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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 intergration.

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.Theprocessistime-consumingandmay 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, CNNslearnsfeaturesdirectlyfromrawdata,whichhelps us improve accuracy and consistency.

Even with these improvements, some challenges still exist,especiallyinunderstandinghowthemodelswork andusingtheminreal-lifesituations.Mostdeeplearning models work as "black boxes," making it difficult for medicalexpertstorelyontheirpredictions.Tosolvethis 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 providesvisualinsightsandgeneratesautomatesreports. The system is designed to support healthcare professionals, reduce delays in diagnosis, and make healthcare more accessible in distant locaations.

II. LITERATURE REVIEW

Recent advancements in deep learning have improvedthe accuracy of brain tumor detection using MRIimages. Various Convolutional Neural Network (CNN) models like RESNET, EFFICIENTNET etc and transferlearning 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 comparedtotraditionalmachinelearningmethods.Their work highlights the effective use of deep feature extraction in medical imaging tasks and how a modelcan 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 appl`ications. The proposed NeuroScanAI system addresses these gaps by introducing transfer learning, Grad-CAM visualization and automated PDF reportgenerationin asinglesystem.

III. METHODS AND MATERIAL

A. Dataset

Dataset Description This study utilized a dataset of approximately3,000magneticresonanceimaging(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 wasfully 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 ratioof70%,15%,and15%,respectively.

B. Data Preprocessing

To enhance the generalization of the model and reduce the risk of overfitting, various preprocessing pipelines wereimplemented.Initially,allMRIscanswerecropped and resized to standard dimensions compatible with the input requirements of the selected Convolutional Neural Network (CNN). The pixel values of the MRI scanswere 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

ModelArchitectureandTrainingProtocol

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 significantlyreducingcomputationalpowerand 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

ExplainabilityandInterpretability

To addresstheinherentopacity of deeplearningmodels, 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 mostheavily influenced the model's tumor prediction. This visualenhancementofmodeltransparencyisintendedto 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. ExplainabilityusingGrad-CAM

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

Thisimproves:

- Modeltransparency
- Trustamongmedical professionals
- Diagnosticinterpretability

Metric	Value(%)
Accuracy	83.25

G. SystemImplementation

Thesystemisimplementedusing:

- ProgrammingLanguage:Python
- Libraries: TensorFlow, OpenCV, NumPy, Pandas, Matplotlib
- Interface:Gradio/ Streamlit
- PDFGeneration:ReportLab
- Deployment:HuggingFaceSpaces

H. WorkflowofProposedSystem

- UseruploadsMRI image
- Image preprocessing
- CNNmodelprediction
- Grad-CAMvisualization
- PDFreportgeneration
- Outputdisplayedviawebinterface

IV. RESULTS AND DISCUSSION

4 Experimental Setup

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

- TrainingSet:70%
- ValidationSet:15%
- TestingSet:15%

The model was trained using transfer learning with MobileNetV2asthebasearchitecture.Performance was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

5 PerformanceMetrics

Theperformanceofthemodelissummarizedin Table 1.

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Table1:PerformanceMetricsofProposedModel

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

- Misclassificationsmainlyoccurbetween:
  - Glioma↔Meningioma
- Themodelperformswellindistinguishing tumorvsnotumorcases

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

Class-wise Performance

Table2:ClassificationReport

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:

- HighestperformanceisobservedinPituitary tumor classification
- Slight confusion exists between Glioma and Meningioma,duetosimilarvisualpatternsin MRI images

ConfusionMatrixAnalysis

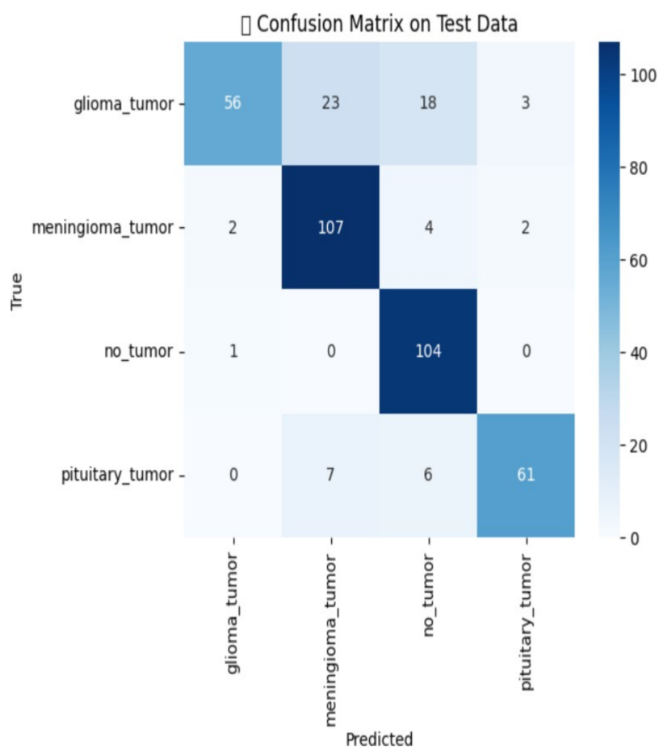

Fig.1.ConfusionMatrixofCNNModel

Discussion:

- Mostpredictionsliealongthediagonal→ indicatingcorrectclassification

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Training Performance

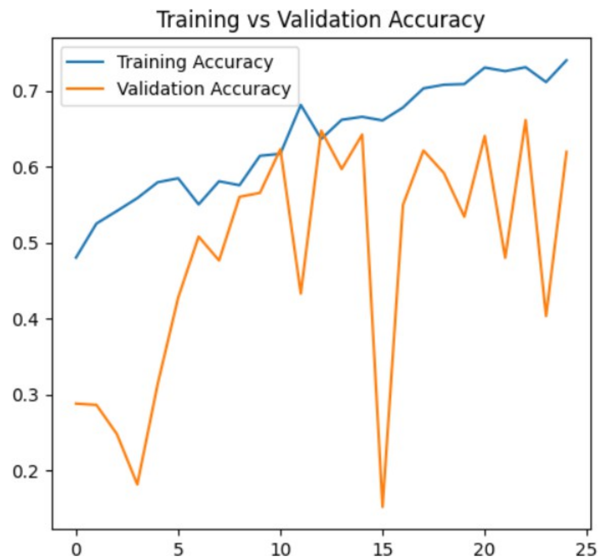

Fig.2.TrainingandValidation Accuracy

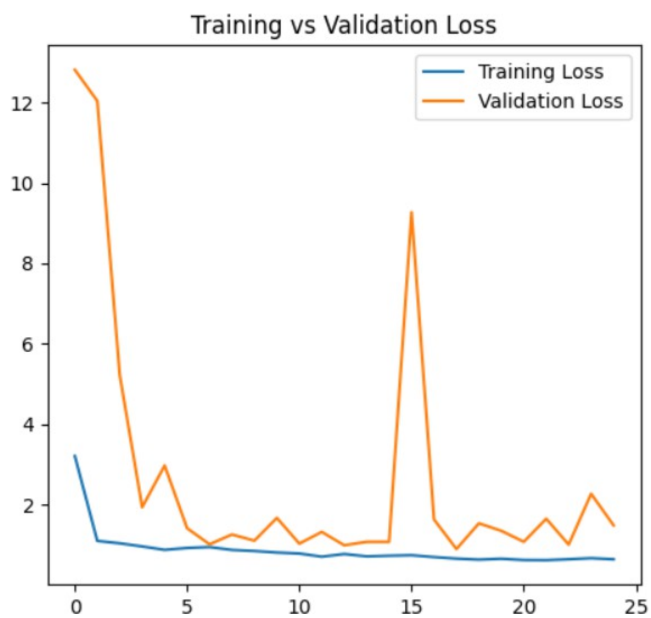

Fig.3.TrainingandValidationLoss

Discussion:

- Accuracycurveshowssteadyimprovementover epochs
- Validationaccuracycloselyfollowstrainingaccuracy→lowoverfitting
- Lossdecreasesconsistently,indicatingstable learning

Grad-CAMVisualizationResults

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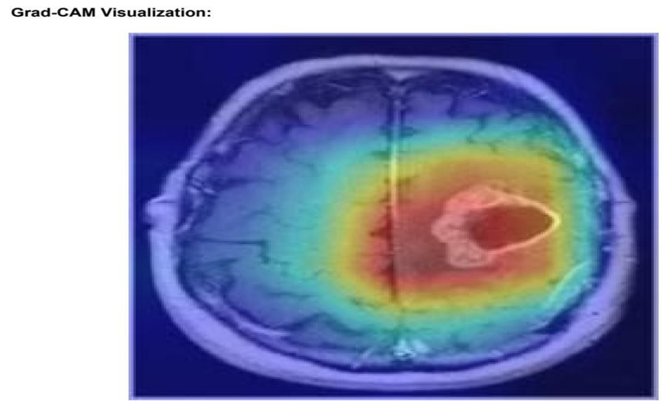


Fig.4.Grad-CAMOutputforTumor Localization

Discussion:

- Grad-CAMhighlightstumor-affectedregions clearly
- Providesvisualexplanationofmodel decisions
- Enhancestrustandusabilityinmedical applications
- Usefulforassistingradiologistsindiagnosis

User Interface and Output

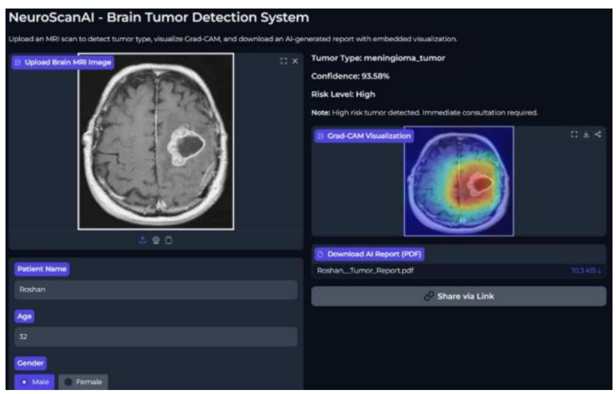
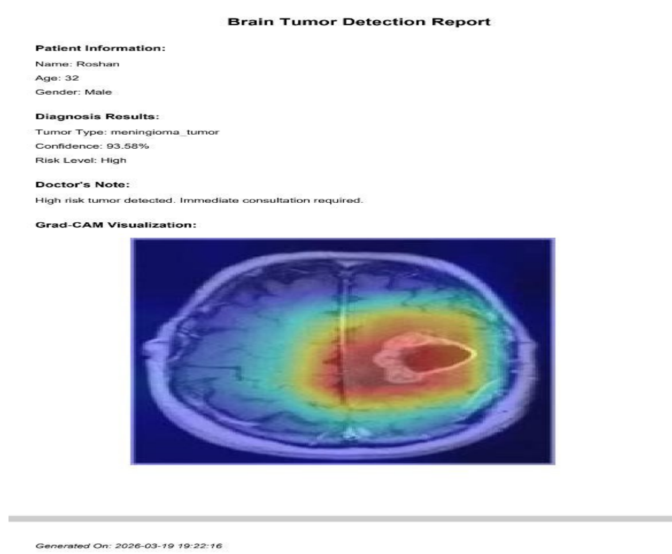


Fig.5.WebInterfaceforMRIUpload



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.GeneratedPDF Report

Discussion:
- Theinterfaceallowseasyimageuploadand instant prediction
- Reports include:
  - Patientdetails
  - Tumortype
  - Confidencescore
- Improvesreal-worldusabilityandautomation

ComparativeAnalysis

Table3:ComparisonwithExistingMethods

Method	Accuracy (%)	Remarks
Traditional ML	50-60	Requires manualfeatures
BasicCNN	65-75	Moderate performance

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

Discussion:
- Theproposedmodeloutperformstraditional approaches
- Transferlearningsignificantlyimproves accuracy
- AdditionofGrad-CAMprovidesinterpretability (key advantage)

Key Observations
- Transferlearningimprovesperformancewith limited data
- Grad-CAMenhancesexplainability
- Systemperformswellinreal-timescenarios
- Slightimprovementspossibleinclassseparation

Limitations
- Limiteddatasetsize
- 2DMRIimagesonly(novolumetric analysis)
- Minorconfusionbetweensimilartumortypes

V. CONCLUSION

This paper presented "NeuroScanAI", a deep learning- based system for brain tumor detection using MRI images. The proposedsystem uses transfer learningwith CNN models to achieve an accuracy of approximately 83–84%. Grad-CAM visuals enhance model by highlighting tumor regions, while the web interface and automated PDF report generation improve practical use and make the system moreeffectivefor 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

EventhoughtheproposedNeuroScanAIsystemgivesus 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.Inadditiontothis(ViT)whichisVision

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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