IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ∺ Peer-reviewed & Refereed journal ∺ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14741

Classification of Brain Tumours Using Deep Learning Techniques

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Abstract: Brain tumours are potentially fatal anomalies in neural tissues that need to be identified quickly and properly classified in order to be treated. This study offers a deep learning and image processing framework for automated brain tumour detection. The study combines preprocessing, feature extraction, and classification into a single model by using convolutional neural networks (CNNs) to recognise and categorise different types of tumours from MRI scans. When compared to traditional machine learning techniques, experimental results show notable increases in accuracy. The suggested approach provides a dependable tool to help radiologists make clinical decisions more quickly, reduce human error, and aid in early diagnosis.

Keywords: Brain tumour, MRI, Deep Learning, CNN, Image Processing, Medical Diagnosis

I. INTRODUCTION

Abnormal and unchecked brain cell proliferation, which can be potentially harmful, is a hallmark of a brain tumour. The two types of tumours are primary, which start in the brain, and metastatic, which spread to other organs. They can also be malignant (high-grade, rapidly developing, and cancerous) or benign (non-cancerous). Gliomas (originating from glial cells), meningiomas (originating from the meninges), and pituitary tumours (growing in the pituitary gland) are among the additional classifications of brain tumours made by the World Health Organisation (WHO) according to their cellular origin and activity [1-9].

1.1 VISUALISING MODULITIES

One common diagnostic method for evaluating tumours is magnetic resonance imaging, or MRI. Because there is no harmful radiation involved, MRI is the recommended safe technique for detecting brain tumours. Brain tumours are typically diagnosed and treated via magnetic resonance imaging (MRI)[9-10]. An MRI image is typically composed of a matrix of distinct pixels. Because glioblastomas are infiltrative tumours, it might be difficult to tell them apart from healthy tissues because of their hazy borders. MRI methods like Fluid Attenuation Inversion Recovery (FLAIR) and T1 (spin-lattice relaxation) are frequently utilized to image internal body components. MRI imaging was chosen as the modality for identifying the precise classification of brain tumours because of the benefits it provides over alternative techniques. The overall prognosis of the disease can be improved by using Magnetic Resonance Scans to accurately identify the type of brain tumour and diagnose it early. This reduces the possibility that the cancer will spread to other tissues. Magnetic Resonance Imaging (MRI) can also reveal detailed information on the nature of a tumour and how it affects certain anatomical structures. To find tumours, monitor their growth, and cure them, medical imaging is crucial.

II. MATERIALS AND METHODS

The most prevalent and lethal kind of brain tumours are called gliomas, which can be either benign (Low-Grade Glioma) or malignant (High-Grade Glioma). The best way to find gliomas is by magnetic resonance imaging (MRI), in which radiologists manually separate the regions of oedema, non-enhanced tumour, and enhanced tumour. Nevertheless, this procedure is laborious and prone to mistakes. In the identification and classification of brain cancer, deep learning models in particular, Convolutional Neural Networks, or CNNs have demonstrated better performance than conventional techniques. The same hyperparameters were used to test the AlexNet CNN model, which was trained with RMSprop, ADAM, and SGDM optimisers. Combining CNN features with machine learning classifiers such as SVM, discriminant analysis, KNN, and Naive Bayes improved classification even further. This method increased computing efficiency and accuracy.

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2.1 Research Participants:

A total of 196 normal participants, 200 samples with glioblastoma multiforme (malignant), and 130 samples with low-grade gliomas (benign) are included in this study. The TCIA database provided public access to the MRI images used in this study.

2.2 CNN and machine learning algorithms combined

CNN is used to extract features, and four supervised machine learning classifiers—Discriminant analysis, SVM, K-NN, and Naive Bayes Classifier—are then used for tumour classification. Figure 1. displays the block schematic for identifying brain tumours using combined CNN and ML techniques

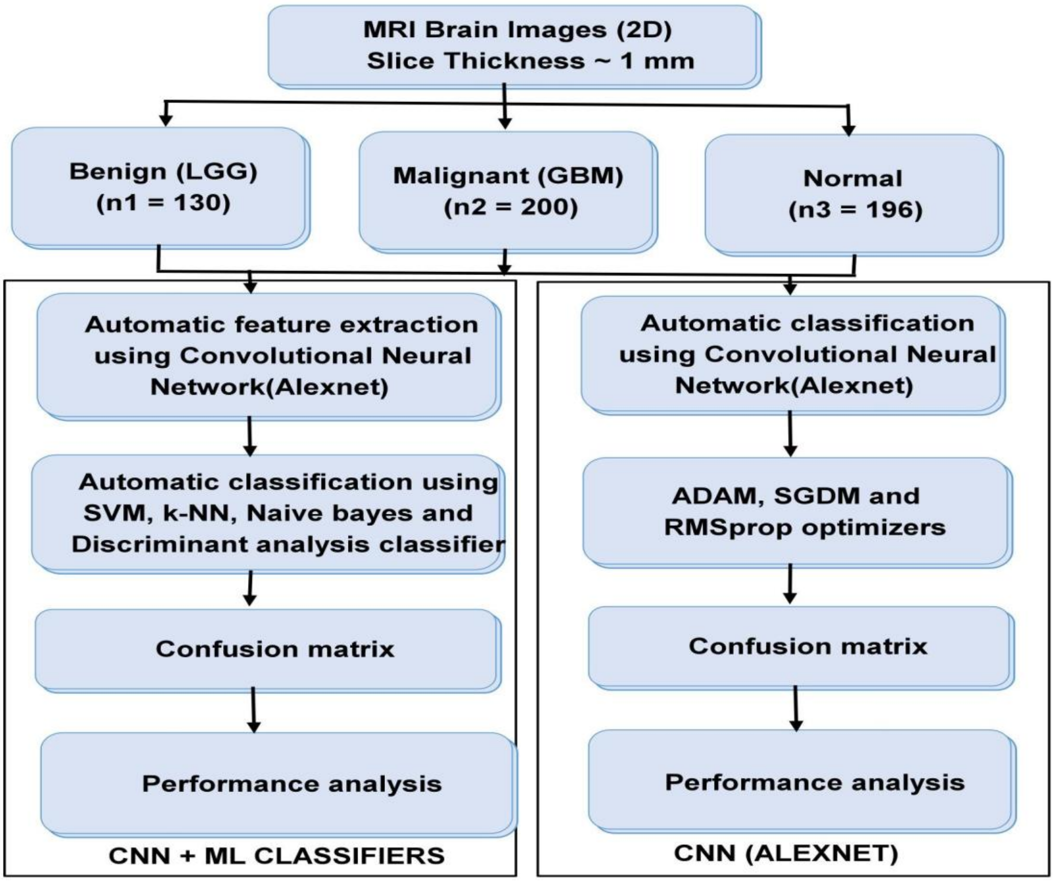

Figure 1. Block schematic for using CNN and ML Classifiers to classify brain MRI images

SVM: Support Vector Machines (SVMs) are mostly used for classification and regression. It is an effective supervised machine learning algorithm. Finding the hyperplane that separates data into discrete classes while boosting the margin between groups is the main objective. The margin is the separation, for each class, between the nearest data point and the hyperplane.

KNN: In KNN, without explicitly assuming anything about the distribution of the underlying data, this instance-based, non-parametric learning approach relies solely on the facts.

Naive Bayes: It is a well-liked probabilistic machine learning technique for classification issues. The core concept of Naive Bayes is the Bayes theorem, which connects conditional probabilities of events. When used for classification, it analyses every feature to ascertain the probability of a particular class [40, 41]. Naive Bayes has many advantages, such as being computationally efficient and handling large feature spaces. In circumstances where the independence assumption is true or nearly accurate, it operates effectively. It functions effectively with tiny datasets and is comparatively easy to implement.

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2.3 Automatic Feature Extraction and Evaluation Using CNN

Deep learning was significantly impacted by the Convolutional Neural Network (CNN) architecture known as AlexNet. Below is a summary of its main elements:

Input Layer: In input layer 227x227 pixel picture is fed into AlexNet.

Convolutional Layers: It is made up of five convolutional layers that extract different features from the input image using kernels. To capture both local and global patterns, these layers use a mix of small and big filters [42–44].

ReLU Activation: Following each convolutional layer, Rectified Linear Unit (ReLU) activation is used to provide non-linearity, which enhances training convergence and enables the network to learn intricate feature associations.

Max Pooling: The first and second convolutional layers are followed by max pooling layers, which reduce spatial dimensions while maintaining crucial information. This improves the network's resilience to translation and distortion and aids in the capture of invariant features.

Normalization: In order to improve feature contrast and the network's capacity for generalisation, this layer is deployed after the first and second convolutional layers to normalise activations within local neighbourhoods.

Fully Connected Layers: Following the convolutional layers come three fully linked layers, each with 4096 neurones. Each neurone in the layer above and the layer below is connected by these layers. Learnt high-level representations of input features were mapped to certain classes.

Dropout: To address overfitting, the first two fully connected layers employ dropout. This technique randomly sets a fraction of neuron activations to zero during training, promoting redundancy learning and improving generalization.

Softmax Layer: The last completely linked layer has 1000 neurones. The softmax activation function, which generates a probability distribution across classes, allows the network to predict class probabilities for incoming images.
Together with learning rate and epochs, the optimisers RMSprop, SGDM, or ADAM should be used in training conditions. The dataset was trained with a learning rate of 0.0001 over 100 epochs. The testing findings showed that the ADAM performed better than the other optimisers in every way. The CNN design for brain tumour detection is displayed in Figure.

2.4 Novel BT-GPM NET and Fine-Tuned CNN Models For Identification Of Brain Tumours

To create a novel deep learning classifier model (BT-GPM net) that is capable of classifying brain tumours into three different groups: pituitary tumours (LGG), meningiomas (LGG), and gliomas (HGG).To evaluate the suggested network against CNN models that have already been trained, such as ResNet-18, ShuffleNet, and AlexNet**.**

To categorize brain tumors as gliomas, meningiomas, and pituitary tumors, the Convolutional Neural Network (Brain Tumor-Glioma Pituitary Meningioma net) was developed. The tumors were classified using pre-trained CNN models (AlexNet, ResNet-18, and ShuffleNet), and the models' performance was contrasted with BT-GPMnet's.

A series of 3064 T1 weighted CE MR images of three distinct brain tumor types are meningioma (708 * 4 = 2832 samples), glioma (1426 * 4 = 5704 samples), and pituitary tumor (930 * 4 = 3720 samples) were subjected to the aforementioned techniques. The MRI dataset underwent several augmentations (between one and three times), and the aforementioned techniques were used to the supplemented dataset. The goal of this effort is to use a deep neural network to diagnose subtypes of brain tumors. The BT-GPM net's initial four blocks (A, B, C, and D) use four layers to extract important features, and block E uses those features to categorize the images as either glioma, pituitary tumor, or meningioma. Additionally, 16 3x3 filters are used in the first and second convolutional layers, 32 3x3 filters are used in the third and fourth convolutional layers, and 64 3x3 filters are used in the fifth convolutional layer. Because it transforms the raw output scores into probabilities and makes the results interpretable, the softmax activation function is utilized in the last layer of neural networks intended for multi-class categorization. A probability between 0 and 1 is assigned to each class score, and the sum of all class probabilities equals 1. For jobs like brain tumor identification, where distinct types of tumors must be distinguished, this probabilistic interpretation makes it easier to choose the most likely class among several alternatives. The block diagram of the suggested BT-GPM net for classifying brain tumors is displayed in Figure 2.

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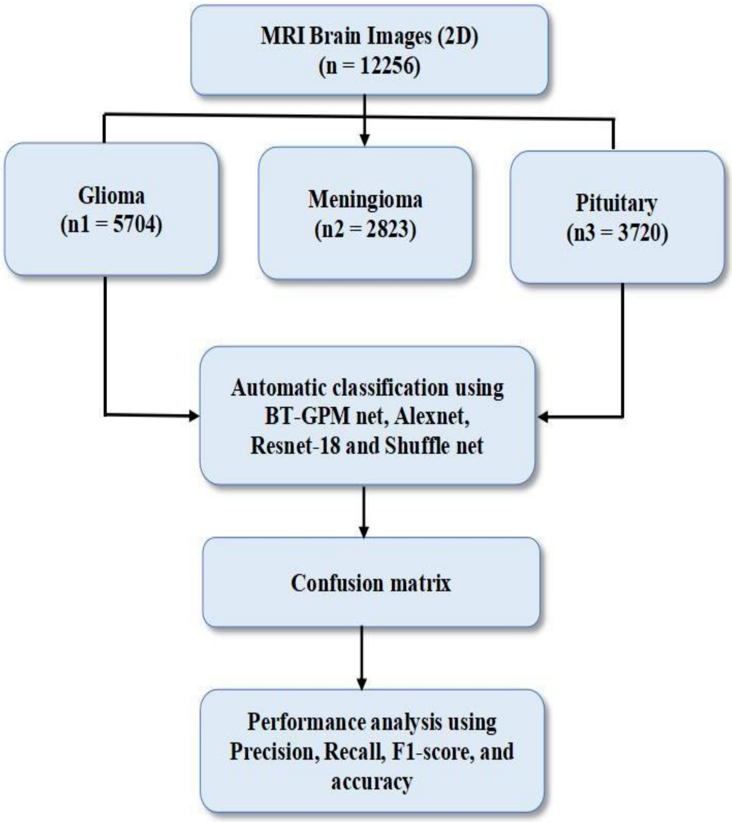

Figure 2. Block diagram of the suggested BT-GPM technique

III. RESULTS AND DISCUSSIONS

Over the past ten years, the use of Convolutional Neural Networks (CNNs) for image classification has been increasingly widespread. Creating a CNN model that can successfully handle every classification problem and produce satisfactory results is not feasible. As a result, a unique Convolutional Neural Network (CNN) model is assigned to every problem type. Carefully selecting and extracting pertinent features is essential to improving the classification process, as is making sure there are a sufficient number of training samples. Deep learning models' innate capacity to learn characteristics on their own has led to an increase in their popularity. Notably, though, these models require a significant amount of memory and computing power. Therefore, it is still necessary to build a little model that produces precise results in a condensed amount of time. In this study, a Convolutional Neural Network (CNN) model is developed that successfully overcomes the drawbacks of earlier methods.

The test dataset was used to evaluate the networks. Depending on the particular issue, inputs, and anticipated results, the CNN model's architecture and complexity vary. For classification, a new Convolutional Neural Network (CNN) model is used in this study. The model's goal is to use Magnetic Resonance Imaging (MRI) to detect and classify brain tumours. A dataset of 12,256 photos of brain tumours was used by the LS model and the pre-trained Convolutional Neural Network (CNN) models. The Tensor Flow framework and the Keras package in Python 3.7 were used to conduct the experiment. Before being used to train the model, the photos were resized. 70% of the data was in the training set, 20% was in the testing set, and 10% was in the validation set. The 3064 MR pictures from a dataset that was made accessible on the Figshare database were used to create the Magnetic Resonance Imaging (MRI) brain tumour images. 2451 samples were deliberately selected for testing out of the 8579 samples that were collected for training in the three times augmented dataset. Furthermore, 1226 samples were obtained for validation purposes. A comparison between the results of the new LS net and those of well-known, state-of-the-art CNN models is essential.

Both the ADAM and SGDM optimisers were used in this case. It has been discovered that applying the ADAM to the task of identifying brain cancers into many classes significantly improves accuracy. The LS model and other popular CNN networks were compared based on the performance indicators derived from the test data. When compared to the

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other networks that are currently in use, the suggested LS model performed better. Table1 explain the result of ADAM Optimizer using various CNN models (VGG16, VGG19, InceptionV3, Xception, Mobile Net, Proposed CNN model)

TABLE 1: EVALUATION OF THE CNN CLASSIFIER'S EFFICACY WITH LS NET (TESTING DATA)

CNN Models	**Class**	**Precision**	**Recall**	**F1-Score**	**Accuracy**
OPTIMIZER		**ADAM Optimizer**			
VGG 16	**Glioma**	**0.79**	**0.97**	**0.87**	**83%**
	Meningioma	**0.93**	**0.37**	**0.53**	
	Pituitary	**0.88**	**0.97**	**0.92**	
VGG 19	**Glioma**	**0.74**	**0.98**	**0.84**	**79%**
	Meningioma	**0.89**	**0.19**	**0.32**	
	Pituitary	**0.87**	**0.96**	**0.91**	
Inception V3	**Glioma**	**0.77**	**0.96**	**0.85**	**81%**
	Meningioma	**0.80**	**0.44**	**0.56**	
	Pituitary	**0.94**	**0.90**	**0.92**	
Xception	**Glioma**	**0.98**	**0.70**	**0.81**	**82%**
	Meningioma	**0.79**	**0.87**	**0.82**	
	Pituitary	**0.73**	**0.99**	**0.84**	
Mobile net	**Glioma**	**0.78**	**0.98**	**0.87**	**85%**
	Meningioma	**0.91**	**0.55**	**0.69**	
	Pituitary	**0.98**	**0.89**	**0.93**	
Proposed CNN model	**Glioma**	**0.88**	**0.95**	**0.91**	**91%**
	Meningioma	**0.93**	**0.69**	**0.80**	
	Pituitary	**0.91**	**0.97**	**0.94**	

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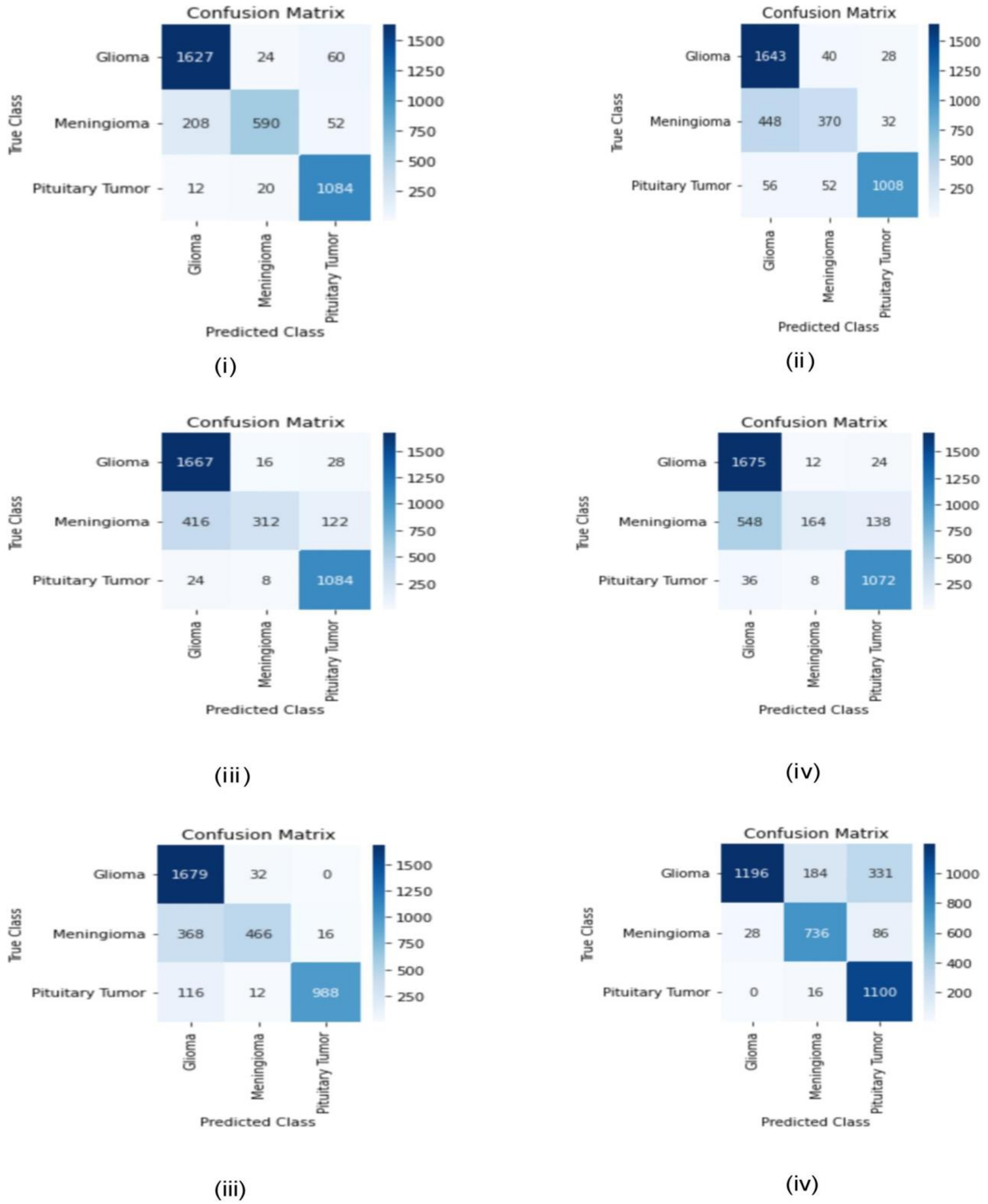

Figure 3 presents the confusion matrix for the following models: (i) LS Net, (ii) InceptionV3, (iii) VGG16, (iv) VGG19, (v) Mobile Net, and (vi) Xception model (Figshare - Testing data)

A graph known as the Receiver Operating Characteristic curve (ROC curve) demonstrates the effectiveness of a classification model at various categorization levels. This curve presents the True Positive Rate (TPR) and False Positive Rate (FPR) as two distinct parameters. This curve presents the True Positive Rate (TPR) and False Positive Rate (FPR) as two distinct parameters. The ability of a classifier to differentiate between classes is quantified by the area under the

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curve. An AUC value close to one signifies that a model possesses a high level of separability and is deemed excellent. For the glioma, meningioma, and pituitary tumor classes, the proposed LS net achieved AUC values of 0.91, 0.91, and 0.96, respectively. Figure 4 illustrates

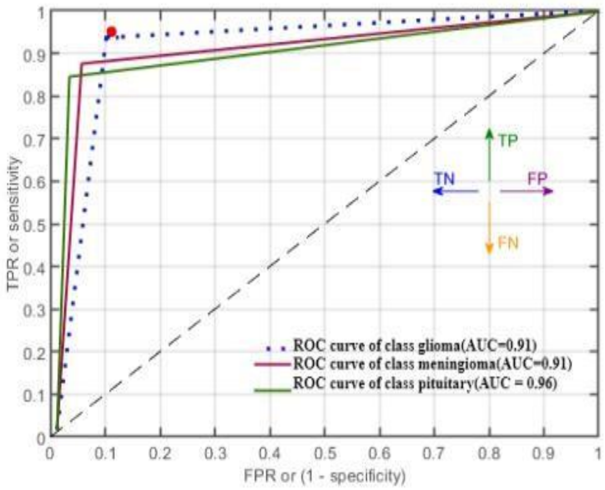

Figure 4 AUC and ROC curve

IV. CONCLUSION

The advancements in artificial intelligence have led to a transformation in machine learning research, shifting the emphasis from feature engineering to architecture engineering. This study focused on the classification of brain tumours. Convolutional Neural Network (CNN) models were employed, incorporating extensive hyper-parameter tuning through grid search. These CNN models were trained on a substantial number of medical images sourced from publicly available datasets. The efficacy of our newly developed CNN model, alongside several state-of-the-art techniques, was evaluated. The findings indicate that the CNN model can be an essential resource for radiologists and clinicians in corroborating their preliminary evaluations of brain tumours.

Our main objective was to develop an automated brain tumour classifier capable of differentiating between meningioma, pituitary tumours, and gliomas. Conventional methods are hindered by prolonged computation times and reduced accuracy. To overcome these challenges, a 24-layer CNN model was proposed. An accuracy of 81.83%, 83.30%, 85.21%, 82.49%, 79.54%, and 91.73% was attained with Inception V3, VGG-16, MobileNet, Xception, VGG-19, and the newly introduced LS net. Furthermore, using the Flutter framework, an LS net was created as an Android mobile application and assessed with real-time images. Importantly, the JPEG format was employed in this study, which minimizes information loss. Future research will incorporate 3D volumes (DICOM format) to enhance efficiency and further reduce information loss.

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ISSN (O) 2278-1021, ISSN (P) 2319-5940

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