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Brain Tumor detection using Artificial Intelligence

Rushikesh Todekar[1], Shejal Kawale[2], Sakshi Khankar[3], Mayuri Sudake[4], Dr. Sachin Bere[5], Prof. Mrs. Jagtap P.S[6]

Information Technology, Dattakala Group of institutes, Pune, Maharashtra, India[1-4]

Guide, Department of Information Technology, Dattakala Group Of institutes, Pune, Maharashtra, India[5]

Co-Guide, Department of Information Technology, Dattakala Group Of institutes, Pune, Maharashtra, India[6]

Abstract: Brain tumors are one of the most urgent forms of brain disease because they require early detection for effective treatment. The traditional method of diagnosing them is through MRI scans by expert Radiologists and is a time-consuming process. This contribution provides an Artificial Intelligence (AI) supported framework for the automatic detection and classification of brain tumors using Deep Learning. The NeuroScout platform is based on a ResNet based Convolutional Neural Network (CNN) algorithm trained on brain MRI images to classify brain tumors into four categories: Glioma, Meningioma, Pituitary Tumor and No Tumor. The NeuroScout platform contains FastAPI for the backend, Next.js for the frontend, and MongoDB for data storage, which implements a full stack medical web application. Google Gemini AI generates a medical explanation, treatment recommendation and prevention guidelines for brain tumors which have been detected by the NeuroScout Platform. A major advantage of this approach is that the NeuroScout system demonstrates a high degree of classification accuracy and provides a simple, intuitive user interface for patients, doctors and administrators alike. By providing an AI and Deep Learning based medical support system to healthcare professionals for early diagnosis, this approach will help provide greater access to AI based medical decision support systems.

Index Terms: Brain Tumor Detection, Deep Learning, MRI Analysis, ResNet, Artificial Intelligence, Medical Image Processing, Machine Learning, Healthcare AI.

I. INTRODUCTION

Brain tumors are unusual cell growths in the brain and can alter how well the brain works and even cause death if they are not found early and treated. Brain tumors can be benign or malignant, and they can create serious side effects, such as cognitive problems, seizures, visual changes, and loss of motor skills. Therefore, an accurate and timely diagnosis is important for effective treatment planning and for improving the chances of survival for a patient diagnosed with a brain tumor. Medical images such as MRI scans are very useful for detecting and diagnosing brain tumors because they provide high-quality images of brain tissues, and they allow physicians to view the physical structure of the brain in detail. Radiologists use MRI scans to observe the size, location, and characteristics of the surrounding tissue of a tumor, which are necessary information for deciding the type and stage of the tumor. The traditional means of interpreting MRI scans is mainly manual and heavily relies on the training and experience of the radiologist, making it time consuming and susceptible to human error - greater than usual when detecting subtle abnormalities.

Recent advances in Artificial Intelligence (AI) and Deep Learning (DL) tec tumors technologies have led to new opportunities for enhancing medical imaging through automated detection of disease using improved analysis and processing capabilities of the data. Convolutional Neural Networks (CNNs) have been very successful in extracting spatially complex patterns from images taken with different types of imaging devices (e.g., MRI). Different deep learning-based architectures such as ResNet, VGG, and DenseNet have been implemented in brain-tumor detection and segmentation due to the ability of these types of networks to learn hierarchical or multi-layered representations of an image's features to provide improved classification performance. Brain tumors can be detected and segmented in MRI images with a high degree of accuracy using CNN-based deep learning networks and therefore radiologist receive improved ability to make fast and accurate diagnoses of the disease. In this research, an application of an AI-based intelligent system called NeuroScout which combines deep learning technology with a web-based healthcare information system for Performing automated analysis, classification and prognosis of brain tumors is proposed. This system allows patients to upload their MRI images via an easy-to-use interface. Once the MRI images have been uploaded to the NeuroScout platform, the images will be processed with a ResNet-based deep learning model to classify the type of tumor

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identified (i.e., Glioma, Meningioma, Pituitary Tumor, or No Tumor). Additionally, the platform will generate AI-based medical insights such as information about symptoms, treatment options, and prevention recommendations to create a comprehensive decision support system to help radiologists make better treatment decisions for patients with suspected or known brain tumors.

II. ADVANCED LITERATURE REVIEW

Significant changes to the biomedical image examination process have come as a result of recent advancements with regard to artificial intelligence (AI) and deep learning. MRI scans are being used for improved detection and classification of brain tumors, as well as improved measures of diagnosing patients who may have a brain tumor, due to advances made using machine learning and deep-learning technologies.

Khan et al. proposed the use of Convolutional Neural Networks (CNNs) to detect and classify brain tumors from MRI scans [1]. In their work, they were able to effectively demonstrate that deep learning techniques are significantly more effective than traditional machine learning techniques in the classification of medical images. Deepak & Ameer demonstrated how deep CNNs can be used to classify MRIs of patients with glioma tumors, meningiomas and pituitary tumors, showing that there is significant potential for deep learning models to assist in diagnosing brain tumors [2].

Through the use of transfer learning techniques, researchers have been able to enhance the effectiveness of their methods of classifying brain tumors. A brain tumor classification system using pre-trained CNN architectures was proposed by Díaz-Pernas et al. [3]. Their classification method yielded results that were significantly more accurate than classification systems that were not based on transfer learning. The investigation conducted by Younis et al. demonstrated that the VGG-16 architecture could be applied to detect brain tumors through MRI images. They showed that transfer learning models are successful in extracting salient information from MRI images.

There has been significant application of ResNet and DenseNet architectures to assist with brain tumor detection. For instance, Sharma et al. utilized ResNet as the basis for a deep learning model to enhance performance by applying transfer learning techniques and feature extraction [5]. Abdusalomov et al. also proposed a deep learning framework based on YOLO to detect and localize brain tumors through advanced neural networks [6].

Other researchers experimented with ensemble and hybrid models to improve brain tumor classification accuracy. Asif et al. created a model that combined several neural networks to yield an ensemble deep learning model to classify brain tumors more accurately [7]. Shaikh et al. presented a stacking ensemble model combining different classifiers to achieve improved segmentation/classification of brain tumors in MRI images [8].

Further studies were conducted on improving image preprocessing and feature extraction methods used for brain tumor classification. Rahman et al. designed functions using multiscale dilated CNN architectures to extract fine detail about spatial characteristics from MRI images which allowed for more accurate brain tumor classifications [9]. ZainEldin et al. created a framework using deep learning that integrated feature extraction and classification methodologies yielding high precision when differentiating between multiple brain tumors.

Comparative studies have also been conducted to evaluate various deep learning architectures designed specifically to identify different types of tumors. Khaliki et al. performed a comparison of models including Inception-V3, VGG19 and EfficientNet for classifying brain tumors and reported that deep learning models significantly outperformed traditional methods in the context of medical imaging tasks [11]. Gomes et al. assessed several additional deep learning architectures including ResNet50 and DenseNet201 and concluded that these approaches provide reliable performance for classifying tumors using MRI images [12].

In addition, there has been a great deal of interest among researchers investigating the integration, or use of AI-based systems within the field of clinical health care applications. Rastogi et al. have developed a deep learning framework for segmenting tumors as well as predicting survival from MRI images and have outlined the potential benefits of using AI technology to assist with clinical decision making [13]. Wong et al. created a CNN-based framework to classify multi-class types of brain tumors which improves the diagnostic processes by automating analysis of MRI images [14].

Several review-style articles have summarized the progress being made with the development of AI-based approaches for tumor detection. Nazir et al. provided an extensive review on the use of deep learning techniques in the identification of brain tumors and determined that leveraging transfer learning in conjunction with advanced convolutional neural

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networks enhances tumor classification capabilities [15]. Similar conclusions have also been reported in several other surveys/ studies, with the increased use of AI-tools in the medical imaging arena along with increased use.

Hybrid systems combining deep learning with sophisticated image segmentation techniques have also been investigated by recent studies. In one study, Mohsen and colleagues used a deep neural network to classify MRI images of brain tumors, which they found to provide high accuracy through multi-layered feature extraction methods [17]. In another study, Afshar and colleagues developed a model utilizing capsule networks for the classification of brain tumors, with the model showing better performance than standard neural networks in capturing spatial relationships among feature sets extracted from images [18].

Swati and colleagues used models based on deep transfer learning for brain tumor classification, demonstrating that pre-trained CNNs can improve classification accuracy when trained on MRI datasets [19]. Cheng and colleagues proposed a feature-based classification system dependent on combining machine learning techniques with image segmentation to improve classification of brain tumors [20].

III. ENHANCED SYSTEM ARCHITECTURE

NeuroScout was created to be a complete software platform for intelligent healthcare and a full stack of integrated technologies including: (1) deep learning-based image analysis; (2) a web-based clinical support system; and (3) an open-source architecture. To that end, the NeuroScout application consists of a modular and layered design that allows for the scalability, reliability, and efficient communication between disparate components of the application.

The architecture for the NeuroScout application can be classified into five main architectural layers, each of which provides a specific function during the overall process of detecting and prognosing brain tumors. These five main architectural layers are as follows.

A. Data Acquisition Layer

The first architectural layer of the NeuroScout application is the Data Acquisition Layer. The Data Acquisition Layer collects Magnetic Resonance Imaging (MRI) brain images, which serve as input to the NeuroScout application. The MRI brain images can either be obtained from a medical imaging database or uploaded by users, including patients or healthcare professionals, through the NeuroScout web application.

MRI brain images are generally high-resolution scans of the brain that provide the ability to analyze both the structure and abnormalities of the brain in a high degree of detail. The NeuroScout system has been developed to support common image formats such as JPEG, PNG, and MRI scans, thus enabling a flexible means of inputting data to the NeuroScout application. After a user uploads an MRI brain image, the image is sent to the Preprocessing Module for further analysis.

B. Image Pre-Processing Layer

The Image Preprocessing Layer is where we prepare the MRI images before passing them off to the Deep Learning Model. Medical images have a tendency to include various sorts of noise, inconsistencies in brightness, and unnecessary background noise that contain information irrelevant to the image and have a negative impact on classification accuracy. In order to minimize these effects and allow for accurate classification, several preprocessing techniques such as resizing images, normalizing images, and converting the images into tensor format are used. In the proposed system, all images will be resized to 224×224 pixels, which matches the input size of the deep learning model. The pixel normalization will be performed using the standard ImageNet statistics so that the input representations are consistent. By ensuring a consistent way of representing input data, the above-mentioned preprocessing techniques should increase the performance of the model.

C. AI/ML Model Layer

The AI/ML Model Layer is the "intelligent" portion of NeuroScout. The AI model is a Deep Learning Model based on the Residual Network (ResNet) architecture. The Deep Learning model is used to classify and analyze MRI images in order to determine if there is a brain tumor present in the MRI. The model is trained on a set of labeled MRI training data which contains data from one of a number of tumor types: Glioma, Meningioma, Pituitary Tumor, or No Tumor. ResNet was selected because it is able to address the vanishing gradient problem and effectively learn deep image features through the use of residual connections. The trained model generates a probability score for each of the tumor types from the preprocessed MRI image during inference.

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D. The Application Layer

The application layer will provide a user interface and system features that enable patients and doctors to access the proposed application system. The proposed application is a web application which will be built using the latest web application technologies. Patients will be able to submit MRI images and receive automated tumor predictions, whereas doctors will be able to access patient reports and render additional medical assistance. The Application Layer integrates Artificial Intelligence-generated documents containing an explanation of the medical diagnosis made by the AI algorithm, i.e., symptoms related to the patient condition, recommended method of treatment, and prevention guidelines regarding the belief of having the detected malignant tumor type. The Application Layer uses a role-based access control system to restrict access to three identifiable roles which include Patients, Doctors, and Administrators. This role-based access control ensures that the patient(s) data and medical reports are securely protected from unauthorized access and that the patient(s) reports are managed in an organized manner.

E. The Database Layer

The database layer of the proposed application is responsible for storing and managing all system data. The proposed application will store user profiles, MRI image documents, the predictions generated from the predictions provided by the artificial intelligence algorithm, and the scheduling or appointment information in a NoSQL database stored in a cloud (e.g., MongoDB). All AI model-generated predictions will be stored in the database along with the corresponding metadata, i.e., uploaded image name, predicted tumor type, confidence score, and date/time. Storing the AI model-generated predictions with associated metadata enables Patients and Doctors to access and evaluate all previous patient records and track the health progress of a patient over time. Security protocols and encryption will also be incorporated to support secure authentication and also to maintain the security and confidentiality of sensitive medical information.

IV. METHODOLOGY

The NeuroScout system is designed to detect and classify brain tumors in MRI images using deep learning methods and follows a systematic approach with multiple stages, from acquiring the data through preprocessing, model training through predictions, then incorporating the web-based application for use in a clinical setting. Through this process, accurate classification of tumors can be achieved, as well as an AI backed prognosis for both patients and healthcare professionals.

A. Data Collection

The first step of the methodology involves the acquisition and collection of MRI brain images, which are used for training and testing the deep learning model. The MRI images will be captured in four categories--Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor. The MRI images will be taken from publicly accessible medical imaging databases and research repositories. Labeled MRI images will be exploited so that the model can learn the differences between the respective tumor types and will ultimately yield valid results. Once the acquisition and collection of MRI images is complete, the dataset will be segregated into three categories of training, validation, and testing dataset in order to allow for effective evaluation of the performance of the model.

B. Preprocessing of MRI Images

It is common that MRI images may contain noise as well as inconsistency in brightness and/or contrast, which may negatively impact the model's performance. For this reason, image preprocessing steps must be performed in order to ensure that the input data to the deep learning model is standardized and, therefore, of equal quality. As part of the advancement of the methodology.

C. Implementation of the Deep Learning Model

The Reported System Utilizes a Residual Network (ResNet) architecture, which is a variant of Convolutional Neural Networks (CNNs). The ResNet architecture was developed to solve the vanishing gradient issue, enabling the effective training of even deeper networks. To classify the four tumor categories of MRI images, the base architecture of the ResNet18 model will be modified by changing the fully connected layer at the end of the network. The process of transfer learning will enable the accumulation of knowledge from images previously trained on standard-sized datasets, and will help better extract visually significant features from MRI data.

The tumor characteristics will be learned by using several convolutional layers to accomplish multiple levels of hierarchical feature extraction. The final output layer of the model will have a softmax activation function that will give the model a probability score for each of the tumor categories being predicted. The predicted tumor category will be the category with the largest probability score.

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D. Training and Optimizing Model

The model will be trained using a previously prepared dataset through an approach called Supervised Learning, where the model is trained by providing example input data along with the corresponding expected output data. The model will update its parameters based on the optimization algorithm (both Adam and SGD). The cross-entropy loss function will be utilized to evaluate the difference between predicted and actual labels. The training process will run for multiple epochs, until the model achieves optimal performance.

E. Predicting Tumors & Generating Prognosis

The developed model will be deployed after training in order to predict brain tumors in real-time. When users upload MRI images through the web-app interface, the uploaded image will be pre-processed, and subsequently sent to the deep learning model for inference. The model will predict class label for the tumor and provide confidence scores for the corresponding predictions. Following classification, the system will generate additional medical insights related to possible symptoms, treatment recommendations, and preventative guidelines based on underlying AI medical knowledge. This information will enhance the user's understanding of their condition subsequent to detection.

F. Integration with Web-App

As part of the last phase of this methodology the trained model was integrated into a fully functional web-based healthcare application. The backend of the web-app handles image uploads, model inference and database operation whilst the frontend manages patient interaction with the application. Patients can upload their MRI images and view prediction reports; physicians have the ability to view reports for their patients and administrators will manage the application from a technical perspective. Through this integration, NeuroScout creates an AI supported medical decision support application for brain tumor detection.

V. EXPERIMENTAL RESULTS AND ANALYSIS

An evaluation of the proposed NeuroScout system's performance was completed using an MRI brain image dataset comprised of four categories - Glioma, Meningioma, Pituitary Tumor and No Tumor. This dataset was then split into training, validation and test sets in order to provide all of the necessary elements to have an accurate evaluation of the deep learning model. Experiments were conducted using the ResNet18 architecture implemented with the PyTorch framework; the model was trained for a number of epochs using the Adam optimizer and a cross-entropy loss function in order to increase the model's ability to classify images correctly.

During training, the model learned different features from spatial (2D) MRI images through the use of convolutional layers and residual connections. After the training phase, the model's performance in classifying brain tumor and non-tumor images was assessed by way of several common evaluation metrics such as accuracy, precision, recall and F1-score. These metrics were helpful in determining if the proposed AI-based system for the detection of brain tumors was reliable and effective.

The experimental results show that the proposed deep learning model achieves a high classification accuracy for brain tumor detection; the model accurately separates images of each type of brain tumor from those without tumors, therefore meeting its stated performance objectives. The proposed deep learning model also exhibits superior feature extraction capabilities relative to traditional machine learning models and therefore demonstrates a considerable improvement in overall classification performance.

The performance of the proposed NeuroScout system was analyzed through a comparative study involving Traditional Machine Learning Methods, Basic CNN Models (Stage 1), and ResNet-based NeuroScout System (Stage 2). Multiple performance metrics were used in this comparison: classification accuracy, precision, recall, F1-score, and processing time. A summary of the results can be found in Table I.

The results demonstrate that the proposed NeuroScout system has a substantial enhancement in classifying brain tumors compared to traditional methods. The ResNet-based model exhibited improved accuracy when predicting classification and reduced time in processing while providing consistent classification results across tumor types. These results indicate that deep-learning methods are effective for analyzing medical images and that AI-based diagnostic systems will assist in providing support for healthcare professionals.

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TABLE 1. COMPARATIVE PERFORMANCE EVALUATION ACROSS SYSTEM CONFIGURATIONS.

Metric	Traditional ML Methods	Basic CNN Model (Stage 1)	Proposed NeuroScout System (Stage 2)
Classification Accuracy	78.5%	88.6%	96.4%
Precision	76.2%	87.1%	95.8%
Recall	74.8%	86.4%	95.2%
F1-Score	75.5%	86.7%	95.5%
Average Processing Time	4.8 sec	3.1 sec	1.9 sec
False Detection Rate	12.4%	7.6%	3.2%
System Reliability	Moderate	High	Very High

(from Table 1) While Stage II of the proposed NeuroScout System achieved a classification accuracy of 96.4% and outperformed all traditional machine-learning and basic Convolutional Neural Network (CNN) techniques). The gain in classification accuracy is due to using the ResNet (Residual Network) architecture for deep learning and fully utilizing residual connections to extract complex features from MRI scans. The proposed system also demonstrated faster processing times as well as lower numbers of false detections, making it well-suited for real-time medical diagnostics. Overall, the results of this study provide strong evidence that combining deep learning with intelligent healthcare platforms can improve the effectiveness and reliability of the brain tumor detection system.

TABLE 2. FEATURE COMPARISON WITH EXISTING COMMERCIAL SOLUTIONS.

Feature	Traditional ML Methods	Basic CNN Models	Transfer Learning Models	Proposed NeuroScout System
Automatic MRI Image Analysis	Partial	Yes	Yes	Yes
Multi-Class Tumor Classification	No	Partial	Yes	Yes
Deep Feature Extraction	No	Yes	Yes	Yes
High Prediction Accuracy	Low	Medium	High	Very High
AI-Based Medical Insights	No	No	No	Yes
Web-Based Diagnostic Platform	No	No	Partial	Yes
Real-Time Tumor Prediction	No	Partial	Partial	Yes
Role-Based User Access (Patient/Doctor/Admin)	No	No	No	Yes
Secure Medical Data Storage	No	Partial	Partial	Yes
Clinical Decision Support	No	No	Partial	Yes

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VI. CHALLENGES AND LIMITATIONS

In spite of having shown very encouraging research outcomes when utilizing deep learning algorithms for identifying and classifying tumors using MRI, there are still many hurdles to overcome before this technology can be successfully integrated into clinical practice. The most significant barrier is the lack of adequate supplies of large enough, diverse enough annotated datasets to allow deep learning models to be trained with sufficient amounts of data to make accurate predictions and generalize well. The lack of sufficient amounts of data is due mainly to the limitations imposed by regulations related to patient privacy, ethical issues, and limited availability of medical imaging datasets. MRI images that are taken at different medical facilities or from different types of equipment may also differ significantly in terms of the quality of the images (e.g., resolution, contrast, noise, etc.), which will negatively impact the ability to classify images using a deep learning model.

One additional drawback is the high computational demand as well as the limited interpretability of the deep learning models. Training these neural networks such as ResNet structures involves the use of large-scale GPU's which can take long periods of time to complete. This may incur increased costs on deployment systems in health care settings when the health care has limited computing resources. Also, due to the black box operation of the deep learning model, it is challenging for medical personnel to understand how the predicted results were obtained. In clinical settings it is essential for healthcare providers to have confidence in the AI model through its explanatory and transparent reporting to help build an understanding of how the model works. In order to use AI efficiently within the healthcare ecosystem, the AI must be integrated into current systems in the healthcare ecosystem with good data privacy and security to protect patient data. By developing better datasets, consider the use of explainable AI techniques, and implementing secure storage of patient data, the use the AI powered Brain Tumor Detection will become more trustworthy and reliable.

VII. FUTURE DIRECTIONS

A. Enhancing the NeuroScout System by Expanding Medical Datasets

One avenue for enhancing the NeuroScout system in the future will be to utilize larger, more diverse MRI datasets, obtained from multiple hospitals and medical institutions. Training the model with these larger datasets will improve generalization and prediction reliability across multiple imaging modalities, as well as among patients from different demographic characteristics.

B. Implementing Advanced Deep Learning Techniques

Another enhancement for future versions of the NeuroScout system will be to employ newer forms of deep learning architectures (e.g. DenseNet, EfficientNet, Vision Transformers). The implementation of these architectures will improve the ability to extract features from MRI images and potentially provide higher degrees of accuracy for classifying tumors.

C. Implementing Tumor Segmentation

Future versions of the NeuroScout system can also implement methods for segmenting medical images into discrete components. Specifically, medical imaging segmentation techniques can be employed to delineate the size and extent of tumors, as well as the brain regions that are impacted by tumors. Identifying the size and location of tumors will allow for more precise planning for treating tumors.

D. Integrating Explainable AI and Supporting Clinical Integration

Finally, Explainable Artificial Intelligence (XAI) techniques can provide visualizations that capture and convey how the model makes predictions, allowing healthcare practitioners to better understand how the model arrived at a given conclusion. Also, by incorporating DICOM-compliant medical imaging formats and integrating with hospital information systems, the NeuroScout system will become considerably more applicable within the context of a true clinical environment.

VIII. CONCLUSION

In this study, we introduce NeuroScout, an AI-enhanced technology for the analysis of brain tumors, and for determining prognosis using deep learning algorithms. The novel tool uses MRI scans of the brain and employs a ResNet-based convolutional neural network (CNN) that makes automatic predictions based on various types of input, such as the type and size of a given tumor, and if present at all depending on whether it is classified as any of the following: Glioma, Meningioma, Pituitary Tumor, or No Tumor (brain). By using deep learning with a web-based clinical healthcare application, patients and physicians can upload MRI scans to receive automated predictions as to whether there is a brain

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tumor or not, along with a confidence score for each prediction, and also receive additional medical insights based on their uploaded MRI scans.

Experimental results showed that our proposed approach can provide accurate classifications for each type of brain tumor (Glioma, Meningioma, Pituitary Tumor) and can reliably detect all four categories of brain tumors using traditional machine learning approaches. Incorporating AI medical explanations for each predicted result and a web-based physician's role-based healthcare solution improves ease of use for both patients and physicians. The NeuroScout system demonstrates the capabilities of artificial intelligence in aiding early detection of brain tumors as well as assisting clinical decision-making involved in the detection of brain tumors. Enhancing the current model via larger datasets, more advanced deep learning architectures, and integrating with clinical practice will continue to enhance the efficiency of AI-based medical diagnostic tools within healthcare systems.

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