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NeuroTumorXpert: An Advanced Hybrid Deep Learning Model for Multi-Classification of Brain Tumor via Magnetic Resonance Imaging

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ABSTRACT

Introduction: Brain tumors must be detected early in order to improve the patient's prognosis and course of therapy. To create specialized treatment approaches, brain tumors must be properly classified, segmented, and graded. Despite the growing use of MRI in brain exams and improvements in AI-based detection methods, it can be difficult to create a reliable model for tumor diagnosis and classification from MR images.

Objectives: Thus, there is an urgent need for a more automated, effective, and precise method for detecting, classifying, and grading brain tumors. The need was for a solution that could process medical imaging data quickly and reliably, while ensuring accessibility and reducing the dependency on human expertise, ultimately aiding in timely diagnosis and improved patient outcomes.

Methods: Current diagnostic techniques mainly rely on radiologists' manual interpretation, which can cause delays and human error, particularly when malignancies are still in the early stages. Traditional imaging technologies, while useful, often fail to provide precise localization and classification of tumors, especially when dealing with varying shapes, sizes, and textures. So, this paper introduces a multi-classification brain tumor diagnosis model. It combines hybrid methods and deep learning models to detect tumors, classify tumors and grade glioma tumors.

Results: The proposed model, NeuroTumorXpert, has high accuracy, 99.69% for detection via fine-tuned VGG16 model, 99.15% for tumor type classification via fine-tuned InceptionV3 model and 96.64% for glioma tumor grading via Inception-ResNet-v2.

Conclusions: Identifying gaps and comparison was done to find out the lacking areas in past research related to multi classification of brain tumor, advancement in deep learning algorithm on medical imaging to increase accuracy and able to do multi classification.

Keywords: Brain Tumor, Multi-Classification, MRI, Segmentation, Augmentation, Deep Learning.

INTRODUCTION

The brain is one of the biggest and most intricate organ of the human body that holds approximately 100 billion nerve cells, and each cell possesses billions of synapses [1]. The human brain is chief command and control center of the neurological system that governs the organs within the body. Thus, the presence of any disorder in brain is a serious factor in deciding an individual's health. As per World Health Organization (WHO), in 2020, cancer caused more than 10 million deaths all over world and became the second leading cause of mortality [2]. Therefore, the patient has a better survival chance due to early cancer detection.

Brain tumors are classified into four grades (Grades I–IV) on the basis of their malignancy or benign nature. The two traditional methods to recognize and evaluate brain cancers are computed tomography (CT) and magnetic resonance imaging (MRI) [3]. Malignant brain tumors of grades III and IV proliferate rapidly infiltrate other bodily areas and pollute healthy cells. As a result, doctors can better plan the right course of treatment when brain tumors are detected early and classified using MRI and other scans [4]. The three most common important brain tumors are meningioma,

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pituitary and glioma. Pituitary glands produce body's most significant hormones where pituitary brain tumors generally develop and are benign [5]. Gliomas arise from glial cells within a brain [6]. Meningioma tumors mainly develop in covering membrane of brain and spinal cord [1]. Differentiating between malignant and benign brain tissue is major obstacle in detection of brain tumors. Variations in size, form, and location make it more challenging to diagnose brain tumors, which is still an open issue. Brain tumor analysis uses techniques from medical image processing, such as detection, segmentation and classification [7]. Brain tumors classification is essential for identifying the type of tumor early on, assuming any exist. In biomedical image processing, a number of advanced computer-aided diagnosis algorithms are introduced to assist radiologists in more accurately identifying brain cancers and guide patients [8]. A high-grade brain tumor is a dangerous illness that reduces life expectancy. In particular, the patient's life and treatment depend on brain tumor diagnosis [9]. Due to nasopharyngeal carcinoma's (NPC) high variation, low contrast, and fractured margins in MRI. In order to guide a radiologist [10] to detect cancers more correctly, precise tumor segmentation and DL architectures are crucial [11-13].

Automatic segmentation and classification of medical images are significant in diagnostics, brain tumor growth prediction and therapy. Early diagnosis of brain tumor means an accelerated reaction in treatment, improving patients' survival rate. Brain tumor location and classification in large databases of medical images, acquired in routine clinical practice by manual operations, are extremely expensive in time and effort. It is desired and valuable to have an automatic process for localization, detection and classification [14]. There are a number of medical imaging methods that are designed to create pictures for diagnosis of various diseases. Most commonly used are X-rays, MRI, ultrasonic imaging (UI), CT, positron emission tomography (PET) and single-photon emission computed tomography (SPECT) [15].These enable the medical specialist to scan and obtain exact data about various parts of body. It makes it easier to diagnose illnesses and plan treatments. As it produce high-resolution images that accurately depict structure of human brain, MRI is most important and favored technique. MRI gives a strong presentation for all tumor types, including pituitary, glioma and meningioma [16].

The advent of newer technologies, mainly AI and ML over the last couple of years, impacts the medical fraternity immensely because it has provided the medical divisions with a worthwhile tool for assistance, like medical imaging. MRI classification and segmentation are done using ML approaches to help radiologist make decisions. To obtain the most features and selection methods, the supervised method of classifying a brain tumor necessitates special knowledge, though this technique has a tremendous potential [17]. The most widely used techniques for brain tumor detection in literature are ML and DL. ML methods such as support vector machines (SVM), k-nearest neighbor (kNN), decision trees, artificial neural networks (ANNs) have been used in certain proposed studies [18–21]. Nevertheless, mean features must be retrieved for training and both methods work with manually generated features. As a result, feature quality affects the accuracy of detection and classification. For big datasets, machine learning classifiers take significant time and memory [22]. CNN layers are also often employed for voice and picture feature extraction [23]. Because each neuron is coupled to another neuron, ANNs are also used for the extraction of other features [24]. The last layers of medical images in deep learning, however, are fully integrated and operational. For example, the most used DL model is CNN, which is primarily used for image classification [25].

This prompted the proposal of a DL-based solution to improve the effectiveness and accuracy of existing algorithms to detect numerous types of brain cancers and method was experimented on a publicly available dataset. A NeuroTumorXpert model is proposed that is a multi-classification model designed for brain tumor diagnosis. This model carries out three essential tasks: detection of tumor, identification of tumor type and grading of glioma tumors. It exploits segmentation via a UNN-based method and CNN layers that have been optimized to derive rich feature representations from MRI scans. It incorporates deep learning methods, fusing hybrid methodologies with deep learning models. Such a layered hybrid architecture improves the model's diagnostic accuracy at various stages of tumor classification, providing an end-to-end, scalable and intelligent solution for computer-aided neuro-oncological analysis.

The key contributions of the proposed work:

- Comprehensive Multi-Stage Pipeline: Established a hybrid deep learning pipeline with data preprocessing, image augmentation, MRI segmentation, and multi-classification for brain tumor diagnosis.

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- Improved Tumor Analysis: Executed classification for tumor detection, type identification (glioma, meningioma, pituitary), and glioma grading through fine-tuned Inception-based models.
- Model Evaluation & Benchmarking: Performed thorough model comparisons, studying the effect of segmentation and augmentation and compared results against state-of-the-art models.
- Autonomous Diagnostic System: Created a completely automated web-based tool with Streamlit and GPT-4 for real-time AI-powered brain tumor detection and recommendation.

This research study is organized as: Section II contains the related works and section III describes proposed methodology and framework along with dataset description and exploratory data analysis. Section IV presents the results and discussion whereas section V shows state of the art comparison. Section VI provides the study's conclusion and future scope.

RELATED WORKS

An extensive literature survey has been conducted. Research articles on relevant topics related to brain tumor to understand biology, and paper consist of brain tumor classification using DL on MRI, were collected from good-impact journals based on SCI and Scopus between 1999 to 2025. The comprehensive study focused on the current status, limitations, and implementations concerned, mirroring the shift towards deep learning driven deduction and multi classification using MRI.

In this paper, two pre-trained deep neural network models, DenseNet201 and Inception-v3, were concatenated and multi-level features extracted in brain tumor diagnostic method proposed by Noreen et al. [26]. To provide precise tumor classification, the characteristics are taken from different layers, concatenated, and fed into a softmax classifier. On a publicly accessible brain tumor dataset having three classes, the model demonstrated exceptional test accuracies of 99.34% and 99.51%, outperforming state-of-the-art techniques in early identification. Additionally, utilizing PCA and discrete wavelet transformation to improve feature extraction, Mohsen et al. [17] proposed employing DNN to classify brain MRIs in four groups. In their examination of ML and DL methods for brain tumor diagnosis, Abd-Ellah et al. [28] also offered important conclusions, metrics for assessment, and suggestions for further study.

Using two publicly available datasets, Sultan et al. [29] created CNN model to categorize brain cancers. It has a 96.13% classification accuracy for tumor types and a 98.7% accuracy for glioma. The results demonstrate how well model performs in multi- classification brain tumor tasks. Naser et al. [30] introduced a DL method integrating U-Net-based segmentation and VGG16-based transfer learning for lower-grade glioma grading based on MRI. With high accuracy, specificity and sensitivity, the model provides a non-invasive, automatic solution for tumor segmentation, detection, and grading, facilitating efficient clinical diagnosis and decision-making. A transfer learning and fine-tuned DenseNet201-based automated DL method for multiclassification of brain tumor was introduced by Sharif et al. [16]. EKbHFV and a genetic algorithm are used to enhance feature selection, and a multiclass SVM is used to classify combined features. The accuracy of model on BRATS2018 and BRATS2019 datasets are more than 95%.

Ullah et al. [32] proposed a hybrid system that classifies brain MRI into normal and pathological classes, using feed-forward artificial neural networks, discrete wavelet transform, and histogram equalization. Kharrat et al. [33] divide brain tumors into normal or abnormal using support vector machines and genetic algorithms. Additionally, Papageorgiou et al. [34] utilized fuzzy cognitive maps for categorizing gliomas with 93.22% accuracy for high-grade and 90.26% accuracy for low-grade brain tumors. Whereas, Shree and Kumar [35] distributed brain MRI in 2 classes. The probabilistic NN classifier was applied for classification of brain MRI into normal and pathological classes at a 95% accuracy level; GLCM was applied for feature extraction. A hybrid, computationally efficient, auto identification, and classification scheme of tumors was postulated by Rajan and Sundar [36]. With their proposed approach that contains seven very complex stages, they reached an accuracy level of 98%. The major disadvantage of their paradigm is increased computation time because of involvement of many approaches. During last decade, DL algorithms have emerged as one of the preferred tools for classification of brain MRI [37,38]. The deep learning technique uses a data set, and sometimes a pre-processing step is necessary before the salient features are found in a self-learning way [39]. To get around this restriction, Afshar et al. [40] created CapsNets which are very sensitive to background of image.

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The main work is to enable CapsNet to incorporate tissues around the tumor without losing its focus from key target. Another variant of CapsNet architecture is used for classification of brain tumor, taking the tumor coarse borders as extra inputs in its pipeline, to enhance concentration of CapsNet.

Major Research Gaps and Limitations

- Traditional imaging techniques: These methods require manual interpretation by radiologists, leading to delays and higher chances of human error [26].
- Conventional machine learning methods: These approaches lack the adaptability and precision of DL algorithms, particularly when dealing with complex medical information [17,27].
- Recent research has focused more on improving images and creating AI models leveraging advance CNN and Faster R-CNN but little attention has been paid to how sensitive a model is to the prediction, detection, and categorization of tumors and predicting grades of the tumor [28,29].
- The research on brain tumors has predominantly focused on the segmentation and localization of tumors, rather than extensively exploring the categorization of different tumor forms based on factors such as location or grade [29,30].
- The use of imaging methods to detect brain tumors has been extensively studied in the past [16,17,28,31]. However, there is a notable gap in research concerning the exploration of the unique anatomical characteristics of tumors and their correlation with tumor staging and prognosis, presenting an exciting area for future investigation.
- Hardware-dependent & heavy duty AI utilities: These are often expensive and inaccessible to smaller healthcare facilities and difficult to use by medical professionals for day to day diagnosis.

These alternatives were not suitable due to their limitations in cost, accuracy, scalability and adaptability and user experience.

MATERIALS AND METHODS

This subsection emphasizes and expands on the research methodology suggested and suggested framework. It entails MRI data collection, augmentation, segmentation and feature extraction through DL. The system identifies the presence of tumors, classifies tumor type and goes further to grade glioma tumors from Grade 1 to 4, thus providing accurate and automated diagnosis.

Methodology

This section explains the step-by-step methodology followed for tumor multi-classification as shown in figure 1. Four distinct datasets were appended to formed merged dataset/directory. Finally merged directory which combining MRI from all four datasets was used for segmentation and multi classification brain tumor diagnosis model. Figure 2 shows proposed methodology.

Fig. 1. Proposed Methodology

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The proposed model, NeuroTumorXpert, helps in accurately predicting first binary classification tumor or non-tumor, second classification is predicting type of tumor and third classification is predicting Glioma tumor into four distinct grade basis size, location of tumor 1-4.

Proposed Framework

Figure 2 shows step- step approach followed for developing proposed model for multi classification brain tumor diagnosis model. This comprehensive workflow ensures accurate, efficient, and scalable tumor detection, significantly reducing diagnostic errors. The innovation for brain tumor detection involves a systematic, stepwise approach that integrates advanced image processing and artificial intelligence methods.

Fig. 2. Representation of proposed framework

Dataset Description

The authors used four individual benchmarked datasets consisting of dataset a, b, c, d as shows in Table 1. Also, Brats dataset is used which is benchmarked dataset consist of Glioma grade HGG/ LGG, for multi-classification model development.

Table 1: Description of datasets

Dataset	Source of Data set	Volume details	Year of data set and Author
Dataset A [39]	https://figshare.com/articles/dataset/brain_tumor_dataset/1512427/5	3064 T1-weighted contrast-enhanced images with three kinds of brain tumor	2017, Authored by Jun Cheng
Dataset B [40]	https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri	This dataset comprises 3264 T1, T2, and fluid-attenuated inversion recovery MRI images	2020, Authored by Sartaj
Dataset C [41]	https://www.kaggle.com/datasets/pradeep2665/brain-mri	This dataset includes 10000 MRI images of 3 classes of tumors and MRIs with no tumor	2022, Authored by Pradeep
Dataset D [42]	https://www.kaggle.com/datasets/mohamedmetwalysherif/braintumordataset	There are a total of 4292 images in this dataset	2021, Authored by Sherif
Brats [38]	https://www.kaggle.com/datasets/sanglequang/brats2018/data	It contains HGG, LGG labeled grades of Glioma data	2021, Authored by Quang

- Dataset A - Dataset A was selected from General Hospital at Tianjin Medical University and Nanfang Hospital in Guangzhou, China. This is widely used in many research papers and made publicly, Authored

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by Jun Cheng in 2017 [40,41]. The images were captured using a type of MRI technique called spin-echo-weighted imaging, which provides detailed images with a resolution of 512 × 512 pixels [30,42,43]. MRI broken into three categories of Tumor - Glioma (1426), Meningioma (708) and Pituitary tumor (930) from 233 patients.

- Dataset B - Dataset b comprises of identical 3264 T1, T2 and fluid-attenuated MRI and made available by Sartaj in 2020 [44]. For this dataset, the authors referred to a study about accurately detecting brain tumors using deep convolutional neural networks. Dataset split into training and testing. Testing directory includes pituitary (74), meningioma (115), glioma (100), and no tumor (105). Training directory consists of pituitary (827), meningioma (822), glioma (826), and no tumor (395).
- Dataset C - Dataset C consists of 10000 MRI and entire data split into training, testing and validation. This dataset made available by Pradeep in 2022 [45]. Dataset is equally classified all MRI into 4 classes - meningioma (2500), pituitary (2500), glioma (2500), and no tumor (2500).
- Dataset D - Dataset d consists of 4292 MRI and made available by Sherif in 2021[46]. In this particular dataset, the authors have taken a reference from [47,48]. This dataset split all MRI into training and testing and each of these directory contains pituitary, meningioma, glioma and no tumor.
- Brats Dataset - It contains HGG, LGG labeled grades of Glioma data labeled basis on High grade and Lower grade and made available by Quang in 2021 [49]. There are 1050 HGG (High Grade Glioma] and 375 LGG [Low Grade Glioma].

Merged dataset combines images from the four individual datasets (A-D) into merged dataset after appending and then removal of duplicated images so keep only identical images. The overall quantity of images in every dataset and the combined directories are appended to the merged dataset, ensuring a comprehensive and unified dataset for further analysis and multi classification model development as shown in figure 3.

This approach ensuring a comprehensive and unified dataset, which helps in overcome challenge faced by most authors in handling data deficit, model biases since unequal distribution of label data.

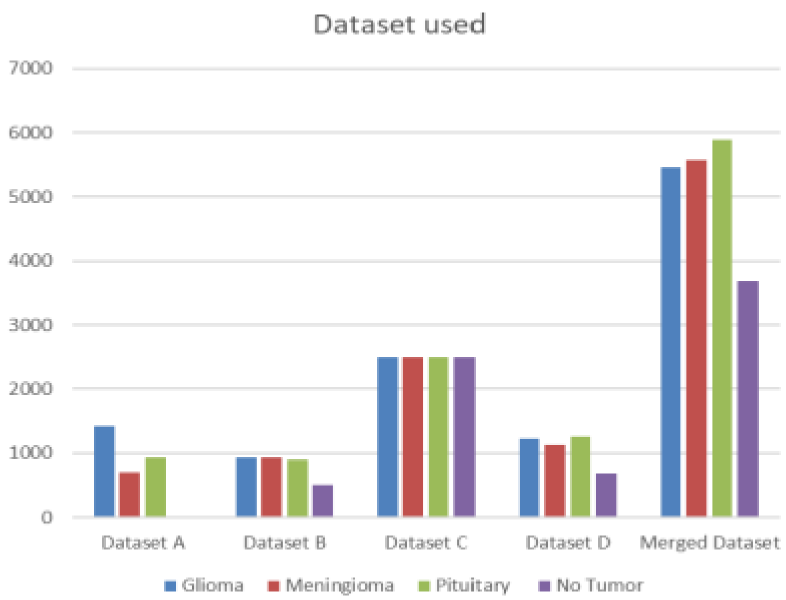

Fig. 3. Distribution of dataset

Exploratory Data Analysis

Merged data set consists of 3,681 samples with no tumor label and 16,939 samples with tumor identifier. Figure 4 shows sample MRI scans sorted into two groups: tumor (bottom row) and non-tumor (top row). To aid in the differentiation of tumors from healthy brain tissues in medical imaging, each category has three illustrated cases that demonstrate the visual distinctions in brain structures for both conditions.

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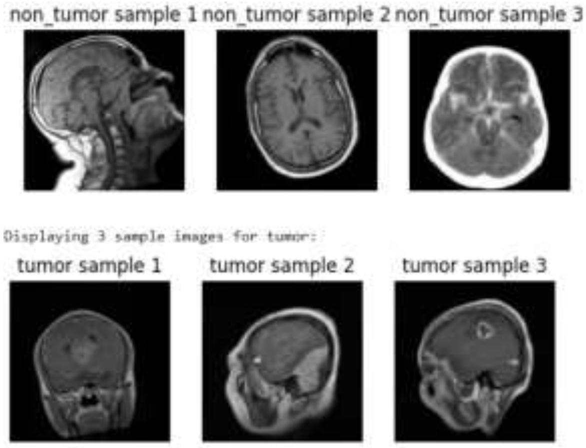


Fig. 4. Sample of MRI for tumor classification

Figure 5 demonstrates the data distribution of tumor over non tumor, consist of 3681 no tumor label and 16,939 samples with tumor identifier.

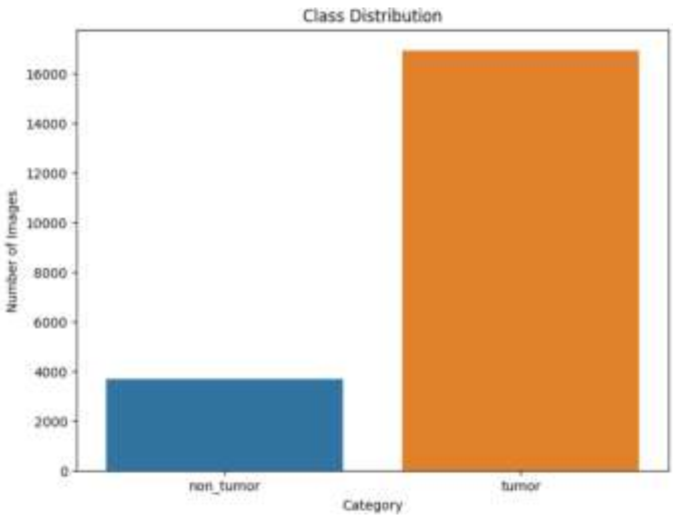
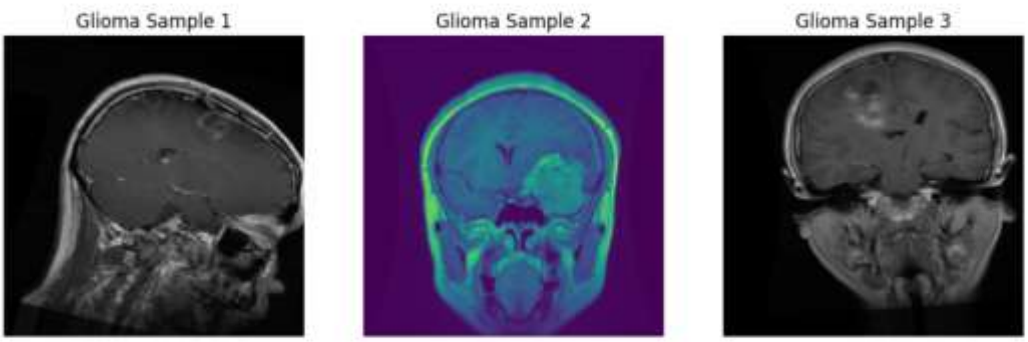


Fig. 5. Plot shows the data distribution of non tumor over tumor

Merged dataset consist of 5463 MR images of glioma, 5586 of meningioma and 5890 of pituitary tumor MRI which shows good distribution of all three types. Figure 6 shows sample MRI scans sorted into three groups: Glioma (top row), Meningioma (Middle row) and pituitary (bottom row).



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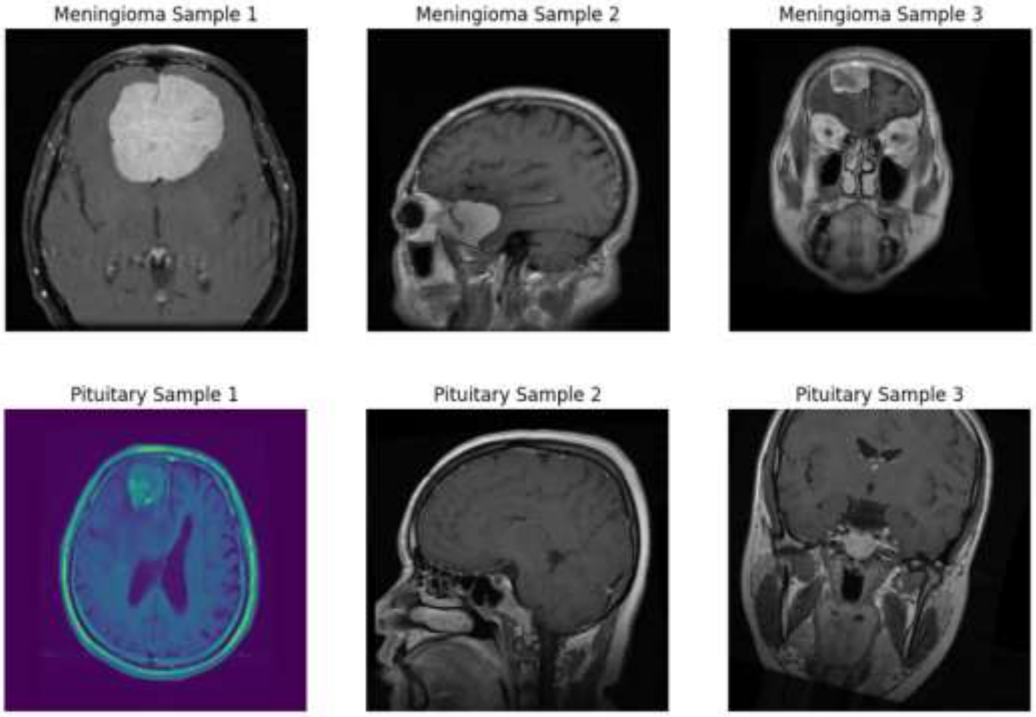

Fig. 6. Sample of MRI for Tumor Classification

Figure 7 illustrates the data distribution of all three tumor which shows equal distribution to avoid any data biases and overfitting issues, consist of 5463 of Glioma, 5586 of Meningioma and 5890 of Pituitary tumor MRI.

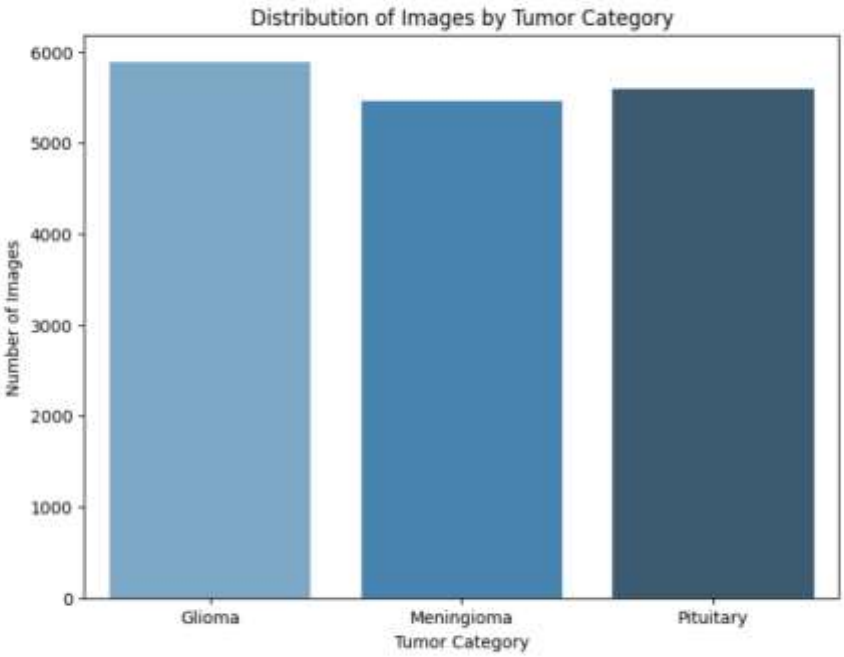

Fig. 7. Plot shows the data distribution of all three tumor

Image Augmentation

Each MRI original image has undergone to preprocessing steps consists of applying 9 different image augmenting techniques on each image. Image augmentation techniques include Horizontal flip, Vertical flip, rotation, Adjustment on Brightness, resizing & zooming, Filtering like mode & sobel filter, grayscale conversion, unsharp masking, and &

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noise addition. There is total 20620 MRI and post preprocessing total images used for model development is 185,580 images. Figure 8 shows original image along with images processed on 9 different augmentation technique.

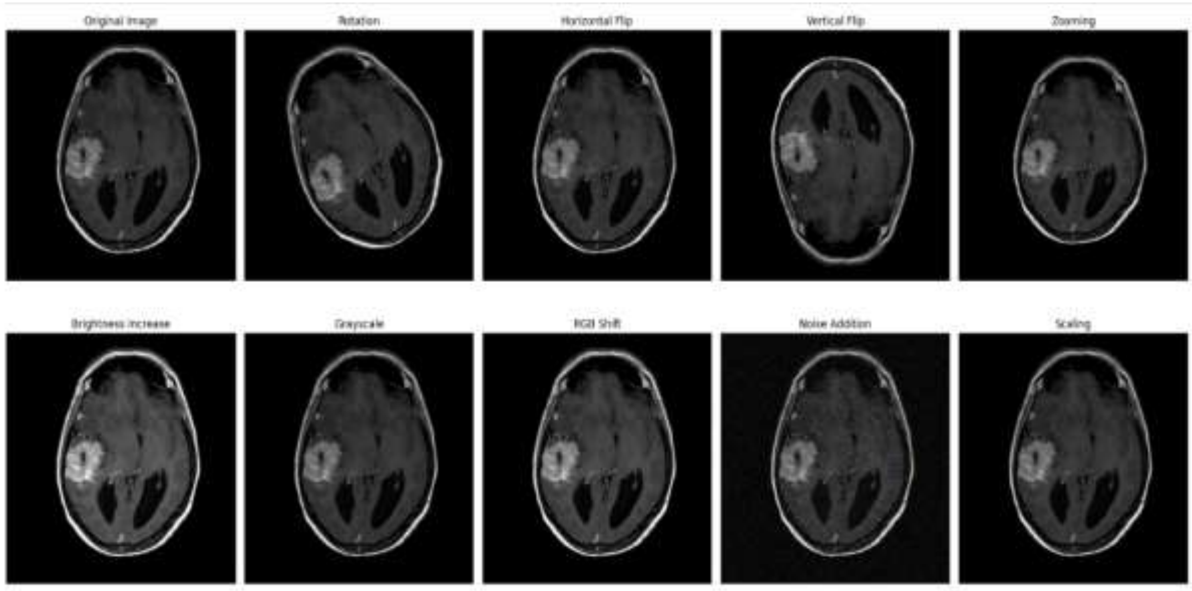

Fig. 8. Image augmentation techniques applied on each MRI

MRI Segmentation

Four distinct datasets are appended to form the merged dataset which is finally used for model development. A masked dataset is used to train segmentation model. To improve the input images by segmenting regions of interest (e.g., tumor) before feeding them into the classification model.

Using advanced segmentation algorithms U-Net, the system isolates tumor region from surrounding brain tissue. This is a critical step as it focuses analysis on the specific region of interest, eliminating irrelevant data. U-Net a pre trained model is utilized for predicting segmentation mask. A segmentation process is then applied to isolate tumor regions from the surrounding brain tissue. Important characteristics like texture, intensity, and shape are taken out of these divided areas for additional examination.

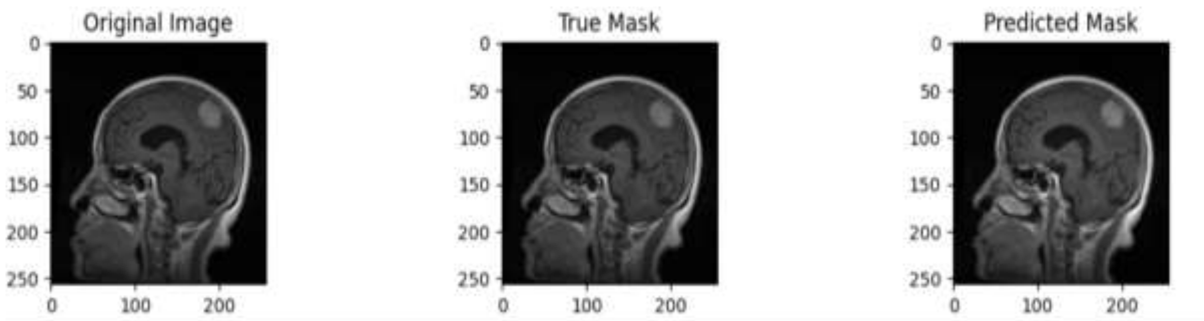

Fig. 9. Representation of true mask and predicted mask of original image

Figure 9 display original images, true masks and predicted masks. The original brain MRI picture, the anticipated segmentation mask and the real segmentation mask are contrasted in this image. The real mask shows the ground truth region of interest, whereas predicted mask shows model's output. The comparison proves that model can perfectly identify target area.

RESULTS AND DISCUSSIONS

In this section, the experimental findings of the proposed hybrid DL approach for brain tumor diagnosis is discussed. The model performance is evaluated with three critical tasks: tumor detection, classification of tumor type, and

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grading of glioma tumors. Extensive testing is performed on augmented and segmented MRI datasets with help of state-of-the-art models like VGG16, Inception V3 and ResNet. Comparative analysis points out the influence of segmentation and image augmentation on classification accuracy. Furthermore, findings confirm the strength of the fully autonomous system for real-time diagnosis. Performance is assessed using standard metrics, setting up the model's credibility in clinical decision support situations.

Classification I – Tumor detection

The dataset consists of training, validation and testing sets. To improve diversity of training data and avoid overfitting, the train_datagen uses multiple augmentations, including rotation, shifting, shearing, zooming, brightness adjustment, and flipping. However, for validation and test data, only rescaling is applied (no augmentation) to ensure this data remain representative of original dataset. 60% of the data is allocated for training, 20% for testing and rest 20% is reserved for validation.

NeuroTumorXpert, the proposed model leverages fine tune VGG16, advance deep learning CNN network which trained on huge dataset of medical images, allowing enabling it to pick up intricate details for the binary diagnosis of brain tumors either MRI present with tumor or no tumor. Weights from ImageNet that have already been trained are imported into the VGG16 model (weights='imagenet'). A custom classifier is introduced for fine-tuning when the top classification layer (include_top=False) is removed. The rest of the layers are frozen to keep the learned features from before and avoid overfitting, and the last 10 layers are left unfrozen for fine-tuning. 2 fully connected (dense) layers with batch normalization, dropout, and ReLU activation function are added for regularization. Adam optimizer with learning rate of 1e-4 is utilized for training. As task involves multi-classification, categorical cross-entropy is utilized as loss function. Train_generator is used to train model for up to 100 epochs, and it is then validated using the validation_generator and the training process is monitored using the defined callbacks to avoid overfitting and make sure the optimal model is preserved. Figure 10 shows network architecture of VGG 16.

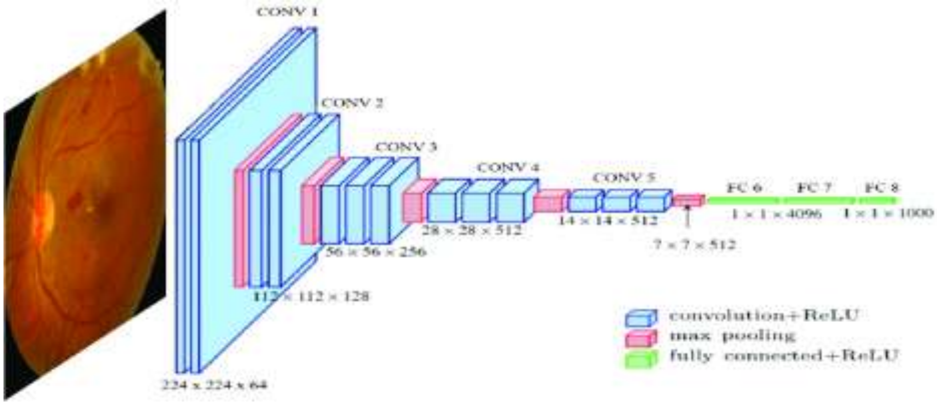

Fig 10. Representation of true mask and predicted mask of original image

Classification I Model performance

Sklearn measures are used to evaluate recall, F1-score, accuracy and precision. The performance of model on both visible and invisible data is displayed in Tables 2 and 3. Proposed model achieve 99.69% accuracy in predicting Tumor detection.

Table 2. Proposed Model for Classification I performance using Model accuracy KPIs

Training Accuracy	0.9969
Training Loss	0.0235
Validation Accuracy	0.9706
Validation Loss	0.1582

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Table 3. Proposed Model for Classification I performance using Model KPIs on unseen data

Tumor Class	TP	TN	FP	FN	Accuracy	Precision	Recall	F1 Score
Tumor	2651	586	25	0	0.9979	0.9935	0.9985	0.9979
Non Tumor	586	2651	0	25	0.998	0.993	0.996	0.9952

Figure 11(a) shows plotting accuracy on epoch. The validation and training loss of a model over time is shown in figure 11 (b). A consistent drop in training and validation loss indicates learning and demonstrates how effectively the model is working.

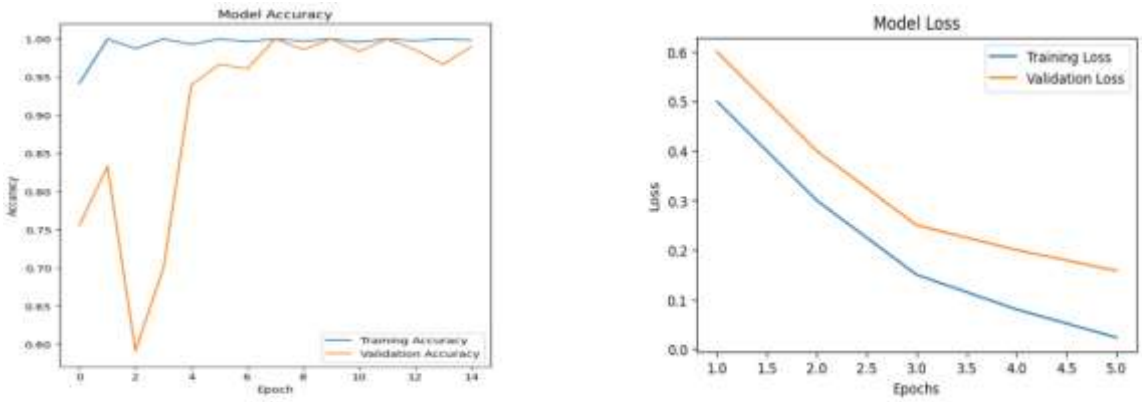

Fig. 11. Model plotting of proposed model of classification I (a) Accuracy (b) Loss

Figure 12 shows confusion matrix to show how model performing while all cases. 2651 predicting correct as Tumor and 586 are predicting correctly non tumor MRI. Only 25 are predicting wrong, non tumor cases are predicted tumor.

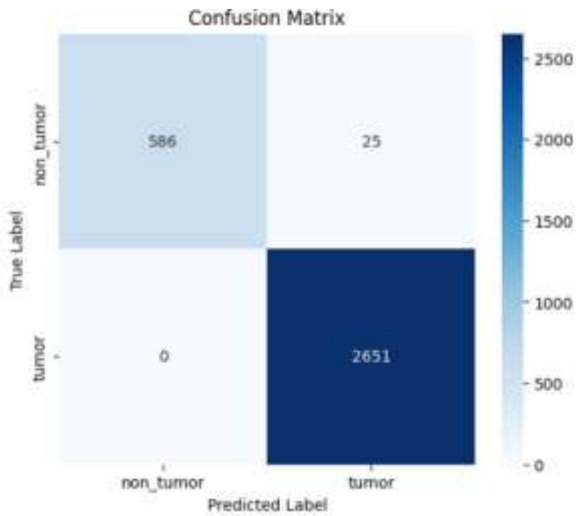

Fig. 12. Proposed Model performance using confusion matrix on unseen data

Comparative analysis of proposed model with state-of-the-art for Classification I

Table 4 displays the comparison of NeuroTumorXpert predicting binary tumor detection either tumor or no tumor. Proposed model shows the highest accuracy of 99.69% over state-of-the-art advance DL architectures.

Table 4. Comparative analysis for Classification I

State of the Art Model	Training Accuracy	Training loss	Validation accuracy	Validation Loss
VGG 16	0.9900	0.0204	0.9851	0.0543

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ResNet101	0.9960	0.0017	0.9904	0.0611
VGG19	0.9933	0.022	0.9833	0.0607
EfficientNet B0	0.9870	0.0359	0.9817	0.1067
Proposed Model, NeuroTumorXpert	0.9969	0.0235	0.9706	0.1582

Classification II – Tumor Type detection

NeuroTumorXpert leverage fine tune Inception V3 for Tumor type detection. This approach involves training DL model for image classification using InceptionV3, a pre-trained CNN model. Confusion matrices and classification reports evaluate model performance after it has been refined on a specific dataset. The ImageNet dataset consist millions of tagged photos in different categories, is used to pre-train the model, making it highly effective for transfer learning. Loaded InceptionV3 using weights that were already trained and excluding top classification layer to add a custom classifier and set the input shape to (299, 299, 3) to match required input size for InceptionV3.

InceptionV3 model is designed for 1000 classes (ImageNet). A custom classifier was added to the main model in order to modify it for a particular job (classifying three types of tumors). A dense layer with 128 units that is fully connected was added for the classifier, and ReLU was turned on and employed a softmax activation in last layer to detect tumor types using multi-class classification. To effective training, Adam optimizer with the learning rate set to 1e-4 and categorical cross-entropy loss were utilized while compiling the model. When 60% of the data was retained for training and 20% for validation and testing. The training of model was conducted a maximum of 20 times. The network structure of Inception V3 is illustrated in Figure 13.

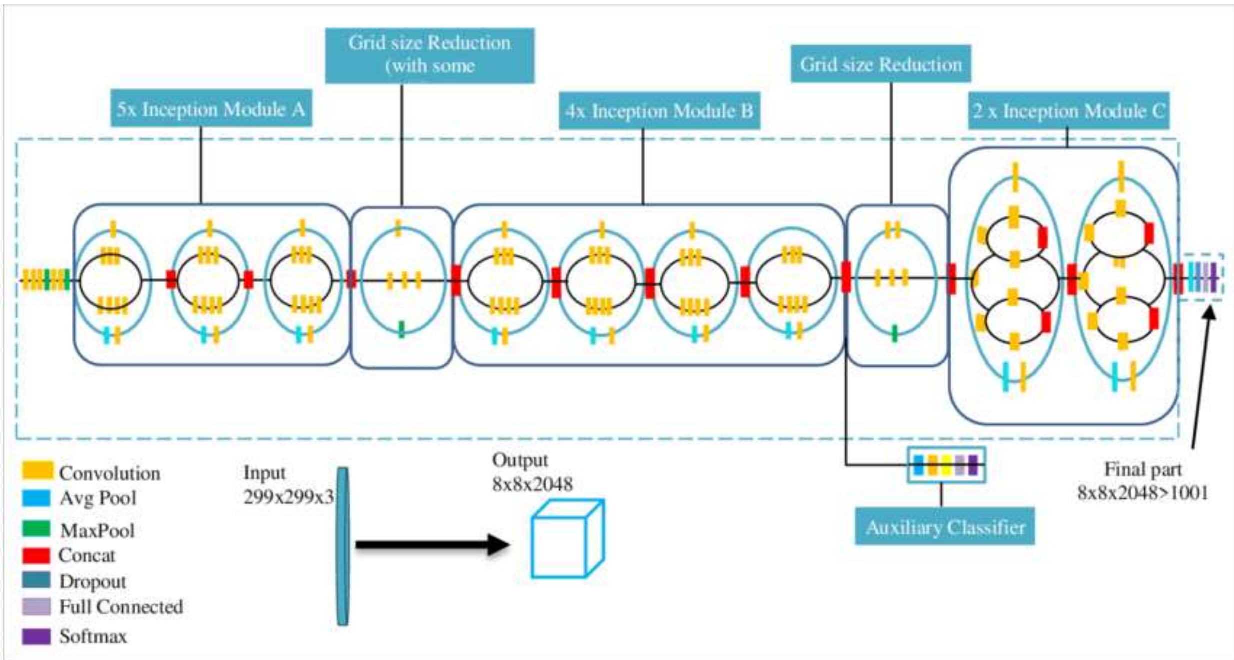

Fig. 13. Proposed Model Architecture for classification II

Classification II Model performance

Sklearn metrics are utilized to determine precision, recall, accuracy, and F1-score. The performance of model on visible and invisible data is displayed in Tables 5 and 6. NeuroTumorXpert achieves 99.15% accuracy in predicting Tumor type (Glioma, Pituitary, Meningioma).

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Table 5. Proposed Model for Classification II performance using Model accuracy KPIs

Training Accuracy	0.9915
Training Loss	0.0211
Validation Accuracy	0.9004
Validation Loss	0.1688

Table 6. Proposed Model for Classification II performance using Model KPIs on unseen data

Tumor Class	TP	TN	FP	FN	Accuracy	Precision	Recall	FPR	TNR	F1 Score
Glioma	908	1628	187	77	0.9050	0.8292	0.9218	0.1030	0.8970	0.8731
Meningioma	695	1918	45	142	0.9332	0.9392	0.8304	0.0229	0.9771	0.8812
Pituitary	828	1887	36	49	0.9696	0.9583	0.9441	0.0187	0.9813	0.9511

Figure 14 (a) shows plotting of model accuracy on number of epoch. The validation and training loss of a model over time is shown in figure 14 (b). A consistent drop in training and validation loss indicates learning and demonstrates how effectively the model is working.

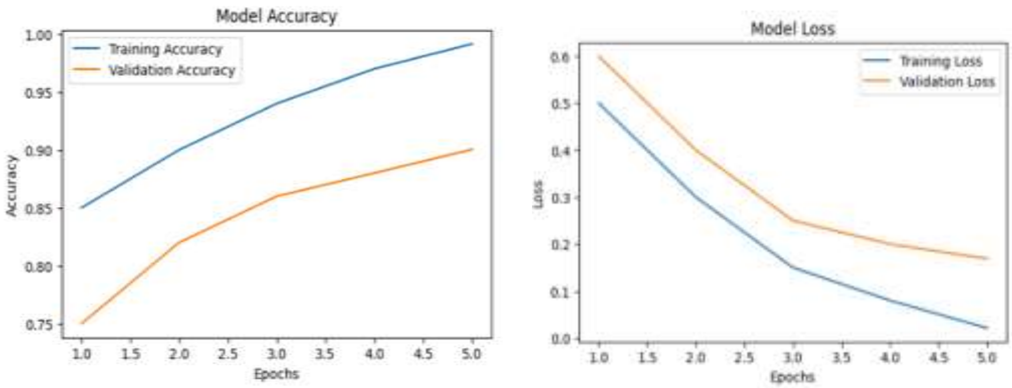

Fig. 14. Model plotting of proposed model for classification II (a) Accuracy (b) Loss

Figure 15 shows confusion matrix to show how model performing while predicting True positive and false negative cases. 908 predicting correctly Glioma Tumor, 695 predict correctly meningioma and 828 predict correctly Pituitary tumor. Very less number was detected wrong shows overall model accuracy in detecting tumor with higher accuracy.

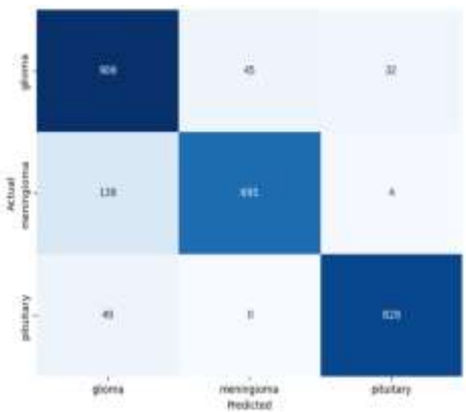

Fig. 15. Proposed Model performance for classification II using Confusion matrix on unseen data

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Classification III – Glioma Grade detection

Multi classification brain tumor diagnosis model leverage Inception-ResNet-v2 running on segmented dataset to detect classification III (Grade of Glioma Tumor) into grade 1, 2, 3 and 4 for glioma tumor. Inception-ResNet-v2 is hybrid DL architecture which merge strengths of two popular architectures: Inception and ResNet. It integrates feature extraction capabilities of inception module with the residual connections of ResNet. Last few layer was fine tuned to predict accurately Grade of Glioma Tumor.

Brats dataset comprising of HGG, LGG grades of Glioma, which is further segmented using KNN clustering into four grades. HGG divide into Grade 3/ Grade 4 and LGG divide into Grade 1/ Grade 2 and then segmented dataset split into 60-20-20% on training, testing and validation dataset. Figure 16 displays network architecture of Inception-ResNet-v2, which hybrid deep learning networks combining two deep learning networks, Inception and ResNet.

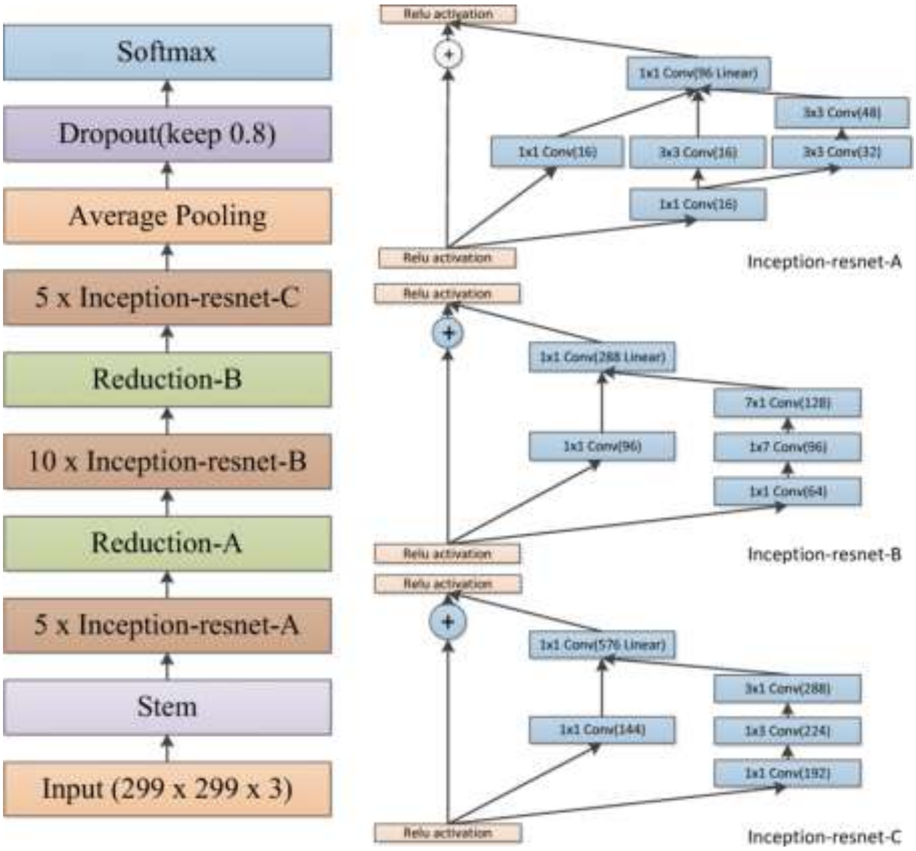

Fig. 16. Proposed Model Network architecture for classification III

Classification III Model performance

Sklearn metrics are employed to compute precision, recall, accuracy, and F1-score. Model performance on both visible and invisible data is shown in Tables 7 and 8. For glioma tumors, NeuroTumorXpert predicts tumor grade (Grades 1, 2, 3, and 4) with 96.64% accuracy.

Table 7. Proposed Model for Classification III performance using Model accuracy KPIs

Training Accuracy	0.9664
Training Loss	0.1239
Validation Accuracy	0.6389
Validation Loss	1.6523

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Table 8. Proposed Model for Classification III performance using Model KPIs

Tumor Class	TP	TN	FP	FN	Accuracy	Precision	Recall	FPR	TNR	F1
Grade I	64	201	8	7	0.9464	0.8889	0.9014	0.0383	0.9617	0.8951
Grade II	64	200	9	7	0.9429	0.8767	0.9014	0.0431	0.9569	0.8889
Grade III	65	203	6	6	0.9571	0.9155	0.9155	0.0287	0.9713	0.9155
Grade IV	65	206	3	6	0.9679	0.9559	0.9155	0.0144	0.9856	0.9351

Figure 17 (a) shows plotting of model accuracy on number of Epoch. The validation and training loss of a model over time is shown in figure 17 (b).

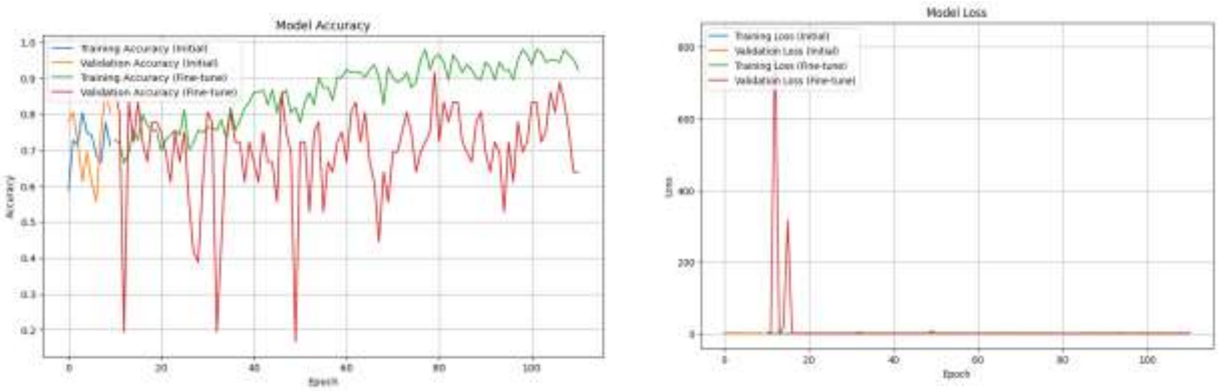

Fig. 17. Model plotting of proposed model for classification III (a) Accuracy (b) Loss

Figure 18 shows confusion matrix to show how model performing while predicting True positive and false negative cases. A very less cases were wrongly predict in False positive and False negative shows overall model accuracy in detecting Glioma tumor grade with higher accuracy in unseen data.

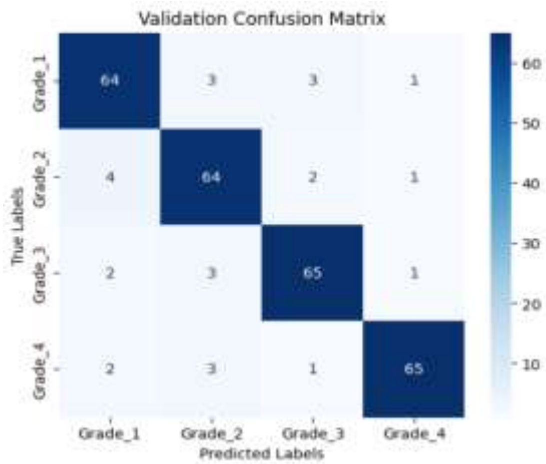

Fig. 18. Confusion matrix on unseen data of proposed model for classification III

Fully Autonomous System

Author built fully autonomous system using streamlit web application which can be consumed by medical professional to upload MRI as input and then system runs all the computational tasks like image processing, feature extraction and detecting tumor, type of tumor and grade of tumor in case system detect Glioma along with generate brain tumor diagnosis report powered by LLM.

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The process illustrated in figure 19 represents an integrated pipeline for the analysis of medical images and multi classifications of tumour. Starting with raw MRI, it goes on in succession through preparatory data, extraction of features, and multi classifications. After classification is done, the pipeline saves the data to Pinecone VectorDB for efficient storage and later retrieval. The model proceeds to create a summary of the results, which presents a compact diagnostic summary. The system automatically generates a PDF report for keeping records or clinical use. The system finally displays results, signifying the end of the process, presenting a seamless and efficient diagnostic process.

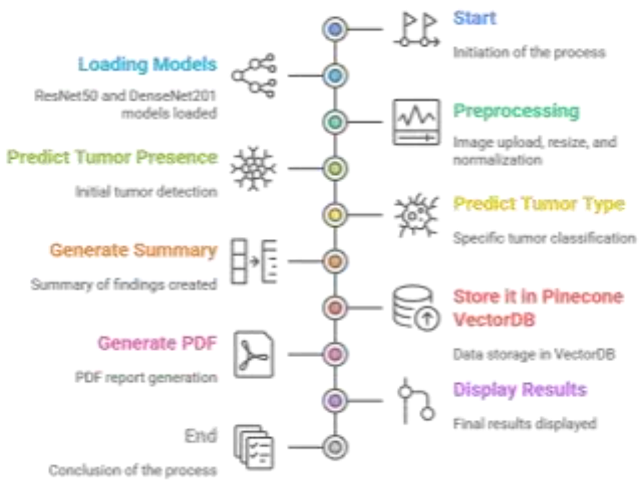

Fig. 19. Approach for Fully Autonomous system for Medical Practitioners

The system determines whether it indeed has a tumor, specifies its type, and gives the severity or grade. This pipeline, using more complex forms of computation, streamlines the diagnosis in medical imaging so that the assessments can be more quick and accurate in brain tumors. A modular workflow ensures flexibility, where components can be optimized separately for enhanced performance. The final contribution of this work is a strong, efficient and affordable diagnostic system to assist radiologists in clinical decision-making.

COMPARATIVE ANALYSIS OF STATE-OF-THE-ART WITH PROPOSED MODEL

Table 9 shows NeuroTumorXpert performance on unseen data detecting accurately with high accuracy. Classification I detecting Tumor shows 99.69% accuracy, classification II detecting type of tumor (Glioma, Pituitary and Meningioma) shows accuracy of 99.15% and classification III detecting grade of Glioma tumor shows accuracy 96.64%.

Table 9. Performance of NeuroTumorXpert on unseen data

Classification 1 Detection	Model Accuracy	TP	TN	FP	FN	Accuracy	Precision	Recall	F1 Score
Tumor	99.69%	2644	513	99	6	0.9678	0.9639	0.9977	0.9804
Non Tumor		513	2644	6	99	0.9678	0.9886	0.8382	0.9071
Classification 2 Tumor Class		**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Glioma	99.15%	4537	8624	392	1054	0.9011	0.9205	0.8115	0.8624
Pituitary		3429	10175	760	243	0.9313	0.8186	0.9338	0.8721
Meningioma		4070	10044	174	319	0.9663	0.9589	0.9273	0.9428
Classification 3 Tumor Grade		**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Grade 1	96.64%	64	201	8	7	0.9464	0.8889	0.9014	0.8951
Grade 2		64	200	9	7	0.9429	0.8767	0.9014	0.8889
Grade 3		65	203	6	6	0.9571	0.9155	0.9155	0.9155
Grade 4		65	206	3	6	0.9679	0.9559	0.9155	0.9351

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Table 10 shows NeuroTumorXpert performance comparison against state-of-the-art research papers from 2000 until 2025 and identified few base papers for comparison falling into same objective of multi classifications. However most papers are covered only two classifications as part of research scope, classification I (Tumor detection), Classification II (Type of tumor – Glioma, Pituitary, meningioma), there are very rare paper which actually covering all three classification including classification III detecting of grade of Glioma tumor. NeuroTumorXpert shows higher model accuracy from the recent research done in the area brain tumor.

Table 10. Performance comparison of state-of-the research with proposed model

Paper Reference	Year	Methodology	Classification Type	Accuracy
Atika A [34]	2024	Deep CNN	Multi Classification	96%
Md. Saikat Islam Khan [32]	2022	Combine VGG16 architecture	Multi Classification	96%
Ayadi et al. [30]	2021	CNN	Multi Classification	94%
Woźniak et al.	2021	CNN	Multi Classification	95%
Emrah Irmak [28]	2020	Deep CNN Architecture	Multi Classification	92%
Badža and Barjaktarović [27]	2020	CNN	Multi Classification	96%
Swati et al. [38]	2019	AlexNet, VGG16, VGG19	Multi Classification	94.8%
Afshar [39]	2018	Capsule Network	Multi Classification	86%
Proposed Model - Multi classification Brain Tumor Diagnosis Model		Hybrid approach leveraging transfer learning with UNN based segmentation	Classification 1(Detect Tumor)	99.69%
		Deep CNN with transfer learning using inception V3	Classification 2 (Type of Tumor)	99.15%
		Hybrid Model	Classification 3 (Grade of Glioma Tumor)	96.64%

The proposed multi-classification brain tumor diagnosis model, NeuroTumorXpert performs better than the existing works, with 99.69% accuracy for tumor detection, 99.15% for tumor type classification, and 96.64% for Glioma grading. In comparison with previous models (86% to 96% accuracy), it shows considerable improvements with powerful hybrid deep learning approaches.

CONCLUSION AND FUTURE SCOPE

Brain tumor classification is essential for accurate diagnosis and therapy planning. A comprehensive multi-classification brain tumor diagnosis model is proposed in NeuroTumorXpert, which can identify brain tumors, classify their type and grade glioma tumors with great accuracy. The solution provides a complete diagnostic process, starting from tumor detection to classification into types—glioma, meningioma, and pituitary—and grading glioma tumors into Grade 1 to Grade 4 using a hybrid deep learning method. With the optimized deep CNN architectures, the model considerably boosts diagnostic accuracy and maintains early detection with accurate precision. Classification 1, employing a fine-tuned VGG16 model for the detection of tumors, had an accuracy of 99.69%. Classification 2, utilizing a fine-tuned Inception V3 model for tumor type identification (Glioma, Pituitary, and Meningioma), had an accuracy of 99.15%. Classification 3, employing the Inception-ResNet-v2 model for Glioma tumor grading, had an accuracy of 96.64%. Automated processing raises efficiency levels by lowering analysis time and reduces specialist dependency to provide initial diagnostic results through MRI input alone. Its implementation as a web application on commodity computing hardware guarantees accessibility and scalability, making it feasible for multiple medical facilities. In addition, the study employs sustainable medical imaging protocols using fine-tuning methods and transfer learning techniques that improve performance while minimizing computational expense. The model can be expanded in the future to incorporate multi-modal imaging data, including PET and CT scans, and to account for additional types of brain illnesses. Real-time mobile-based diagnostic tools can also be created to facilitate point-of-care decision-making in rural areas.

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