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Analysis of Deep Learning Techniques for Brain Tumour Classification from CT & MRI Images

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Abstract:
Brain tumour detection in an initialpoint is a critical step to saving human life. Computed Tomography (CT) and Magnetic Resonance Image (MRI) provide very detailed information about brain tumour tissues. So the segmentation of tumour region is possible from pancreatic CT and brain MRI. CT and MRI is a non-invasive technique and it does not produce any harmful radiation to the patient. The patient suspected of tumour undergoes radiological evaluation such that the area, location and grade of the tumour can be predicted from the CT and MRI analysis. This critical information helps the doctors to decide about further treatment like chemotherapy, surgery, or radiation. The diagnosis requires an accurate and very fast segmentation and classification of CT and MRI images. But nowadays radiologists are doing this task manually and it is a tedious and time-consuming procedure. Also, there is a chance of variation in the result from one expert to another. Here comes the significance of automatic segmentation and classification of tumour types with the help of computers.The proposed work aims to develop an efficient system that can detect pancreatic and brain tumour and can classify the pancreatic CT and brain MRI into normal, benign or malignant. This work can be categorized into two approaches. Thus the dataset prepared for this research work contains CT and MRI images.The first approach proposes traditional machine learning technologies to achieve the goal. Image pre-processing, feature extraction, segmentation and classification are the various steps of the traditional machine learning method. A detailed investigation is performed through various feature extraction techniques and classification techniques for pancreatic (CT) and brain MRI. Discrete Wavelet Transform (DWT) feature, Grey Level Co-occurrence Matrix (GLCM) feature, Gabor feature, Tamura features and Edge Orientation Histogram (EOH) features and their combinations are used for the extraction of CT and MRI features. Benign tumours are non-cancerous, but malignant tumours are cancerous. In the first approach, the Support Vector Machine (SVM) is the main classifier used for pancreatic CT and brain MRI classification as normal, benign or malignant.
In this technology, a huge amount of data and machines with high computational capabilities like Graphic Processing Unit (GPU) are available. Thus the second approach of this paper is to exploit all these available resources to produce accurate results. In this part, deep learning, the latest fast growing technology introduced in 2015 is used for the classification of brain MRI. A Deep Convolutional Neural Networks (DCNN) model is proposed to perform the classification task efficiently. The CNN results are compared with the results of a simple neural network classifier. This method provides accurate and it shows that deep learning based classification outperforms traditional machine learning techniques which produce an accurate result only. This research work again concentrates on the Transfer Learning (TL) methods to classify pancreatic CT and brain MRI.

Keywords: SVM, DCNN, MRI Images, CT, Brain Tumour.

I. Introduction

A brain tumour is characterized by abnormal cell growth in the human brain. There are two different types of brain tumours: “low grade (1 and 2) and high grade (3 and 4)”. Benign brain tumours are described as the low grade that is non-cancerous tumours and it doesn’t spread to other brain parts (**NHS, 2020)**. Similarly, malignant tumours are described as the high grade that is cancerous tumours, so spread quickly to other parts of the body (**Siddique, 2020**).The patient’s survival rate will rise with an early diagnosis of a brain tumour. Among the number of imaging techniques, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scansare widely used by medical professionals due to their resolution image quality and extensive convenience. Contrast agents used in MRI images are essential for making a medical diagnosis. As a result, there is a greater need for novel MRI contrast materials with better understanding andperformance.

In medical imaging, a substance known as a contrast agent is utilized to enhance the contrast of body organization. The contrast-enhanced MRI images used in the proposed work are analyzed.The most common technique is MRI imaging because it is a non-invasive imaging modality that offers distinct tissue contrast. MRI produces internal images of the human organs by using strong magnetic fields and radio waves. Compared to EEG scanning, MRI is more effective because it provides more precise information about the internal organs. These various MRI techniques produce

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various kinds of tissue contrast images. As a result, it offers useful details about tumour structure and facilitates the diagnosis and segmentation of tumours and their sub-regions.

Gliomas, meningiomas, pituitary tumours, pineal gland tumours, and ependymomas are a few examples of primary brain tumours. Glial cell-derived tumours known as Gliomas, this is the most common type of brain tumour, and they can be detected using MRI images of various types, including "T1(T1-weighted), T1c(T2 weighted contrast enhanced), T2(weighted), and fluid attenuated inversion recovery (Flair)". An important aspect of the treatment process is early tumour detection. To classify the MRI as normal or abnormal, the radiologist employs classification techniques. The tumour type is identified for the alternative treatment process if the outcome is unusual(**Kuraparthi, 2021**).

II. Traditional Machine Learning Technologies

Support Vector Machine is a supervised machine learning-based binary classifier that implementssuperior than other machine learning classifiers. A controlled learning approach is the SVM method. In order to classify between two classes, SVM creates a hyperplane in high-dimensional feature space (**Rajesh, 2016**). The idea of decision planes serves as the foundation for support vector machines. A decision plane divides a group of objects with varying levels of class involvement. The SVM approach was used for brain tumour classification and disclosure (**Vani, 2017**).

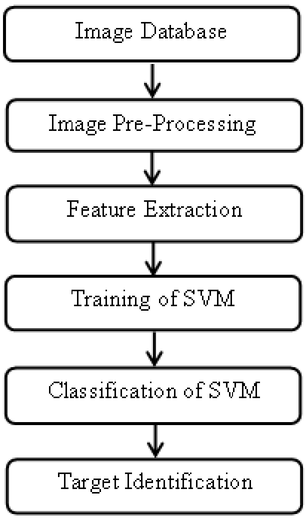

Figure 1. Implementation of SVM

The classification process of SVM is represented in above Figure 1.SVM is a flawless method that performs better in both MRI and CT tumour images. Hence, SVM is a supervised machine learning techniqueit can be processed through training and testing phases.

Different kernel approaches, including linear, radial basic function, and quadratic kernel function, are used in the SVM classification algorithm.

Linear SVM: The training sequences are linearly separable, making it the simplest. The following gives a linear model of the type (**Nandpuru, 2014**). Figure 2 displays a basic linear SVM classification flow.

$$f(x) = w^T x + b \qquad (1)$$

Where,
x- Set of training samples
w- Weight vector
b- Bias or threshold parameter

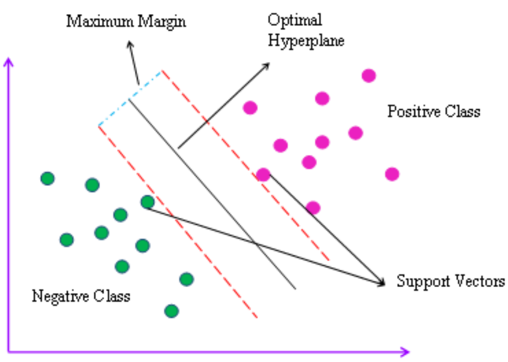

Figure 2. Linear SVM Classification

III. Methodology

The main aim of this research paper is to give deep convolutional neural network architecture for brain tumour classification using T1-weighted contrast enhanced brain MRI. The most distinctive features are produced by convolution of tiny filters with the input patterns, and these features are then utilised to train the classification network. In figure 4, the suggested block diagram is displayed. In this section, the dataset and the comprehensivemethodology for classifying brain tumours are discussed. It consists of a set of a process such as a collection of dataset, dataset description, image preprocessing, brain tumours classification using deep CNN and system performance evaluation. The current work's phases are outlined in the following categories:

3.1 DatasetCollection and Description

The brain tumour dataset collected from the Kaggle database comprises 2475 T1-weighted contrast enhanced images. The dataset contains three types of brain tumour:Glioma tumour (826), Meningioma tumour (822), and Pituitary tumour (827). All the images were stored in .jpg format. MRI dataset samples of Glioma, Meningioma, and Pituitary Tumours are represented in Table 1 and figure 3.

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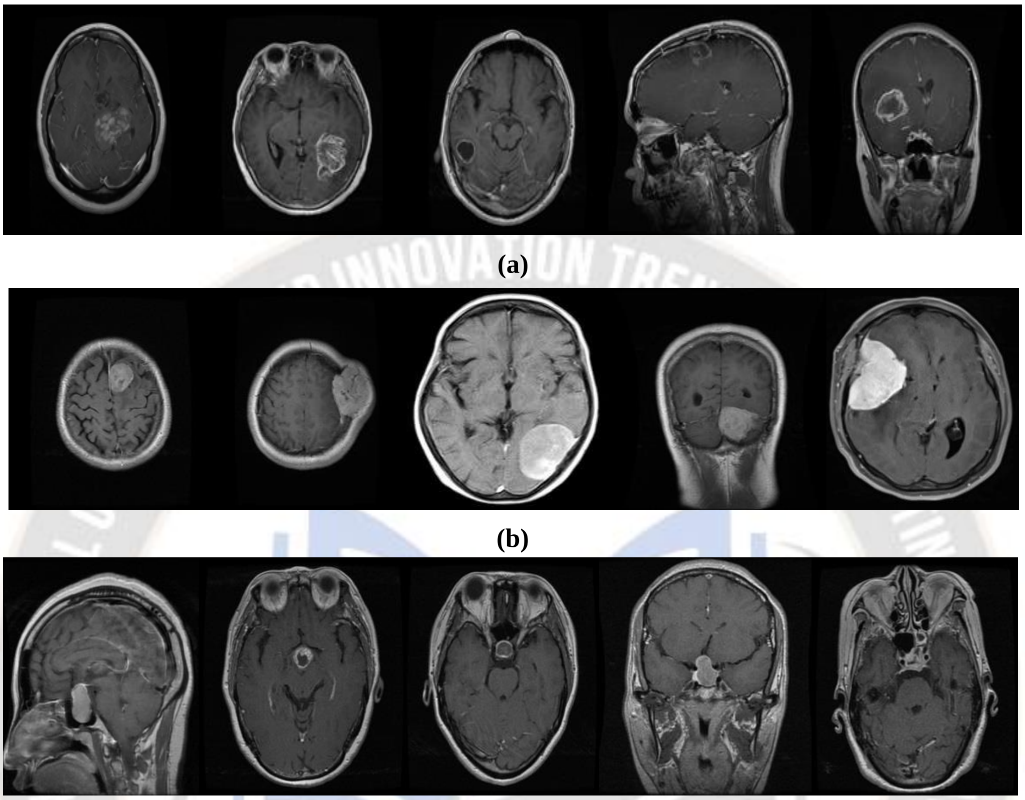
Table 1: Representation of MRI Dataset

	Glioma	**Meningioma**	**Pituitary Tumours**	**Total No. Of Samples**
Training samples	826	822	827	2475
Testing samples	100	115	74	289



(a)

(b)

(c)

Figure 3.MRIDataset Samples of (a) Glioma (b) Meningioma (c) Pituitary Tumour

3.2 Preprocessing

In the training phase, preprocessing, feature extraction, and classification are performed to make a prediction model. The detection of tumours and anomalies in the brain is made possible by T1c magnetic resonance imaging. Its contrast and intensity may be impacted by outside noises, as well as by the surrounding surroundings. Therefore, preprocessing is necessary to reduce unnecessary noise and enhance image contrast.

3.3 Tumour Classification using CNN

CNN is a particular kind of neural network model that is capable of reliably extracting key elements from pictures, analyzing those features, and classifying them. Due to this, CNN is better suited to the task of image classification than any other traditional deep learning model (Khan, 2020).CNN has many kinds of architectures but it is generally organized with three main layers, the convolution layer, pooling layer and fully connected layer. The convolutional layers just work at specific locations and not everywhere. The proposed block diagram is shown in figure 4**.**

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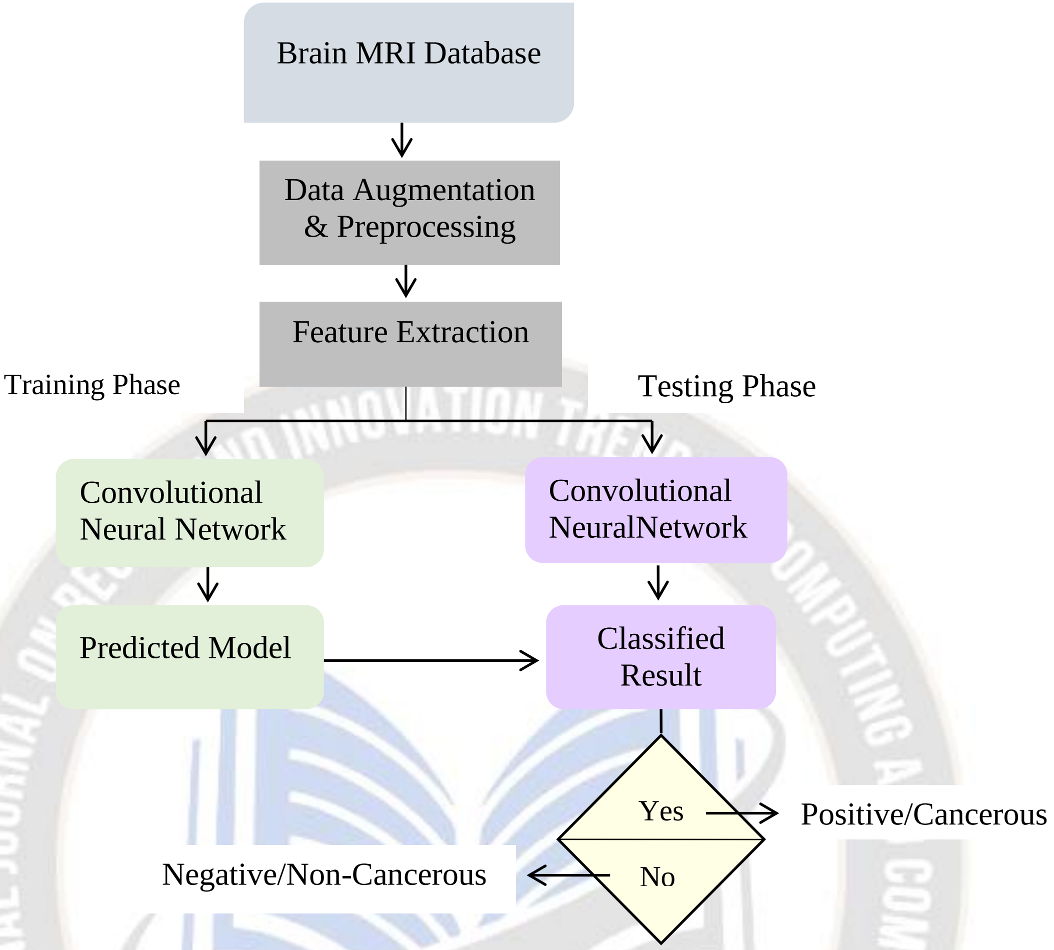

Figure 4. Block Diagram of the Proposed Work

This method transforms the layer that came before it into the layer, separating the distinctions from the original data. The pooling layer then initiates to use the information from the previous layer and attempts to simplify the process. The fully linked layer executes the features that have been gathered from all preceding layers to produce the necessary categorized outputs. A new DCNN architecture is shown in Figure 5.

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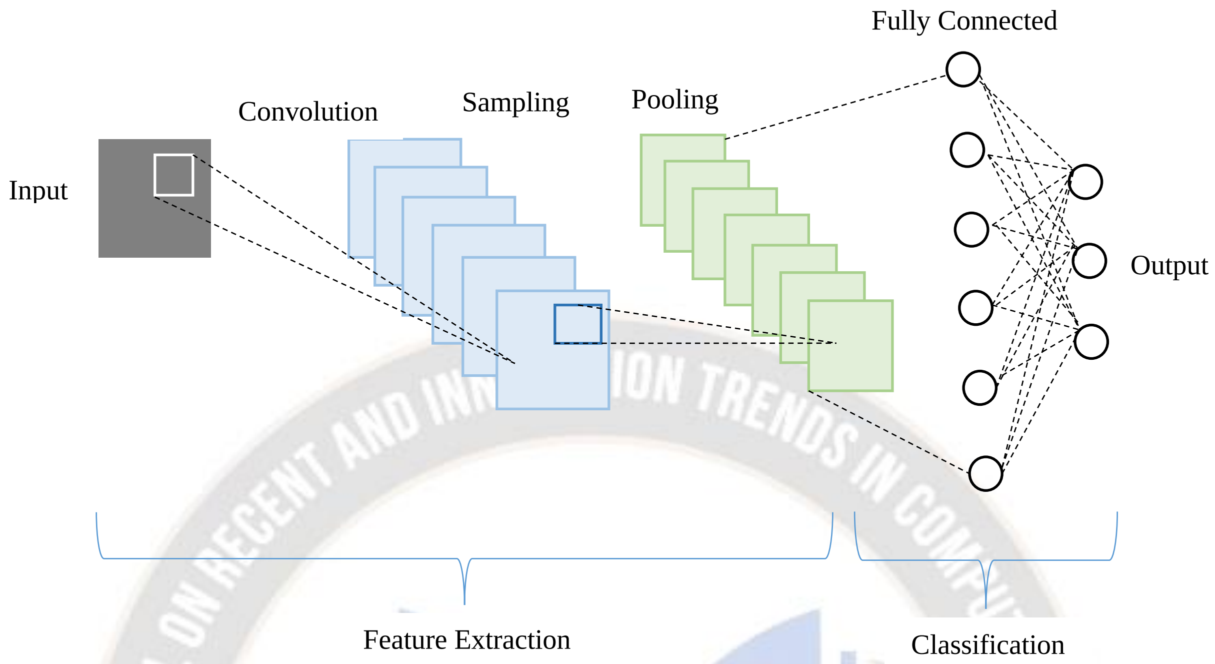

Figure 5.DCNN Architecture

2.4 CT Images with Brain Tumour

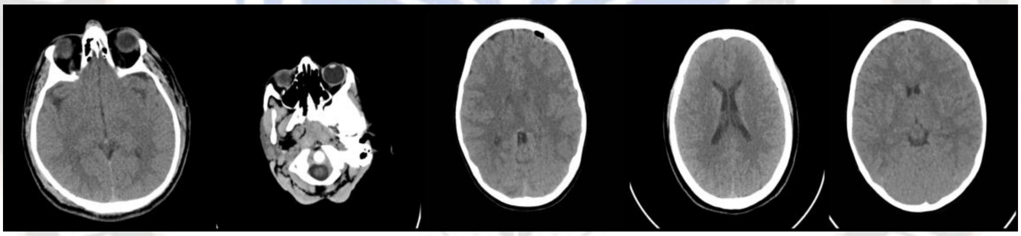

Figure6. Sample CT Tumour Images

The core structure of the bones, organs, and tissues can be seen in a computed tomography image. X-rays are used in CT scans to provide details on the structure. For accurate tumour classification, CT images are used. In Figure 6, a few of the CT images are displayed. CNN network is quickly becoming popular in the field of computer vision. In this study, we suggested a deep convolutional Neural Network (CNN) model that can correctly categorize brain tumours. As a result, the tumours treatment begins at an early stage (Ruba, 2020).

IV. Results and Analysis

The proposed DCNN uses a pre-trained VGG-16neural network as a base network for brain tumour detection and classification. The selected MRI dataset consists of glioma, meningioma, and pituitary tumours as mentioned in **Figure 7**. The "Global Average Pooling Layer (GAPL)", also recognized as the average pooling layer employed in this design, executes spatial pooling of the feature map to minimizeoverfitting by limiting the total number of parameters in the network.In the entire data, 80% was considered for training, 10% for validation, and the remaining 10% for testing. A confusion matrix, as mentioned in table 2, can be used to visualize a classifier model's performance when a double class classification problem is taken into account. Figure 8 shows the sample of the average pooling layer.

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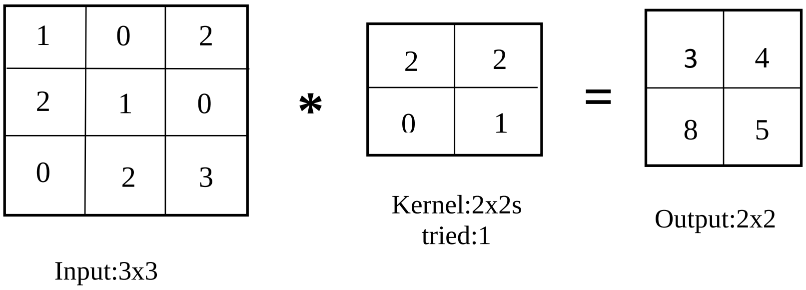

Figure 7. Sample Convolutional Layer

The average pooling layer process is used after a convolutional layer. It extracts features more smoothly than max pooling.

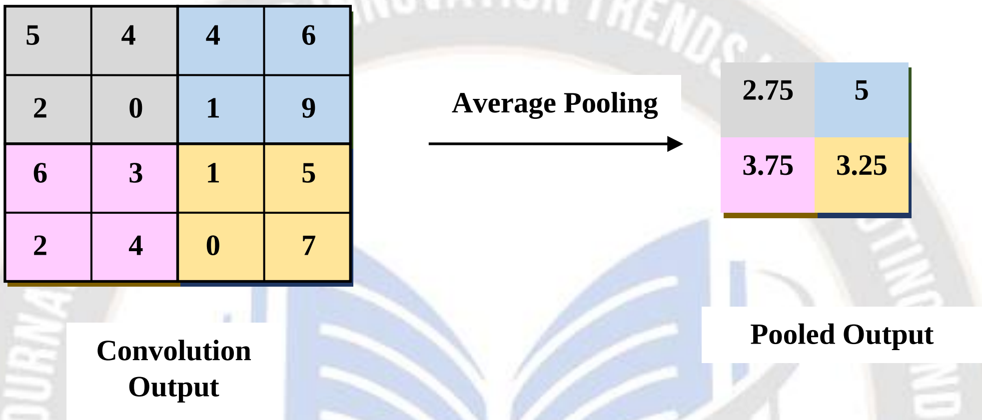

Figure 8. Sample Average pooling Layer

Table 2: Confusion Matrix

	Forecasted Positives	**Forecasted Negatives**
Actual Positive	TP (True Positive)	FN (False Negative)
Actual Negative	FP (False Positive)	TN (True Negative)

Table 2 represents the confusion matrix. With reference to the confusion matrix, the overall accuracy can be obtained as follows,

$$Overall\ Accuracy\ (\%) = \frac{TP + TN}{TP + FP + TN + FN} \qquad (2)$$

However, to clarify the supremacy of the proposed work, precision, recall, F1 values, cohen's Kappa, average precision recall rate, and accuracy for finding the DCNN network's performance is also calculated. Equation 3, 4, 5 and 6 provide these metrics respectively.

$$Precision\ (P) = \frac{TP}{TP + FP} \qquad (3)$$

$$Recall = \frac{TP}{TP + FN} \qquad (4)$$

$$F1\ Value = \frac{2\ (Precision\ X\ Recall)}{(Precision + Recall)} \qquad (5)$$

$$Cohen's\ Kappa = \frac{P_0 - P_e}{1 - P_e} \qquad (6)$$

Where,

$$P_0 = \frac{TP + TN}{TP + FN + FP + TN} \qquad (7)$$

$$P_e = P_{Yes} + P_{No} \qquad (8)$$

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$$P_{Yes} = \frac{TP + TN}{TP + FN + FP + TN} X \frac{TP + FP}{TP + FN + FP + TN} \quad (9)$$

$$P_{No} = \frac{FP + TN}{TP + FN + FP + TN} X \frac{FN + TN}{TP + FN + FP + TN} \quad (10)$$

The respective performance standards of the evaluating metrics are mentioned in **Table 3**. The projected deep CNN method functions better to find out the brain tumour in MRI.

Table 3: DCNN Performance Table

Performance Evaluating Metrics	Average Values for MRI	Average Values for CT
Precision	0.95	0.994
Recall	1.02	0.996
Accuracy	0.98	0.996
F1 Values	0.96	0.985
Average precision recall rate	0.94	0.996
Cohen's Kappa	0.93	0.976

Table 4: Glioma, Meningioma and Pituitary Tumours Average Precision

Recall_8 Points	Precision Rate of Glioma	Precision Rate of Meningioma	Precision Rate of Pituitary Tumour
0	1	1	1
1	1	1	1
2	1	1	0.98
3	0.9	1	0.96
4	0.87	1	0.95
5	0.87	0.98	0.85
6	0.85	0.91	0
7	0	0	0

The Precision Vs Recall curves for Glioma, Meningioma and Pituitary tumours in MRI Images are illustrated in Figure 9. The average precision rate of Glioma, Meningioma and Pituitary Tumours are mentioned in Table 4.

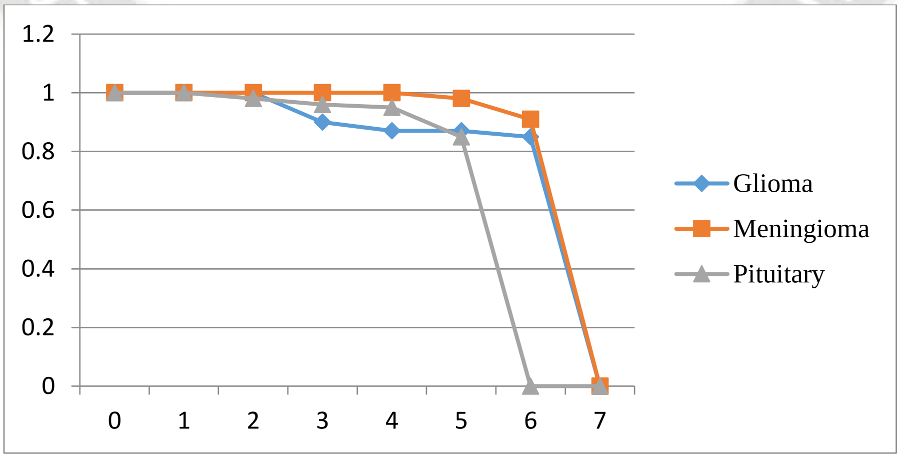

Figure 9. Precision Vs Recall curves for Glioma, Meningioma and Pituitary tumours in MRI Images

The effectiveness of the model was evaluated by comparing the proposed CNN classifier model with previous neural network methods. The comparison of performance is shown in table 5. The suggested method performs better than the earlier developed methods, with an accuracy of 98%.

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Table 5: Performance Comparison of DCNN Model

S.No	Algorithms	Accuracy
1	Layered 2D DNN(Amin, 2018)	0.95
2	SMO with SVM (Mohsen, 2017)	0.93
3	LinkNet (Hemanth, 2019)	0.91
4	DCNN (Proposed Method)	0.97

V. Conclusion

Advanced deep learning algorithms for brain tumour identification can help to reduce effort and expedite the detection procedure because it is very crucial in the medical science domain. In this work, DCNN is good enough to automatically diagnose brain tumours on both MRI and CT image datasets and resulted in an accuracy of 97%. A pre-trained VGG-16 network was used to train the model more quickly and efficiently.The developed deep CNN classifies three main brain tumour classes (Glioma, Meningioma, and Pituitary). Preprocessing the image data is done initially in the proposed work. The network then uses the DCNN model to classify the images. The model uses the average pooling layer to reduce overfitting. It aids the model's focus during the training phase on the most obvious patterns. Consequently, there is a higher likelihood of generalization, which maintains the model's stability.With a final accuracy of 98%, average precision of 0.95, recall of 1.02, and F1 value of 0.96, the system performs admirably. The suggested methodology also yields better CT imaging results. Consequently, the CNN classifier will be crucial in the medical industry and in saving valuable lives.

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