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DEEP LEARNING-BASED BRAIN TUMOR CLASSIFICATION MODEL USING CONVOLUTIONAL NEURAL NETWORK AND DATA AUGMENTATION TECHNIQUES

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Abstract: Brain tumors are among the most aggressive and fatal forms of cancer; therefore, early and accurate detection is essential for improving treatment outcomes. This study presents a brain tumor classification model that leverages deep learning techniques to facilitate the automatic identification of tumor types. The model employs convolutional neural networks (CNNs) to analyze magnetic resonance imaging (MRI) scans and classify brain tumor images into specific categories. CNNs have proven to be highly effective in feature extraction and image classification, making them a reliable approach for processing medical imaging data and enhancing diagnostic precision. The dataset used in this study consists of publicly available MRI images that have undergone preprocessing to ensure uniformity and improved quality. The model is trained using supervised learning, in which labeled images are used to help the network recognize patterns associated with different tumor types. Data augmentation techniques are also applied to improve generalization and mitigate over fitting. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, showing significant improvement over traditional ML methods. Deep learning-based models offer a powerful tool for enhancing the accuracy and efficiency of brain tumor diagnosis, providing valuable support to clinicians in medical practice. Future research will focus on expanding the dataset and exploring advanced model architectures to optimize performance and reliability.

Keywords: Brain Tumor Classification, Deep Learning, Convolutional Neural Networks, Medical Image Processing, Supervised Learning, Data augmentation, Classification Model

1. INTRODUCTION

Brain tumors are among the most deadly forms of cancer and have a high death and morbidity rate. Millions of people worldwide are diagnosed with brain tumors each year. The optimal course of treatment for these cancers depends on their classification (John et al., 2019). Correct classification of brain tumors into benign (non-cancerous) and malignant (cancerous) categorhyuies is essential for enhancing treatment results. Magnetic resonance imaging (MRI) is frequently used by doctors to identify and diagnose brain tumors due to its non-invasive nature and ability to provide clear images of soft tissues (Doe et al., 2020). However, identifying MRI images by hand can be subjective, time-consuming, and error-prone (Smith et al., 2021). Thus, creating automated technologies that assist radiologists in diagnosing patients more quickly and accurately is essential.

In recent years, deep learning, a subfield of artificial intelligence (AI), has emerged as a potent instrument for medical image analysis. Convolutional neural networks (CNNs), one of the several deep learning methods, have demonstrated exceptional performance in image recognition and classification (Zhang et al., 2020). Because they can automatically extract significant features from data, CNNs are very good in handling challenging image classification problems, such as medical imaging (Li et al., 2021). Unlike traditional ML methods that require manual feature extraction, CNNs can directly learn features from images, leading to better accuracy and faster classification. Using deep learning for brain tumor classification has gained much attention due to the ability of CNNs to produce highly accurate results faster than traditional methods (Kumar et al., 2022). Several studies have shown that CNN-based models outperform older algorithms in terms of precision, sensitivity, and specificity in tumor classification (Singh & Gupta, 2023). For example, John et al. (2019) developed a CNN model that achieved over 90% accuracy in classifying brain tumors from MRI images, demonstrating the effectiveness of DL techniques in this field. These models can detect small differences between various types of tumors, which may not be easily observed by the human eye.

Despite these advances, using deep learning for brain tumor classification remains challenging. The lack of large, annotated datasets that are crucial for training these models to ensure they work well in real clinical settings is a major issue (Ali et al., 2021). The scarcity of labeled medical images, especially for rare tumor types, makes developing robust models difficult. Additionally, differences in MRI acquisition methods, data noise, and tumor appearance variations across patients can cause inconsistencies in model performance (Nguyen et al., 2020). To address these issues, data augmentation techniques, such as rotating, flipping, and adjusting contrast, are used to artificially increase the size of the training dataset, thereby improving the performance of the model on new, unseen data (Jones et al., 2022).

Another important factor in using deep learning for medical imaging is the need for easy-to-understand models. CNNs are often seen as "black boxes" because of their complex structure, but doctors need to know how the model arrives at its conclusions, especially in critical diagnoses like brain tumors (Tariq et al., 2021). Advances in explainable AI (XAI) aim to solve this problem by creating methods that show which parts of the magnetic resonance imaging (MRI) scan influenced the model’s decision (Patel et al., 2023). Transparency is essential for building trust in AI systems among medical professionals and ensuring their adoption in clinical workflows. As deep learning models improve, there is also an increasing interest in creating more efficient architectures that require less computational power while maintaining high accuracy (Wang et al., 2022). Techniques such as transfer learning and lightweight convolutional neural networks (CNNs) have made it possible to deploy brain tumor classification models on smaller devices, such as smartphones and embedded systems, allowing for real-time diagnostics in remote areas with limited resources (Chen et al., 2023). Additionally, integrating these models with cloud-based platforms offers the possibility of remote consultations, where specialists can access magnetic resonance imaging scans and diagnostic tools from any location.

This study focuses on the development of a deep learning model for brain tumor classification using CNNs. The model uses publicly available magnetic resonance imaging datasets and applies preprocessing methods to ensure the data is consistent. The CNN learns to distinguish between different tumor types with high accuracy using supervised learning. The model is evaluated using performance metrics such as precision, recall, and F1-score, and data augmentation techniques are applied to improve the model’s reliability. The use of deep learning models for medical image analysis, especially brain tumor classification, can significantly impact radiology. These models can reduce the workload of medical professionals and provide a second opinion that can improve diagnostic accuracy and patient outcomes by automating tumor detection and classification. As more data become available and models are refined, AI will likely play a larger role in clinical practice, leading to more personalized and efficient health care.

2. LITERATURE REVIEW

Medical professionals have long struggled with brain tumor diagnosis and categorization. Conventional approaches, such as radiologists manually reviewing magnetic resonance imaging (MRI) scans, are efficient but frequently time-consuming, highly subjective, and subject to expert variation (Patel et al., 2021). Computer-aided diagnosis (CAD) systems have benefited radiologists by increasing the precision and consistency of brain tumor classification during the last decade (John et al., 2019). With an emphasis on the development of deep learning techniques in this area, this section examines several methodologies employed in brain tumor categorization.

2.1 Traditional Brain Tumor Classification Methods

In the past, machine learning techniques such as support vector machines (SVMs), random forests (RFs), and k-nearest neighbors (k-NN) were frequently used in brain tumor classification. These techniques needed to manually extract features such as the tumor's texture, intensity, or shape to make predictions (Zhang et al., 2018). Although these techniques were effective in certain situations, they were unable to manage the complexity of MRI images because of their dependency on manually selected characteristics (Kumar & Gupta, 2020). Furthermore, manually extracting features is time-consuming, necessitates specialized knowledge, and can result in errors, particularly when the data is ambiguous or noisy (Li et al., 2020).

2.2 Rise of Deep Learning in Medical Imaging

Deep learning, particularly convolutional neural networks (CNNs), have recently revolutionized image classification tasks in a variety of domains, including medical imaging. CNNs eliminate the requirement for feature selection by automatically extracting significant details from raw images (Gupta et al., 2022). The ability of these networks to learn both basic and sophisticated properties enables them to distinguish between malignancies and healthy brain tissue.

According to several studies, CNNs are successful in classifying brain cancers. For instance, Pereira et al. (2016) classified gliomas using a CNN model and discovered that it performed better than previous techniques in terms of accuracy and dependability. Hossain et al. (2020) also used CNN to categorize MRI scans into malignant (cancerous) and benign (non-cancerous) tumors with an accuracy of above 95%. These findings demonstrate how DL can increase the accuracy of medical diagnoses. CNN models are valuable tools for tumor classification because they can generalize well to new data and are trained on large labeled datasets.

2.2.1 Preprocessing techniques in deep learning

Tumor classification model performance is directly impacted by MRI image quality. Before entering the images into the deep learning model, preprocessing techniques are frequently used to improve the images because MRI scans can occasionally contain noise or other problems. Common pre-processing processes include noise reduction, contrast enhancement, and picture intensity normalization (Wang et al., 2021). Data augmentation, including flipping or rotating photographs, is also used to expand the dataset, particularly when there are few accessible images (Chen & Liu, 2019). These procedures are crucial because it can be challenging to train precise models on medical imaging datasets due to their frequently small size.

2.2.2 Transfer Learning and Model Optimization

Transfer learning represents a significant advancement in the application of deep learning to medical applications. Transfer learning allows for the fine-tuning of models pre-trained on huge datasets, such as Image Net, for more focused, smaller tasks, such as brain tumor categorization (Singh & Patel, 2022). While enhancing performance, TL reduces the amount of time and resources required for training. For example, Azad et al. (2021) achieved excellent results when they applied TL to the categorization of brain tumors even with a short dataset.

To make DL models faster and less resource-intensive, it is also critical to optimize them for efficiency. Mobile Net and Efficient Net are examples of lightweight architectures that enable models to function on devices with constrained processing power without sacrificing accuracy (Wang et al., 2021). The development of diagnostic tools that can be applied in clinical settings in real-time or in locations with restricted access to cutting-edge technology benefits greatly from this.

2.2.3 Deep Learning Challenges for Brain Tumor Classification

Deep learning has improved the classification of brain tumors; however, several issues remain. The requirement for large datasets is one of the main issues. Although medical datasets are frequently tiny and unbalanced, particularly for rare tumor types, CNNs perform best when trained on large datasets (Nguyen et al., 2020). The challenge of identifying medical images is further compounded by the fact that it takes a lot of time and requires skilled radiologists to mark each image. Another difficulty is that CNNs are sometimes viewed as "black boxes," which makes it difficult to comprehend how they arrive at their conclusions. This lack of transparency can be problematic in the medical field because physicians must comprehend the reasoning behind the classification of the model (Tariq et al., 2021). Researchers are developing explainable artificial intelligence (XAI) techniques that highlight significant regions of the image and provide concise explanations of the decision-making process of the model (Patel et al., 2023). These techniques are crucial for fostering confidence in AI technologies and ensuring their application in medical care.

2.3 Future directions in brain tumor classification

Future studies on the categorization of brain tumors will probably concentrate on enhancing the precision and dependability of models through the creation of increasingly complex architectures and the utilization of various data types, such as merging genetic information with MRI pictures (Kumar et al., 2023). Furthermore, the problem of tiny datasets may be resolved while maintaining patient privacy with the use of novel techniques, such as federated learning, in which models are trained on data from several sources without transferring the data (Wang et al., 2022). For AI models to be trusted and applied in clinical settings, more effort must be made to make them easier to understand.

3. PROBLEM STATEMENT

Medical diagnosis still faces significant challenges in classifying brain cancers using magnetic resonance imaging (MRI) due to the intricacy and variations among tumor types. Conventional manual classification techniques differ among specialists and frequently result in human error. Current ML methods rely mostly on the manual selection of characteristics from photos, which is inefficient when dealing with complicated data. Although deep learning, and CNNs in particular, have demonstrated a great deal of promise in addressing these issues, other obstacles must be addressed before these models can be extensively implemented in hospitals. Below are the challenges:

i. **Lack of large datasets:** Deep learning models need a large number of labeled images to work well, but there are not enough high-quality, labeled datasets in medical fields, especially for rare tumors (Nguyen et al., 2020).

ii. **Variability in MRI scans:** Differences in how MRI scans are taken and the presence of noise in the images can reduce the model's accuracy and lead to inconsistent results.

iii. **"Black box" problem:** Deep learning models are often not transparent, meaning it is difficult to understand how they make decisions. Doctors need models that not only give accurate results but also explain how they arrived at their conclusions (Tariq et al., 2021). Without this, doctors may not fully trust AI systems.

iv. **Need for improvement:** A better system that uses deep learning techniques, such as data augmentation, transfer learning, and explainable AI, is needed to address these challenges. The system should be highly accurate and reliable and should provide clear explanations that doctors can understand and trust.

4. AIM AND OBJECTIVES OF RESEARCH

The main aim of this research is to create and apply a deep learning model to effectively and precisely categorize brain cancers from MRI images. The model will be a useful tool for physicians to identify and differentiate between various tumor types by using the power of CNNs and sophisticated image processing techniques to enhance diagnosis.

The specific objectives are as follows:

i) To examine existing approaches to brain tumor classification and identify issues with manual feature extraction and older ML techniques;

ii) To develop a convolutional neural network (CNN) model that can reliably classify brain tumors from magnetic resonance imaging (MRI) images with little assistance from humans;

iii) To enhance the quality of MRI images before their use in the model by applying image preprocessing methods such as noise reduction, contrast enhancement, and normalization;

iv) To use data augmentation techniques to increase the size of the dataset and enhance the capacity of the model for generalization, particularly in cases where the amount of data is small or uneven;

v) To assess the model's performance by comparing it to conventional methods using metrics such as accuracy, precision, recall, and F1 score.

vi) To make the model interpretable by using explainable artificial intelligence (XAI) techniques to demonstrate how the model makes decisions and which aspects of the MRI images were most crucial.

These objectives aim to investigate the development, use, and assessment of a deep learning model for brain tumor classification.

5. MATERIALS AND METHODS

The procedures used to develop and evaluate a CNN model for MRI image-based brain tumor classification are described in the Materials and Methods section. This section is broken down into several crucial phases, including data collection or acquisition, picture preparation, model construction, performance testing, and setup. Each step, including the instruments, methods, and procedures employed, is thoroughly described below.

i. Data Acquisition

a) **Dataset Description:** The main dataset used in this study comprises MRI images of brain tumors from publicly available medical imaging collections. Images are divided into different tumor types, such as gliomas, meningiomas, and pituitary tumors, which are necessary for model training.

Source: The dataset can be obtained from a public repository, such as The Brain Tumor Segmentation Challenge or Kaggle.

Size: The dataset contains 400+ [30MB] MRI images with corresponding labels.

Format: The images are JPEG.

The dataset was selected for its high-quality imaging, balanced class distribution, and comprehensive annotation, making it suitable for training a deep learning model for tumor detection.

b) Data Splitting: The dataset is split into three parts: Training Set: Used to train the CNN model (70% of the dataset). Validation Set: Used to adjust the model and select the best settings (15% of the dataset). Test Set: Used to check how well the model works (15% of the dataset).

ii.Pre-processing

a) Image Pre-Processing: It is important to improve the quality of MRI images before using them. The following steps are taken:

i. Normalization: Adjusting the brightness of the images so that they have similar levels, making them more consistent.

ii. Noise reduction: Using filters such as Gaussian blur to reduce unwanted spots or noise and make the images clearer.

iii. Contrast Enhancement: Methods such as histogram equalization are used to make the tumor areas easier to see.

iv. Resizing: The size of the images is changed to match the input size needed by the CNN model.

b) Data augmentation: To prevent over fitting and strengthen the model, the following data augmentation methods are used:

i. Rotation: Randomly turning images to add variety in their angles.

ii. Flipping: Images are flipped horizontally or vertically to increase the number of examples.

iii. Scaling and Cropping: Change the size of images and take smaller sections to imitate different zoom levels.

The following is a representation of the data augmentation process:

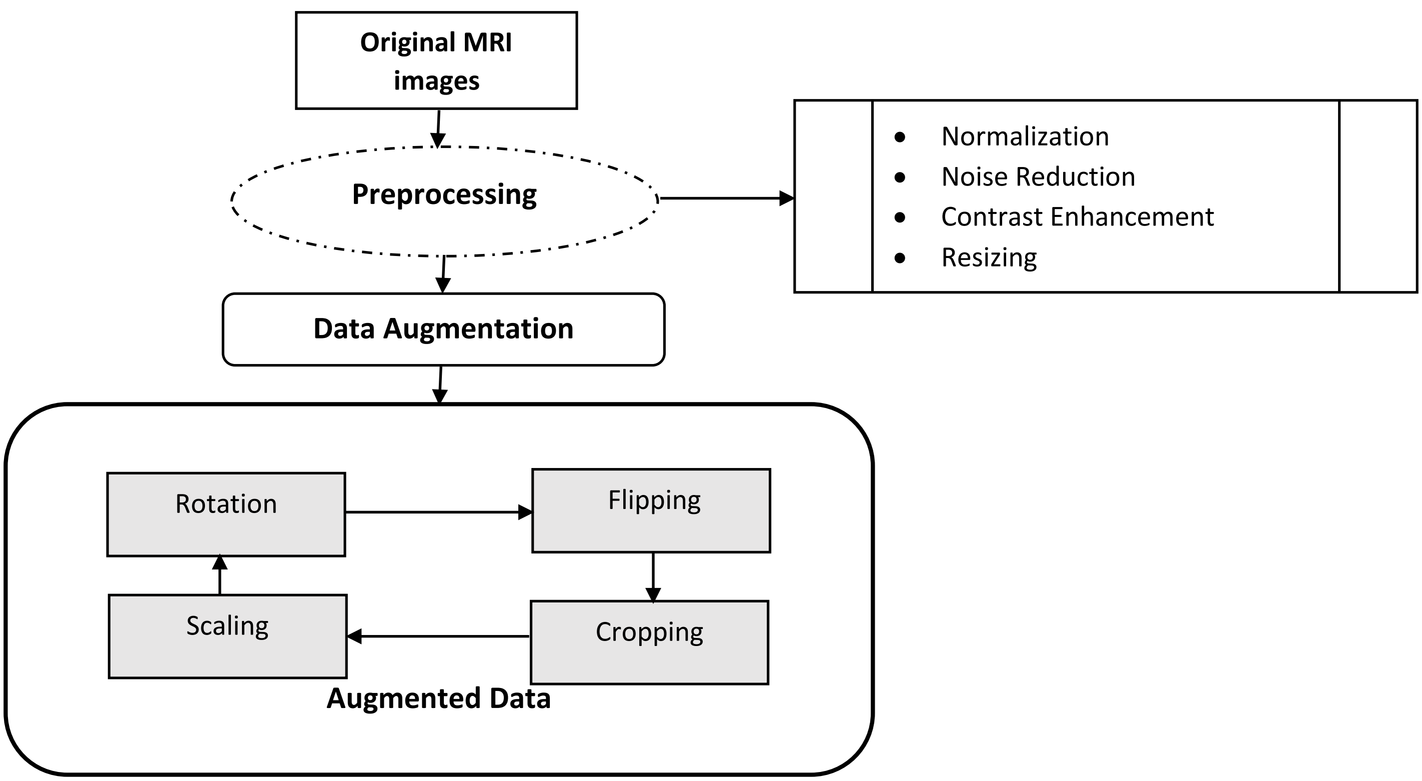

Figure 1: Data augmentation workflow

iii. Model Development

a) Model Architecture

The CNN model is built to classify brain tumors using pre-processed MRI images. It consists of several layers:

i. **Input Layer:** This layer receives resized MRI images to a standard size.

ii. **Convolutional Layers:** This layer is used to extract important features from images using filters.

Feature extraction with VGG19 (Convolutional Layer):

The VGG19 convolutional neural network extracts hierarchical features from MRI images. For an input image I of dimensions W×H×C, where W is the width, H is the height, and C is the number of channels, the convolutional layer transforms ***I*** using kernels $K_{i,j}$ as follows:

$$F_{x,y} = \sigma\left(\sum_{i=0}^{k} \sum_{j=0}^{k} I[x+i, y+j] \cdot K_{i,j} + b\right)$$

Where:

- $F_{x,y}$ represents the feature map output.
- Where k is the kernel size.
- Where b is the bias term.
- σ (sigma) is the activation function, typically ReLU (max(0,x)).

These extracted features F are passed through multiple layers, including pooling and fully connected layers, to reduce dimensionality while retaining the input image's essential characteristics.

iii. **Activation Layers:** This layer applies functions such as ReLU to make the model learn nonlinear patterns.

iv. **Pooling Layers:** This layer reduces the data size while keeping key features using max pooling.

v. **Fully Connected Layers:** This layer combines the features and produces the final classification results.

vi. **Output Layer:** This layer is used to provide the classification result for each tumor type using the softmax function.

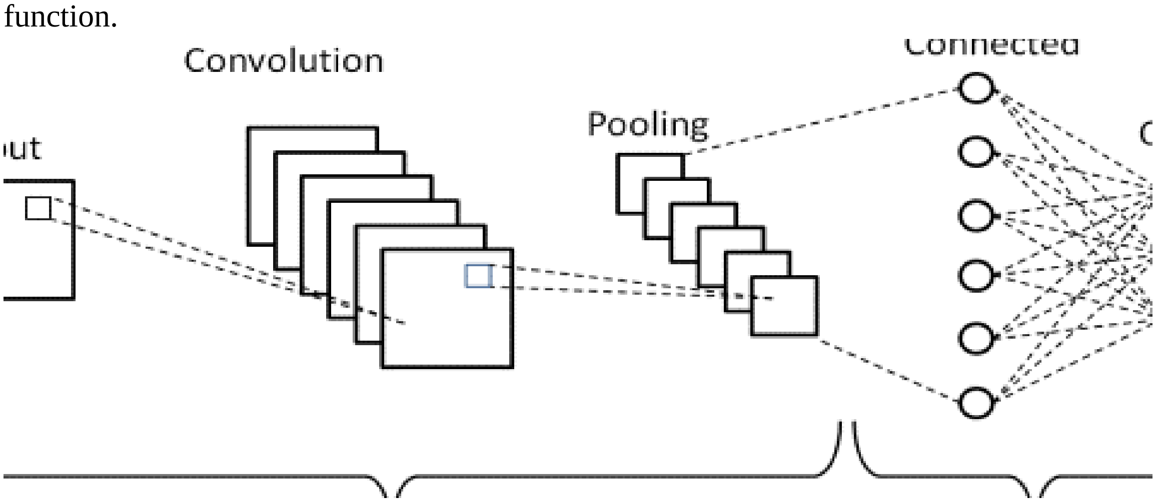

Figure 2: Architecture of the CNN model (Sai Balaji, 2020)

b) Model Training

Model training consists of the following:

i. **Optimizer:** The Adam optimizer was used to reduce the loss and improve the accuracy of the model.

ii. **Loss Function:** Categorical cross-entropy is applied for multi-class classification.

iii. **Learning Rate:** A scheduler adjusts the learning rate during training to help the model better learn.

iv. **Epochs:** The model is trained for a set number of epochs with early stopping to prevent over-fitting.
v. **Batch Size:** A certain number of images are processed at once to balance speed and accuracy.

The model was trained using the Adam optimizer and CCL function. Early stopping and learning rate schedulers were used to prevent over-fitting and improve convergence. The following is the program sample:

model.compile (optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
History = model.fit(train_dataset, validation_data=val_dataset, epochs = 50, callbacks = [early_stopping])

c) Transfer Learning

Transfer learning is used to improve the model using pre-trained models, such as the visual geometry group (VGG16):

i. **Pre-trained model selection:** Choose a model that works well for image classification.
ii. **Fine-tuning: The** final layers of the pre-trained model were modified and retrain on the brain tumor dataset.

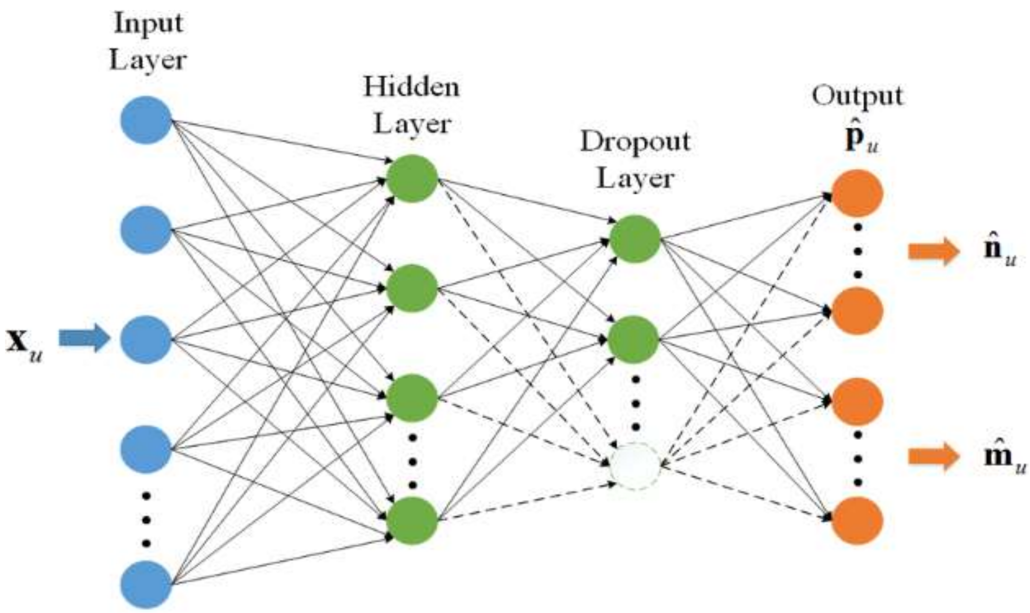

Figure 3: Structure of VGG16

iv. Model Evaluation

The performance of the CNN model was measured using these metrics:

i. **Accuracy:** The percentage of correct classifications.

Equation:

Accuracy = TP + TN
Total Instances (TP + TN + FP + FN)

ii. **Precision and recall:** Measures how well the model identifies true positive and negative cases.

Equation:

Precision = true positives (TP)
TP + FP

Recall = TP + FN
True Positives (TP)

iii. **F1 score:** A single score that combines precision and recall.

Equation:

$$\textbf{F1-Score} = \frac{2 \cdot \text{Precision+Recall}}{\text{Precision} \cdot \text{Recall}}$$

The following Python function calculates these metrics:

```
from sklearn.metrics import classification_report
y_pred = model.predict(test_images)
report = classification_report(test_labels, y_pred.argmax(axis = 1), target_names=class_names)
print(report)
```

This implementation effectively translated the mathematical model into a working deep learning solution, providing reliable predictions for brain tumor classification.

v. System Deployment

a) **Integration:** The trained model is connected to a clinical decision support system. This system works with magnetic resonance imaging machines to automatically classify new images and assist radiologists with their diagnoses.

b) Deployment Platform

i. Software Environment: The model is deployed using Python **Streamlit** Platform. Platforms such as TensorFlow Serving or Flask API can also be used.

ii. User Interface: A simple user interface (GUI) is created to allow the medical staff to interact with the model and view the classification results.

c) Performance monitoring: The system is regularly checked for accuracy and performance after deployment. The model is updated and retrained as new data become available to keep it working well.

6. RESULTS

This study developed a deep learning-based brain tumor classification model using convolutional neural networks and data augmentation techniques. These are screenshots of the output from the integration of the developed system.

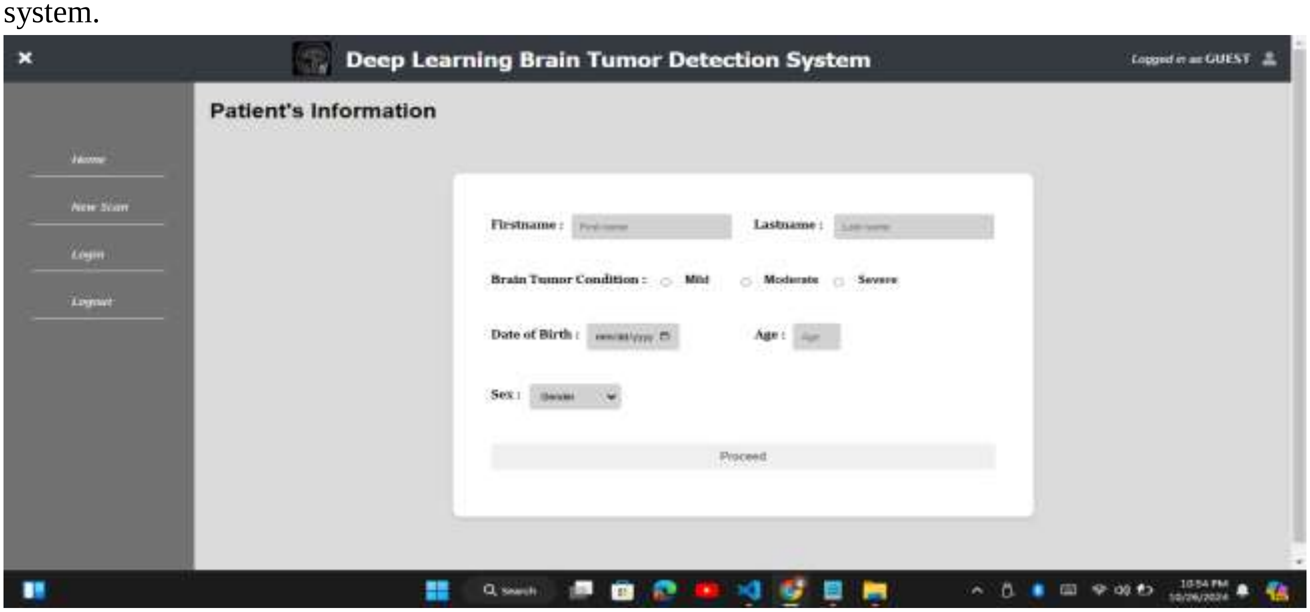

Figure 4: Patient information page

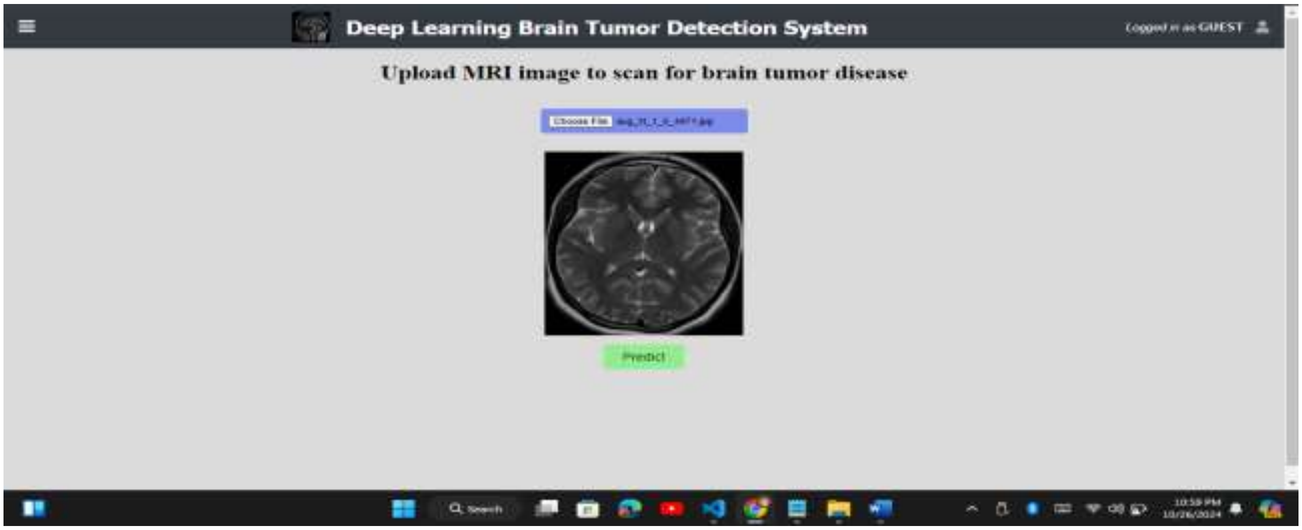

Figure 5: Patient's MRI upload page

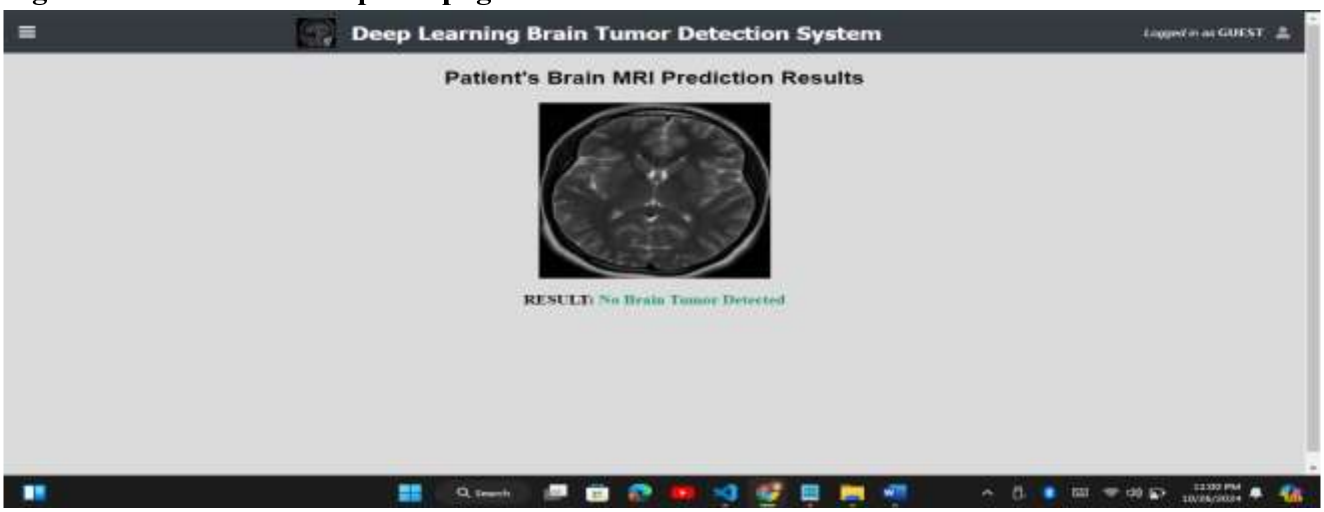

Figure 6: MRI prediction result page signifying no brain tumor

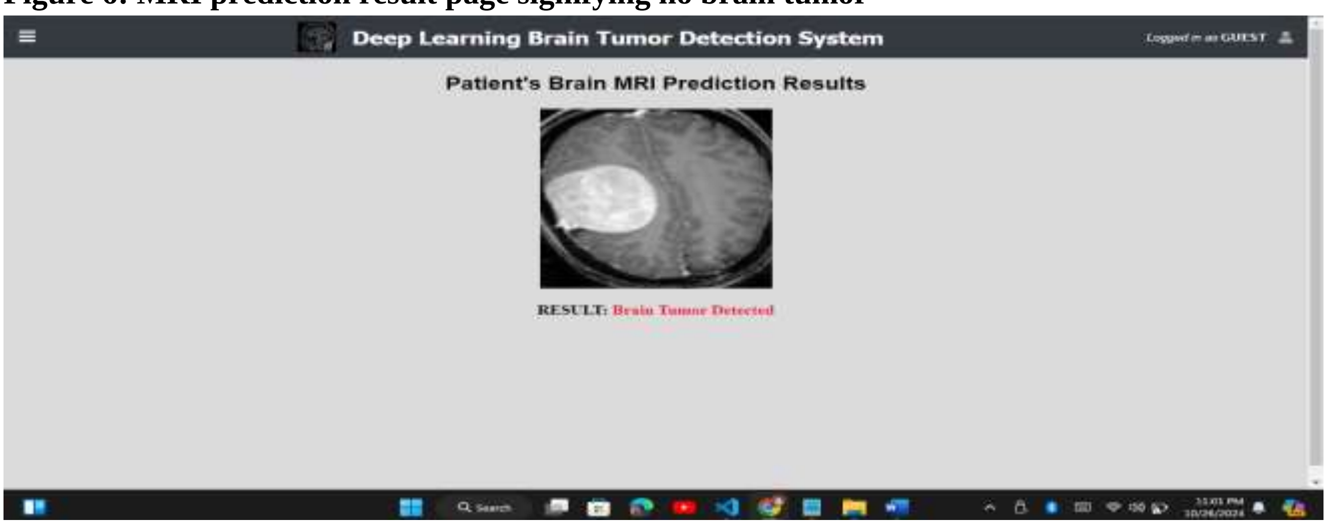

Figure 7: MRI Prediction Result Page Signifying the Presence of Brain Tumor

7. DISCUSSION

The developed model implemented an end-to-end brain tumor classification/detection system that leverages Django and pre-trained VGG19, a convolutional neural network model, to facilitate MRI-based diagnostics. Users can submit necessary patient data, such as name, age, and brain tumor condition, through the user-friendly patient's information page, as shown in Figure 1. The form includes several required fields, such as gender and a range for the brain tumor condition, to ensure complete patient records. This data is then processed and stored, enabling the system to associate MRI results with unique patient identifiers. Following the submission of this information, the user is sent to the MRI upload page, where they can upload an MRI image for tumor analysis (Figure 2). By keeping picture analysis distinct from patient data entry, this structured flow not only keeps an organized record of patient data but also expedites the process.

The backend's predefined function processes the uploaded MRI picture by reading it and resizing it to 240 240 pixels to satisfy the VGG19 model's input shape requirements. The prediction is saved in the database with the patient's data for convenient retrieval and display on the results page. The results page visually communicates the prediction with intuitive color-coded messages: green indicates no tumor detection (Figure 3), and red indicates a tumor detection (Figure 4). The interface offers an easy-to-understand display of diagnostic results to help medical practitioners in a clinical setting. The combination of Python Django and machine learning in this system provides a scalable, effective, and user-friendly diagnostic tool that may speed up the screening procedure for brain tumors.

8. CONCLUSION

In summary, the brain tumor classification system, which combines Django with deep learning, offers a simplified method for early and precise tumor diagnosis and constitutes a substantial breakthrough in medical diagnostics. This system can analyze MRI scans with high accuracy by using the VGG19 model's demonstrated efficacy in image categorization. This enables quick and easy diagnosis of brain cancers. By putting in place an intuitive interface for data entry, MRI picture upload, and result retrieval, the technology guarantees that medical professionals can make well-informed decisions with little complexity. This could improve patient outcomes by enabling prompt diagnosis and classification.

Traditional classification and diagnostic techniques, which can be laborious and rely on a great deal of manual analysis, can be replaced with this automated classification and detection system, which blends in smoothly with clinical workflows. Being a digital solution, it can be used in a variety of medical contexts because it not only solves the restrictions of diagnostic delays but also allows for scalability. With additional training and validation using larger datasets, this system has the potential to reach even higher accuracy, making it a useful tool in contemporary medical practices aimed at enhancing mental tumor detection efficiency and diagnostic precision.

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