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AUTOMATED BRAIN TUMOUR DETECTION BY USING DEEP LEARNING FROM MAGNETIC RESONANCE IMAGING

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ABSTRACT

The emerging field in many medical diagnostic applications is automated flaw detection in medical imaging. Automated brain tumour diagnosis in MRI is essential because it offers details about aberrant tissues needed for treatment planning. Human inspection is thestandard procedure for flaw detection in magnetic resonance brain pictures. Due to the volumeof data, this strategy is impracticable. Therefore, reliable and automatic classification systems are necessary to reduce the number of human deaths. Therefore, automated tumour identification techniques are being developed in order to reduce radiologists' time and achievea proven level of accuracy. Due to the intricacy and variety of tumours, MRI brain tumour detection is a challenging undertaking. The main goal of this study is to use MRI images to locate and diagnose a brain tumour. We suggest using deep learning methods to get around the shortcomings of conventional classifiers. Through MRI, it is possible to effectively find cancer cells in the brain using deep learning and image classification. This paper's main goal is to use MRI images to locate and diagnose a brain tumour.

KEYWORDS: Brain tumour detection, Deep learning, CNN, MRI Images.

INTRODUCTION

Groups of odd cells that form lumps or outgrowths are called tumours. One of the many millions of cells in our body could be the source. A brain tumour is sometimes referred to as an intracranial tumour when the brain's cells reproduce uncontrollably, grow out of control, and impair the organ's ability to function normally. There are two ways that a brain tumour can form: either it starts in the brain and spreads to other areas of the body, or it starts in other areas of the body and starts in the brain. Our brain is enclosed in the stiff framework of the skull. Therefore, any development there can prevent the brain from functioning normally. The pressure inside our brains can occasionally rise as a result of a tumour's occasionally rapid growth. How much a brain can influence other parts of the body depends on its growth pace and location. There are cancerous and benign tumours, which are two different types of tumours. Additionally, nerve pressure from brain tumours has the potential to seriously harm the brain and even result in death. The tumour's exact origin is unknown. Doctors are learning more about brain tumours through several clinical studies, with the goal of preventing them in the future and treating patients with brain tumours as effectively as possible.

Medical imaging is very important in the diagnosis of many disorders in the medical field. Doctors and specialists can obtain a detailed understanding of the brain's anatomy using the brain imaging approach. Numerous diagnostics, including a neurological exam, an imaging test, and a biopsy, may be advised by doctors. This aids in the earliest possible diagnosis of disorders of the brain and their appropriate treatment. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) tests are two examples of contemporary advanced imaging procedures for the brain. Through the X-rays absorbed by brain tissue during computed tomography, pictures of the human brain are created. The subject is fed through a hollow, cylinder-shaped device. The amount of X-rays absorbed by the tissue determines the image quality. Soft tissues absorb light less efficiently than hard tissues do, and fluids barely absorb any light at all. As a result, CT has trouble resolving brain structure.

An MRI examination, which is non-invasive and painless, can also be used to identify brain tumours. Strong magnetic fields and radio waves coupled to a computer are used in the MRI imaging technique to provide a detailed image of interior body structures such as images of organs, soft tissues, bones, etc. The detection of tumours and their sizes can be greatly aided by using MRI with contrast agents. Typical conventional MRI sequences include T1 and T2 weighted images, Fluid Attenuated Inversion Recovery (FLAIR), axial contrast, etc.

Brain tumour are manually diagnosed using MRI technology by a human expert, which takes time because the manual interpretation may take longer. Additionally, a wrong perception could result in a flawed course of treatment. Therefore, we may apply deep learning algorithms to accurately evaluate the ailment and provide a more objective study and diagnosis. The key purpose of this paper is to identify and detect a tumour in the brain using MRI images. Brain tumour are manually diagnosed using MRI technology by a human expert, which takes time because the manual interpretation may take longer. Additionally, a wrong perception could result in a flawed course of treatment. Therefore, we may apply deep learning algorithms to accurately evaluate the ailment and provide a more objective study and diagnosis. The major objective of this work is to identify and diagnose a tumour in the brain using MRI images.

LITERATURE SURVEY

Ahmed Kharrat et al.[1] developed a system to detect brain tumours from cerebral brain MRI images. The model consisted of an enhancement process, segmentation, and classification process. The process of segmentation was carried out using wavelet transform and the K-means algorithm was used for classifying the tumour into malign and benign. Riries, Rulaningtyas et al.[2] performed different edge detection methods, namely Robert, Prewitt, and Sobel for detecting the edge of brain tumours. The result showed that the Sobel method was more suitable and had a smaller mass than the other two methods. The tumour detection and localization systems were developed by K. Sudharani et al.[6] to correctly detect and localise tumours in the brain. Advanced morphological techniques were applied to detect the region of the tumour using MR images. Bhavana Ghotekar et al.[7] used GLCM for feature extraction to detect the tumour and an SVM classifier for classification of the MR images from the extracted features. The SVM approach resulted in having a specificity of 67.74%, a sensitivity of 91.52%, and an accuracy of 83.33%.

PROPOSED METHODOLOGY

Deep learning is a subfield of machine learning that deals with algorithms powered by artificial neural networks that mimic the structure and operation of brain-like processes. It may be fully or partially supervised or unsupervised. Deep learning is a technique where a computer model learns to do classification tasks directly from images, sound signals, or text.It could be thought of as an automated projective analysis method. While deep learning algorithms are arranged hierarchically with increasing complexity and generalisation, typical machine learning techniques are linear and time-consuming. Additionally, how accurately the feature sets are defined affects how effective conventional methods are. Every input is givena nonlinear transformation in deep learning, and each algorithm uses what it has learned to create a statistical model as an output. The iterations come to an end when the output reaches the highest level of precision. We termed it deep because there are many processing layers in the network that the data must move through. Deep learning has the advantage of increasing accuracy because the software builds the feature set independently and without supervision.

A convolutional neural network is a deep learning method that takes an input image, assigns biases and learnable weights to specific items in the image, and then uses those weights and biases to distinguish one object from the other objects in the image. Compared to other classification methods, CNN requires the least amount of preprocessing. The manual engineering of filters used in conventional methods provides them with adequate training, but CNN is capable of learning these filters and various features. By using the right filters in an image, a CNN model can capture the spatial and temporal dependencies. Because there are fewer factors involved and the weights can be reused, this architecture performs flawless fitting to the picture dataset. In other words, the network is being trained to recognise and comprehend the complexity of the image more accurately. The CNN model can condense the images into a simpler format for processing while still producing accurate predictions. As a result, it's crucial to create an architecture that can scale to big datasets and is effective in learning characteristics.

Multilayer perceptrons are generalised variants of CNNs, which are being regularised. These MLPs often refer to a fully connected network, where each layer's neurons are linked to those in the layer above them. This network's "complete connectivity" is a feature that can cause the data to overfit. In order to prevent overfitting of the data, CNN employs regularisation techniques such as weight decay, dropout procedures, or skipping connections. An input, an output, and hidden layers with many convolutional layers, normalising layers, fully connected layers, and pooling layers make up the CNN layers. It contributes to improving the speed and effectiveness of image processing, leading to a system that makes it easier to train for both image and natural language processing. Additionally, CNNs use a fundamentally different method of regularisation that makes use of the data's hierarchical structure, and they can build up more complex patterns by starting with smaller, simpler patterns. The CNN recognises forms or other larger object components as the input data moves through its layers, eventually detecting the target item. CNNs are therefore less complex yet more efficient than other archaic methods. The following architecture applies to CNN:It begins by providing an input image.

- It is applied to several filters in order to create a feature map.
- A ReLU function is used to improve nonlinearity.
- A pooling layer is used for each feature map.
- A single lengthy vector is created by flattening the pooled images.
- A fully connected neural network contains the vector.
- The network processes the features. The "voting" of the classes is provided by the topfully connected layer.
- It is trained through forward and backward propagation for certain numbers of epochs.Until a precise neural network is constructed with trained weights and feature detectors, this process is repeated.

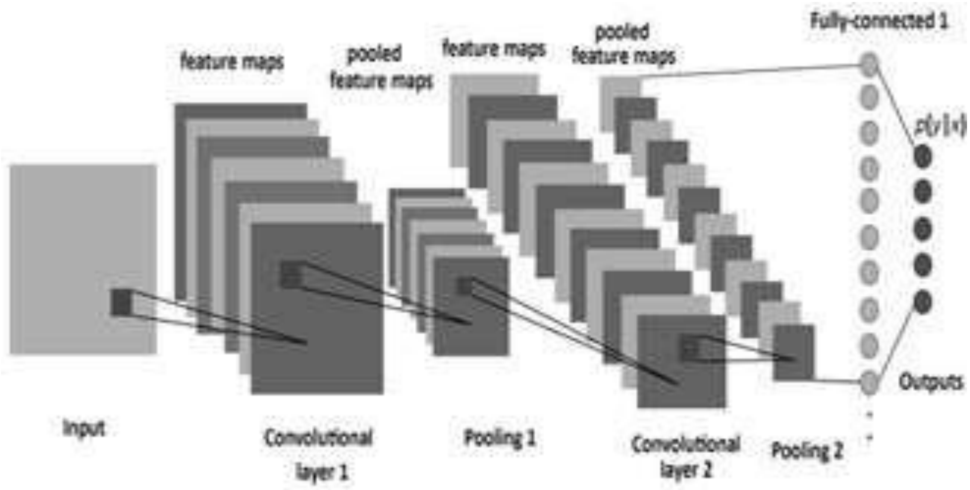

Figure 1: CNN Model.

The Convolutional Neural Network that is used to categorise the photos is created using Keras, a Python neural network API. Convolution, pooling, and fully connected layers make up the majority of CNN's layers. Convolutional layers can be added after the first layer, which is the convolutional layer. The pooling layers and the fully-connected layer are the following layers. The CNN model is displayed in Figure 1. The suggested method uses brain MR images to back-to-back and continuously detect and classify brain malignancies into two distinct classes, namely the normal class and the tumour class. Convolutional Neural Networks in particular, along with other Deep Learning techniques, have been used to achieve this.

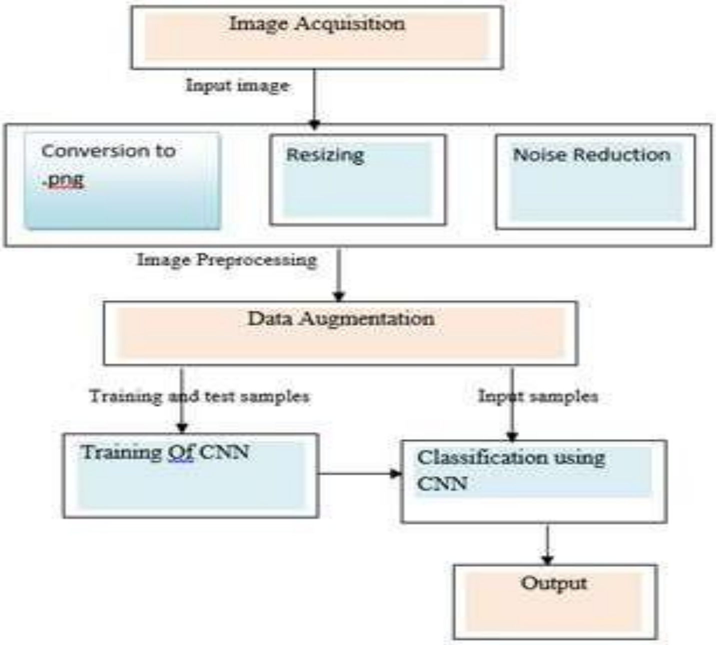

Figure 2: Flow Diagram for the proposed work.

1. Keras

Keras was created with the goal of facilitating quick research experiments with deep neural networks. It is sectional, expandable, and user-friendly. It is a recommended Python library for deep learning. Numerous versions of commonly used neural network building blocks are implemented in Keras. It lowers the number of user operations while providing clear error signals thanks to its reliable and simple APIs (application programming interfaces). The "KerasImageDataGenerator" class allows for the usage of the least amount of data. When more images are needed, this class generates a largenumber of random transformations.

2. Image Acquisition

Radiopedia is used to gather MRI images for both healthy and brain tumors. Every classification of vision starts with image acquisition. The process of recovering or obtaining an image from numerous sources—typically a hardware-based source for processing—is known as image retrieval. The resultant image has not been modified in any way. After the image has been retrieved, it can be preprocessed using a variety of methods to do various visualisation activities that are necessary to finish the task that was started.

3. Image Pre-Processing

Certain operations on images at the most fundamental level of abstraction are referred to as preprocessing. It describes each change made to the raw data before it is used as an input by a machine learning or deep learning algorithm. It is done to enhance the image and get rid of any incorrect information that was gathered but is irrelevant.

4. Building a CNN

In a convolutional neural network's typical architecture, convolution layers come first, then non-linear units, then pooling layers, and ultimately the fully connected network, which produces the output.

i) Convolution Layers

The primary building block of CNN is the convolution layers, and most of the computation takes place in them. In Figure 3, convolutional layers with feature mapping and activation functions are displayed.

For example, if an image 'x' consists of a 2D array of RGB-encoded pixels, x [a] is the input pixel, and 'w' is the kernel, the result of applying a mathematical function is referred to as a feature map.

The equation is given as follows

$$s[t] = (x * w)[t] = \sum_{a=-\infty}^{a=\infty} x[a]w[a+t] \qquad (1)$$

where s[t] =single output or feature map,

x= input,

w= kernel or filter.

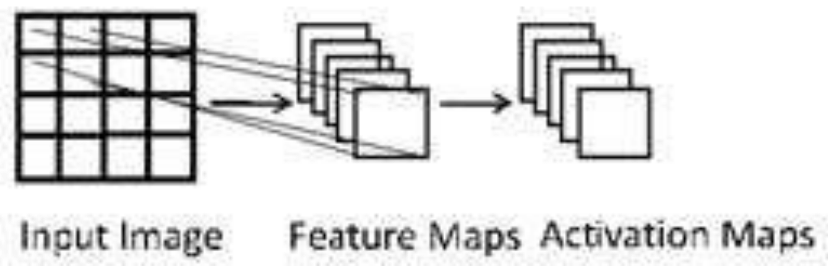

Figure 3: Convolution Layers.

ii) Non-Linear Units

Image classification is a nonlinear problem where a non-linear unit increases non-linearity in the input images. And in this project, non-linearity is being achieved through the Rectified Linear Unit (ReLU) function, which is an activation function. After each convolutional phase, a CNN applies a ReLU transformation to the feature map, activating nonlinearity in the model.

Figure 4: Rectified Linear Unit (ReLU).

Figure 4 shows the graph of Rectified Linear Unit. The equation for the ReLU activation function is as follows:

$$\text{Equation: } f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \qquad (2)$$

$$\text{Derivative: } f'^{(x)} = \begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases} \qquad (3)$$

iii) Pooling Layers

In contrast to the convolution layer, which has weights, the pooling operation is connected to a filter that runs through the input. The pooling technique provides average, minimum, and maximum pooling. The following are some benefits of using a pooling layer:

- It helps in reducing the number of parameters and decreasescomputational cost.
- It also controls overfitting.
- It also reduces the amount of storage.

iv) Fully Connected Layer

Every node in the output layer of a layer that is fully connected connects to a nodein the layer above it. Using the characteristics that were gathered from the preceding layers and their corresponding filters, this layer computes classification. In order to identify the images, the flattened matrix traverses a fully linked layer, much like a multilayer perceptron network. Layer connectivity is shown in full inFigure 5

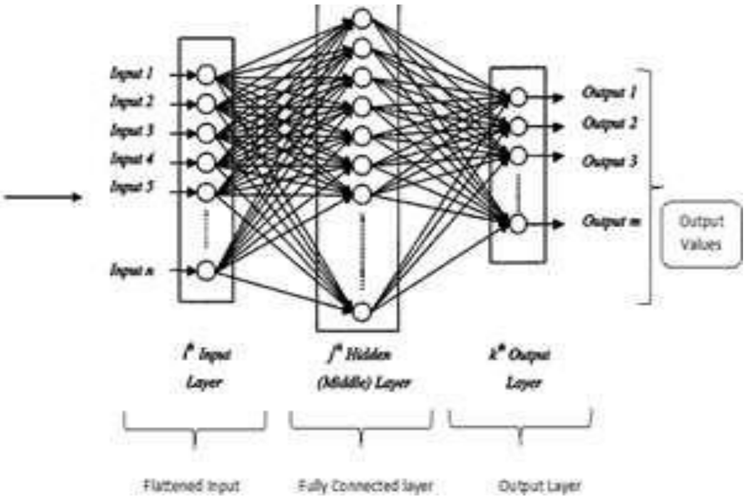

Figure 5: Fully Connected Layer.

v) Image Augmentation

Without adding extra images, image augmentation is done to enhance the data sets. The amount of data being utilised to train the model is increasing. Deep learning models require a large amount of training data to make an accurate prediction.So, in order to create a better generalised model, we need to supplement the currently available data.

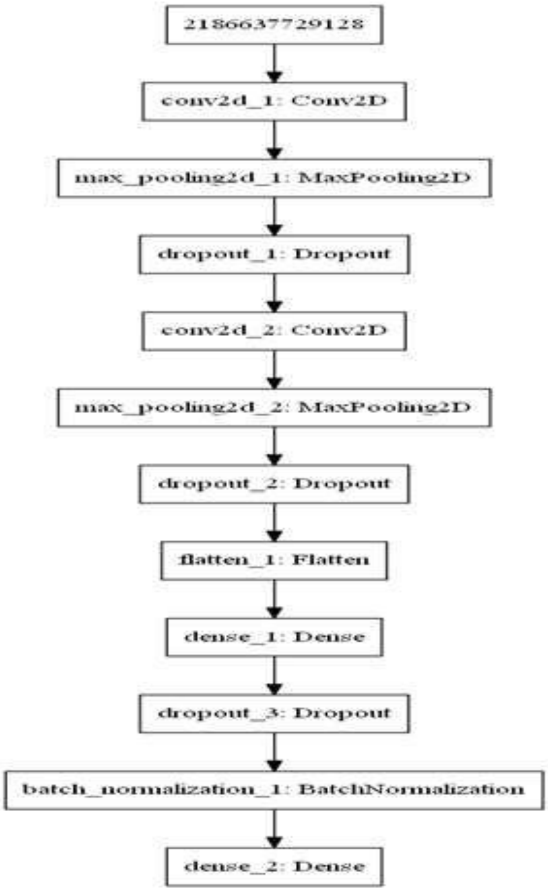

Figure 6: Shows a 2D CNN of the proposed method.

Figure 6: 2D Convolutional layer Experimental Results And Discussions

The dataset contains 2000 MR images, of which 1000 are images of tumours and 1000 are images of normal tissue. The network is trained using a total of 2000 MR images, of which 1000 are normal MR images and 1000 are tumours. 197 images from normal and 233 images from tumour MR images are utilised to evaluate the network using 430 images. In the validation process, 197 MR images of normal tissue and 233 images of tumour tissue were taken and processed.

Figure 7 shows a model accuracy graph. Similarly, Figure 7 shows the model loss graph along with the model accuracy. The system's model loss for training reaches a minimum loss of 0.150, while its validation loss for testing reaches a minimum loss of 0.214.

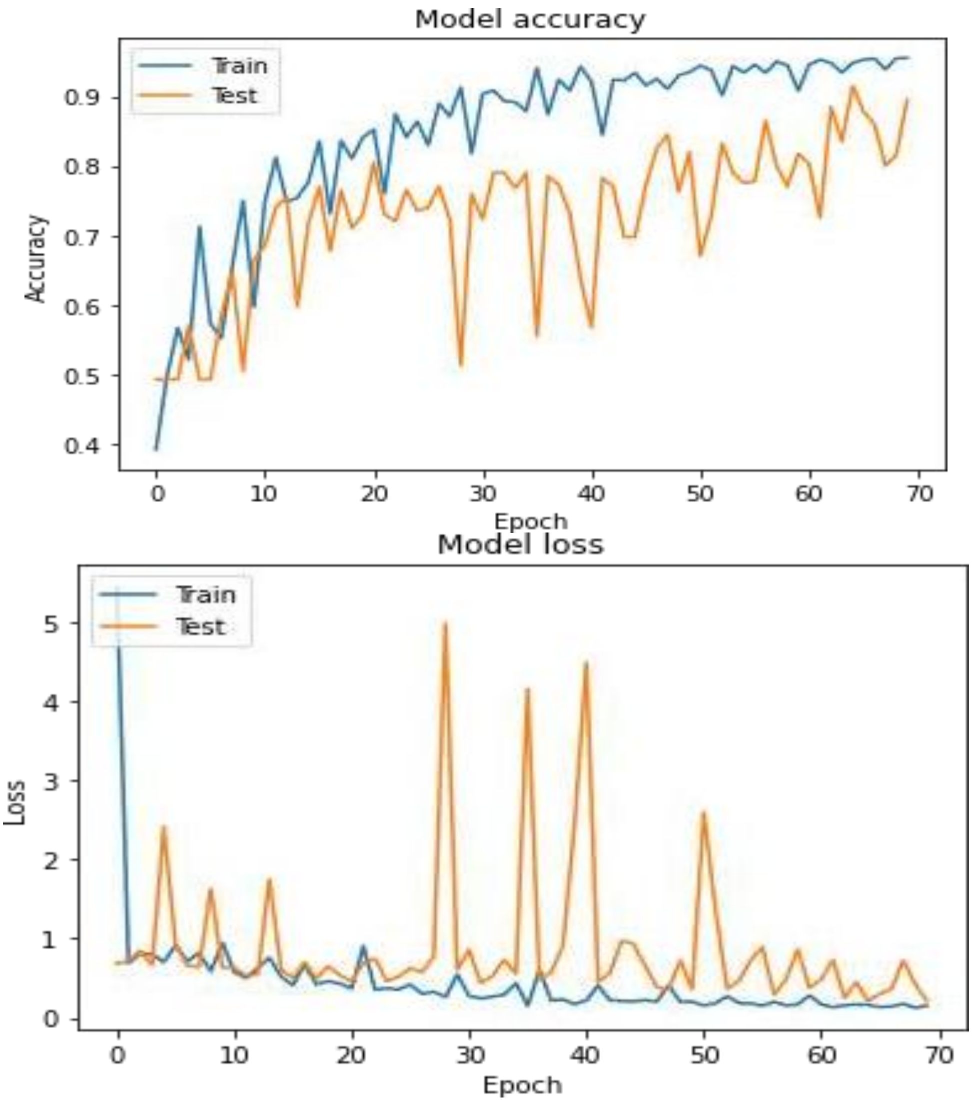

Figure 7: Model accuracy and model loss.

Table 1: Performance Table

In Percentage (%)	Precision	Recall	F1 Score	Accuracy
Proposed methodology2D CNN	Normal-87 Tumor-94	Normal-93 Tumor-88	Normal-90 Tumor-91	90

The overall accuracy of this method is 90% in 70 epochs.

Out of the 430 samples used to validate the normal samples in Table 2, all 430 samples were predicted as normal, and only two (two samples) of the 430 tumour samples were wrongly predicted.

Table 2: Confusion Matrix.

Validation Samples	Predicted yes	Predicted No
Normal Samples	430	0
Normal Samples	428	2

The model performs best with 2D convolutional layers. When using a 1D convolutional layer, the model loss is higher and the accuracy is lower. When using a 3D convolutional layer, the model loss decreases but the accuracy remains lower. Therefore, 2D convolutional best fits themodel with higher accuracy.

Classification Report

Precision	Recall f1-score		Support	
NORMAL	0.87	0.93	0.90	197
TUMOR	0.94	0.88	0.91	233
accuracy		0.90		430
macro avg	0.90	0.90	0.90	430
weighted avg	0.90	0.90	0.90	430

Precision, recall, and F1 Score were used to measure the systems' performance. and the overall accuracy is given in Table 1.

As performance indicators, parameters like prevalence and error rate can be used. The error rate is calculated by the addition of false positives and false negatives to total cases.

$$\text{Error rate} = \frac{FaPv+FaNv}{Total\ cases}$$

And prevalence is calculated by the actual positive number of cases upon total cases.

$$\text{Prevalence} = \frac{Actual\ positive\ cases}{Total\ cases}$$

We used these measures since they are the standard parameters generally used for performance comparison: precision (specificity), recall (sensitivity), and F1-score.

Table 3: Comparison.

Name of methods	Precision	Recall	F1 Score	Accuracy
AMT[6]	90%	88.9%	89.44%	89.2%
GLCM + SVM[7]	67.74%	91.52%	77.52%	83.33%
Genetic Algorithm(GA)[8]	71.34%	69.05%	70.18%	67.25%
2D CNN (Our Proposed method)	90.5%	90.5%	90.5%	90%

In Table 3, accuracy is compared with other methodologies. Compared to other methods,ours has the highest accuracy.

CONCLUSIONS

The existing diagnosis system, carried out by human experts, can now benefit from clinical support from computer-aided AI systems**.** The proposed method classifies the brain MRI images into tumour and non-tumour classes with an accuracy of 90%. The system evaluation produces the best outcomes when compared to the existing system, with a sensitivity and specificity of 90.5 and 90.5%, respectively.

REFERENCES

1. Kharrat Ahmed, Benamrane Nacéra, Messaoud Mohamed Ben, and Abid Mohamed, "Detection of brain tumour in medical images", 3rd International Conference on Signals, Circuits, and Systems (SCS), 2010; 1-6. DOI: 10.1109/ICSCS.2009.5412577, February.
2. Riries Rulaningtyas and Khusnul A, "Edge Detection for Brain Tumor Pattern Recognition", in International Conference on Instrumentation, Communication, Information Technology, and Biomedical Engineering, DOI: 10.1109/ICICI-BME.2009.5417299, Feb2010.
3. "Brain Tumour Detection Using Neural Network," Pankaj Sapra, Rupinderpal Singh, and Shivani Khurana, International Journal of Science and Modern Engineering (IJISME), ISSN: 2319-6386, August 2013; 1(9).
4. "A deep learning-based segmentation method for brain tumour in MR images," IEEE 6th International Conference on Computational Advances in Bio and Medical Sciences, October 2016.
5. Ruixuan L, L. Zhao, and Kebin J, "Brain tumour image segmentation based on convolution neural network," IEEE 9th International Congress on Image and Signal

Processing, BiomedicalEngineering and Informatics, 2016.

6. K. Sudharani and T.C. Sarma, "Advanced morphological technique for automatic brain tumour detection and statistical parameter evaluation," International Conference on Emerging Trends in Engineering, Science, and Technology, 2016; 24: 1374-1387. doi:10.1016/j.protcy.2016.05.153.
7. Bhavana Ghotekar and K. J. Mahajan. "Brain Tumor Detection and Classification using SVM", National Conference on Innovative Trends in Science and Engineering, July 2016; 4(7): 180–182.
8. Kiruthika Lakshmi V, C.amarsinghfferoz, and Asha Jenia Merlin J, "Automated Detection and Segmentation of Brain Tumor Using Genetic Algorithm," International Conference on Smart Systems and Innovate Technology (ICSSIT). CFP18P17-ART, IEEE Xplore Part Number; ISBN: 978-1-5386-5873-4, 2018.