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RAG-Enabled Workflow Automation for MRI Brain Tumor Classification Using Transfer Learning

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***Abstract*—Brain tumors using magnetic resonance imaging (MRI) plays critical role in clinical decision making. Manual analysis takes time and subject to observer knowledge and experience. While most deep learning models achieved high accuracy in tumor classification, but most of them operate as black box models, lacking automation, interpretability, and structured clinical reporting.**

this paper proposes an automated end-to-end framework for MRI based tumor classification and clinical report generation using transfer learning and RAG. A pretrained classification model fine tuned on brain MRI images is employed to classify tumors, while an automated workflow build using n8n used for image processing, model inference, result interpretation and report generation using LLM. RAG module enhances explainability by predicting in relevent contextual information, enabling generation of human readable reports The aim of this work is to improve how brain tumor classification models are actually used in clinical practice. In existing studies, the main focus was on achieving high accuracy, In this project, automation, interpretation of results, and report generation are addressed together within a single pipeline. The results show that the system performs reliably on MRI data and reduces the need for manual work. As a result, the overall workflow becomes easier to use and more suitable for supporting clinicians. The model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score.

***Index Terms*—Brain tumor classification, magnetic resonance imaging, transfer learning, retrieval-augmented generation, workflow automation, clinical decision support**

I. Introduction

Brain Tumors are from the most critical neurological conditions due to their impact on cognitive abilities and have a high death rate if not detected in the early stages. MRI is widely used for the diagnosis of brain tumors because of its ability to produce detailed images of soft tissues without radiation; however ,manual interpretation of MRI images from radiologists is time-consuming process and vary based on individual experiences and expertise, leading to inconsistencies in diagnosis.

In previous years, deep learning techniques have demonstrated strong potential in classifying brain tumors based on their malignant or benign nature, and automating tasks of classification. Convolutional neural network(CNN) and transfer learning approaches makes it easier to use knowledge learned from large-scale datasets. This enabled reliable performance even when data is limited. Despite achieving high accuracy, many existing systems focus only on predicted results and function as only an evaluation matric which restricts their integration in a real-world environment.

Clinical decision support systems need more than just accurate prediction results. In real hospital settings, these systems are expected to handle data automatically, explain their outputs clearly, and produce reports that clinicians can understand without extra effort. Many existing deep learning approaches do not address these requirements and are often limited to experimental or laboratory use. As a result, there remains a clear gap between research developments and their practical adoption in clinical environments. In addition, workflows that rely on manual steps increase both the cognitive load and the operational effort required from healthcare professionals.

To deal with these issues, this work introduces an automated framework for classifying brain tumors from MRI scans and generating clinical reports. The system uses a transfer learning-based deep learning model together with a Retrieval-Augmented Generation (RAG) component to make the results easier to understand and properly documented. Workflow automation is handled through the n8n platform, which connects image input, model inference, and report generation into a single pipeline. By focusing on accuracy with automation and interpretability, the presented approach makes AI based diagnostic tools more reliable for real clinical use.

II. Problem Statement and Motivation

Accurately identifying brain tumors from magnetic resonance imaging (MRI) scans is an important part of clinical diagnosis and treatment planning. In recent years, deep learning models have achieved encouraging results in tumor classification tasks. However, several issues still limit their use in real medical environments. Many existing studies place most of their emphasis on improving classification accuracy, while important aspects such as system integration, result interpretation, and automation are often overlooked, reducing their practical clinical value.

One major drawback of many existing deep learning–based systems is that they do not offer a fully automated diagnostic workflow. Tasks such as image preprocessing, running the model, interpreting the output, and generating reports are often performed manually or through poorly connected stages. This kind of fragmented setup slows down the overall process and increases the chance of human error. In addition, many deep learning models acts like black box models, they provide limited insight in how classification is being made, which can reduce confidence and trust among clinicians. Another challenge is clinical reporting. Even when a model is able to classify the correct tumor type, the task of preparing structured medical reports is still handled by radiologist. This reporting process takes alot of time and can vary from case to case, which may lead to inconsistencies. When prediction results are not accompanied by clear explanations or automatically generated reports, it becomes difficult to translate algorithmic outputs into meaningful clinical decisions.

The motivation for this work comes from the need to reduce these gaps. The goal is to design a single, integrated system that combines reliable tumor classification with automated processing and explainable reporting. Transfer learning is used to improve MRI-based classification accuracy, while Retrieval-Augmented Generation (RAG) supports contextual interpretation of results. Workflow automation through the n8n platform connects these components into a complete pipeline, making the overall system more suitable for real clinical use.

III. Objectives

The goal of this research is to build an automated system for brain tumor classification and clinical report generation using MRI data, with emphasis on practical use in real clinical environments. Rather than focusing only on model accuracy, this work aims to develop a solution that can be easily integrated into routine diagnostic workflows.

- To design and implement a deep learning–based model for brain tumor classification using transfer learning to improve accuracy and generalization on MRI data.
- To create a fully automated pipeline that manages inputs and image preprocessing, and result handling through the n8n workflow automation platform.
- To add a Retrieval-Augmented Generation (RAG) approach for generating structured, explainable, and clinically meaningful reports from model predictions.
- To increase the transparency and explainability of the model outputs in order to improve trust and usability in real clinics.
- To evaluate the performance of the proposed system in terms of classification accuracy, automation efficiency, and its effectiveness as a clinical decision support tool.
- To compare baseline deep learning models with the proposed transfer learning–based approach to assess performance improvements.

IV. System Architecture and Workflow

The proposed system is implemented as an automated end-to-end framework that brings together brain tumor classification, workflow automation, and explainable clinical reporting. A modular architectural design is adopted so that individual components can be scaled, understood, and integrated more easily into real clinical environments. The framework consists of a transfer learning–based classification model, a RESTful API for system communication, a Retrieval-Augmented Generation (RAG) component for interpretability, and workflow orchestration managed through the n8n automation platform.

A. Overall System Architecture

Fig. 1. Overview of the proposed RAG-enabled automated brain tumor classification framework, illustrating deep learning-based classification, retrieval-augmented report generation, and workflow automation using n8n.

Fig. 1presents a high-level view of the proposed system, showing how deep learning–based tumor classification is combined with Retrieval-Augmented Generation for report interpretation, along with automated workflow management using the n8n platform.

The system is divided into four parts, MRI image input and preprocessing, tumor classification, workflow automation, and report generation. MRI scans can be provided as image fille. Before classification, the images preprocessed to standardize their resolution and normalize pixel values so that the model receives consistent inputs.

Tumor classification is performed through a deep learning model trained with transfer learning. The trained model is accesible through a Flask based REST API, which allows it to interact smoothly with the automated pipeline. The API provides prediction outputs as the predicted tumor class along with probability values. These outputs are then used for analysis and for generating clinical reports.

The n8n acts as the main aspect for workflow management. It controls the sequence of system operations, handles data exchange between services, and ensures that each step from image submission to report generation runs smoothly. By automating these all processes, the system will reduces the need for manual work and helps improve overall processing efficiency.

B. Workflow Automation Using n8n

The automated workflow starts when an MRI image received in the n8n platform, and then sends it to the classification API for classification of tumor type. After that, API returns the predicted results, then n8n processes the output to identify the presence of a malignant tumor along with the associated confidence level.

Once classification is done, the workflow triggers the Retrieval-Augmented Generation process. Relevant information, such as similar past cases or related literature data, is combined with the model's predictions. This combined information is then passed to a language model, which generates a structured clinical report based on both the prediction results and the retrieved context.

Finally the system deliver a clinical report that is easy to interpret by radiologist and patients. The report includes a summary of the diagnostic, confidence on classification from the model, and next steps.Since the whole process is automated, the workflow delivers consistent output across all cases and supports traceability and efficiency, making the system well suitable for clinical use .

C. Retrieval-Augmented Generation for Clinical Reporting

To make the classification results easier to understand, a Retrieval-Augmented Generation (RAG) method is added to the framework. Instead of creating reports using only the predicted tumor class, related reference information is first retrieved and then combined with the prediction output. This aids in place the result in a clearer context.

With this approach, the generated reports become more meaningful and easier to read for medical staff. The report not only shows the final decision but also provides supporting information that explains how the result was reached. This converts non-interpretable model outputs into information that can be practically used during clinical.

D. Dataset Description

The experiments are performed using a publicly available MRI brain tumor dataset that contains labeled images from four categories: glioma, meningioma, pituitary tumor, and non-tumor cases. The MRI images come from different sources, which results in variations in image quality, resolution, and tumor appearance.

the dataset includes 5,712 images for training and 1,311 images for testing. Because the number of images are not same in all classes, class weighting is applied for individual classes during training to reduce the effects of class imbalance on final classification.

Before training, all images are preprocessed and resized to a fixed input size required by the model. The dataset divided into training, validation, and testing splits to allow proper performance evaluation. Data augmentation is applied only to the training data to increase variation and limit bias towards overfitting, The validation and test sets are left unchanged to better represent real conditions.

V. METHODOLOGY

This section tells how brain tumor classification is implemented using MRI images. It describes the steps used to prepare the data and how transfer learning is used in the model. The training process of the deep learning model is also discussed here. The main idea is to get stable classification results while keeping the model simple and practical for clinical use.

A. Baseline and Proposed Models

To check how well the proposed method performs, a basic convolutional neural network is trained first using the same dataset and preprocessing steps. This model is used as a simple reference so that the effect of transfer learning can be compared fairly.

After that, a transfer learning model based on EfficientNet is fine-tuned for brain tumor classification. Pre-trained weights are adjusted using MRI images so the model can learn tumor-specific features. By comparing the results of the baseline model with the fine tuned model, it clear that using transfer learning helps improve classification performance and makes training more stable.

B. Data Preprocessing

Image preprocessing done before training because MRI images collected from different sources may have different quality. Some images have change in size, brightness, or include unwanted noise. To make the data more suitable for training, all MRI images were resized to a fixed input size required by the deep learning model. Pixel values are also normalized to limit variations introduced by different imaging machines.

Simple noise reduction steps are applied to remove unwanted artifacts while keeping important image details. During training, data augmentation techniques such as rotation, flipping, and scaling are used to increase variation in the dataset. These steps provide aid to model to learn better and reduce overfitting when it will tested on new MRI samples.

C. Deep Learning Model

For tumor classification, a hybrid of convolutional neural network is used with transfer learning. In this project, EfficientNetB0 used as the baseline model because it works well and does not require too much resources. The first layers are kept unchanged and already contain learned weights, which helps the model pick up basic patterns from MRI scans before learning tumor-specific features.

To make the network suitable for brain tumor classification, extra fully connected layers are added at the top of the base model. These layers are trained on the MRI dataset to aid the model to learn about different tumor categories. On the other hand only the top layers are fine tuned, which reduces training time and computational cost while still providing stable and reliable classification results.

D. Transfer Learning Strategy

Transfer learning is used because there are only a limited number of labeled medical images available. Instead of training the model from start, it uses knowledge and data already learned from very large image datasets and uses this knowledge to MRI image classification. During training, the initial layers of the network are frozen because they focus on general visual features. The deeper layers then fine-tuned so the model can learn patterns that are specific to different tumor types.

The model is trained using a supervised learning method, where the correct labels are already known. Categorical cross entropy issed as the loss function to measure the difference between predicted and actual labels. An adaptive optimizer is used to keep the training process stable. The performance of the model is evaluated using common classification metrics such as accuracy and confidence scores, which help determine how reliable the predictions are.

E. Model Training and Evaluation

The model is trained using a supervised learning with labeled MRI images. Training parameters like learning rate and batch sizes are optimized to keep the training process smooth, optimized and to minimize overfitting. Validation results are monitored during training to check how well the model performs on unseen data.

Model performance is evaluated using common classification metrics such as accuracy, precision, recall, and F1-score. These metrics are used to get a better understanding of how the model performs across different tumor classes, especially where the data is not evenly distributed. The results of the transfer learning model are also compared with baseline models to observe any performance improvements.

F. Model Interpretability

To make system explainable and gain clinical trust, gradient based visualization techniques are used to make predictions explainable. Grad-CAM is used to highlight affected regions based on which our model made such decisions. This helps clinicians understand which area in MRI influenced models decisions reducing unexplainability of existing deeplearning models

The improved Grad-CAM visualization accurately localizes tumor regions, with strong central activation across all tumor classes, further validating the clinical interpretability of the proposed model.

VI. Results and Discussion

This section overview the outputs obtained from base model and fine tuned transfer learning model. The performance analyzed by training and validation accuracy and loss values in different epochs. These results shows how model learn over time and how well it will generalize.

A. Training and Validation Performance

The baseline model shows steady learning patterns, with training accuracy increasing while validation keep getting lower value. validation loss shows some fluctuations which indicates limited generalization and sensitivity to variation in data. this suggest baseline model is prone to overfitting

On the other hand, fine tuned transfer learning model achieves highest validation accuracy with stable convergence. Training accuracy reached saturation earlier, and validation accuracy keeps improving consistently, showing effective feature transfer from pre trained weights. Although a gap between training and validation loss remains.

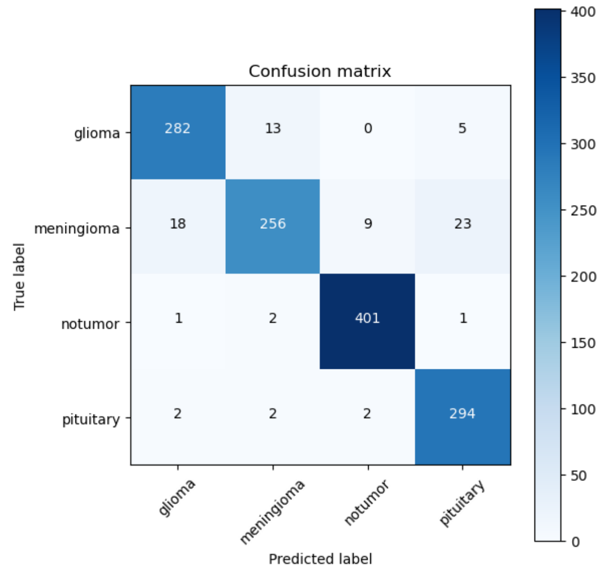

Fig. 2. Confusion matrix of the proposed transfer learning model evaluated on the test dataset across four classes: glioma, meningioma, pituitary tumor, and non-tumor.

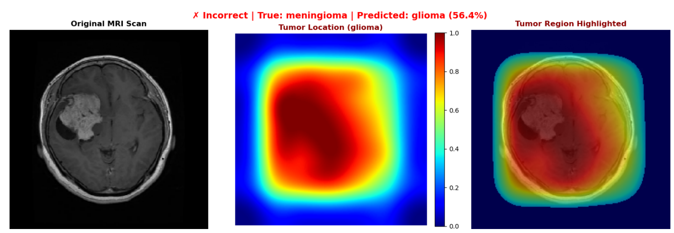

Fig. 3. GradCAM visualization for a correctly classified example. The heatmap highlights the tumor region impacting most significantly to the model's decision.

B. Accuracy and Loss Analysis

The training and validation accuracy graph shows that fine tuned model learn faster as compared to baseline model. Validation accuracy keeps getting stable in the time of training. This show that model is able to generalize well without being prone overfitting. this behavior also can be seen in loss curves where training loss gradually decreases.

These observations shows that using transfer learning for classification improves the training process, especially when

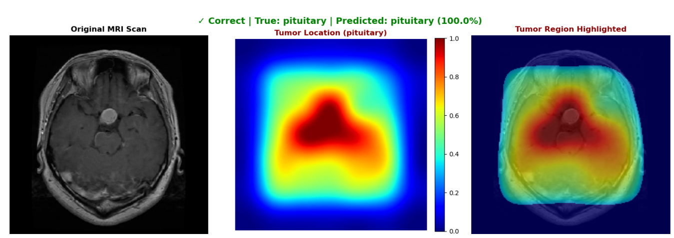

Fig. 4. GradCAM visualization for a correctly classified example. The heatmap highlights the tumor region contributing most significantly to the model's decision.

the available dataset is not enough or limited. The model was able to learn useful features more efficiently and produce more accurate results across each epochs. Similar learning trends have also been observed in other brain tumor classification experiments that use pre-trained models.

TABLE I
PERFORMANCE METRICS ON THE TEST DATASET (VALUES IN %)

Model	Acc.	Prec.	Rec.	F1
Baseline CNN	91.8	91.5	91.3	91.4
Proposed TL model	**94.1**	**94.2**	**94.1**	**94.1**

C. Discussion

The results show that the transfer learning–based model performs better than the baseline model, especially in terms of validation accuracy and training stability. The combination of preprocessing, model fine-tuning, and workflow automation helps the system operate correctly from input to output without extra manual steps.Some overfitting can be noticed in the later training epochs, but the overall validation trends still indicate that the approach works well.This issue could be further reduced by using additional regularization techniques or a larger dataset. When the classification model combined with automated report generation and explainable outputs, the system becomes more practical and easier to use in a clinics.

As shown in Fig. 2, the model performs well across all tumor classes, with only a small number of misclassifications. The results clearly show that tumor and non-tumor cases are correctly distinguished in most instances. Fig. 3 is a case in which the model makes an incorrect prediction. The issue occurs because that some tumor have similar features, which makes hard to predict real class and can confuse the classifier. Although the prediction is wrong, the Grad-CAM heatmap still highlights areas of the image that are clinically important. This indicates that the model is looking at relevant regions of the MRI scan, even when it does not produce the correct final label. Fig. 4, on the other hand, shows a correctly classified example. The activation map is concentrated mainly around the tumor region, indicating that the model is able to localize important features when the prediction is correct. This supports the interpretability of the classification results.

Table I Shows the performance of the model on the test dataset. in comparison to our baseline CNN only model, the hybrid transfer learning based model achieves higher accuracy, precision, recall, and F1-score. These results shows that the model generalizes better across different tumor classes and produces more accurate predictions.

VII. CONCLUSION AND FUTURE WORK

This paper presented a system for brain tumor classification that automates the entire pipeline of brain tumor classification using MRI images, with clinical report generation. The system uses a hybrid of a deep learning classification model and transfer learning approach, automated workflows using the n8n, and explainable report delivery using a Retrieval-Augmented Generation (RAG) approach. By automating the full pipeline, this system reduces manual effort and makes the overall process easier to use.

Experimental results show that the transfer learning–based model produces reliable classification results compared to a baseline model. The automated workflow improves consistency in classification of tumors and reduces tasks that was repetitive, while the use of RAG and visualization techniques aided in understanding how predictions are being made. Together, these components make the system more practical for use as a basic AI-assisted diagnostic support tool.

There are some limitations in this project. This system is only tested and validated on one datasets, and its performance may differ when applied to data collected from different hospitals or imaging devices. Important factors such as regulatory requirements, patient privacy, and real-time deployment were not addressed in this project and require further study.

In future work, focus will be on extending the system by including additional medical data and information such as patient history and radiology reports to improve clinical reporting. Testing the model on larger, more classified and more diverse datasets would also aid in improving system reliability. Further improvements in explainability and optimization for real-time use in hospital systems can make the framework more suitable for real clinical applications.

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