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Robust Brain Tumour Detection Using Deep Convolutional Neural Networks Models

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ABSTRACT

Detection and analysis of brain tumors from Magnetic Resonance Imaging (MRI) scans are essential for the early detection and treatment of brain cancers. Manual analysis of the MRI images is a time-consuming process for radiologists, as there are possibilities of human errors, especially while handling large volumes of medical images. An automatic brain tumor image classification method utilizing Deep Learning algorithms is proposed to counter this problem. For this project, three different models of deep learning are applied. First, a personal solution of the Convolutional Neural Network (CNN) architecture is developed as a basic model to identify the spatial features of the MRI images. Second, VGG16, a transfer learning model developed earlier for other large-scale image databases, is utilized to tap into the experience gained from handling large-scale image databases [5]. Third, ResNet50, a more complex model of the residual network architecture, is applied to overcome the problem of a disappearing gradient during the backward propagation process to achieve better results for the classification process of the brain tumor dataset [6]. The proposed system can also provide real-time prediction, and any new MRI image can be uploaded by the user, showing the predicted tumor type with the confidence score. The experimental findings prove that the transfer learning models achieve higher performance compared to the basic CNN, among which ResNet50 obtained the top result. This work verifies deep learning and transfer learning in medical image analysis and delivers a trustworthy way of automatic brain tumor classification.

Index Terms—Brain MRI, Tumor Classification, CNN, VGG16, ResNet50, Deep Learning, Transfer Learning.

INTRODUCTION

The brain is one of the most elaborate and essential organs in the body, controlling all functions of the body. A brain tumor is an abnormal growth of cells within or around the brain that can disturb normal brain function and lead to grave consequences in health. Brain tumors are two types. They are: Benign and Malignant. That's why early detection helps in reducing complications while treatment for patients. MRI is a widely used method for detecting tumors in the brain, as it offers a high-resolution image of soft tissues [2]. It is an effective diagnostic tool, although the analysis of MRI images requires a domain expert with quite a lot of experience. Manual MRI image processing is painful work for any radiologist, since a large number of images have to be analyzed, which increases workload and misdiagnosis [14]. AI, which in particular features Deep Learning, flourishes automated systems with much promise for image classification and pattern recognition tasks [11]. A CNN has become the backbone in almost all image-based applications of AI due to its potentiality to extract hierarchical features from an image automatically [11]. Convolutional Neural Networks have high accuracy in disease detection and classification in medical imaging [1]. This particular research work aims to design and develop a deep learning-based tumor classification model using MRI images for classification. The model is intended to identify images belonging to one of the following categories: glioma, meningioma, pituitary tumor, and no tumor. The design incorporates the use of both personalized CNN models and more sophisticated models like VGG16 [5] and ResNet50 [6]. The principal goals of this research are: 1) Designing and developing an automated system for classifying brain tumors. 2) Comparing the performance of a basic CNN and models using transfer learning providing the patient with accurate predictions about tumors. 3) To overcome dependence on manual analysis and to help physicians. 4) This study illustrates the application of deep learning techniques to the medical field and its ability to enhance diagnosis.

LITERATURE SURVEY

Garg and Ritu [9] proposed a hybrid ensemble-based approach for the detection and classification of brain tumors from MRI images. In fact, before this work, most of the systems depended on a single classifier, which often had problems with accuracy and generalization due to the complex structure of brain tumors. They noticed that various classifiers perform well on different feature sets, but no single model was able to achieve consistently high performance. In order to solve the problem, the authors came up with the design of a hybrid ensemble classifier, which would combine strengths from multiple machine learning techniques. In their work, they first preprocessed MRI images to filter out noise from the image and improved the quality of the images. Skull stripping and contrast stretching were considered for enhancing tumor visibility. Following preprocessing, texture features, shape features, and intensity features were extracted from MRI images using hand-crafted feature extraction. These features were critical in describing tumor characteristics such as irregular boundaries and variations in intensity. These features were input into various classifiers, such as Support Vector Machine, K-Nearest Neighbor, and Decision Tree classifiers. Alternatively, the authors have not used only one classifier but combined the models in an ensemble way by combining their outputs. The decision will be given by the majority vote, reducing misclassification errors. Experimental results demonstrated that the accuracy of the hybrid ensemble classifier was higher than that achieved by the individual classifiers. The results indicated that the proposed system had good efficiency in the classification of non-tumor and tumor images, as well as for different tumor types. One of the significant benefits of the proposed technique was its robustness, where the effect of noisy data was reduced due to the ensemble learning process. However, this model relied heavily on handcrafted feature extraction, which calls for expert knowledge and careful selection. Moreover, the performance of the model was sensitive to feature quality. Further, deep learning was not fully utilized here, which itself has shown superior performance in automatic feature learning [11].

Tandel et al. (2019) [14] presented a review of deep learning techniques for classifying brain cancers. The authors discussed limitations of conventional image processing methodologies in dealing with complex tumor structures and variations within MRI images. The various CNN architecture with its strengths on tumor detection, segmentation, and classification were analyzed. They highlighted the advantages of deep learning models for feature extraction automatically without intervention. This paper also discussed some challenges concerning overfitting, less availability of medical datasets, and high computational costs. The study concluded that accuracy and reliability in brain tumor analysis have significantly improved using deep learning methods. However, large-sized datasets and optimized architectures are necessitated for clinical applications.

Abdusalomov et al. (2023) [8] have proposed deep learning algorithms for detecting brain tumours on MRI image data. This research is primarily concerned with improving the accuracy of the diagnosis of tumours using efficient CNN models. They have described the implementation of several models of deep learning and pre-processing methods for feature improvement. This research has been able to show powerful results not only for demarcation but also for differentiation of tumours. This research has been able to tackle significant problems like imbalance and noise associated with an MRI image. Although the performance is excellent, they have found that these models are computation- and dataset-intensive.

Mathivanan et al. (2024) [3] presented a detection system for a brain tumor using deep learning and transfer learning techniques. The authors utilized deep pretrained CNN models due to the drawback of small datasets pertaining to medical scenarios. By fine-tuning these pretrained networks, the system was able to achieve utmost accuracy in detecting tumors from MRI images. The study showed that transfer learning reduced training time while improving the accuracy of classification. Experimental results demonstrated the efficiency of the proposed model compared to traditional machine learning methods. However, the system still relied on good-quality MRI images and proper tuning of parameters. The authors claimed that such transfer learning-based deep learning models constitute an effective and practical solution for accurate detection of brain tumors.

Saeedi et al. (2023) [7] proposes a brain tumor detection system based on MRI using CNN combined with selected machine learning techniques. The research aims to enhance the performance of the detection by incorporating deep features along with state-of-the-art classical classifiers. Various CNN models were tested along with different machine learning algorithms to find out the optimal combination providing the best result. The accuracy of the proposed system is better along with reduced false detection rates. However, the model involves long preprocessing and feature optimization techniques. The authors identified that the integration of deep learning with machine learning improves the classification performance and can support doctors' decisions in medical diagnosis. They opined that hybrid approaches can provide a reliable solution for the diagnosis of brain tumors.

Chakrabarty (2019) [15] came up with a publicly available dataset of brain MRI images that could be used for the detection of brain tumors. This dataset helped in overcoming the challenges that researchers faced in acquiring labeled medical images, mainly because of accessibility and privacy problems. This dataset includes images of both tumor and non-tumor areas in the brain that could be classified appropriately using the images. This dataset also assists in the evaluation of various machine learning and deep learning approaches that could be compared in experiments. Though the dataset has limitations in its size, augmentation could be performed on the images. The author also pointed out that open-source datasets are significantly important in developing Automated Brain Tumor Detection approaches.

Ali et al. (2012) [8] examined the Random Forest algorithm and the Decision Tree algorithm. The authors described how decision tree classifiers are interpretable but are prone to overfitting. In order to address this problem, the Random Forest algorithm was proposed. This algorithm is based on a combination of many decision trees. The algorithm trains every decision tree with different random samples of the dataset as well as different random subsets of its features. This increases accuracy while preventing overfitting. The authors confirmed through their study that Random Forest is more generalizable with lower variability than decision tree classifiers. It is more computationally intensive.

Simonyan and Zisserman (2021) [5] designed the VGG16 convolution neural network model for image recognition at a large scale. This model introduced the concept of using small 3×3 convolution filters stacked deep to learn more. VGG16 proved to be outstanding in recognizing images of the ImageNet dataset and is widely used today in transfer learning tasks. Because of its deep layers, the model is able to capture detailed information from the image. It consumes high computational power and memory. In spite of this drawback, the model is widely used in the analysis of the human brain tumor image because of its powerful feature extraction abilities.

PROBLEM STATEMENT

Brain tumor is one of the most threatening and life-limiting conditions in the nervous system and needs an early and correct diagnosis to enhance survivability and treatment efficacy. Magnetic Resonance Imaging (MRI) is the most preferred diagnostic imaging technique used for diagnosing a brain tumor because of its higher contrast and non-invasive imaging nature [2]. However, the task of analyzing the results of an MRI image by a specialist is a complicated and time-consuming task prone to several errors. An increased number of medical imaging results is further contributing to the workload of medical staff, potentially causing diagnostic delays and inconsistencies [14]. The existing techniques for the identification and segmentation of brain tumors involve extensive manual feature extraction and the application of Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and clustering-based segmentation techniques [10]. The drawback of these techniques is their complexity, which arises as individual techniques have to be developed for image preprocessing, image segmentation, feature extraction, and the classification process. Also, the generalization capability of the existing techniques gets affected as the images are quite complex. Recent advances in deep learning, especially in the area of Convolutional Neural Networks (CNNs), reveal the substantial potential of automating the analysis of medical images through the end-to-end learning of hierarchical features directly from the images [11]. However, despite such advances, the common drawbacks present in the previously proposed deep learning solutions include the effects of overfitting within the small size of the medical databases, the lack of comparisons between different network structures, and the inability to demonstrate substantial robustness within the context of practical usage with actual medical images. Many of the existing approaches are specific to the detection or the segmentation of tumors in the images and do not offer comprehensive solutions to the tumoral classification problem into different classes [4]. Consequently, the existence of a computerized and accurate brain tumor classification system that is able to differentiate between different types of tumors and normal brain MR images is of extreme importance. It needs to incorporate the advantages of deep learning and transfer learning to perform superior classification with decreased training time and dependency on large datasets [3]. The issue that is addressed in this project is to design and examine the performance of the proposed framework by using the baseline CNN and state-of-the-art techniques of transfer learning using VGG16 [5] and ResNet50 [6] in classifying brain MRI images into glioma, meningioma, pituitary tumor, and no tumor classes so as to improve diagnosis and reduce human involvement.

METHODOLOGY

The proposed methodology targets the design of an automatic brain tumor classification system by employing deep learning approaches for the analysis of Magnetic Resonance Imaging (MRI) information. The full process of the proposed system for brain tumor classification includes data acquisition, preprocessing, modeling, evaluation, and prediction. The proposed methodology will be established to achieve high classification performance efficiency.

Data Collection And Organization The data employed in this project involves MRI images of the brain, which have been categorized into four classes. These classes are no tumor, glioma, meningioma, pituitary tumor [15]. The data in the project is designed in such a way that every folder symbolizes a label. Thus, the supervised learning process is more effective.

Data Preprocessing Model performance and training stability are improved by Preprocessing. All the given MRI images are resized to a fixed dimension of 128 × 128 pixels for maintaining uniformity and to reduce computational cost. The images are then normalized by scaling pixel values to the range [0, 1]. Any defective or unreadable images removed to prevent noise in training. This preprocessing ensures that the deep learning models receive standardized input data[13].

Dataset Splitting After the preprocessing step, the resultant set is again separated into the training and testing set,by keeping the ratio of the two at 80:20. This is tracked by the training and testing process to check the generalization capacity of the models developed.

Training Configuration Using the Adam optimizer[12] and categorical cross-entropy loss function, All models are trained.

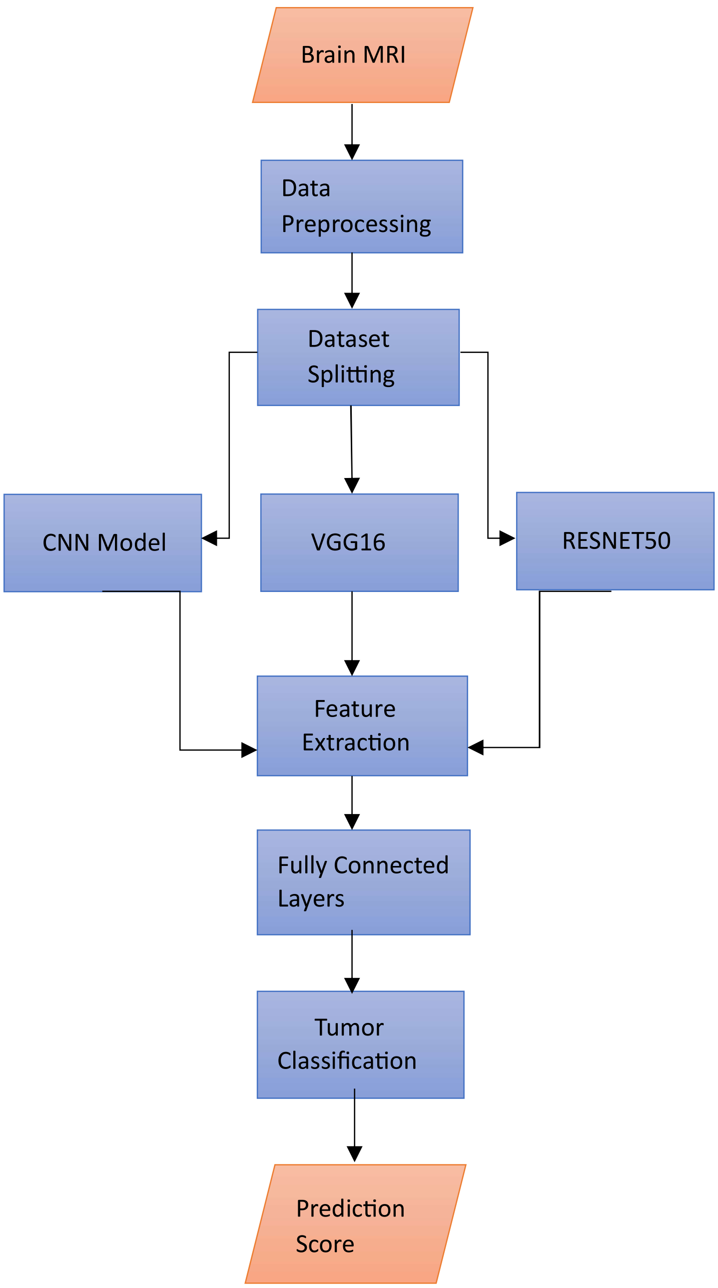

Fig. 1: Flowchart of the Proposed Brain Tumor Classification System

Training is conducted with a batch size of 32 for 10 epochs. Model performance is observed using validation accuracy. The trained models on test MRI images are evaluated to predict the tumor type along with confidence scores. The predicted class and probability, demonstrating the system's effectiveness in automated brain tumor classification are displayed in the final output.

ARCHITECTURE DIAGRAM

The architecture diagram explains the complete process of the proposed brain tumor classification system using the concept of deep learning. The proposed system will integrate the implementation of different techniques of deep learning, they are customized CNN model, VGG16 model [5], and ResNet50 model [6] for proper classification of brain MRI images. The architecture can be classified into two main phases, namely Model Implementation and Model Training and Evaluation. Model Implementation Phase is a custom design for CNN. This entails a series of convolutional layers for identifying spatial features in the MRI images, by ReLU activation functions for including non-linearity. Max pooling layers are also added for reducing the dimensions. Fully connected layers perform reasoning, and dropout layers prevent overfitting [13]. Second, the VGG16 transfer learning method makes use of the pretrained VGG16 network [5]. The pretrained convolutional layer is frozen to leverage the image features learned from the ImageNet image dataset. The architecture enables systematic performance comparison and selection of the best-performing model for brain tumor classification. This structured and modular design ensures scalability, reliability, and improved diagnostic accuracy.

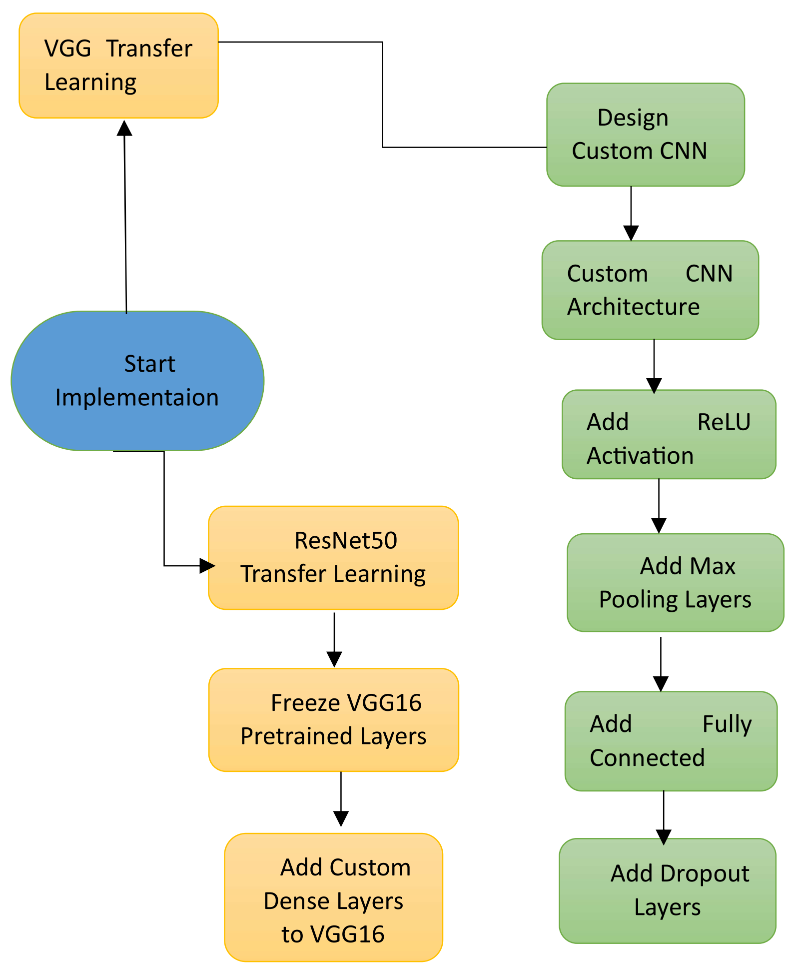

Fig. 2: System Architecture

ALGORITHM

Input:

Labeled brain MRI image dataset consisting of four classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor

Output:

Predicted tumor class and a trained deep learning classification model

Step 1: Dataset Acquisition

Brain MRI images are collected from publicly available benchmark datasets. The acquired dataset contains labeled MRI images corresponding to four tumor categories. The dataset is divided into training and testing subsets to enable supervised learning and performance evaluation.

Step 2: Image Preprocessing

Each MRI image is resized to a fixed resolution of 224 × 224 pixels to ensure compatibility with deep learning architectures. Pixel intensity values are normalized to improve numerical stability and accelerate model convergence. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and reduce overfitting.

Step 3: Model Initialization

Deep learning models are initialized for feature extraction and classification. A baseline CNN is initialized with randomly assigned weights, while transfer learning models VGG16 and ResNet are initialized with pretrained weights obtained from the ImageNet dataset. The pretrained convolutional layers are configured to retain learned features relevant to visual representation.

Step 4: Model Training

The models are trained using the Adam optimizer, which provides adaptive learning rates for efficient optimization. The categorical cross-entropy loss function is employed to handle multi-class classification. During training, model parameters are updated iteratively, and training accuracy and loss values are recorded at each epoch to monitor learning progress.

Step 5: Performance Evaluation

Model performance is evaluated using training and validation accuracy and loss curves. These metrics are analyzed to assess convergence behavior and identify potential overfitting or underfitting issues. The trained models are further evaluated using classification accuracy and consistency across tumor classes.

Step 6: Tumor Prediction

For a given unseen MRI image, the same preprocessing steps are applied before inference. The trained model predicts the tumor class by generating probability scores for each category, and the class with the highest probability is selected as the final prediction.

MODEL TRAINING PROCEDURE

The preprocessed brain MRI dataset was utilized for training the deep learning models to learn discriminative features for proper tumor classification. In the training, the dataset was divided into training and validation subsets in order to check the learning behavior and generalization capability of the models. Using the Adam optimizer [12] and categorical cross-entropy loss function, the weights of the model were updated using the backpropagation algorithm for minimizing the loss and maximizing classification accuracy, at every epoch. Training and validation metrics were tracked to monitor the convergence of the model and to identify overfitting and stability in the performance [13].

TRAINING AND VALIDATION ACCURACY

The Training and Validation Accuracy Curve shows the training and validation accuracy of the model for different epochs. The training accuracy gradually increases, indicating that the model is able to extract proper features from the MRI images. The training accuracy plot is followed closely by the validation accuracy, displaying that the model has strong generalization skills. Small variations are seen in the validation accuracy, which are always expected while training deep models due to natural variations in the training dataset. The fact that both training and validation accuracies are so closely matched indicates that there is no overfitting issue.

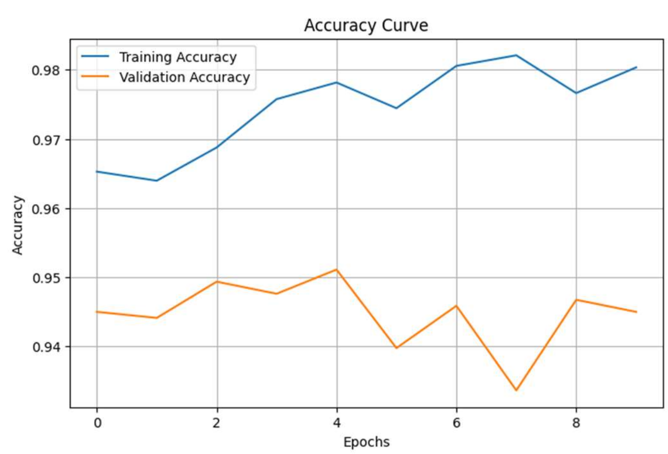

Fig. 3: Training and Validation Accuracy Curve

TRAINING AND VALIDATION LOSS

The Training & Validation Loss Curve shows the behavior of error reduction throughout the training of the model. The training loss steadily reduces for the increasing numbers of epochs, which shows effective optimization of the model and successful learning of features. The validation loss starts reducing but shows slight variations in the latter epochs. This shows that though the model is still able to fit the data, the performance does not change for the unseen data. The difference between the two losses shows a balance in learning and acceptable generalization capabilities for the tumor classification task.

Fig. 4: Training and Validation Loss Curve

RESULTS

This section presents the experimental results obtained from the implementation of the proposed deep learning–based brain tumor classification system. Three models were evaluated: a custom Convolutional Neural Network (CNN), VGG16 transfer learning model [5], and ResNet50 transfer learning model [6]. The models were trained and tested with a preprocessed brain MRI dataset in four categories: glioma, meningioma, pituitary tumor, no tumor [15]. The baseline CNN model, a satisfactory performance was obtained, capable of learning spatial features by means of MRI images. But its precision was relative to a lesser degree than the transfer learning models, since it demanded learning features from scratch. There was slight overfitting of the CNN which was reduced with the help of dropout layers [13]. The transfer learning model of VGG16 was better. Accuracy of classification as compared with the CNN baseline. By effectively leveraging ImageNet trained weights [5], high-level features that have been extracted out of MRI images, which lead to greater convergence speed and generalization on the validation dataset. The ResNet50 transfer learning model provided maximum classification accuracy [6]. The residual features in ResNet50 facilitated deeper features, preventing gradient vanishing that causes learning, resulting in excellent performance and consistency. ResNet50 also recorded higher scores in confidence during prediction on unseen MRI images. The trained models were also assessed appropriating validation metrics and loss.

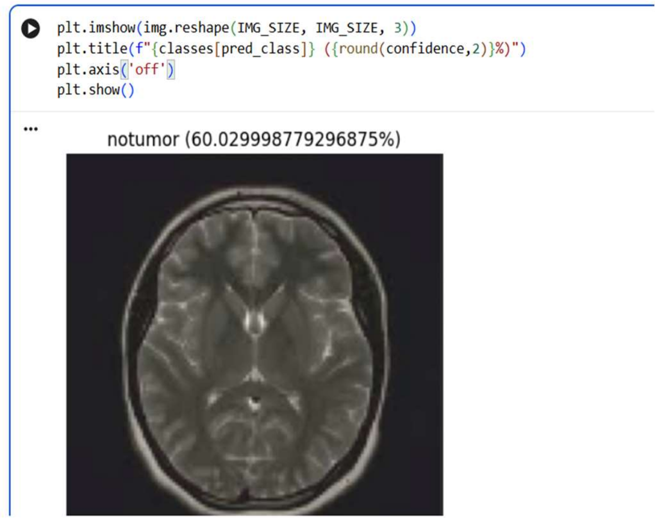

Fig. 5: No Tumor

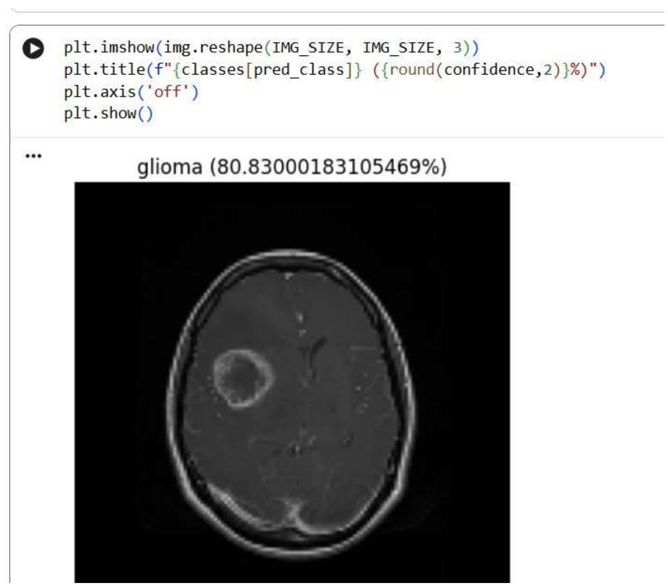

Fig. 6: Glioma

Transfer learning significantly increases the classification performance[3]. The results confirm that ResNet50 is the most suitable model for automated brain tumor classification in the proposed system.

```
plt.imshow(img.reshape(IMG_SIZE, IMG_SIZE, 3))
plt.title(f"{classes[pred_class]} ({round(confidence,2)}%)")
plt.axis('off')
plt.show()
```

...

meningioma (71.63999938964844%)

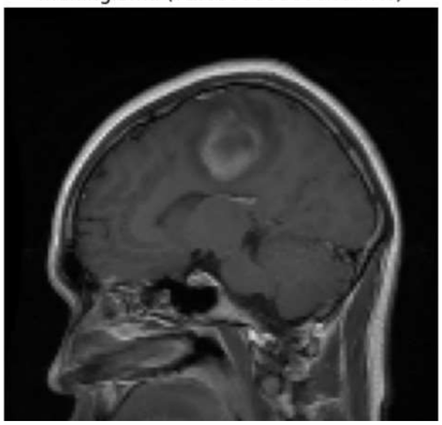

Fig. 7: Meningioma

```
plt.imshow(img.reshape(IMG_SIZE, IMG_SIZE, 3))
plt.title(f"{classes[pred_class]} ({round(confidence,2)}%)")
plt.axis('off')
plt.show()
```

...

pituitary (92.69000244140625%)

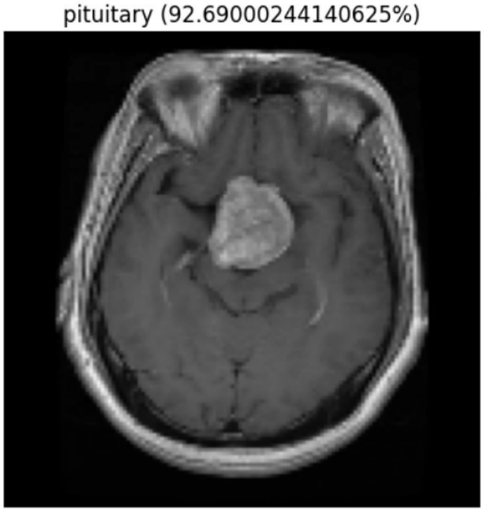

Fig. 8: Pituitary

Discussion

The VGG16 transfer learning model [5] greatly helped in the improvement of the accuracy of the model as well as its training time. The application of the pre-trained weights from ImageNet helped in the efficient extraction of low level to mid level features. The drawback of the VGG16 model is that its architecture is deep, thereby consuming more computation time compared to the ResNet50 model [6]. Among all models tested, the one that performed better in terms of accuracy is the ResNet50. This is because the residual learning ability of the ResNet50 has enabled it to learn deeper features compared to the other models [6]. Moreover, the vanishing gradient issue has also been overcome in the case of the ResNet50. The comparative study proves that the transfer learning model performs better than the baseline CNN model in terms of accuracy, robustness, and training speed [3]. Even though the proposed system performs well, it is dependent on both size and variability of input data. Future improvements might involve segmentation of a tumor [4], a larger annotated data set, or incorporation of Explainable AI tools.

CONCLUSION

This initiative has successfully validated the idea of employing deep learning methods to classify brain tumours using Magnetic Resonance Imaging (MRI) [1]. At the heart of the effort is the need to develop and test an efficient classification model that is able to classify brain images of the MRI type that belong to four different conditions – gliomas, meningiomas, pituitary tumours, and those that have no tumours. This effort seeks to overcome the drawbacks of classification that occur with the diagnostic method that is manual and machine learning based.

From the experimental analysis, it is observed that the baseline CNN model had the ability to learn meaningful spatial features from the MRI images with acceptable classification performance. But its accuracy and generalization skills were not satisfactory because of training the model from scratch with a smaller dataset. To address such challenges of training a model from scratch with a smaller dataset, transfer learning models such as VGG16 [5] and ResNet50 [6] were used. Out of the various models tested, the performance of ResNet50 was the best. The concept of residual learning helped in the extraction of features for deeper layers, thus avoiding the problems of degradation and vanishing gradients [6]. As a consequence, the generalization capabilities of the model improved for unknown MRI images, and the confidence level of tumor classification was improved. The graphical representation of the performance of different models aptly testifies to the fact that the use of transfer learning helps in improving the efficiency of brain tumor classification systems [3].

The proposed system overcomes the issues of manual feature selection, is less time-consuming for diagnosis, and minimizes errors that may be caused by a human. The proposed system can perform successfully as a multi-class classification system. However, it could be made better by adding more data to it and developing its framework to focus on tumor localization [4].

Literally, this project is an exemplification of the great potential that there is with deep learning [11] and the technique of transfer learning when it comes to applications related to medical image analysis [14]. The conclusion here is that this technique has provided a great foundation upon which future projects can be based.

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