

MRI IMAGE ANALYSIS FOR EARLY BRAIN TUMOR DETECTION USING DEEP LEARNING

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Abstract—Brain tumors are among the worst conditions affecting the human CNS and constitute a threat to human life in case they are not diagnosed at a correct stage. The process of diagnoses of brain tumors is carried out by Magnetic Resonance Imaging (MRI), which has been preferred for its capabilities to produce high-resolution images of soft tissues without requiring radiation. However, manual analysis of MRI images is a tedious process and also relies on the expertise of professionals. The differences in size and positions of the tumors further add to the complexity of the task, hence increasing the chances of inaccuracies. It is for this reason that a reliable system for the classification of the tumors is required. In this project, there is the presentation of an automated approach for the classification of brain tumor images based on the use of deep learning for the classification of MRI images of the human brain into four categories: glioma, meningioma, pituitary tumor, and the absence of the tumor. In the proposed approach, there is the use of image preprocessing methods for the improvement of the classification process. For the storage of images, there is the use of a folder-based approach. In this research, three models based on deep learning are applied. A personal Convolutional Neural Network model is used as a baseline model for learning spatial features from the MRI images directly. Besides that, two models based on transfer learning are applied, namely VGG16 and ResNet50, using ImageNet pretrained weights for learning features for improved performance in classification. The pre-trained convolutional layers are fixed, while personal full layers are attached for training them for the task related to the imaging domain. Experimentation on this topic has proved that although the baseline CNN has a

satisfactory level of performance, there is a considerable lack of generalization compared to transfer learning models. The accuracy level of the VGG16 model is improved with a rapid convergence point because of its strong ability to extract deep features. In all models implemented, ResNet50 has a highest level of accuracy and stability. The ability to remove vanishing gradients in deep features is applicable in ResNet50 because of residual connections. The results prove that the effect of the brain tumor classification is indeed improved through the concept of transfer learning. The proposed method can be useful to the radiologist to some extent by reducing the efforts to a noticeable extent. In the future, the method can be extended to the area of brain tumor segmentation.

Index Terms—Brain Tumor Classification, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Network (CNN), Transfer Learning, VGG16, ResNet50, Medical Image Analysis, Image Preprocessing.

I. INTRODUCTION

Human brain is a highly complicated and an important organ of the human body which regulates vital physiological and cognitive processes. Any disorder of the brain can have a dire impact on the quality of life of a person and even may be life threatening. Brain tumor is a condition of un-normal growth of cells in the brain or the central nervous system. Brain tumors may be benign (non-cancerous or normal), or malignant (cancerous), and the degree to which they are considered to be severe depends on the type of brain tumor, its size, location, and rate of growth. The timely and precise diagnosis of brain tumors is a key to proper treatment planning and the increased survival rate of the patients. One of the most popular modes of imaging used in the diagnosis of brain tumor is Magnetic Resonance Imaging (MRI) because it is not an invasive procedure and it has a high quality of soft tissue contrast. MRI gives clinical details of the structure of the brain tissues that allow clinicians to detect abnormalities with high levels of accuracy. In spite of these benefits, the process of MRI scans interpretation is a difficult and timeconsuming one. To analyze the MRI slices, radiologists have to do it manually, and this is why they may make a mistake because of exhaustion, subjective analysis, and inter-observer changes. Moreover, there exist slight differences in the appearance of tumors between patients, and they complicate proper diagnosis. The conventional ways of diagnosis of brain tumor uses heavy manual inspection and the use of traditional image processing. Some of the classical methods that have been applied in tumor detection and segmentation include thresholding, region growing, K-means clustering, and fuzzy Cmeans clustering. Although such methods are reasonable in a controlled setting, they do not tend to generalize to actual data well because of changes in the shape, intensity, and location of tumors. Moreover, these approaches involve manual creation of features and the majority of parameter optimization, thus being less efficient and resistant. In recent years, automated medical image analysis has become the focus of many studies due to the fast development of artificial intelligence (AI) and machine learning. Deep learning, which is a branch of machine learning, has shown superior results in image classification,

object detection as well as pattern recognition problems. In particular, CNNs have demonstrated exceptional success at being able to extract hierarchical features directly on provided raw image data without any manual feature engineering. This is particularly applicable to medical imaging tasks like brain tumor detection and classification where CNNs are the most appropriate in this case. Deep learning-based methods in recent years have been applied successfully to the brain MRI analysis to perform such tasks as tumor detection, tumor segmentation, and tumor classification. The CNN-based models are trained to learn low-level features (edges and textures) during the training first few layers and gradually acquire higher-level semantic features as the layers get deeper. Nevertheless, the training process of deep CNN models in its purest form needed a lot of labeled data and tremendous computer power. Medical data are not always big because of issues of privacy and the high cost of obtaining expert annotation that can result in overfitting and worse generalization.

Transfer learning has come in to overcome these problems. Transfer learning entails the application of already trained deep learning models, which have been trained on rich feature representations on large scale datasets like ImageNet. VGG16 and ResNet50 models can be modified to use medical imaging by retraining the last few layers or fine-tuning. This method saves a lot of time on training, enhances accuracy and generalization, even in the case of comparatively small medical datasets. The proposed project is aimed at creation of automated brain tumor classification with the help of deep learning methods. The purpose of the proposed system is to categorize the brain MRI images into four categories, namely, glioma, meningioma, pituitary tumor, and no tumor. These are some of the most frequently diagnosed types of tumors of the brain and should be treated differently. To make a good clinical decision and treatment planning, it is important that the type of the tumor is accurately classified. The suggested methodology will have several steps, such as the acquisition of the dataset, image preprocessing, model training, evaluation, and prediction. Image preprocessing (resizing and normalization) is used to normalize the input data and enhance the speed of training. The data is structured in a folder format which allows the supervised learning and effective labeling. The data is then separated into training and testing sets to test the performance of the models on the unknown data. In this work, three deep learning models are applied and compared. The baseline method employed to learn the effectiveness of learning features directly out of the MRI images is a custom CNN model. Secondly, two transfer learning models VGG16 and ResNet50 are used to improve the classification accuracy. VGG16 is characterized by its deep and homogeneous structure, whereas ResNet50 is the network with added residual connections, which enables training deeper networks

to train successfully, without the vanishing gradient issue. The models are tested against such metrics as training accuracy, validation accuracy, and loss curves. A comparative analysis is undertaken to determine the best model that can be used to classify brain tumor. The experimental findings indicate that transfer learning models are superior to the baseline CNN, where ResNet50 has the most accurate and stable results. Residual learning is the reason why ResNet50 can identify complicated patterns in the MRI images and as such, it is incredibly useful in classifying medical images. The proposed system is able to also predict the tumor class in addition to confidence scores of each prediction. The characteristics make the system more interpretable and reliable which makes it an appropriate clinical decision support tool. The system will be used to classify brain tumors in order to lower the number of people involved in manual work, decrease the number of diagnostic mistakes, and assist radiologists in the faster and more accurate diagnosis of brain tumors. To conclude, it is possible to say that this project has demonstrated the feasibility of deep learning and transfer learning methods in medical image analysis. The brain tumor classification system that is created as a result of this work is more accurate, efficient, and reliable than the traditional ones. The suggested methodology forms the basis of the future developments, such as the tumor segmentation, the multimodal imaging integration, and the real-time implementation at the healthcare setting.

II. LITERATURE REVIEW Content here.

III. PROBLEM STATEMENT

Diagnosis of brain tumor through Magnetic Resonance Imaging (MRI) is a critical and complex process and in the past, diagnosis was done through manual interpretation by qualified radiologists. The growing quantity of the MRI data and the change in the size, shape, texture, and location of the tumor increase the time needed to provide an accurate diagnosis and is highly susceptible to human error. The traditional machine learning and the conventional methods of diagnosis demand manual extraction of feature and they are not very robust making them poor in terms of accuracy and generalization. Moreover, the current systems are usually not able to effectively distinguish different types of tumor and normal brain tissues with limited datasets that they have been trained on. Lack of automated, reliable, and efficient classification system augments diagnostic work and slows down clinical decision-making.

Thus, it turns out that there is a great need to come up with an automated brain tumor classification system that could classify MRI images into several categories of tumors with the help of sophisticated deep learning methods. It needs to be based on efficient feature extraction, a reduced role of the human factor, enhanced diagnostic accuracy, and consistent

and reliable outcomes to assist medical professionals to detect brain tumors in the earliest and most accurate way possible.

IV. METHODOLOGY

In this study, we suggest a brain tumor classification framework based on an automated deep learning framework with Magnetic Resonance Imaging (MRI) scans. The framework involves a systematic pipeline for preparing datasets, preprocessing, model design, training, evaluation, and prediction. The general goal is to correctly identify brain MRI images into four categories, which include glioma, meningioma, pituitary tumor, and no tumor.

1. MRI Dataset Acquisition and Structuring

The data set in this paper is brain MRI images in a folder structure of directory structure whereby each folder is assigned a particular tumor category. The data has four categories: glioma, meningioma, pituitary tumor and no tumor. This hierarchical structure is a folder-based structure that lets students learn under supervision with directory names being used to infer the class label. The images are chosen because MRI images have high contrast resolution with soft tissues; furthermore, it has been widely used in clinical diagnosis of brain tumors.

B. Data Preprocessing

To achieve the consistency of the data and improve the model performance preprocessing is an important step. Each MRI image is downsized to constant resolution of 128 x 128 pixels to equalize the size of input and simplifies the computation. The pixel intensity values are scaled to the range [0, 1] by using Min-max scaling for enhancing numerical stability and fastens the convergence when training models.

A data validation is also done so that corrupted or inaccessible images are eliminated in the dataset. This will make sure that the images used in training and testing are of high quality in MRI, which will enhance robustness and reliability of the models.

C. Train-Test Split

The dataset that is preprocessed is split into the training and testing sets (80 20). Model parameter learning is done on the training set and model generalization is done on the testing set. An assigned random number is used so that the results can be reproduced.

D. Feature Extraction Using Deep Learning Model

To identify the discriminative features in MRI images, three types of deep learning arrangements are used and compared:

The first one is the Custom Convolutional Neural Network (CNN).

A baseline CNN is a model that is created by employing numerous convolutional layers with 3 x 3 kernel, and then maxpooling layers. Convolutional layers extract spatial features of low level, i.e., edges, textures, and shapes and max-pooling layers reduce both spatial dimensions and computational

expenses. The feature maps acquired are flattened and inputted into a fully connected dense layer holding 128 neurons. A dropout rate of 0.5 is applied to avoid overfitting

2) VGG16 Transfer Learning Model

The model used to carry out feature extraction based on transfer learning is the VGG16 model, which has been trained on the ImageNet dataset. In order to retain the features, the convolutional layers in the VGG16 model are made untrainable. The additional layers to this trained model are the fully connected layers, which have custom layers upon it to adapt the model to brain tumor classification. This process reduces training time and improves accuracy, particularly where the number of datasets is small.

3) ResNet50 Transfer Learning Model.

ResNet50 is used as more powerful architectures of transfer learning that involves residual connections in order to overcome the vanishing gradient problem. With such skip connections, the training of deep networks can be effectively trained by directly flowing the gradient. Like VGG16, the frozen pretrained layers are added and task-specific dense layers are added. The ResNet50 model also has a high level of learning and complex features of MRI images which lead to better classification performance.

E. Classification Layer and Prediction of the Output.

Both models have completely connected layers and a softmax activation function for the features that are extracted.. The softmax layer gives probability scores of each of the four classes of tumors. The most probable class is used as the final prediction. The confidence scores are also indicated to give the confidence of the prediction made by the model.

F. Model Training and Performance Optimization

The Adam optimizer is used to train all models and has adaptive learning rates to achieve effective convergence. Categorical cross-entropy loss function is applied, because it is a multi-class classification task. The models are trained over a number of fixed epochs using a batch size of 32. there is the dropout regularization which is used to reduce overfitting and enhance generalization.

G. Performance Evaluation

The training and validation accuracy, as well as loss curves, are used to evaluate the performance of models. This is done through comparative analysis with the purpose of comparing the performance of the baseline CNN with transfer learning models. The analysis shows the effect of deep pretrained architectures on accuracy and stability in classification. H. Prediction on MRI B6. Rebates. The most successful model is applied to make predictions of the tumor types of unseen MRI images after the training process. The preprocessing steps of the input image are the same as the predictions are done. The predicted tumor classification and the associated score of confidence are shown, which increases the interpretability and clinical relevance.

I. Summary of Methodology

The suggested methodology entails the combination of preprocessing, feature extraction, transfer learning, and classification in one system of detecting brain tumors. The system is able to obtain strong and precise tumor classification by using the technique of the baseline CNN learning with the most recent pretrained architectures and retains the computational efficiency.

V. PROPOSED SYSTEM

The offered system introduces a deep learning-based system with an automated classification of the brain tumors with the Magnetic Resonance Imaging (MRI) scans. The main aim of the system is to help the medical practitioners by offering a precise, effective, and dependable means of categorizing the brain MRI images into a set of four classes: glioma, meningioma, pituitary tumor and no tumor. The system will minimise diagnostic mistakes and enhance the clinical decision-making process by decreasing the reliance on manual interpretation.

It operates under a sequence of steps which include MRI image data collection and pre-processing. Any MRI images that are fed into it are rescaled to a fixed size of 128 x 128 pixels to maintain consistency and matching deep learning models. Normalization of pixel intensity is used to reduce values of 0 to 1 to enhance the stability and convergence of the training. Data validation step is included to eliminate corrupted or unreadable images hence improving the data set reliability. The images undergo preprocessing and then they are fed to a multi-branch feature extraction structure. The framework combines three deep learning networks, i.e., a custom Convolutional Neural Network (CNN), VGG16, and ResNet50. The CNN model as a baseline is able to extract low-level spatial features like edges and textures directly on MRI images. VGG16 and ResNet50 on the other hand are based on the transfer learning which involves high level and complex feature representations based on pretrained weights of the image net dataset. The already trained convolutional layers are kept frozen with additional custom fully connected layers being added so as to tune the models to the medical imaging field.

The features that have been extracted are sent to fully connected layers that have dropout regularization to minimize overfitting. The last layer is a softmax classifier that creates probability scores of each class of tumor. The most probable class is considered the predicted type of tumor and provided with a confidence score which is the certainty of the prediction.

The system is trained on Adam optimizer and categorical cross-entropy loss function to overcome multi-class classification. The training and the validation accuracy and loss are used as metrics of performance. The experimental findings show that the transfer learning models are more successful

than the baseline CNN, where the highest accuracy and stability are reached by ResNet50.

Generally, the system proposed is a great fusion of preprocessing, deep feature extraction and transfer learning to achieve a powerful brain tumor classification system. The system can be implemented in clinical workflows using it as a decision support tool and be expanded in the future to tumor segmentation and real-time deployment.

VI. ARCHITECTURE DIAGRAM

The proposed system architecture will be used to conduct automatic brain tumor classification of Magnetic Resonance Imaging (MRI) scan based on a multi-branch deep learning framework. In its architecture, both a Convolutional Neural Network (CNN) that is designed and a transfer learning model (VGG16 and ResNet50) are introduced to yield powerful and discriminative features of brain MRI images. The general system is subdivided into several sequential steps such as the input acquisition, preprocessing, feature extraction, classification and the prediction of the output.

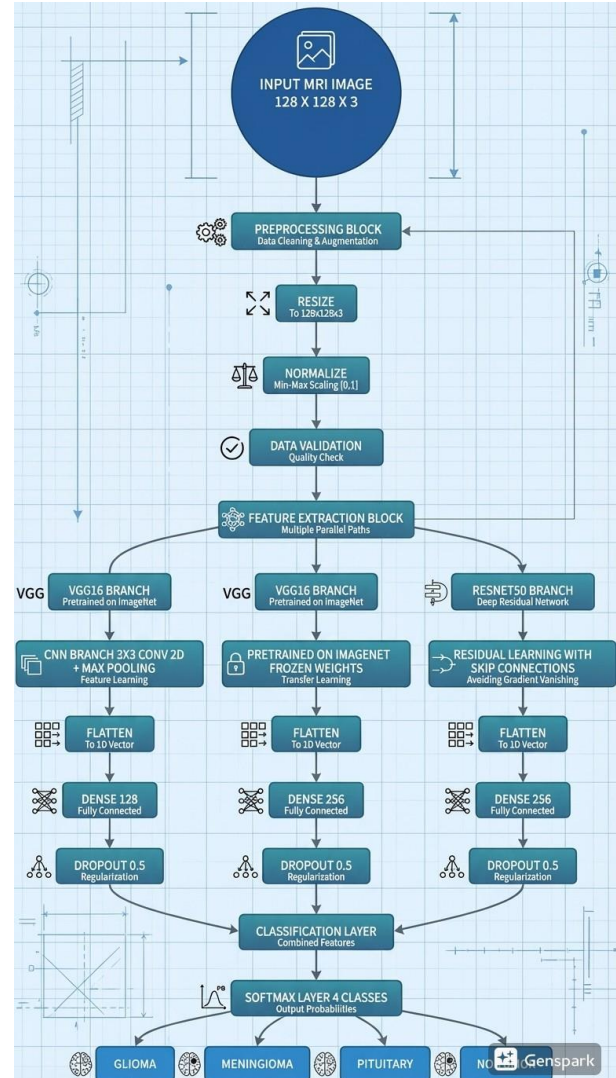


Fig. 1: System Architecture

The input is an MRI image that is normalized into a constant resolution of 128 x 128 x 3. Normalization of the input dimensions is to make sure it is consistent throughout the dataset and is compatible with deep learning models. The choice of MRI images is because of the high maintainability of soft tissue contrast, and non-invasive nature, which is no less effective in the diagnosis of brain tumors. The image is then subjected to the preprocessing block which is important in improving the quality of the data and performance of the model. This block comprises of resizing, normalization, and data validation processes. First, we'll resize the images so they all fit the required input dimensions, then use minmax scaling to normalize the pixel values into a consistent 0 to 1 range. Normalizing data this way keeps the numbers steady during training, which helps the model learn much faster. The validation of data eliminates data corruption, or poor quality data, and only trustworthy data is sent to the learning models. Following the preprocessing, the image is sent to the feature extraction block which is a three parallel branch. This multi-branch approach enables the system to be able to learn complementary representations with the same input image. The initial branch is a traditional CNN branch and it has several convolutional layers with 3x3 kernels and then max-pooling operations. This branch is taught about low-level spatial properties including edges, textures and local patterns directly out of the MRI images. Transforming features, flatten, dense, and dropout layers are used to decrease the overfitting. The second branch uses the architecture of VGG16 which is pretrained on ImageNet. Convolutional layers are frozen so as to retain learned visual characteristics and transfer learning can be effected. This branch is concerned with the highlevel abstract representation extraction. An incensed dropout regularization and a fully connected dense layer are integrated into the model to fit it to medical image classification. The third branch is based on a deep residual network ResNet50, which includes skip connections to address the vanishing gradient issue. The result of the residual learning is that the model can learn more profound and complicated feature hierarchies, which leads to better stability and accuracy in the classification.

The products of each branch are sent to a classification layer and then to a softmax layer that generates the probability scores of four classes, namely glioma, meningioma, pituitary tumor, and no tumor. The probability of that class is the highest resulting in the final prediction.

All in all, the multi-branch architecture is useful in integrating the power of the baseline CNN learning and sophisticated transfer learning models, to come up with a powerful, precise, and scalable brain tumor classifier that can be used in clinical decision-making.

VII. ALGORITHMS

Algorithm 1 : Preparation and Preprocessing of Brain MRI Data .

Input: Raw brain MRI images Output: checked and process MRI information.

Steps:

- 1) Obtain brain MRI images and classify them based on the classification: glioma, meningioma, pituitary tumor and no tumor.
- 2) Name classes using the name of the folders in order to permit supervised learning.
- 3) Read every MRI image in data set directory.
- 4) Reduce all images to 128 pixels / sq. 5) Normalize the scale pixel intensity values to the range [0, 1] so as to improve numerical stability.
- 6) Check data to remove invalid and unread data.
- 7) Sequence the images and labels that were processed in arrays.
- 8) Split the data into the training and testing sets in 80:20. 9) Export the processed and cleaned data to be used in training the model.

1. Image Resizing

Each MRI image is resized to a fixed resolution:

$$I_r = \text{Resize}(I, 128 \times 128)$$

2. Pixel Normalization

Min-max normalization is applied:

$$I_n(x, y, c) = \frac{I_r(x, y, c)}{255} \text{ such that } I_n \in [0, 1]$$

3. Label Encoding

Class labels are assigned as:

$$y \in \{0, 1, 2, 3\}$$

Corresponding

glioma, meningioma, pituitary, no tumor.

One-hot encoding:

$$y = [y_1, y_2, y_3, y_4], y_i \in \{0, 1\}$$

4. Dataset Split

$$\mathcal{D} = \mathcal{D}_{train} \cup \mathcal{D}_{test}$$

$$|\mathcal{D}_{train}| = 0.8 |\mathcal{D}|, |\mathcal{D}_{test}| = 0.2 |\mathcal{D}|$$

Algorithm 2 : CNN-based extraction and classification algorithm

Input: Processed MRIs. Product: Tumor classification prediction.

Steps:

- 1) Initiate a Convolutional Neural Network framework.
- 2) To obtain spatial features, convolutional layer which consists of 3 x 3 filters is applied.
- 3) Max-pool in a bid to reduce spatial dimensions.
- 4) Repeat convolution and pooling to be able to learn hierarchical features.
- 5) Flatten the obtained feature maps into a one dimensional feature.
- 6) The flattened features are transferred to a full connected dense layer.
- 7) Minimize overfitting by using drop out irregularization.
- 8) Get softmax activation function of classes.
- 9) The final forecast is the choice of the most probable type of class.

1. Convolution Operation

For input feature map X and kernel K :

$$Z_{i,j,k} = \sum_{m,n,c} X_{i+m,j+n,c} \cdot K_{m,n,c,k} + b_k$$

2. ReLU Activation

$$A_{i,j,k} = \max(0, Z_{i,j,k})$$

3. Max Pooling

$$P_{i,j,k} = \max_{(m,n) \in \Omega} A_{i+m,j+n,k}$$

4. Flattening

$$f = \text{Flatten}(P)$$

5. Fully Connected Layer

$$h = \sigma(Wf + b)$$

6. Dropout Regularization

$$h' = h \odot r, r_i \sim \text{Bernoulli}(p)$$

7. Softmax Classification

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^4 e^{z_j}}$$

Algorithm 3: Vgg16 Transfer Learning Brain Tumor Classification.

Input: Processed MRIs. Product: Tumor classification prediction.

Steps:

- 1) Load ImageNet weights of the pretrained VGG16 model.
- 2) Removed original layers of VGG16 of classification.
- 3) All the previously trained convolutional layers are stopped to save the learned features.
- 4) Fed feed forward the VGG16 convolutional base is fed with fed feed forward MRI images.
- 5) Normalize deep feature maps that are obtained.
- 6) Add a 256 dense fully connected layer.
- 7) Normalize the dropouts as a means of improving generalization.
- 8) Classify the tumors using a softmax classifier.
- 9) Obtain the forecast of the nature of tumour with the accuracy.

1. Feature Extraction

Pretrained VGG16 convolutional base:

$$F_{vgg} = f_{VGG16}(I_n)$$

2. Freezing Pretrained Layers

$$\frac{\partial \mathcal{L}}{\partial \theta_{VGG}} = 0$$

3. Fully Connected Layer

$$h = \sigma(W_{256} F_{vgg} + b_{256})$$

4. Dropout

$$h' = h \odot r$$

5. Softmax Output

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^4 e^{z_j}}$$

Algorithms 4: Transfer Learning ResNet50 to examine Brain tumor. Input: Processed MRIs. Product: Tumor classification prediction.

Steps:

- 1) Load ImageNet weights of ResNet50.
- 2) Destroy the first levels of upper classification.
- 3) Freeze Weights Freeze weights.
- 4) Pass MRI images with skip connected blocks.
- 5) Get to know enduring profound semantic characteristics.
- 6) Even the features extracted representation.
- 7) Add a 256 dense fully connected layer.
- 8) Apply dropout regularization to minimize overfitting.
- 9) Softmax layer is applied to classify the images into tumors.

1. Residual Learning

For input x :

$$y = \mathcal{F}(x, W) + x$$

2. Deep Feature Extraction

$$F_{res} = f_{ResNet50}(I_n)$$

3. Fully Connected Layer

$$h = \sigma(W_{256}F_{res} + b_{256})$$

4. Dropout

$$h' = h \odot r$$

5. Softmax Classification

$$\hat{y}_k = \frac{e^{z_k}}{\sum_{j=1}^4 e^{z_j}}$$

Algorithm 5 : Training and Optimization of the model. Input: Training dataset Output: Training models of classification.

Steps:

- 1) Initialize CNN, VGG16 and ResNet50.
- 2) State categorical cross- entropy loss.
- 3) Adam optimizer is effective in the weight updates.
- 4) Training every model with a fixed amount of epochs with training dataset.
- 5) The results of the testing dataset.
- 6) Validation error and loss and follow-up training.

7) Optimize by means of optimizer adaptation.

8) Train models in the store, which can be utilized in future prediction and assessment.

Algorithm 6 : The predictions on unknown tumor MRI images are revealed in the algorithm. Input: New MRI image Output: Tumor type and score of confidence.

Steps:

- 1) Trained model of load classification.
- 2) Read the input MRI image.
- 3) Redo the preprocessing of resizing the image and normalizing the image.
- 4) Insert the picture on the trained model.
- 5) Get scores of softmax layer.
- 6) Identify the likelihood of the maximum likelihood of the tumor.
- 7) Display the tumor type and the confidence score predicted.

1. Input Preprocessing

$$I_{test} \rightarrow I_n$$

2. Forward Pass

$$\hat{y} = f_{\theta^*}(I_n)$$

3. Tumor Class Prediction

$$\hat{c} = \arg \max_k \hat{y}_k$$

4. Confidence Score

$$\text{Confidence} = \max(\hat{y}_k)$$

VIII. EXPERIMENTAL RESULTS

Three architectures VGG16 transfer learning model, ResNet50 transfer learning model and a custom Convolutional Neural Network (CNN) were used to compare the performance of the system. All the experiments were done in a preprocessed MRI dataset (four categories of tumors) of glioma, meningioma, pituitary tumor, and no tumor. The initial CNN model showed stable learning performance during training and was capable of extracting elementary spatial patterns of the MRI images. Accuracy of training steadily increased with the number of epochs; validation accuracy pattern was moderate and showed no significant decrease which is an indicator that it had limited generalization potential. The point of this behavior is that it is difficult to train deep models with just relatively small medical datasets. VGG16 transfer learning model was significantly higher in performance than the baseline CNN. With the pretrained

ImageNet weights it took less time to achieve convergence in the model and the model had more steady training and validation accuracy curves. The losses associated with the validation process were always lower than those of the CNN, which validated enhanced feature extraction and decreased overfitting. The best and most stable results were obtained with the ResNet50 model which was compared with the rest of the architectures. This was made possible by the existence of residual connections which provided the ability to effectively train deeper layers and so the model was able to learn complex pattern and tumor specific features using the MRI scans. ResNet50 was able to achieve higher classification and incidence as well as show little variation between train and validation performance which is a sign of strong generalization.

Along with the accuracy, confidence of prediction was also examined with respect to unseen MRI images. The ResNet 50 model produced more and coherent confidence values in all tumor classes, which improved the accuracy of the automated diagnosis. The system could also identify tumor types accurately even with difficult cases with minor visual variations. An analytical evaluation of the three models shows clearly that transfer learning has a great propensity to improve classification. Although the CNN is a convenient benchmark, trained architectures like VGG16 and ResNet50 have better robustness and stability. In general, the results of the experiments show the efficiency of the offered system and its appropriateness to automated classification of brain tumors as a tool of clinical support.

IX. DISCUSSION

The experimental analysis of the suggested brain tumor classification system provides the efficiency of deep learning methods, in particular, transfer learning, in processing multimodal medical imaging data. The findings indicate that there are distinct differences in performance between the baseline CNN, VGG16, and ResNet50 models, which offer important information as to the advantages and drawbacks of each solution.

The baseline CNN, despite containing the ability of learning basic spatial features in MRI images, had a low ability to generalize. This drawback can be explained by the fact that deep networks need to be trained with large annotated datasets in order to be trained. Although dropout regularization reduced the degree of overfitting to a certain degree, the CNN model was not able to learn higher-level semantic information that are important in classifying visually similar tumor classes. The CNN was, however, a good reference architecture, and one with which other fresher models can compare.

The VGG16 transfer learning model was found to be better with terms of classification and training stability. The model used the ability to determine meaningful feature

representations using pretrained weights without the need to have a large amount of training data. The convergence rate and the minimized loss of validation show that transfer learning can successfully cope with the problem of the lack of data in medical imaging. Nevertheless, VGG16 was somewhat more expensive to compute than ResNet50 because of its deep but homogenous architecture.

The model most resistant in the proposed system was ResNet50. The residual connections allowed further learning of features without having to face the problem of vanishing gradient leading to high accuracy and consistency. This low difference between training and evaluation performance implies high generalization, which indicates that ResNet50 can be used in the real-world diagnostic setting very readily. The increased scores of assurance offered by this model also increase confidence in the automated predictions.

The other observation is that preprocessing affects the overall system performance. Image size and normalization increased training stability among all models by a great deal. This was also aided by the organization of the dataset into a structured form that enhanced efficient supervised learning that minimized the ambiguity of labels.

Clinically, the proposed system can serve as a decision support system that can be used reliably instead of substituting medical professionals. Radiologists can also use the system to prioritize cases and decrease diagnostic workload by the system offering consistent predictions and confidence measurements. Nevertheless, the lack of segmentation to tumors reduces interpretability as the clinicians may sometimes need localized tumor margins.

On the whole, the discussion substantiates the claim that incorporation of transfer learning in automated analysis of MRI significant enhances the classification outcome. Additional improvements to be made in the future should deal with segmentation, bigger datasets, and explainable AI techniques to enhance transparency and clinical uptake.

X. CONCLUSION

In this study, an automated deep learning framework was offered to classify brain tumors based on Magnetic Resonance Imaging (MRI) scans. The proposed system was relevant in categorizing the brain MRI images into four and this included glioma, meningioma, pituitary tumor, and no tumor. The system remedied major problems that are linked to manual diagnosis and other conventional machine learning strategies by incorporating preprocessing, deep feature extraction, and transfer learning.

To examine the performance and the generalization ability of three models, custom CNN, VGG16, and ResNet50, the comparative evaluation of these models was made. The baseline CNN proved that it is possible to classify tumors automatically but exhibited weaknesses in dealing with

complex MRI features. Transfer learning models on the other hand greatly enhanced stability and accuracy in classification. One of them, ResNet50 was the most effective overall as it incorporated the Residual learning mechanism, which allowed effective training of deep networks and better feature representation.

The experimental findings attested that transfer learning is very effective in the medical image analysis, especially when one is faced with few annotated datasets. The suggested system generated predictable and precise predictions and confidence scores, which improved its interpretability and facilitated clinical decisions. The system can be of help to the radiologists as it helps to lessen diagnostic workload and human error.

In spite of the promising outcomes of the proposed framework, some limitations are present. The system is currently limited to the image level classification and does not feature tumor localization and segmentation. Also, the assessment was conducted on a small number of data, which could influence extrapolation to a wide variety of clinical environments.

The next step in the future will be to expand the system to tumor segmentation with encoder-decoder systems like UNet with VGG16 or ResNet backbones. The use of larger and multi-institutional data sets, explainable AI methods and realtime application plans will also make the proposed system more applicable to clinical practice. In general, this work shows that deep learning-based solutions can be instrumental in the process of automated diagnosis of brain tumors and optimal healthcare outcomes.

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