0.5) it will choose $y2$ or else $y1$. Therefore in case study 1 the tested image is $y2$ with score 0.17045 and0.82955,

It means 82.9% it is $y2$

Where, $y1$ is cancerous

$y2$ is non cancerous

Figure 10: Tested or output image

4. PERFORMANCE ANALYSIS

1. In this section we can calculate the accuracy factor by the varation in iteration and accuracy and in nextthe variation in learning rate and accuracy is shown by table and plot between them ,respectivelyas shown in following figures 9 ,figure 10 andtable1,table2

Table 1: 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

The above table shows the 100% mini batch accuracy with theminimum loss with increasing in iterations.
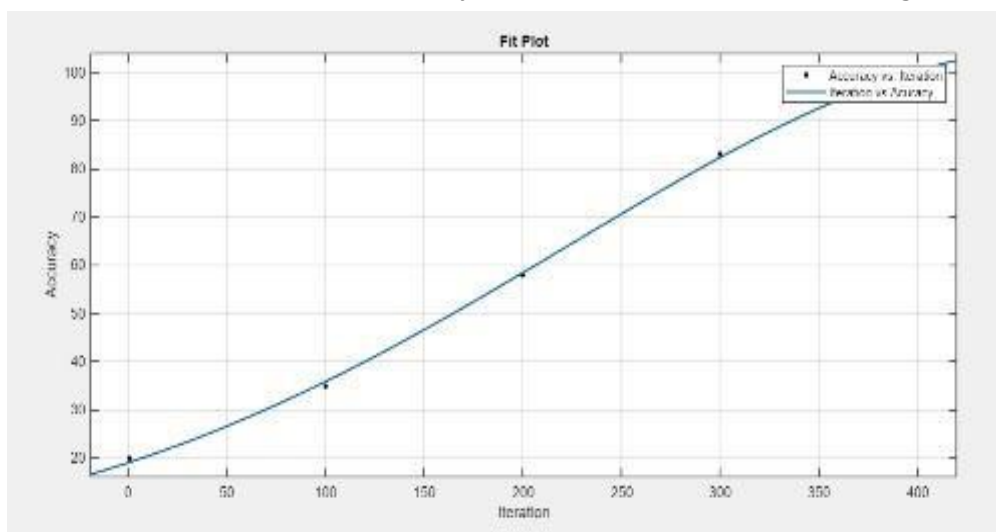

Figure 11: variation of iteration vs. accuracy plot

The above graph shows the increasing in iterations the accuracy will be change and gives good result in maximum iterations.

Table 2: variation of learning rate vs. accuracy table

S.NO.	LEARNINGRATE	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%

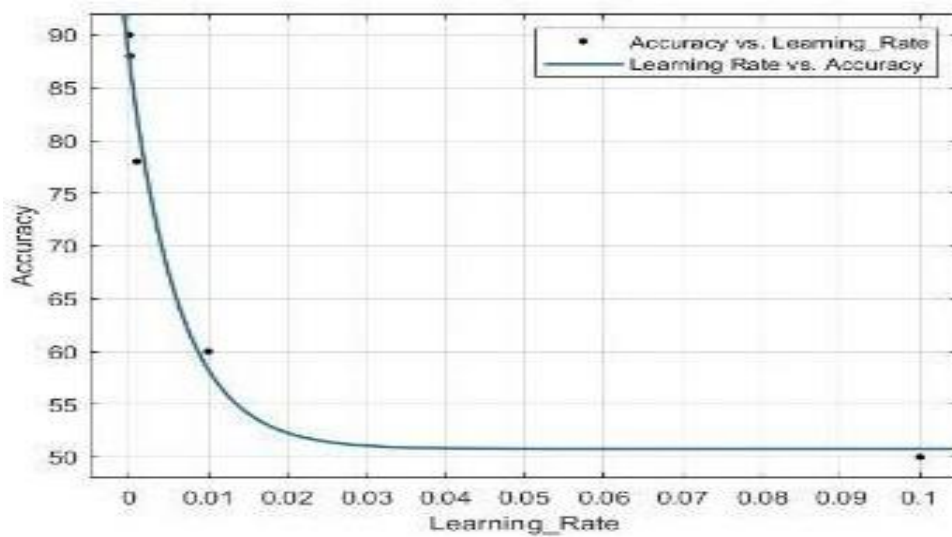The above table shows the maximum accuracy with the changing in learning rate.

Figure 12: variation of learning rate vs. accuracy plot

CASE STUDY 2

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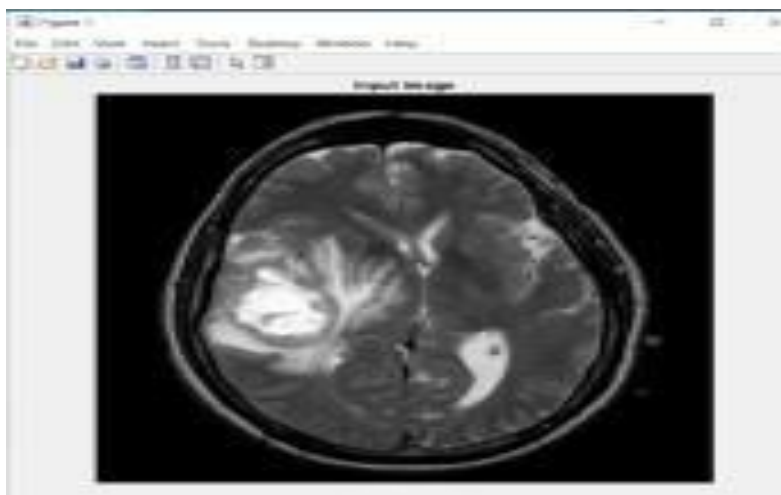

Figure 13: input image

Curvelet image: The wavelet notion is expanded upon by the curvelet. Curvelets offer a representation of the picture that is much sparser than that of conventional wavelet treatments. The input image is transformed using the curvelet transform technique to produce the feature-enhanced image in figure 7. The three scales of the curvelet coefficient, as illustrated in figures 4,5, and 6, can be used to achieve this.
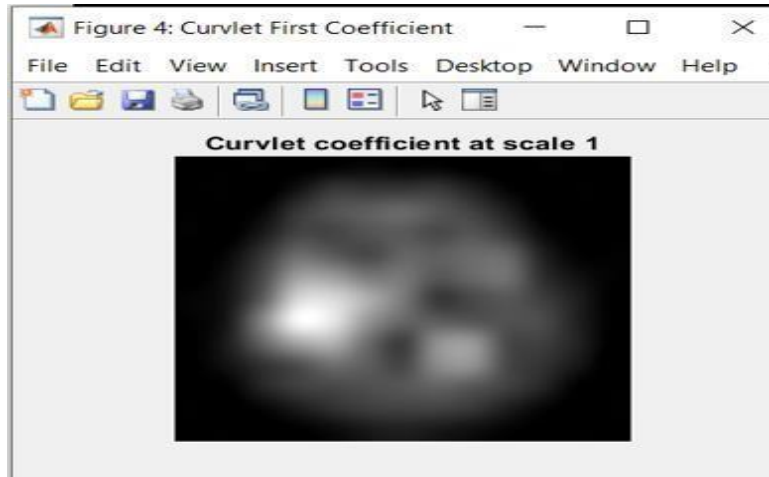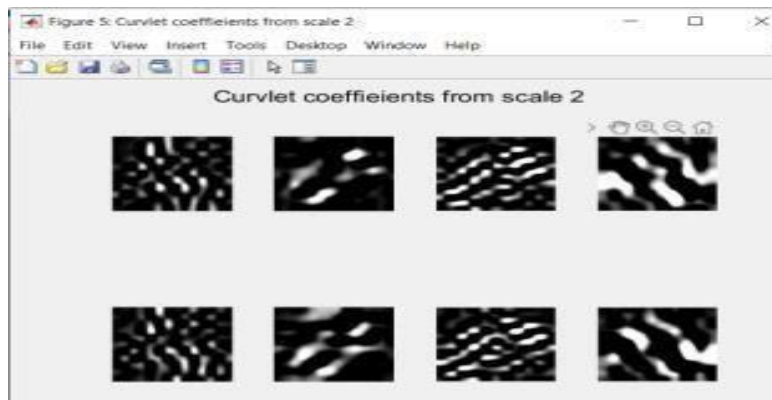
Figure 14: curvelet coefficient image at scale 1

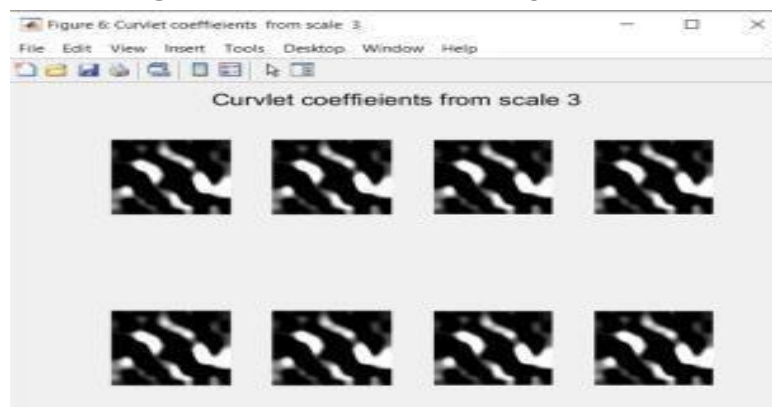**Figure 15:** Curvelet coefficient image at scale 2

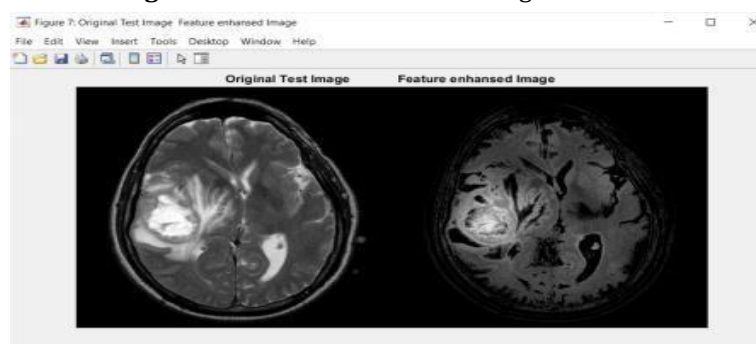**Figure 16:** Curvelet coefficient image at scale 3

Figure 17: Feature enhanced image

DISEASE IDENTIFICATION

This section identify the disease of an image tha the image is 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 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 probabailities by using softmax layer for 2input there will be 2 output of softmax layer it is activation layer

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

Let the output of fully connected layer is $y1$ and $y2$

The classification layer just predict the output according to the probability, if probability is (>0.5) it will choose $y2$ orelse $y1$. Therefore in case study 2 the tested image is $y1$ with score 0.91854 and 0.081456,

It means 91.8% it is $y1$

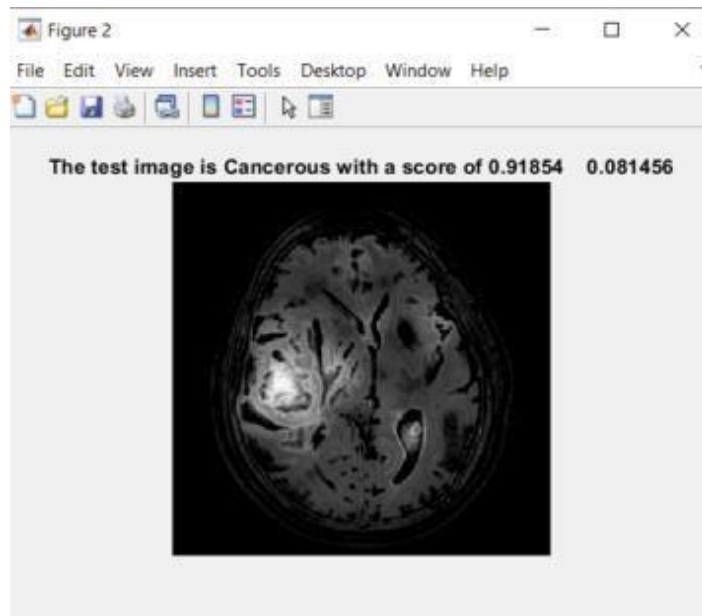Where, $y1$ is cancerous

$y2$ is non cancerous

Figure 18: Tested or output image

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 3, table 4

Table 3: 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.
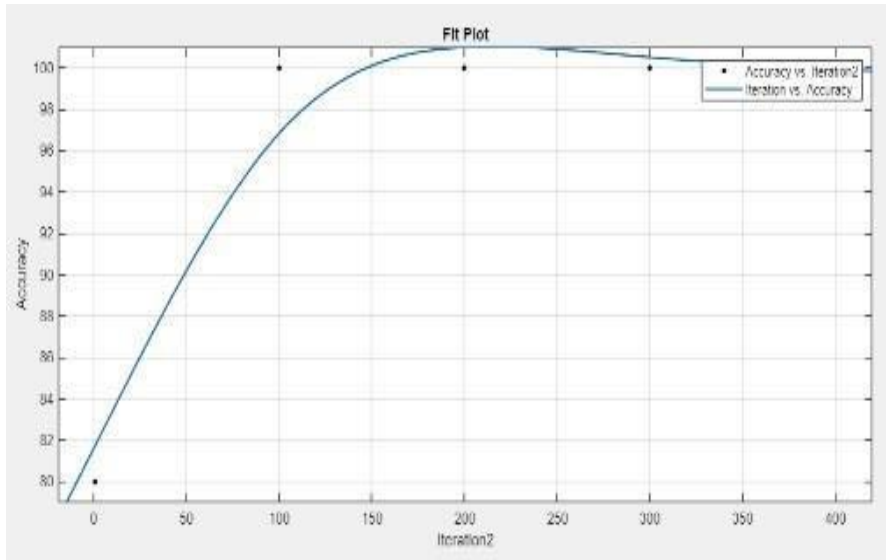
Figure 19: Iteration vs accuracy plot

The above graph shows the increasing in iterations the accuracy will be change and gives good result in maximum iterations

Table 4: 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%

The above table shows the maximum accuracy with the changing in learning rate.
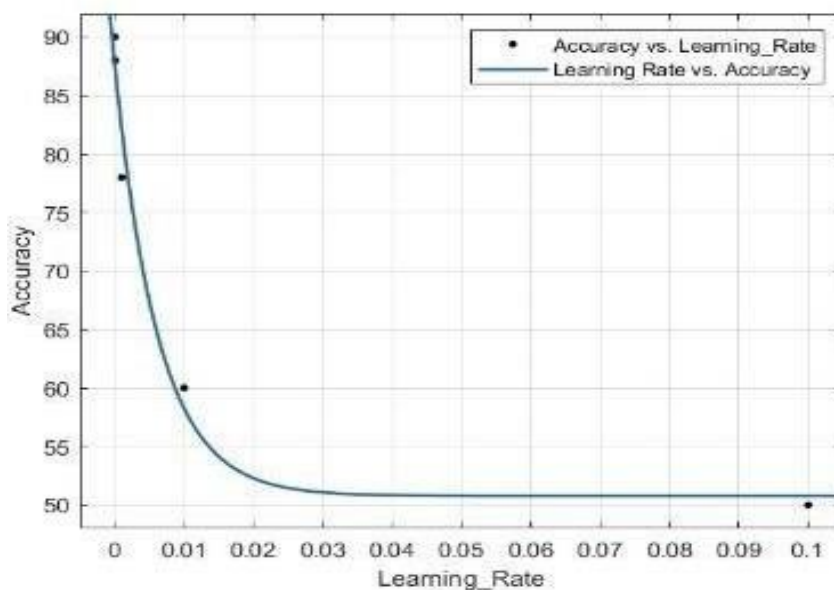

Figure 20: Variation of learning rate vs. Accuracy.

V.   COMPARISON TABLE

The suggested CNN and curvelet method and the current CNN and k-means algorithm are contrasted in this section. Table 5 compares the epoch and micro batch loss and demonstrates that the suggested technique produced better results than the current algorithm.

Table 5: comparison table with existing technique

S. no	Reserch work	Technique	Epoch	Minibatchaccuracy	Mini batch loss
1	CNN based image classification and detection of abnormal ities in MRI brain images	CNN+k-means algorithm	100	100	0.10 88
2	Proposedmodel	CNN+curvelet transform	10	100	0.04 12

VI.   CONCLUSION

The suggested method has been put into practise effectively. 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 method outperforms current algorithms and is highly 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.

VII.   REFERENCES

[1]   P. Muthu Krishnammal and S. Selvakumar Raja, "Convolutional Neural Network based Image Classification and Detection of Abnormalities in MRI Brain Images", International Conference on Communication and Signal Processing, April 4-6, 2019, IEEE, India..

[2]   Dr. Talib M. Jawad Abbas, Mays Yousif, "Brain cancer detection using Curvelet Transform and Neural Network", International Journal of Scientific & Engineering Research, Volume 7, Issue 10, October 2016.

[3]   DC Febrianto1, I Soesanti , H A Nugroho, "Convolutional Neural Network for Brain Tumor Detection", 2nd International Conference on Engineering and Applied Sciences (2nd InCEAS), 2020

[4]   J. Seetha and S. Selvakumar Raja, "Brain Tumor Classification Using Convolutional Neural Networks", Biomedical & Pharmacology Journal, September 2018. Vol. 11(3), p. 1457-1461

[5]   Arkapravo Chattopadhyay, Mausumi Maitra, "MRI-based brain tumour image detection using CNN based deep learning method", https://doi.org/10.1016/j.neuri.2022.100060 2772-5286/© 2022 The Author(s). Published by Elsevier Masson SAS

[6]   Hasan Ucuzal, Şeyma YAŞAR, Cemil Çolak, "Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface".

[7]   Daisuke Hirahara, "Preliminary assessment for the development of CADe system for brain tumor in MRI images utilizing transfer learning in Xception model", 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE).