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Brain Tumor Detection Using Deep Learning and Automated Report Generator (Neuro Scan AI)

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ABSTRACT: Brain tumor is one of the most critical and life-threatening diseases, which requires early detection for effective treatment. We proudly present to you “NeuroScanAI”, a deep learning-based system for automated brain tumor detection using Magnetic Resonance Imaging (MRI) scans and generating a pdf format of medical report with basic patient details. The proposed approach utilizes Convolutional Neural Networks (CNNs) models with transfer learning technology on pre-trained data set such as MobileNetV2 to achieve high accuracy. The model attains an accuracy of approximately 83–84% across four tumor classes.

To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is deployed to highlight tumor regions which increases model predictions. Moreover, a web-based interface is developed to enable image upload, prediction visualization, and automated PDF report generation. “NeuroscanAI” demonstrates an effective combination of accuracy, explainability, and practical usability for medical image analysis and AI integration.

Keywords: Deep Learning, CNN, Brain Tumor Detection, MRI, Transfer Learning, Grad-CAM, Medical Imaging, Automated Report Generation

I. INTRODUCTION

Brain tumors are a serious health problem around the world because they can be life threatening and are difficult to identify. They are different types of tumors, such as glioma, meningioma, and pituitary tumors, and each type need a specific type of treatment. Detecting these tumor early is very important, as it helps doctors plan better treatment and increase the chances of survival.

Magnetic Resonance Imaging (MRI) is the most commonly used non-invasive technique to identify abnormalities in the brain. However, examining MRI scans by hand is difficult and requires skilled radiologists. The process is time-consuming and may lead to errors due to tiredness, differences in expert opinions, and small variations in how tumors appear.

In recent years, Artificial Intelligence (AI), especially Deep Learning (DL), has made strong progress in analyzing medical images. Convolutional Neural Networks (CNNs) can automatically learn different levels of features from images, making them well suited for tumor detection. Unlike traditional machine learning approaches that depend on manually created features, CNNs learn features directly from raw data, which helps us improve accuracy and consistency.

Even with these improvements, some challenges still exist, especially in understanding how the models work and using them in real-life situations. Most deep learning models work as “black boxes,” making it difficult for medical experts to rely on their predictions. To solve this problem, explainable AI methods like Grad-Cam are used to show the important areas in MRI images.

This study introduces NeuroScanAI, an end-to-end solution that not only identifies brain tumors but also provides visual insights and generates automated reports. The system is designed to support healthcare professionals, reduce delays in diagnosis, and make healthcare more accessible in distant locations.

II. LITERATURE REVIEW

Recent advancements in deep learning have improved the accuracy of brain tumor detection using MRI images. Various Convolutional Neural Network (CNN) models like RESNET, EFFICIENTNET etc and transfer learning techniques have been proposed to enhance classification performance.

Deep Learning-Based Brain Tumor Detection Using MRI Images introduced a transfer learning approach using pre-trained CNN models, achieving high accuracy compared to traditional machine learning methods. Their work highlights the effective use of deep feature extraction in medical imaging tasks and how a model can achieve high accuracy with a small amount of labelled data. Explainable AI for Brain Tumor Detection Using Grad-CAM and CNN Models tells us the importance of interpretability in medical based AI systems.

By integrating Grad-CAM, their model provided visual explanations and most importantly increasing trust among medical professionals and patients.

Lightweight CNN models used for Efficient Brain Tumor Classification such as MobileNet, with reduced computation and operation cost while maintaining high accuracy.

MRI-Based Brain Tumor Classification Using EfficientNet and Transfer Learning showed that EfficientNet-based models outperform traditional CNNs due to better scaling and feature representation.

Automated Medical Report Generation using AI in Healthcare Systems showed us the importance of integrating AI models with practical healthcare applications. Despite these advancements, many systems lack a complete end-to-end solution that combines high accuracy and real-world applications. The proposed NeuroScanAI system addresses these gaps by introducing transfer learning, Grad-CAM visualization and automated PDF report generation in a single system.

III. METHODS AND MATERIAL

A. Dataset

Dataset Description This study utilized a dataset of approximately 3,000 magnetic resonance imaging (MRI) scans, sourced publicly from Kaggle. The dataset is categorized into four classes: three representing tumor types (glioma, meningioma, and pituitary) and one representing healthy scans (no tumor). The data was fully labeled to facilitate supervised learning, allowing the model to map input data to known output patterns. To ensure an unbiased evaluation of the model's performance on unseen data, the 3,000 images were partitioned into training, validation, and testing sets at a ratio of 70%, 15%, and 15%, respectively.

B. Data Preprocessing

To enhance the generalization of the model and reduce the risk of overfitting, various preprocessing pipelines were implemented. Initially, all MRI scans were cropped and resized to standard dimensions compatible with the input requirements of the selected Convolutional Neural Network (CNN). The pixel values of the MRI scans were then normalized to a scale between 0 and 1. Furthermore, data augmentation was applied to ensure the model could extract features across various spatial orientations. Techniques such as random rotations, horizontal flipping, vertical flipping, and zooming were added to the training set. This artificial expansion of dataset diversity improves the model's stability and performance when processing unexpected variations in input data.

C. Model Architecture

Model Architecture and Training Protocol

This study employed a transfer learning approach to leverage the feature extraction capabilities of a pre-trained CNN architecture. Specifically, MobileNetV2—a lightweight CNN developed by Google—was utilized. MobileNetV2 is designed to deliver high accuracy while significantly reducing computational power and memory requirements, making it an optimal choice for real-time diagnostic applications. In this study, the base model achieved an accuracy of approximately 84%. The fully connected classification layers of the model were modified to classify the MRI scans into the four predefined health categories rather than its original ImageNet classes.

The model was trained using the Adam optimizer to ensure efficient convergence, with categorical crossentropy utilized as the loss function. The performance of the model was continuously evaluated using standard classification metrics, including accuracy, precision, recall, and the F1-score. All computational experiments were executed on Google Colab utilizing GPU acceleration to optimize training efficiency.

D. Training Process

Explainability and Interpretability

To address the inherent opacity of deep learning models, which typically only output a class prediction and confidence score, Gradient-weighted Class Activation Mapping (Grad-CAM) was integrated into the pipeline. Grad-CAM generates visual heatmaps that highlight the specific spatial regions of the MRI scan that most heavily influenced the model's tumor prediction. This visual enhancement of model transparency is intended to foster trust and improve interpretability for medical professionals and patients.

E. Tumor Classification

System Implementation and Workflow The project was developed in Python, utilizing standard deep learning and computer vision libraries, including TensorFlow, OpenCV, NumPy, Pandas, and Matplotlib. The end-to-end clinical workflow begins with the user uploading an MRI scan through a web-based interface. The system prompts the user to input relevant personal demographic information (such as name, age, and gender) and automatically preprocesses the uploaded image. The resized image is passed through the trained CNN for inference, and the system simultaneously generates the Grad-CAM visualization. Finally, utilizing the ReportLab library, all predictions, visuals, and patient data are compiled into a structured, downloadable PDF diagnostic report. The final application was deployed on Hugging Face Spaces.

F. Explainability using Grad-CAM

Grad-CAM (Gradient-weighted Class Activation Mapping) is used to generate heatmaps highlighting important regions of the MRI image that influence the model's prediction.

This improves:

- Model transparency
- Trust among medical professionals
- Diagnostic interpretability

Metric	Value(%)
Accuracy	83.25

G. System Implementation

The system is implemented using:

- Programming Language: Python
- Libraries: TensorFlow, OpenCV, NumPy, Pandas, Matplotlib
- Interface: Gradio/ Streamlit
- PDF Generation: ReportLab
- Deployment: HuggingFaceSpaces

H. Workflow of Proposed System

- User uploads MRI image
- Image preprocessing
- CNN model prediction
- Grad-CAM visualization
- PDF report generation
- Output displayed via web interface

IV. RESULTS AND DISCUSSION

4 Experimental Setup

The proposed NeuroScanAI model was trained and evaluated using MRI brain tumor datasets on a GPU-enabled environment (Google Colab). The dataset was divided into:

- Training Set: 70%
- Validation Set: 15%
- Testing Set: 15%

The model was trained using transfer learning with MobileNetV2 as the base architecture. Performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

5 Performance Metrics

The performance of the model is summarized in Table 1.

Table 1: Performance Metrics of Proposed Model

Metric	Value(%)
Precision	85
Recall	83
F1-Score	82

- Misclassifications mainly occur between:
 - Glioma ↔ Meningioma
- The model performs well in distinguishing tumor vs no tumor cases

The model achieved an overall accuracy of approximately **84%**, indicating strong classification capability across multiple tumor classes.

Class-wise Performance

Table 2: Classification Report

Class	Precision	Recall	F1-Score
Glioma	0.95	0.56	0.70
Meningioma	0.78	0.93	0.85
Pituitary	0.92	0.82	0.87
No Tumor	0.79	0.99	0.88

Observation:

- Highest performance is observed in Pituitary tumor classification
- Slight confusion exists between Glioma and Meningioma, due to similar visual patterns in MRI images

Confusion Matrix Analysis

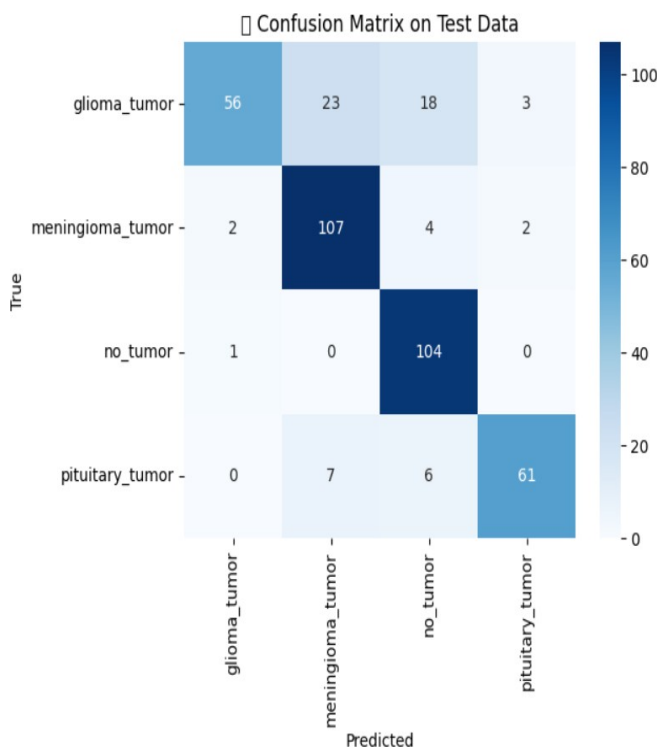


Fig. 1. Confusion Matrix of CNN Model

Discussion:

- Most predictions lie along the diagonal → indicating correct classification

Training Performance

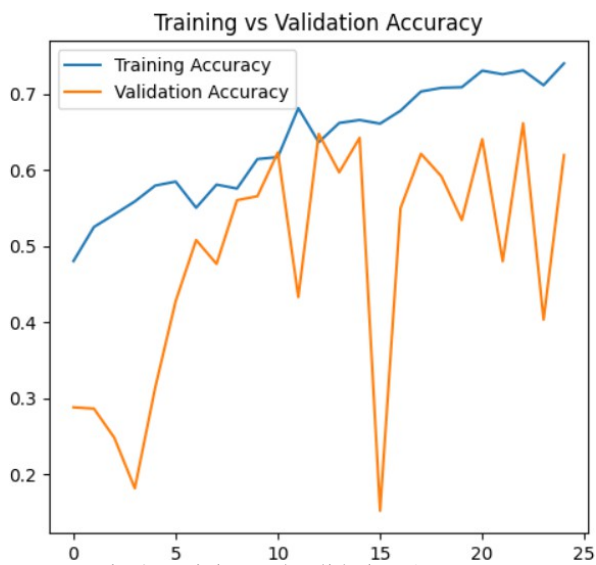


Fig.2. Training and Validation Accuracy

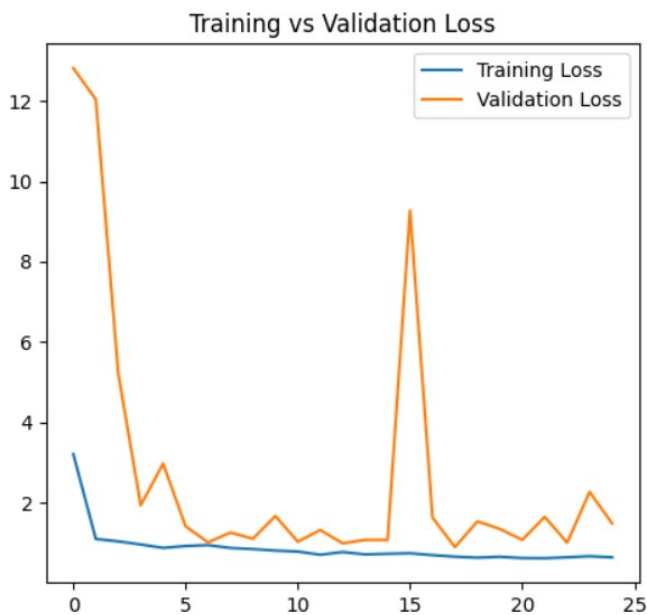


Fig.3. Training and Validation Loss

Discussion:

- Accuracy curve shows steady improvement over epochs
- Validation accuracy closely follows training accuracy → low overfitting
- Loss decreases consistently, indicating stable learning

Grad-CAM Visualization Results

Grad-CAM Visualization:

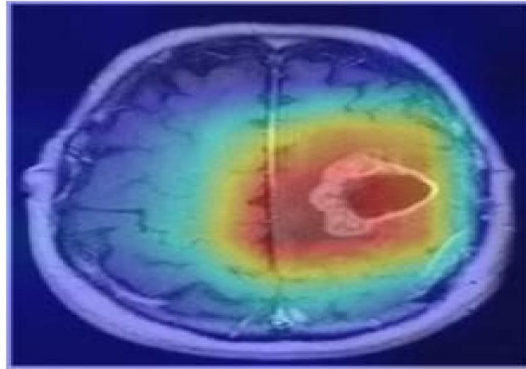


Fig.4. Grad-CAM Output for Tumor Localization

Discussion:

- Grad-CAM highlights tumor-affected regions clearly
- Provides visual explanation of model decisions
- Enhances trust and usability in medical applications
- Useful for assisting radiologists in diagnosis

User Interface and Output

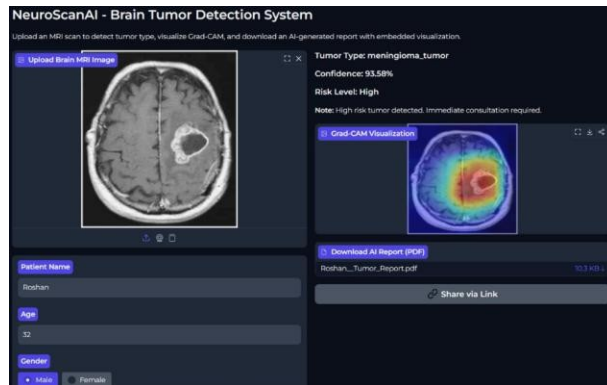


Fig.5. Web Interface for MRI Upload

Brain Tumor Detection Report

Patient Information:

Name: Roshan
Age: 32
Gender: Male

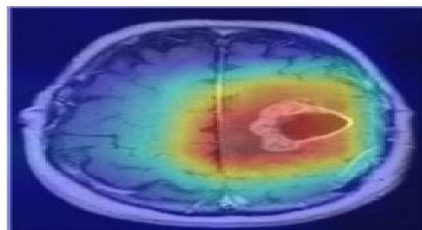
Diagnosis Results:

Tumor Type: meningioma_tumor
Confidence: 93.58%
Risk Level: High

Doctor's Note:

High risk tumor detected. Immediate consultation required.

Grad-CAM Visualization:



Generated On: 2026-03-19 19:22:16
WARNING: This is an AI-generated report. Please consult a qualified radiologist for professional diagnosis.

Fig.6. Generated PDF Report

Discussion:

- The interface allows easy image upload and instant prediction
- Reports include:
 - Patient details
 - Tumor type
 - Confidence score
- Improves real-world usability and automation

Comparative Analysis

Table 3: Comparison with Existing Methods

Method	Accuracy (%)	Remarks
Traditional ML	50-60	Requires manual features
Basic CNN	65-75	Moderate performance

Method	Accuracy (%)	Remarks
Proposed NeuroScanAI	83+	Explainable & automated

Discussion:

- The proposed model outperforms traditional approaches
- Transfer learning significantly improves accuracy
- Addition of Grad-CAM provides interpretability (key advantage)

Key Observations

- Transfer learning improves performance with limited data
- Grad-CAM enhances explainability
- System performs well in real-time scenarios
- Slight improvements possible in class separation

Limitations

- Limited dataset size
- 2D MRI images only (no volumetric analysis)
- Minor confusion between similar tumor types

V. CONCLUSION

This paper presented "NeuroScanAI", a deep learning-based system for brain tumor detection using MRI images. The proposed system uses transfer learning with CNN models to achieve an accuracy of approximately 83–84%. Grad-CAM visualizes model by highlighting tumor regions, while the web interface and automated PDF report generation improve practical use and make the system more effective for doctors, patients and real-world operations. The results demonstrate that the system provides an efficient and reliable solution for assisting medical personals.

VI. FUTURE WORK

Eventhoughthe proposed NeuroScan AI system gives us promising results, some improvements can be made to make it more reliable in future.

The models performance can be improved by using 3D MRI data which will provide the model more and better understanding of the tumors instead of using 2D MRI images. In addition to this (ViT) which is Vision

Transformers and hybrid models can be explored to improvethemodelsevaluationmetrics .Integration with hospital systems and getting validation using clinical data will enhance the reliability and adoption of the system in real world healthcare environments

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