Brain Tumor Prediction Using MRI In CNN Algorithm

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Abstract - *Magnetic Resonance Imaging (MRI) involves high precision when diagnosing brain tumors and expert interpretation, and hence the importance of automated support systems. The given paper introduces a deep learning model of comparative analysis of MRI sequences based on a custom Convolutional Neural Network (CNN) that predicts the adaptive diagnosis. The suggested system will categorize brain MRI images into four types, namely: Glioma, Meningioma, Pituitary Tumor, and No Tumor. A sample size of 7,023 MRI images is used, and further subdivided into training, validation, and testing subsets to have a strong analysis. Image resizing, image normalization, and real-time data augmentation techniques are used as preprocessing methods to improve generalization and reduce overfitting. The CNN model is designed to have three layers of convolutional filter expansion (32, 64, 128) preceded by max-pooling, dropout regularization, and a softmax classifier. This model will be trained on the Adam optimizer with categorical cross-entropy as a loss and early stopping to ensure the best convergence. The results of the experiments prove that the validation accuracy is 79.93 percent and the test accuracy is 79.33 percent. The system demonstrates high detection rates of normal cases, which indicates that the system can be used as an aid to fast and accurate clinical screening in neuro-oncology cases.*

Keywords - *Brain Tumor Classification, MRI, CNN, Deep Learning, Medical Image Analysis, Adaptive Diagnostic Prediction, Multi-Class Classification, Data Augmentation, Computer-Aided Diagnosis (CAD), Neuro-Oncology.*

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1. Introduction

Brain tumors are one of the most dangerous neurological conditions and the diagnosis is crucial to increase the survival rates in time. Magnetic Resonance Imaging (MRI) is the imaging modality most commonly used in the detection of brain abnormalities as it is the best in soft-tissue contrast with multi-sequence imaging. Conventionally, interpretation of MRI is at the discretion of professional radiologists hence making interpretation time consuming and prone to inter-observer variation. In recent years, automated image analysis has attracted the interest of many researchers due to the development of artificial intelligence, especially deep learning. CNNs have proven to have outstanding ability to extract spatial hierarchical features in medical images. Over the past few years, CAD systems, based on CNN, have reported encouraging outcomes in terms of tumor classification and segmentation, and detection, which can serve as an aid to improve clinical decision-making and diagnostic reliability. Despite the fact that many studies have used deep learning methods in the classification of brain tumors, there are still a number of limitations. A lot of the current methods are based on transfer learning on large pre-trained models (VGG16 and ResNet50) that can be computationally intensive and are not necessarily trained to be MRI-specific.

Also, the majority of studies concentrate on a mere accuracy of the models and do not incorporate the solution into a realistic and user-friendly clinical system.It has received little attention on comparative MRI sequence analysis and adaptive diagnostic prediction. Moreover, numerous systems do not have secure authentication, patient data management, and automatic report generation, limiting the applicability in practice. As a result, a lightweight, deployable, and clinically applicable CNN-based model with a balance in performance, efficiency, and accessibility is needed.

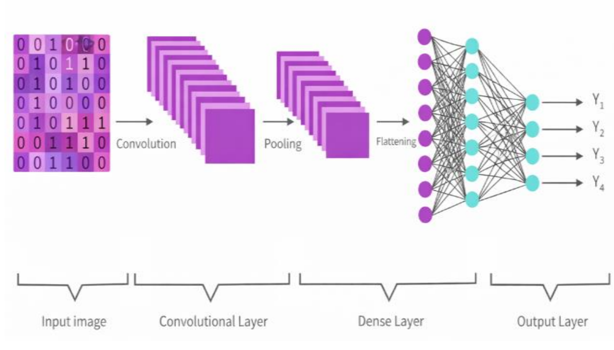

Fig 1. CNN Architecture

This project is driven by the fact that the need of having reliable and automated diagnostic tools in neuro-oncological field has been on the increase especially in areas where accessibility to specialized radiologists is a problem. The early identification of brain tumors has a major impact in terms of planning the treatment as well as patient prognosis. Nevertheless, manual MRI interpretation may be laborious and insensitive. With the help of CNN-based adaptive diagnostic prediction, one can offer speedy and stable preliminary screening support. Besides, the model can be incorporated into a convenient web application to facilitate accessibility to hospitals and telemedicine platforms. It is not aimed at substituting the medical professionals but supporting them in making decisions. Creating a lightweight but efficient system capable of working on a small hardware also encourages this study to more realistic and scalable healthcare solutions. The classification of brain tumors using MRI images has several challenges. Differences in sequences of MRI, types of scanners, resolution of the images, and noise may cause substantial differences in the performance of a model. Imbalances in classes among types of tumors, especially among common and less common types of tumor, complicate the training. The intensity patterns of the tumor regions are frequently similar and classified in two different classes, e.g. between glioma and meningioma. The other important issue is that of overfitting in dealing with small medical sets. Generalizing to unseen clinical data is made possible only through a strong preprocessing and augmentation strategy. Additionally, the incorporation of AI models within convenient applications and the preservation of security, privacy of data, and efficient inference speed is another technical challenge. The problem of these obstacles is necessary to get credible adaptive diagnostic prognosis.

The tasks that are part of this project will involve the design and implementation of a custom CNN-based model to classify brain tumors on four classes using MRI images. It includes the preprocessing of datasets, their augmentation, model training, validation, as well as its performance evaluation, based on metrics of accuracy, precision, recall, F1-score, and confusion matrix. The system also involves educated deployment as an authenticated secure web application to the staff and patients on a role basis. MRI upload, adaptive diagnostic prediction, visualization of the confidence score, and automatic PDF generation are integrated to make it more clinical. Nevertheless, the latest design is limited to a single-modality MRI data and lacks the integration of hospitals in real-time or tumor segmentation. Possible extensions in the future are multi-modal fusion and explainable AI.

2. RelatedWorks

MRI classification of brain tumors has enjoyed massive developments as the deep learning method has evolved at a high rate. The traditional CNNs and transfer learning methods were the major ones that were used in early deep learning to enhance the accuracy of the classification process. As an example, Deepak and Ameer [25] applied a deep CNN features with transfer learning to improve the performance of tumor classification, which shows that pretrained architectures are effective in medical image classification.

On the same note, Badzja and Barjaktarovic [24] used CNN-based classification systems, which delivered competitive scores on standard MRI datasets.The accuracy of classification could be enhanced by Cheng et al. [18], who refined the deep CNN architecture, which emphasizes the role of architectural optimization. The systematic review of the Tandel et al. [23] and Muhammad et al. [19] surveys of deep learning methods in the brain tumor processing showed that there is an increasing trend to replace traditional machine learning with end-to-end deep neural networks.As multimodal MRI data started to be more available, it started to become a trend where the researchers combined multiple imaging sequences to increase the precision of the diagnostic results. Khan et al. [22] suggested powerful feature selection and multimodal framework to be applied in improving tumor differentiation. It was found that a combination of different MRI modalities (T1, T2, FLAIR) can greatly enhance the classification performance as different tumor features are captured [13 and 14]. These experiments demonstrated that multimodal approaches decrease the ambiguity between classes of tumors and enhance the generalization of the different datasets. In addition, Alanazi et al. [21] have employed deep learning alongside the conventional machine learning classifiers and developed hybrid systems that take the advantage of both deep feature extraction and classical optimization methods. Gupta et al. [16] went a step further to suggest hybrid deep learning models to combine handcrafted features with learned features to make them more robust.

In 2022, the scope of the research was widened to more sophisticated architectures and explainability. Hossain et al. [20] studied the application of vision transformers with CNNs and were able to show that transformers can learn long-range dependencies in MRI images. The transformer-based paradigm was an orientation to attention-based models of features across the globe. At the same time, research focused on enhancing medical AI system transparency. Grad-CAM-based explainability methods were also included in the study of Siddique et al. [11], which allowed visualizing tumor-related areas, which enhanced the confidence of clinicians in automated outcomes. Cheng et al. [18] also kept tuning CNN-based classification functions, whereas more comprehensive reviews like Muhammad et al. [19] offered their understanding of the current issues, such as data scarcity, overfitting, and poor interpretability.In 2023, the efficiency and architectural sophistication were also improved. Liu et al. [15] suggested lightweight CNN models trained using transfer learning to minimize computational complexity without affecting the accuracy. This was specifically useful in real-time and edge deployment cases. A concept proposed by Raza et al. [17] was attention-directed mechanisms in which discrimination of visually similar types of tumor was enhanced. Sharif et al. [13] extended the multimodal methods by using a wide range of MRI sequences to enhance the detection and classification. These developments were a compromise between accuracy, computing efficiency, and usefulness. Besides, hybrid architecture and the incorporation of CNNs with other deep learning elements went on to become popular, as evidenced by

Gupta et al. [16].

Multi-sequence MRI-based models with vision transformers attained significant progress in situational interpretation and categorization error [7]. Wang et al. [8] suggested the use of multi-scale CNNs with attention modules to achieve accurate tumor grading and classification, which is used to overcome the challenge of intra-class variability. Zhang et al. [10] proposed hybrid 3D CNN- transformer networks, which could conduct segmentation and classification at the same time, which enhanced the representation of spatial features. The role of privacy preserving frameworks became more topical where Ali et al. [9] proposed federated learning methods that allow collaborative training of models across hospitals without sharing of sensitive patient information. The article by Kumar et al. [12] has created light real-time classification systems that can be deployed on edge devices, showing the necessity of making AI solutions accessible to such environments with resource constraints. Furthermore, explainable deep learning models also continued to develop, which confirmed their clinical adoption [11].

Self-supervised learning strategies were suggested by Chen et al. [1] to utilize unlabeled data on the MRI images with a view to greatly advance performance on situations with limited labelled data. Patel et al. [2] proposed the multi-task learning models that can simultaneously complete both tumor segmentation and classification, which results in a better sharing of features and generalization. The article by Liu et al. [3] used diffusion models to augment synthetic MRI data, which was useful in overcoming the problem of class imbalance and making a model stronger. The work of Ahmed et al. [4] also advanced federated and privacy-preserving deep learning frameworks, which allowed collaborating with multiple centers and ensuring their safety. Zhou et al. [5] suggested Bayesian deep learning methods to measure uncertainty of predictions, which give reliability measures of great importance in clinical decision-making. The study by Sharma et al. [6] has created a complete end-to-end web-based AI system with automated reporting, which bridged a gap between the research models and in-the-field clinical implementation.

Ref. No.	Year	Title	Methodology
[25]	2021	Brain Tumor Classification using Transfer Learning	Transfer Learning (Deep CNN)
[24]	2021	CNN-based Brain Tumor Classification	Conventional CNN
[22]	2021	Multimodal Brain Tumor Classification	Multimodal Deep Learning
[20]	2022	Vision Transformers and CNNs for Tumor Classification	CNN + Vision Transformer
[18]	2022	Enhanced Deep CNN for Tumor Classification	Enhanced CNN Architecture
[15]	2023	Efficient Lightweight CNN for Brain Tumor Classification	Lightweight CNN + Transfer Learning
[17]	2023	Attention-Guided Deep Learning Model	Attention-guided CNN
[7]	2024	Vision Transformer-based Brain Tumor Classification	Vision Transformer (ViT)
[8]	2024	Multi-scale CNN with Attention for Tumor Grading	Multi-scale CNN + Attention
[9]	2024	Federated Learning for Brain Tumor Classification	Federated Learning
[10]	2024	3D CNN and Transformer Hybrid Model	3D CNN + Transformer Hybrid
[11]	2024	Explainable Deep Learning using Grad-CAM	Explainable AI (Grad-CAM)
[1]	2025	Self-Supervised Learning for Brain Tumor Classification	Self-Supervised Learning
[2]	2025	Multi-task Learning for Classification and Segmentation	Multi-task Learning
[3]	2025	Diffusion Models for Synthetic MRI Augmentation	Diffusion-based Data Augmentation
[4]	2025	Federated and Privacy-Preserving Deep Learning	Federated + Privacy-Preserving DL
[5]	2025	Uncertainty-Aware Brain Tumor Classification	Bayesian Deep Learning
[6]	2025	End-to-End Web-Based AI System for Tumor Diagnosis	Web-Based AI System

Table 1. Comparative Analysis on Literature Paper

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3. Problem statement

The correct and prompt diagnosis of brain tumors through Magnetic Resonance Imaging (MRI) is a major issue in clinical practice. Radiologists are subjective and prone to inter-observer variability in manual interpretation of MRI scans, particularly in differentiating between closely related types of tumors like glioma, meningioma and pituitary tumors. Resource-limited healthcare facilities also face the problem of diagnostic and treatment planning delays due to the shortage of specialized neuroradiologists. Even though the advancements of deep learning methods have demonstrated encouraging outcomes, a great deal of current systems focus on model accuracy without focusing on practical implementation, computational performance, and clinical application. Also, inconsistent variations in MRI sequences, noises, and imbalance of the classes make it difficult to classify reliably. Thus, the lightweight, versatile CNN-based diagnostic system, which can correctly identify the presence of brain tumors based on the MRI image and can deliver a secure and user-friendly interface and clinically significant output to aid early screening and decision-making, is necessary.

4. Existing System

The current brain tumor diagnostic systems mainly use the traditional machine learning and early deep learning procedures. The classical methods, including the Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), the Random Forests and the Decision Trees, have been popularly applied alongside the hand-designed features, like the texture descriptors (GLCM), shape statistics, and the wavelet transforms. Although these approaches were fairly successful on controlled data, they were very sensitive to noise and preprocessing errors and also they were highly dependent on manual feature extraction and human domain experience. The introduction of deep learning led to the increased popularity of CNNs and transfer learning with pretrained models including VGG16, ResNet50, and InceptionV3 as they have the ability to better represent features. Nevertheless, such models usually require a considerable number of computational resources and substantial training data, hindering their implementation in a real clinical setting. Also, the majority of current systems do not have any secure user authentication, patient management, and built-in reporting capabilities and therefore do not have the ability to be deployed outside of research prototypes and their applicability to the clinical diagnostic workflow is limited.

5. Methodology

The suggested system is systematic using modular pipeline in order to provide systematic development, assessment, and implementation of the brain tumor classification framework. All modules are created to manage a certain stage of the workflow, including data preparation and clinical reporting.

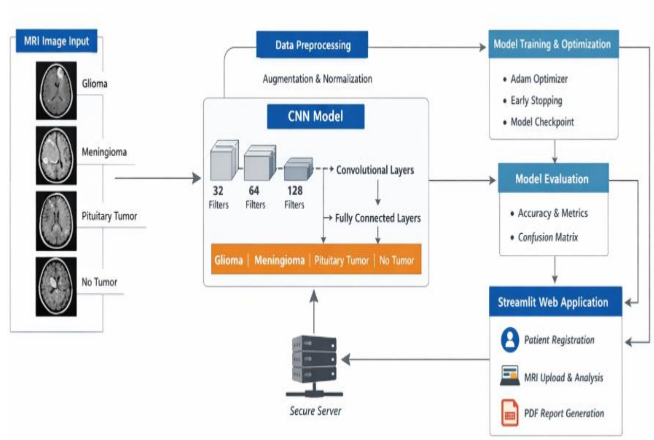


Fig 2. Flow Chart

A. Data Acquisition and Preprocessing

The role of this module is to gather and train MRI data to be utilized in a model. It uses a publicly open dataset with four classes, namely Glioma, Meningioma, Pituitary Tumor, and No Tumor. The sample is further broken into training, validation and testing sets through stratified sampling to ensure there is balance in terms of classes. Preprocessing involves standardisation of all images to 150 x 150 so that the input dimensions are the same. To enhance the numerical stability of the training process, pixel values are brought to the [0,1] range. Images that are in grayscale are changed to 3 channel RGB, where required. Random rotation (within -20 W), width/height shift (within -20 W), zoom, shear, and horizontal flipping are used as data augmentation methods and they are dynamically selected during training to increase generalization and reduce overfitting due to small medical datasets.

B. CNN Model Architecture Design

This module aims at developing a light but efficient CNN architecture to classify brain tumors of multiple classes. The network comprises three convoluted blocks that contain three filter sizes of 32, 64, and 128 respectively and are followed by the ReLU activation and two 2x2 max-pooling layers of spatial down-sampling. These layers are used to remove hierarchical features like tumor edges, textures and intensity variations. The layer of feature maps is flattened and sent to a full-connected dense layer containing 512 neurons and ReLU activation. There is an introduction of a dropout layer of 0.5 to overcome overfitting. The last layer employs the softmax activation that has four output neurons that are associated with the types of tumors.

C. Model Training and Optimization

Here, CNN model is trained to use the augmented training dataset. The model is trained on the Adam optimizer (learning rate = 0.001) and categorical cross-entropy loss function, which is appropriate when the task is a multi-class classification. The maximum epochs that are trained are 20 and a batch size of 32.

The patience value of 6 epochs is used to ensure that early stopping is applied to avoid overfitting and restore the most successful weights. The highest version of the model in terms of accuracy in the validation is saved as model checkpointing. The convergence behavior is analyzed by monitoring the training and validation accuracy/loss curves and making sure that the learning process is stable.

D. Model Evaluation and Performance Analysis

This module measures the performance of the trained model with the unseen test set, in order to measure the performance of the trained model objectively. Each class is computed to standard classification measures like accuracy, precision, recall and F1-score. A confusion matrix is created in order to represent patterns of misclassification, especially between similar tumors. Graphs History graphs (accuracy and loss curves) are also plotted to ensure that they are converging correctly, and to notice over- and under-fitting. This test is necessary to ensure that there are consistent performances of the model on all categories and it can be used in clinical screening purposes.

E. Web Application and Deployment

The deployment module is a web-based interface based on the Streamlit framework that includes the trained CNN model. The application also has role-based access and has two portals, one accessed by hospital employees and the other by patients. The patients are allowed to sign up using their personal information, such as date of birth to calculate their age automatically. The dashboard has a friendly MRI upload service that accepts JPG, JPEG and PNG. When the model is clicked on the text of analyze now, inference is done and the predicted tumor type is shown with a onfidence score being represented as a progress bar. Colors are used to recommend ideas to make them easier to interpret.

F. Automated Report Generation

This module produces a report in the form of a downloadable PDF file after it has been analyzed with the ReportLab library. The report contains patient demographics, scan date, predicted tumor type, confidence percentage, recommendation text and as well as MRI image uploaded in the report itself. The PDF is designed using formatted headers, footers, time stamps to make it appear professional enough to be part of the clinical records.

6. ProposedModel

The NeuroScan AI proposed system is an automated brain tumor classification system, which is end-to-end and offers adaptive diagnostics prediction based on a tailor-made CNN. The system has four categories of MRI images which are: Glioma, Meningioma, Pituitary Tumor and No Tumor. An efficient feature extraction and proper multi-class classification are attained by using a lightweight CNN architecture that consists of three convolutional layers (32, 64 and 128 filters), max-pooling, dropout regularization and a softmax output layer. The model is trained with early stopping and model checkpointing using the Adam optimizer to improve on generalization and overfitting. In addition to the development of the model, the system is implemented by a safe web application based on Streamlit with role-based access control, patient registration, and automatic age calculation, MRI upload and analysis dashboard, visualization of confidence scores, and automatic generation of PDF reports with built-in images.

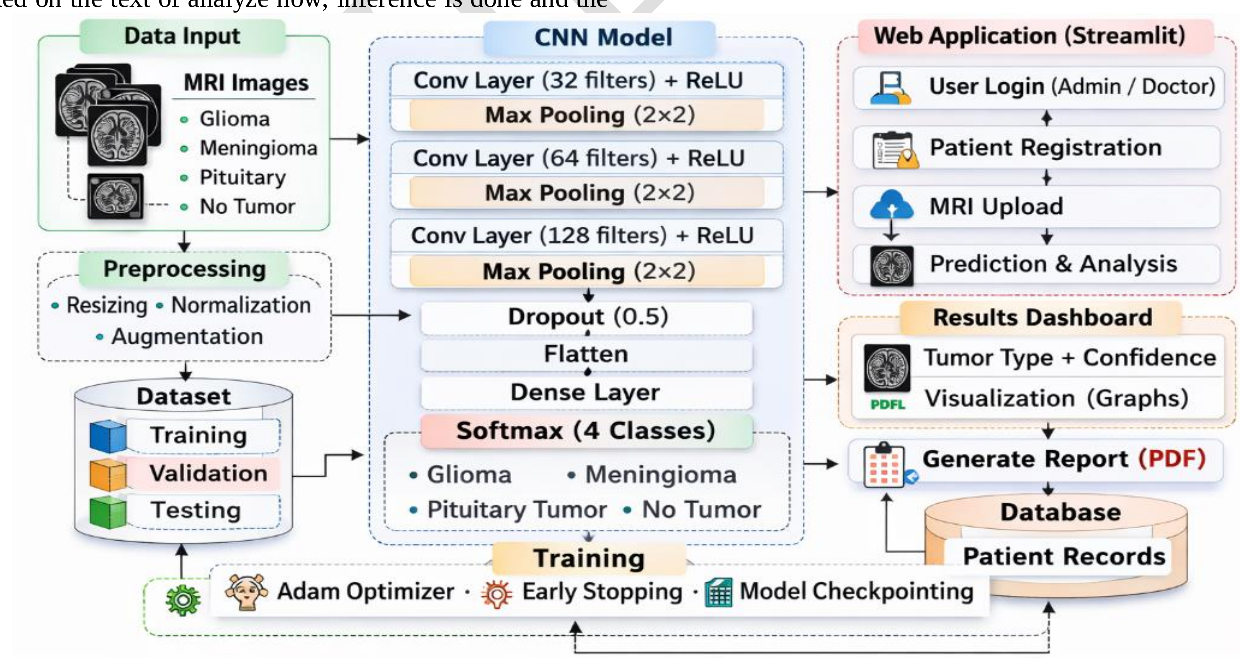


Fig 3. Proposed Architecture

Fig 4. Work Flow

7. Result and Discussion

The developed NeuroScan AI system was rallied on Python with the TensorFlow and Keras packages to develop deep learning models. KerasImageDataGenerator was used to do image preprocessing and augmentation. The interface of the web application was created on the basis of the Streamlit framework, and the creation of PDF reports was done with the help of the ReportLab library.

Fig 5. Data set

The dataset was 7,023 MRI images and was divided into four classes, that is, Glioma, Meningioma, Pituitary Tumor, and No Tumor. Stratified sampling was used to divide the dataset into training, validation and testing sets of 65, 15 and 20 percent respectively. Each of the images was resized to 150×150 pixels and was normalized to an [0,1] interval.

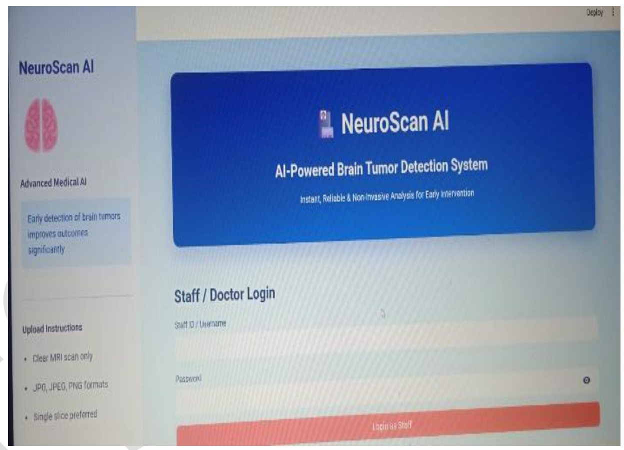


Fig 6. Login Page

The CNN was trained up to 20 epochs with 32 as a batch size and Adam as an optimizer (learning rate = 0.001). Early termination using patience of 6 epochs and model checkpointing were used to store weights that performed the best. The trained CNN model scored validation accuracy of 79.93 and test accuracy of 79.33 and showed consistency performance in both validation and unseen data.

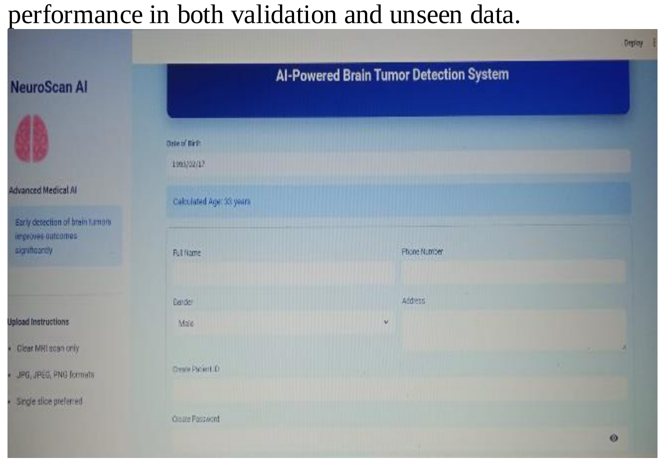


Fig 7. Patient Data Entry

The fact that the validation and the test accuracy are very close implies that the ability of the generalization remains unchanged and there is minimum decline in performance as there is an exposure to the new MRI samples. A high performance was observed in the classification report of No Tumor cases as the recall of the No Tumor cases was 99.26. This high recall has a clinical significance, since this high level of recall ensures that there are no misleading cases of normal cases identified, and the chances of unnecessary medical interventions are minimized.

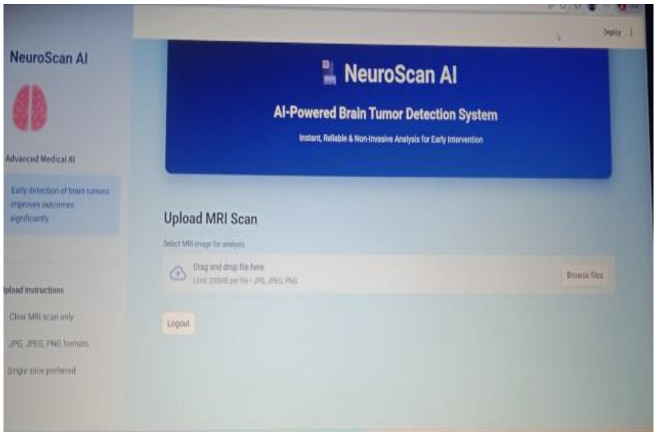


Fig 8. Image Uploading Page

The model showed an average result in the classification of Glioma and Pituitary Tumor classes. Although these classes were found with fair degree of precision, there were instances of misclassifications because of the similarity in the tumor morphology and intensity features in the MRI images. Meningioma showed a relatively low recall rate of 50.33% which shows a confusion with other types of tumors. It indicates that the model experiences difficulties in separating the characteristics of meningioma and the appearance of other tumor patterns, which is something to improve in the future. Analysis of Confusion matrix indicated that a repetitive pattern of texture and intensity among some tumor groups increased prediction uncertainty.

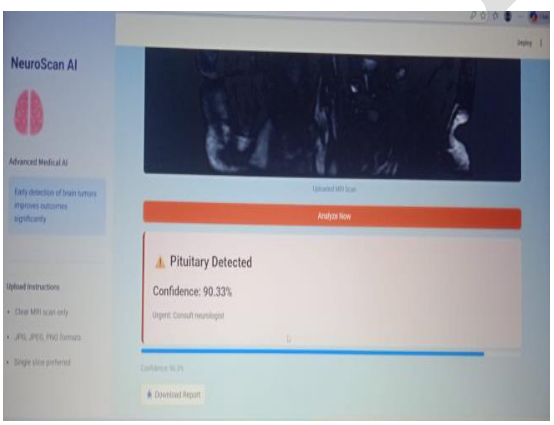
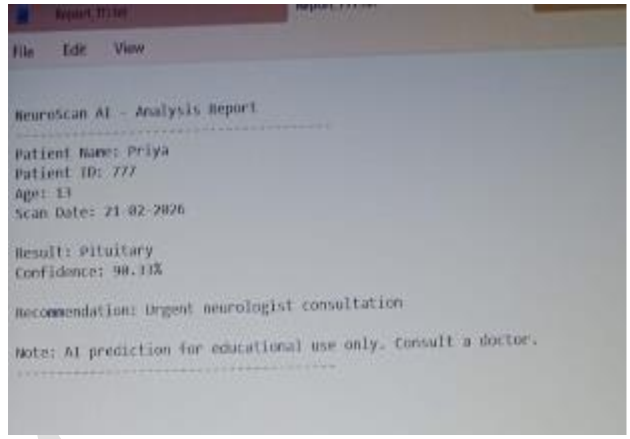


Fig 9. Prediction Page

The dropout regularization, data augmentation, early stopping, and model checkpointing were all successfully used to enhance the generalization and manage the complexity of models. The designed web application was able to combine the trained CNN model that allowed real-time MRI upload, automatic prediction display, and visualization of confidence score, as well as generation of professional PDF report with embedded images.



NeuroScan AI - Analysis Report

Patient Name: Priya
Patient ID: 777
Age: 13
Scan Date: 21-02-2026

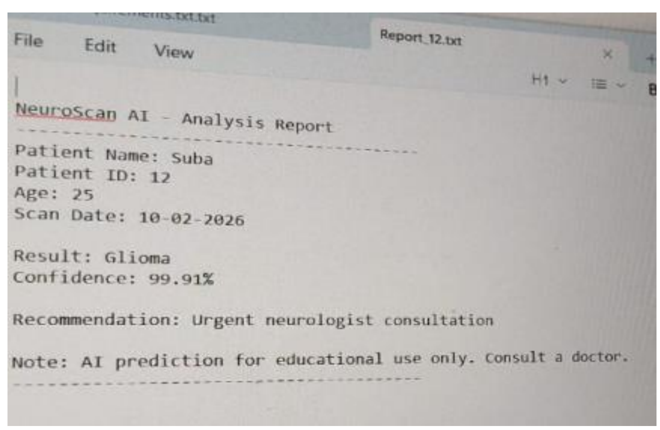
Result: Pituitary
Confidence: 90.33%

Recommendation: Urgent neurologist consultation

Note: AI prediction for educational use only. Consult a doctor.

Fig 10. Patient 1 Report

The time taken to infer an image was also not high, affirming that the system can be run with decent hardware settings to provide practical support of clinical screening. The experiments reveal that the suggested lightweight CNN model can be used to conduct stable multi-class brain tumor classification with a test accuracy of around 79%. The fact that the recall of the No Tumor cases is high indicates that it has high capacity in screening normal patients, which is clinically useful to lower the number of unnecessary follow-ups. Nevertheless, the reduced ability to differentiate meningioma and other forms of tumors emphasizes the difficulty involved in inter-class similarity of MRI images.



NeuroScan AI - Analysis Report

Patient Name: Suba
Patient ID: 12
Age: 25
Scan Date: 10-02-2026

Result: Glioma
Confidence: 99.91%

Recommendation: Urgent neurologist consultation

Note: AI prediction for educational use only. Consult a doctor.

Fig 11. Patient 2 Report

The proposed custom CNN is computationally efficient with ease to deploy as compared to heavy transfer learning models and the accuracy is also competitive. The findings of

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this study can be positively used as initial diagnostic aids, but additional advancements, including transfer learning, attention, and ensemble models or multi-modal MRI fusion, will strengthen the classification performance. In general, the implementation shows a moderate relationship of precision, effectiveness, and usefulness of AI-aided neuro-oncological screening.

8. Conclusion

The study provides a lightweight CNN classification framework on adaptive brain tumor classification on the basis of MRI images. Proposed system has the test accuracy of 79.33% which illustrates that the system is a multi-class predictor with high accuracy in normal cases. Besides the model development, the practical usability is improved with the deployment of a safe web application with real-time analysis and automated PDF reporting. Even though the classification of some types of tumors should be enhanced, the system demonstrates a good prospect as an AI-assisted screening method to aid radiologists with quicker and more reliable neuro-oncology diagnosis.

9. Future scope

Further improvements of the proposed system can be done with the aim of enhancing the accuracy of the classification with transfer learning using sophisticated pretrained models and ensemble. It could be improved by extending the framework into multi-modal MRI sequences (T1, T2, FLAIR) so as to obtain better tumor differentiation (especially challenging classes such as meningioma). The localization and volumetric analysis can be made accurate through integration of tumor segmentation modules. Scalable telemedicine applications can be facilitated by cloud deployment and integration of real time hospital database. Further, more robust, generalized, and reliable training with larger and varied clinical data will be enhanced to be used in real-world diagnoses.

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