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AN EFFECTIVE AND NOVAL APPROACH FOR BRAIN TUMOR CLASSIFICATION USING TRANSFER LEARNING RESNET-50

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Abstract: A brain tumor is an abnormal growth of cells in the brain. These growths can be benign (non-cancerous) or malignant (cancerous), and they can develop within the brain itself (primary brain tumor) or spread from other parts of the body to the brain (metastatic or secondary brain tumor).Early diagnosis and prompt medical intervention are essential to determine the tumor type, develop an appropriate treatment plan, and potentially improve the prognosis. This research project leverages the power of Deep convolutional neural networks (DCNNs) and transfer learning to classify brain tumor into three distinct categories: Meningioma, Glioma, and Pituitary tumor to assist medical professionals in the accurate diagnosis of brain tumor. The project utilizes the ResNet-50 architecture, a well-established deep learning model pre-trained on large-scale image datasets, to extract meaningful features from brain tumor images. The potential of deep learning in medical image analysis contributes to the early detection and classification of brain tumor. The automated classification system benefits in analyzing medical images rapidly, reducing the time required for diagnosis, and reducing the potential for human error and subjectivity in the interpretation of medical images. The results indicate high accuracy and demonstrate the feasibility of using deep learning models for clinical decision support in the field of radiology and neurosurgery. This research holds promise for improving the speed and accuracy of brain tumor diagnosis, ultimately leading to better patient outcomes.

Keywords - Deep Convolutional Neural Networks(DCNN), Brain Tumor, Medical image analysis, ResNet-50, Automated classification, Transfer Learning.

I. INTRODUCTION

Brain tumors, a category of neoplasms that develop within the central nervous system (CNS), pose a significant and often life-threatening health concern. These abnormal growths of cells within the brain can have devastating consequences, affecting cognitive functions, motor skills, and overall well-being. Timely and accurate diagnosis is paramount in enabling prompt medical intervention and improving patient outcomes. Traditionally, the diagnosis of brain tumors has heavily relied on medical imaging, particularly magnetic resonance imaging (MRI) and computed tomography (CT) scans. The interpretation of these images, however, is a complex and labor-intensive task, requiring the expertise of trained radiologists and neurosurgeons. Moreover, the accuracy of diagnosis may vary due to the subjective nature of human interpretation, leading to potential discrepancies and delays in treatment.

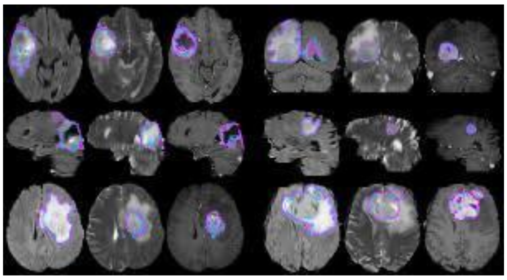

Figure 1. MRI Brain Tumor

This research project endeavors to harness the power of deep learning, specifically the ResNet-50 architecture, to advance the classification of brain tumors into three distinct categories: Meningioma, Glioma, and Pituitary tumors. By employing a transfer learning approach, we aim to capitalize on the knowledge acquired by ResNet-50 from extensive pre-training on diverse image datasets. This allows us to adapt the model to the intricacies of brain tumor classification, fostering a robust and accurate diagnostic tool. The benefits of such a system are manifold. It promises to significantly enhance the diagnostic accuracy, facilitating early detection and timely intervention. Furthermore, it reduces the burden on healthcare professionals by automating the image analysis process, enabling them to focus on treatment planning and patient care. Additionally, the system's scalability and adaptability to handle diverse datasets offer the potential for broader applications in the realm of medical image analysis.

II. LITERATURE SURVEY

Alok Sarkar, Md. Maniruzzaman, Mohammad Ashik Alahe, and Mohiuddin Ahmad utilized the AlexNet Convolutional Neural Network (CNN) in MATLAB to categorize a dataset for training and testing, as well as extracting features from it. These extracted features were then used in the WEKA platform to classify brain tumors in MRI images into categories such as no-tumor, glioma, meningioma, and pituitary tumors, employing classifiers like BayesNet, SMO, NB, and RF. They used a dataset of 3600 images, with an equal number of images per class (900 per class). The MRI images were preprocessed, standardized, and resized to 227 x 227 pixels to accommodate variations in image sizes. AlexNet, with its five convolutional layers, three max-pooling layers, and three fully connected (FC) layers, was the primary model used. The study also utilized techniques like ReLU, dropout, and stochastic gradient descent to improve training speed and reduce overfitting. The classification models included BayesNet, SMO, NB, and RF, with specific parameter choices for each. The study evaluated the model's performance using a confusion matrix and various metrics, achieving the highest accuracy of 88.75%.

Emrah Irmak introduces multiple brain tumor classifications for early diagnosis using CNN models with automated hyperparameter tuning through grid search. Three distinct CNN models are proposed. The first achieves 99.33% accuracy in tumor detection, while the second classifies tumors into five types with 92.66% accuracy. The third model distinguishes glioma tumors into grades II, III, and IV, achieving 98.14% accuracy. Hyperparameters are optimized using grid search. They used four datasets, including RIDER, REMBRANDT, and 3064 MRI images. Grid search helps identify the best parameter combination, and the models are assessed using accuracy, specificity, sensitivity, precision, and ROC curve AUC. An overall classification accuracy of 92.66% is obtained for brain MRIs.

Ayesha Younis, Li Qiang, Charles Okanda Nyatega, Mohammed Jajere Adam, and Halima Bello Kawuwa critically assess solutions using the VGG 16 model for brain tumor detection via a Convolutional Neural Network (CNN). VGG 16 is chosen for its efficiency. Their study offers an effective method for quick, accurate brain tumor detection using MRI. A multilayer CNN is deployed on 253 MRI brain images, 155 of which show tumors. They use Python to handle variations in MRI images, correct artifacts, and normalize intensity. Their CNN model achieves high accuracy, and ensemble techniques further improve the results, with an accuracy of 98.14%.

The proposed research work can aid in better feature extraction and improved generalization, reducing the risk of overfitting, especially when the dataset is limited. RESNET50 is designed with skip connections that facilitate the flow of gradients during training. This helps in training deeper networks more effectively and mitigates overfitting issues. The proposed solution leverages a pre-trained RESNET50 model as a starting point can save significant training time and resources. It can give better results with fewer computational demands and simpler model management.RESNET50, being a well-established architecture, often requires fewer hyperparameter adjustments compared to custom-built CNNs. This simplifies the hyperparameter tuning process . Training a single RESNET50 model is often more efficient than training multiple machine learning classifiers.This project streamlines the workflow, making it more cohesive and less prone to errors. Inference time is also typically faster with deep learning models.

III. IMPLEMENTATION

A brain tumor is an uncontrolled malignant growth of cells in the brain and is considered one of the deadliest types of cancer in people of all ages. Early detection of brain tumors is necessary for appropriate and accurate treatment. This research presents a new and effective brain tumor classification method from magnetic resonance images using ResNet50.The prime goal of this project is to develop an advanced and accurate diagnostic tool that can effectively classify brain tumors into specific categories, including Meningioma, Glioma, and Pituitary tumors, using medical imaging data, particularly MRI and CT scans.

Data Collection: The first and crucial step is the collection of a well-structured and diverse dataset of brain MRI images. The dataset are comprehensive, containing images representing different brain tumor scans. The dataset complies with ethical guidelines and regulations, including obtaining informed consent from patients for using their medical data in research is important. Each image in the dataset is appropriately annotated with its corresponding label, indicating whether it belongs to one of the tumor categories or the no-tumor category. The number of images in each class are balanced to prevent class imbalance issues. It ensures diversity within each class by including images from different patients, different scanners, and various imaging parameters. This diversity helps the model generalize well. We have used BRAIN TUMOR DATASET by Jun Cheng . This brain tumor dataset contains 3064 T1-weighted contrast-inhanced images from 233 patients with three kinds of brain tumor: meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices).

Data Preprocessing: MRI images collected from various sources may have different dimensions. To ensure uniformity, all images are resized to a consistent resolution. The images are resized to 512x512 pixels, which is a common resolution for medical image analysis. Normalization is applied to scale pixel values to a standard range, typically between 0 and 1. This step helps the model converge faster during training and reduces the impact of varying image intensity. Data augmentation is a crucial technique to enhance the model's ability to generalize. Images are randomly rotated by various degrees to simulate different orientations, Horizontal and vertical flips creating mirror images, further diversifying the dataset. The dataset is split into training, validation, and testing sets. A common split ratio is approximately 70% for training, 15% for validation, and 15% for testing. This ensures that the model is trained on a substantial portion of the data while maintaining separate sets for evaluation.The labels associated with each MRI image are one-hot encoded. The categorical labels are converted into a binary format that is compatible with deep learning models.

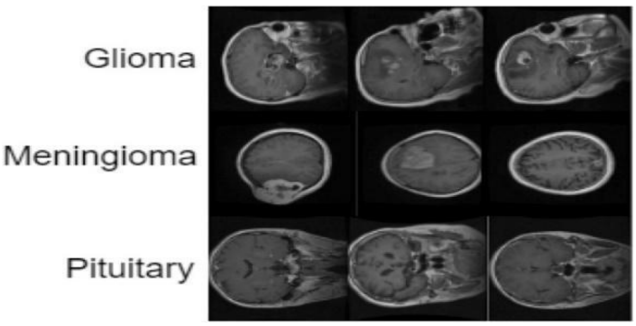

Figure 2. Types of Brain Tumor

Model architecture: ResNet-50, short for Residual Network with 50 layers, is a convolutional neural network architecture. ResNet-50 is particularly known for its deep architecture, which enables the training of very deep neural networks effectively.Input Layer: ResNet-50 typically takes RGB images as input, and the standard image size is 224x224 pixels.Convolutional Layers: The model starts with a 7x7 convolutional layer with a stride of 2. This layer is followed by a 3x3 max-pooling layer with a stride of 2.Residual Blocks: The core idea behind ResNet is the introduction of residual blocks. These blocks allow the network to learn residual functions instead of directly learning the desired output mapping. Residual blocks are stacked to form a deep neural network. ResNet-50 consists of 16 residual blocks, which are organized into five stages.The first stage includes a 1x1 convolutional layer followed by three residual blocks.The second stage has four residual blocks. The third stage also contains six residual blocks.The fourth stage includes three residual blocks. The fifth stage has one residual block. A global average pooling layer is applied after the last residual block. This reduces the spatial dimensions to 1x1 while retaining the depth. A fully connected layer with 1000 units is used as the output layer in the original ResNet-50. This final layer is responsible for predicting the class probabilities for 1000 ImageNet classes in the original task. The activation function used within the residual blocks is typically the rectified linear unit (ReLU).

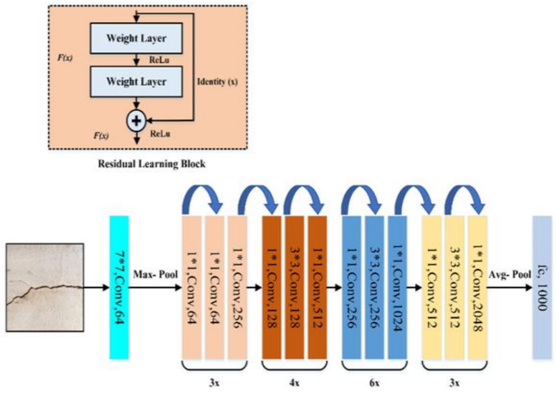

Figure 3.Architecture of ResNet-50

Model customization : The ResNet-50 model is customized to suit the specific task of classifying brain tumors into different categories Meningioma, Glioma, Pituitary. The final fully connected layer of the ResNet-50 model, originally designed for ImageNet's 1000 classes, is modified to match the number of classes in the brain tumor dataset.The number of output units in the final fully connected layer is changed to three to accommodate the three tumor categories.The activation function used in the final layer may be modified based on the specific classification task. The LogSigmoid activation function is applied.The pre-trained ResNet-50 model with the customized final layer is fine-tuned on the brain tumor dataset. During fine-tuning, the model learns to adapt its weights to the features of the brain tumor images. The model is trained to minimize a loss function, typically the Cross-Entropy Loss, which measures the dissimilarity between predicted class probabilities and true labels.The proposed research work specifies hyperparameters for training, including the learning rate and the number of training iterations (epochs). The optimizer used is Stochastic Gradient Descent (SGD) with a momentum term.

Model training The project uses the Cross-Entropy Loss as the loss function for training. This loss function quantifies the dissimilarity between the predicted class probabilities and the true labels.Stochastic Gradient Descent (SGD) is chosen as the optimizer for training. It includes a momentum term of 0.9, which helps accelerate convergence.The training process runs for a specified number of epochs. In this case, the project runs the model for 30 total iterations, which can be adjusted as needed.Lists are initialized to keep track of training losses, validation losses, training accuracies, and validation accuracies during the training process. The model is set to training mode.For each batch of training data, The input data (images) and labels are loaded onto the GPU if available. A forward pass is executed, which involves passing the input data through the model to obtain predicted class probabilities.The training loss is computed based on the predicted probabilities and the true labels.The predicted labels are determined by selecting the class with the highest probability. The number of correctly classified samples in the batch is calculated.The optimizer's gradients are set to zero. Backpropagation is performed, and the model's weights are updated using the computed gradients. Training metrics are tracked, including the training loss and the training accuracy.

Model validation: The model is set to evaluation mode (no gradient updates).For each batch of validation data, The input data and labels are loaded onto the GPU if available.A forward pass is performed to obtain the predicted class probabilities.The predicted labels are determined.The number of correctly classified samples in the batch is calculated.The validation loss is computed.Validation metrics are tracked, including the Validation loss and the Validation accuracy for each batch.

Model Checkpoint Saving: Model checkpoints are crucial for saving the model's state at various stages during training. These checkpoints serve as snapshots of the model's parameters, allowing you to resume training from a specific point and preventing the loss of progress in case

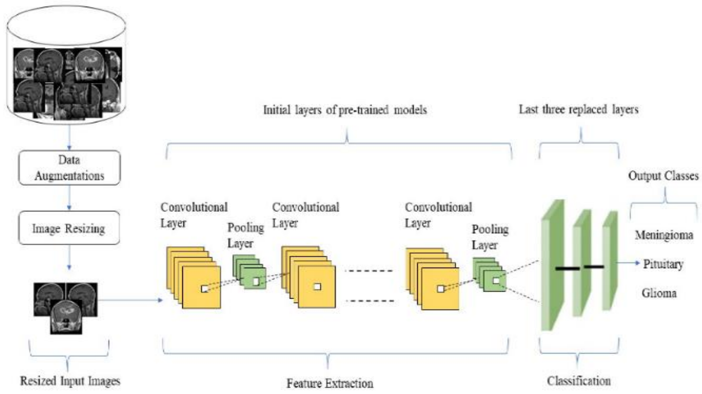

Figure 4. Working of the Model

during training, allowing you to recover your model's state if something goes wrong. These checkpoints provide a reliable mechanism for tracking and resuming training in the Brain Tumor Classification.

GPU Memory: After completing training, the project provides a summary that includes the training duration, GPU memory usage, and GPU memory cache information.

Model testing: The model testing phase in the Brain Tumor Classification project using ResNet-50 involves evaluating the trained model's performance on a dedicated testing dataset. This phase is crucial for assessing how well the model can generalize to unseen data, which is essential for real-world applications. The model is set to evaluation mode ensuring that the model remains consistent and does not learn during the testing phase.The testing dataset is divided into batches to facilitate efficient processing, and a **DataLoader** object is used to iterate through these batches. For each batch of testing data, both the input data and their corresponding labels are loaded. The model generates predicted class probabilities for each image in the testing batch.The predicted labels are determined based on the class with the highest probability. These predictions represent the model's classification decisions for each MRI image.

Performance metrics: It helps assess how well the model classifies brain tumor images. The loss function is a measure of how well the model's predictions match the actual labels. Lower values indicate better model performance.Cross-entropy loss quantifies the dissimilarity between the predicted probabilities and true labels. It encourages the model to assign high probabilities to the correct class.The loss is calculated during both training and validation phases. The model aims to minimize this loss during training.Higher accuracy indicates better classification.It counts the number of correct predictions and divides it by the total number of predictions.Training and validation accuracy are monitored to assess the model's classification performance.Confusion Matrix provides insights into the model's classification errors.Each cell in the matrix represents the count of samples in a specific prediction category. Diagonal cells represent correct classifications, while off-diagonal cells represent misclassifications. The confusion matrix is used to analyze the types and frequency of classification errors in different classes.Classification Report: The classification report provides a summary of important classification metrics for each class, including precision, recall, F1-score, and support. The classification report is used to assess the model's performance on individual tumor classes.Jaccard Similarity Score calculates the size of the intersection divided by the size of the union of two sets. The Jaccard similarity score is used to assess the model's ability to segment tumors accurately.

Model Deployment: After successfully training and validating the ResNet-50 model for brain tumor classification, the initial deployment involves exporting the model, including its architecture and weights. Select a suitable server or cloud-based environment with ample computational resources. Create an API for the model and load the ResNet-50 model using PyTorch within the deployment environment for making predictions. Data preprocessing steps are vital to align input data with the model's expected format. Developing code to handle incoming API requests, particularly for image data and classification, is essential. Ensure predictions are returned in an appropriate format, such as JSON, and format the responses logically. Scalability is essential, and load balancing may be needed for handling multiple concurrent requests. Implement security measures, including authentication, encryption, and access control. Logging and monitoring are crucial for tracking and maintaining performance.For user-facing applications, develop a user-friendly interface. Rigorous testing, including unit, integration, and end-to-end testing, is necessary to ensure the model functions as intended. Thorough documentation for the model and API is essential for users and developers.Implement a continuous integration/continuous deployment (CI/CD) pipeline for automated updates. If healthcare professionals or end users are involved, provide training and guidance on system usage.

Continuous monitoring is essential for tracking accuracy, response times, and user feedback in real-world settings.

The architecture for brain tumor classification using ResNet-50 is a sophisticated and meticulously structured framework designed to harness the power of deep learning for medical image analysis. generalize and make accurate predictions on unseen data. Performance metrics such as accuracy and loss are closely monitored at the end of each training epoch.

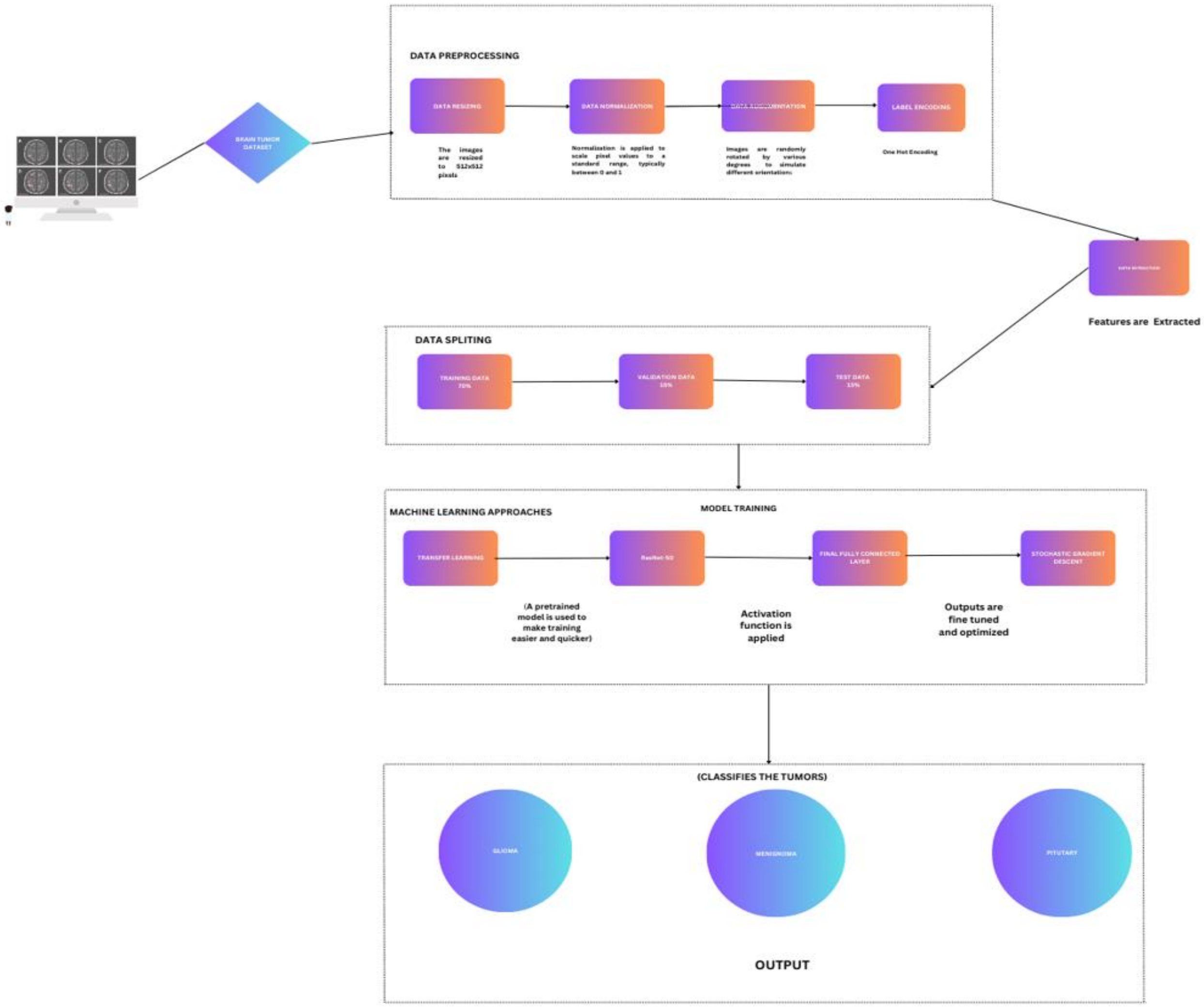

Figure 5. Architecture of the Proposed solution

IV. RESULTS AND DISCUSSIONS

The fundamental goal of our proposed solution was to develop an advanced and accurate diagnostic tool that can effectively classify brain tumors into specific categories, including Meningioma, Glioma, and Pituitary tumors, using medical imaging data, particularly MRI and CT scans. We concluded that our model did not infuse overfitting or underfitting due to the skip connections which facilitates the flow of gradients during training. It leverages deep learning techniques to achieve a high level of accuracy in classifying brain tumors which can aid healthcare professionals in making more precise and reliable diagnoses. We discovered that our deep learning model i.e. ResNet50 , was advantageous over other models for training and classification tasks. It requires fewer hyperparameter adjustments compared to custom-built CNNs. We discovered that training a single well-optimized RESNET-50 model is often more computationally efficient than conducting an extensive grid search, using many classifiers. Various performance metrics were used such as Precision , Recall , f1-score, support.

- Training set - Total length of training samples divided by 100 for every trained sample
  - `int((2144 * 8)/100) = int(171.52) = 171`
- Testing set - Total length of testing samples divided by 100 for every testing sample
  - `int((460 * 8)/100) = int(36.8) = 36`

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FN} \\ F1 &= \frac{2 \times precision \times recall}{precision + recall} \\ accuracy &= \frac{TP+TN}{TP+FN+TN+FP} \\ specificity &= \frac{TN}{TN+FP} \end{aligned}$$

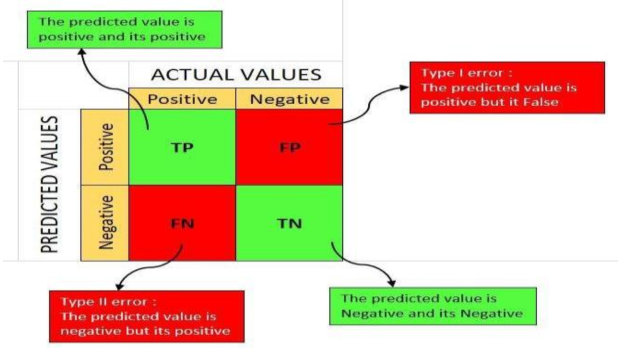

Figure 6. Performance Metrics

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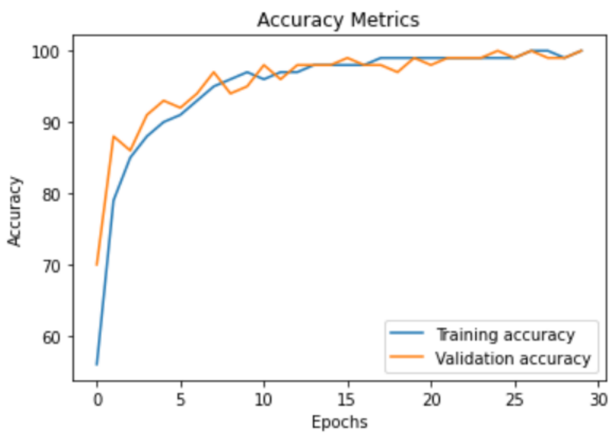
V. COMPARATIVE ANALYSIS

Training and Validation Accuracy between AlexNet and ResNet50 : While both AlexNet and ResNet-50 can achieve high training accuracy, ResNet-50 is generally expected to outperform AlexNet in terms of validation accuracy. ResNet-50's architectural advancements, including residual connections, allow it to capture complex patterns and generalizes well to new and unseen brain tumor images. This improved generalization is vital in medical image classification tasks, where accuracy and reliability are crucial for diagnosis and patient care.



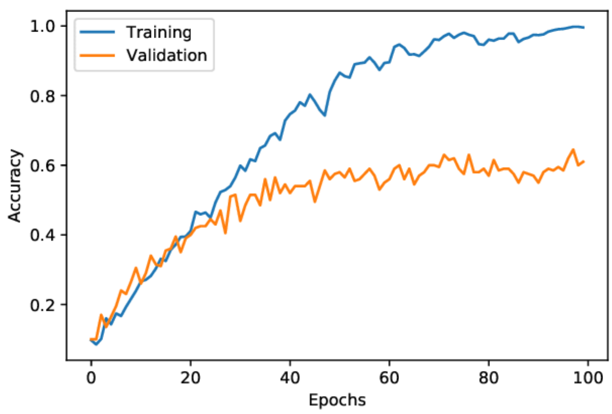
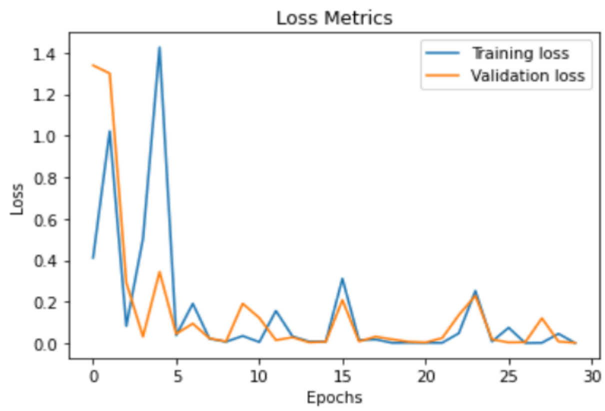


Figure 7. Training and Validation Accuracy of ResNet-50 Figure 8. Training and Validation Accuracy of AlexNet

Training and Validation Loss between AlexNet and ResNet50: ResNet-50 generally outperforms AlexNet in terms of training and validation loss. Its architecture allows for more efficient training by reducing overfitting. The smaller gap between training and validation loss signifies better generalization and robustness to new brain tumor images. While AlexNet can achieve competitive training loss, it often struggles with high validation loss due to overfitting. ResNet-50's architecture contributes to more balanced and lower training and validation losses, making it a superior choice for brain tumor classification where generalization is crucial for accurate and reliable results.



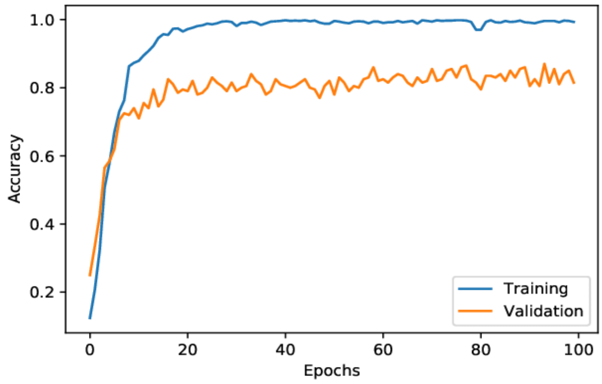


Figure 8. Training and Validation Loss of ResNet-50 **Figure 10. Training and Validation Loss of AlexNet-50**

VI. CONCLUSION

The model achieved a high classification accuracy in distinguishing between different brain tumor types, including Meningioma, Glioma, and Pituitary tumors. The final test accuracy reached approximately 99.32%. ResNet-50, a powerful convolutional neural network (CNN), effectively extracted discriminative features from brain MRI images. The model's architecture allowed it to capture intricate patterns and variations in the data. The training process was robust and efficient, with relatively fast convergence. The model benefited from transfer learning using pre-trained ResNet-50 weights, reducing the amount of data needed for training. Data augmentation techniques, including random rotations and flips, improved the model's ability to generalize across different orientations of MRI images. With further optimization, the model can be deployed for real-time inference, making it valuable for clinicians in diagnostic settings. The project provided comprehensive performance metrics, including a confusion matrix, classification report, and Jaccard index.The potential for integrating interpretability techniques, such as Grad-CAM, was discussed, which could provide transparency into the model's decision-making process. The project lays the foundation for the development of a clinical decision support system for brain tumor diagnosis. The code and methodology provide a valuable resource for educational purposes and further research in medical image analysis and deep learning. The project outlined several future enhancements, such as increasing dataset diversity, real-time deployment, and interpretability.

VII. FUTURE ENHANCEMENTS

Expanding the dataset with more diverse MRI images from different sources and populations can improve the model's ability to handle a wider range of cases and variations. Implement more advanced data augmentation techniques to generate additional training samples. This can include 3D rotations, elastic deformations, and simulated MRI artifacts. Combine multiple deep learning models or architectures to create an ensemble model, which can enhance classification accuracy and robustness. Develop methods for interpreting the model's decisions, such as attention mechanisms or Grad-CAM (Gradient-weighted Class Activation Mapping), to provide insights into the model's decision-making process. Optimize the model and deployment process to provide real-time predictions for MRI scans, making it valuable in clinical settings. Integrate additional patient data, such as clinical information or genetic data, to improve diagnosis accuracy. Implement hardware acceleration using GPUs, TPUs, or dedicated AI hardware to speed up inference and reduce latency. Use AutoML techniques to automate model selection, architecture search, and hyperparameter optimization to find the best-performing model configurations. Adapt the model for deployment on edge devices and mobile applications, enabling remote diagnosis and monitoring. Extend the classification capabilities to include additional brain tumor types and subtypes for a more comprehensive diagnostic system. Develop mechanisms for the model to continuously learn from new data and adapt to changing tumor characteristics over time. Collaborate closely with medical professionals to integrate the system into clinical workflows and validate its accuracy and utility. Engage with the open-source community and collaborate with other researchers to advance the state of the art in brain tumor classification.

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