Brain Tumor Classification: Leveraging Transfer Learning via EfficientNet-B0 Pretrained Model

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***Abstract*—Brain tumor classification from MRI scans is an essential task in medical diagnostics, enhancing the precision and speed of treatment planning. This project introduces a deep learning model that automates the classification of brain tumors by leveraging a pre-trained convolutional neural network (CNN). The model processes MRI images and categorizes them into one of four possible classes: glioma, meningioma, pituitary tumor, or no tumor. By utilizing the EffnetB0 pretrained model, our approach benefits from learned features on a broad range of visual data, allowing for robust feature extraction even with a limited number of medical images. The dataset consists of MRI scans, each labeled according to the tumor type, facilitating supervised learning. The effectiveness of the model is assessed based on accuracy, precision, and recall metrics, aiming to support radiologists by providing a reliable preliminary diagnostic tool that improves the diagnostic workflow for brain tumors.**

Keywords—Brain tumor classification, pre-trained models, Deep learning

I. INTRODUCTION

The classification of brain tumors stands as a cornerstone in the realm of neuro-oncology [1], wielding significant implications for diagnosis, treatment planning, and prognostication. With advancements in imaging modalities, molecular profiling, and computational techniques, the landscape of brain tumor classification has witnessed a paradigm shift, transcending traditional histopathological boundaries[2]. In the pursuit of precision medicine, elucidating the intricate heterogeneity within brain tumors has become imperative, driving the quest for refined classification systems that align with their underlying biological characteristics[3].

Brain tumors constitute a diverse array of neoplasms arising from the intricate milieu of the central nervous system. Their clinical manifestations, therapeutic responses, and prognostic outcomes are inherently linked to their molecular signatures[4], cellular origins, and morphological features. Historically, brain tumor classification has primarily relied on histopathological criteria, encompassing a spectrum from benign to malignant entities. However, this conventional taxonomy often falls short in capturing the nuanced complexities of tumor behavior and therapeutic responsiveness[5].

In recent years, the advent of high-throughput omics technologies has revolutionized our understanding of brain tumor biology, unraveled intricate molecular subtypes and signaled pathways that underpin tumorigenesis and progression[6]. Integrating multi-omic data, including genomics, transcriptomics, epigenomics, and proteomics, has heralded a new era of molecular taxonomy, reshaping our conceptualization of brain tumor classification[7]. This molecular-driven approach not only refines diagnostic precision but also holds promise for personalized therapeutic strategies tailored to the unique molecular profiles of individual tumors[8].

Moreover, the emergence of artificial intelligence and machine learning methodologies has empowered the field with robust computational tools for pattern recognition, feature extraction, and predictive modeling. Harnessing the power of these technologies, researchers have endeavored to develop innovative classification frameworks capable of discerning subtle distinctions between tumor subtypes, thereby facilitating more accurate diagnosis and prognostication[9].

Herein lies the promise of AI in healthcare, particularly in the realm of brain tumor detection. By leveraging advanced algorithms and machine learning techniques, AI systems can analyze vast amounts of medical imaging data with unprecedented speed and precision. These systems can detect subtle abnormalities in brain scans that may elude human perception, leading to earlier and more accurate diagnoses[10].

Moreover, AI-powered diagnostic tools can aid healthcare professionals in decision-making processes by providing supplementary information and insights derived from comprehensive data analysis. This not only enhances diagnostic accuracy but also facilitates personalized treatment planning tailored to individual patient needs[11].

This research paper endeavors to elucidate the contemporary landscape of brain tumor classification, encompassing the evolution from traditional histopathological schemes to molecular and computational paradigms. Through a comprehensive synthesis of literature, we aim to delineate the inherent challenges, current methodologies, and future directions in brain tumor classification, with a focus on advancing precision oncology paradigms for improved patient care and outcomes.

II. Related work

Recent advancements in artificial intelligence (AI) have significantly impacted the healthcare industry, especially in the field of brain tumor classification using deep learning models. This section discusses notable studies and compares their methodologies and outcomes with the findings of our study on brain tumor classification using pretrained EfficientNet models.

A. *Transfer Learning Models*

Khaliki and Başarslan (2024) [12] utilized various CNN-based transfer learning models like EfficientNetB4, VGG19, and Inception-V3 for classifying brain tumors from MRI images. They reported high accuracy levels, demonstrating the effectiveness of transfer learning in enhancing diagnostic processes in healthcare.

Deepa AB and Dr. Vargheese Paul (2024) [13] highlighted the utility of transfer learning in overcoming the challenges of sparse datasets in brain tumor classification.

They proposed a selectively fine-tuned model, integrating max pooling and dense layers into pre-trained architectures, achieving accuracy levels above 90%. This approach effectively mitigates the risk of overfitting, a common issue in medical image analysis due to the high dimensionality and variability of medical images

B. *Comparative Studies and Comprehensive Models*

These studies have explored the potential of CNNs and transfer learning in brain tumor classification. For instance, researchers have compared the performance of different pretrained models such as VGG16, ResNet-50, and InceptionV3, with findings suggesting that these models provide a robust framework for early diagnosis and rapid treatment of brain tumors.

C. *Challenges and Future Directions*

While transfer learning offers a robust approach for leveraging pretrained models on large datasets like ImageNet, challenges remain in terms of model selection and adaptation to specific medical imaging tasks. Future research could explore the integration of more diverse data sources and advanced model training techniques to further enhance the performance and reliability of these systems.

D. *Our Study's Contribution*

Our research contributes to this growing body of knowledge by transfer EfficientNet, a pretrained model, specifically for brain tumor classification. We demonstrated that layers of a pretrained model could significantly enhance classification accuracy when tested on distinct brain tumor types.

The integration of AI and deep learning in medical imaging, particularly using CNNs and transfer learning models, continues to show promising results in improving the accuracy and efficiency of diagnosing critical conditions such as brain tumors. Our study aligns with the current trends and advances the field by fine-tuning EfficientNet models to meet the specific needs of medical imaging diagnostics[14].

III. Materials

The dataset [15] is an open-source brain tumor dataset that merges data from three sources:

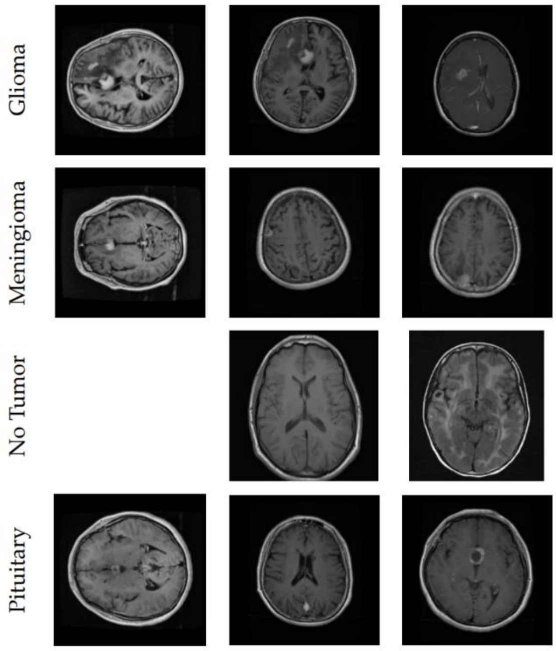

Fig.1. Sample of Dataset.

Figshare , SARTAJ , and Br35H , resulting in a total of 7023 brain MRIs. This dataset represents four categories: healthy brain images, meningioma, pituitary, and glioma tumors. Concretely, there are 2000 images of healthy individuals, 1621 glioma images, 1645 meningioma images, and 1757 of pituitary tumors. Figure 1 shows example MR images from the dataset

We divided the datasets into train, validation, and test. First, we split the datasets into 80% train and 20% test. Then, we split 10% of the training datasets into validation.

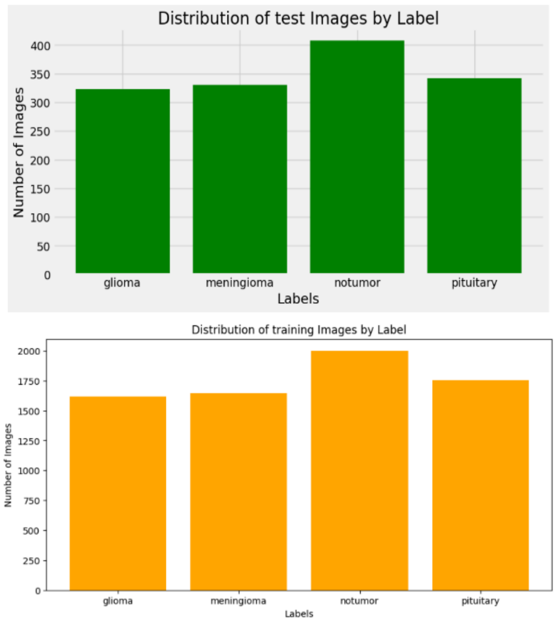

Fig.2. Distribution of Training and Test images by Label.

IV. Methods

A comprehensive explanation of each specific step within the suggested methodology is presented in the subsequent sections.

A. Pre-processing

To begin, the input images are down sampled to $150 \times 150 \times 3$ so that the resulting tensor can be properly processed by the pre-trained EfficientNet model. By maintaining image content and features during scaling, computational effort is reduced during network training.

And then Converting categorical labels to indices. This is achieved by finding the index of each label in a predefined list (labels). This step converts textual or categorical labels into numeric form, which is easier to handle computationally.

After converting the labels to numeric indices, the indices are transformed into a binary matrix format known as one-hot encoding. This is essential for categorical data in classification tasks where the algorithm (like many neural network architectures) benefits from receiving the labels as vectors with a binary class matrix.

This format explicitly defines which class each sample belongs to without implying any ordinal relationship between the classes.

These steps are crucial for preparing the dataset for effective training and evaluation of a neural network model, ensuring that the input data meets the expected format and structure required by TensorFlow and Keras frameworks.

B. Deep learning

Deep learning is a subset of machine learning that focuses on training artificial neural networks to perform complex tasks by learning patterns and representations directly from data. Unlike traditional machine learning approaches that require manual feature engineering, deep learning algorithms autonomously extract hierarchical features from data, leading to the creation of powerful and highly accurate models. In this study, CNN architecture is employed. Convolution neural network Convolutional neural networks represent a breakthrough in deep learning and computer vision. These architectures are specifically designed to extract meaningful features from complex visual data, such as images and video. The inherent structure of the CNN, consisting of convolutional layers, pooling layers, and fully connected layers, mimics the ability of the human visual system to recognize patterns and hierarchical features[16].

Convolutional layers use convolutional operations to detect local features, which are then progressively abstracted by pooling layers that condense the information. The resulting hierarchical representations are then fed into fully connected layers for classification or regression tasks. CNN have redefined the landscape of image recognition, achieving remarkable success in diverse domains ranging from image classification and object detection to face recognition and medical image analysis.[17]

C. Transfer learning

Transfer learning offers a solution to the challenge of limited data availability, particularly in specialized fields like medical imaging, such as brain tumor classification from MRI scans. Unlike traditional machine learning methods, Convolutional Neural Networks (CNNs) automatically extract both low-level and high-level features from data, making them powerful tools for tasks like image classification. However, CNNs often require large datasets to train accurately and avoid overfitting. In cases where obtaining a substantial annotated dataset is impractical, transfer learning comes into play.

Transfer learning involves leveraging the knowledge gained by training models on extensive benchmark datasets like ImageNet and applying it to similar or different tasks, such as medical image classification. While directly using pre-trained CNN architectures for inference on target datasets like MRI scans may not generalize well due to domain differences, fine-tuning the pre-trained models' layers can align them with the specific characteristics of the target images.[18]

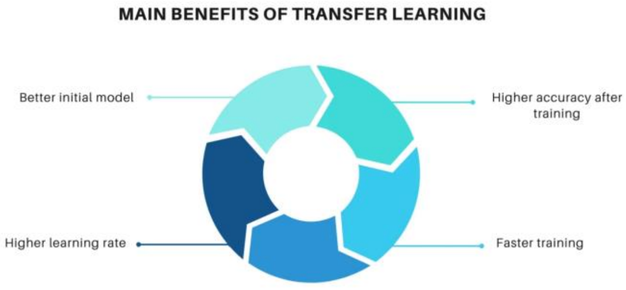

Fig.3. Main Benefits of Transfer Learning.

D. EfficientNet

EfficientNet is a family of scalable and efficient CNN models. The main goal of this series is to achieve better performance with fewer parameters. the term " EfficientNet" is a combination of the words "efficiency" and "network". The model series is mainly used in visual processing tasks such as image classification. EfficientNet is a family of models that delivers competitive results in both performance and computational cost. It offers variations of different size and complexity at different scales. Higher numbered models are typically larger and more complex but require more computing power. It was the top performing model in the ImageNet competition.

In the presented study, transfer learning is applied using pre-trained EfficientNet models, specifically EfficientNetB0 which are transfer learnt using MRI sequences from the MRI brain tumor dataset. Details will be provided in subsequent sections on how the classification layer of these pre-trained models is transferred, along with experimental configurations for training, evaluating the model, and its performance on unseen test instances.[19]

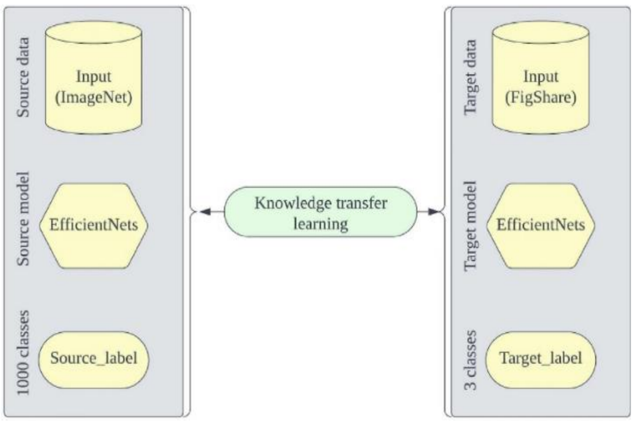

Fig.4. Configuration of Transfer Learning.

E. Model Configuration

The EfficientNet B0 model, pretrained on ImageNet, was employed as the foundational architecture. A common pattern used to adapt a pre-trained model for a new classification task by adding custom layers on top. This is a typical approach in transfer learning where the pre-trained model acts as a fixed feature extractor and the added layers adapt those features to a new task.

Custom Layers: Building upon the feature extraction capabilities of EfficientNet, we extend the model with a sequence of densely connected layers and regularization mechanisms to fine-tune the model for our classification task. The architecture is as follows:

Global Average Pooling 2D Layer: This layer follows the EfficientNet and is used to reduce the spatial dimensions of the output from the base model to a single 1D vector per channel. This reduction helps in minimizing overfitting by reducing the number of parameters in the model.

Dense Layer with 4096 Units (ReLU Activation): The first dense layer is designed to interpret the features extracted by the EfficientNet, using a high number of neurons (4096) to capture complex patterns.

Dropout Layer (30% Rate): To prevent overfitting, a dropout layer is introduced post the first dense layer, randomly setting 30% of the input units to zero during training.

Sequential Dense Layers: Following the initial dense layer and dropout, the architecture includes two more dense layers with 1024 and 512 units respectively, each followed by ReLU activation. These layers further refine the feature representation for the classification task.

Batch Normalization: Between the successive dense layers, batch normalization is employed. This layer normalizes the activations from the previous layer at each batch, maintaining mean output close to 0 and the output standard deviation close to 1. This normalization helps in accelerating the training process by stabilizing learning.

Dropout Layer (50% Rate): Another dropout layer with a higher dropout rate of 50% is added after the batch normalization to enhance the regularization effect, further aiding in mitigating the model's overfitting.

Output Layer (4 Units, Softmax Activation): The final layer of the model is a dense layer with 4 units, corresponding to the number of classes in the classification task. It uses a softmax activation function to output the probability distribution over the four classes.

By integrating a robust pre-trained model with custom-tailored dense layers and regularization techniques, our architecture is designed to tackle the image classification task efficiently and effectively. This setup not only leverages the generalizability of EfficientNet but also adapts to the specific nuances of our dataset through the trainable dense layers.

F. Experimental setup

In the beginning of this section, we will outline the necessary hardware and software requirements for training and evaluating the model. Subsequently, we will delve into the analysis of various hyperparameters, making explicit adjustments until an optimal combination is found. Finally, we will provide a concise explanation of each performance metric used during the model evaluation to conclude this section.

G. Approval for participation

As the data is open source, there are no experiments on humans conducted by the authors. Open source has been studied on MRI images.

H. System requirements

The experiments were conducted on Google Colaboratory, an open-source notebook platform provided by Google. This platform offers access to both free and premium GPU and TPU resources, which are valuable for academic and research purposes. The models were trained using T4 GPU. The coding was done in Python, and the TensorFlow and Keras APIs were used for the backend and frontend of the system, respectively.

I. Hyper parameter settings

Hyperparameters, which are training parameters, was conducted to find the most suitable settings for model training. These hyperparameters include batch size, optimizers, learning rate, epochs, and loss function. Categorical cross-entropy was chosen as the loss function since the task involves classifying brain tumors into glioma, meningioma, and pituitary tumor categories, constituting a multi-class classification challenge. The initial configuration for EfficientNet model involved using Adam as the optimizer and a learning rate of 0.001 (1e−2).

To monitor the model's performance, the validation accuracy was observed every 5 iterations, and the initial learning rate was reduced by a decay factor of 0.2. A dropout rate of 0.2 and 0.5 was employed for further regularization during model training, without affecting the ImageNet weights. The training of EfficientNetB0 was performed over 50 epochs. To evaluate the model's performance and detect overfitting, 10% of the images from the training dataset were set aside as a validation set after each epoch.

Since EfficientNet has been trained on ImageNet, which has 1000 classes, we will likely need to adjust the top of the network for your number of classes:
Remove the top layer (fully connected layer and SoftMax) of the pre-trained model.

Add new layers that are appropriate for our task. Typically, this includes a GlobalAveragePooling2D layer followed by three Dense layers and with the final Dense layer having several units equal to the number of target classes, activated by a SoftMax function for classification tasks. Performance metric evaluation

V. Performance Metric Evaluation

Accuracy, precision, recall, sensitivity, specificity, and F1-score are among the performance metrics employed to assess the overall performance of the proposed model. Furthermore, the generation of a confusion matrix highlights the class-wise predictions made by the model on unseen test examples. Subsequent subsections will delve deeper into each evaluation metric, offering more comprehensive discussions following a brief description of each.[20]

A. Sensitivity (Se)

In the context of medical diagnosis, particularly in tasks like brain tumor categorization, the model’s sensitivity and recall have a crucial role in determining the presence or absence of a brain tumor in a patient. Sensitivity, also known as the true positive rate (TPR), is pivotal; it represents the proportion of accurately predicted positive labels that are indeed positive. The following formula enables the quantification of the model’s sensitivity and recall[21]:

$$Sensitivity\ (Recall) = \frac{TP}{TP + FN} \quad (1)$$

B. Precision

Is a measure of the accuracy of a model's positive predictions. It is defined as the ratio of true positives to the total number of predicted positives, which includes both true positives and false positives. Mathematically, precision is expressed as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

C. Accuracy (Acc)

The accuracy of the model is determined by the ratio of correctly predicted labels to the total number of labels. This yields a percentage that reflects the expected accuracy of the tested model. A formula is available for computing precision, which is a key evaluation metric in classification tasks[22].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

D. F1-score

The F1-score, commonly referred to as the F-measure, serves as the harmonic means between a model’s accuracy and recall. This metric offers a comprehensive assessment of the model’s overall performance. The F1-score underscores the need for a balance between precision and recall. The formula for calculating the F1 score is presented below:

$$F1 - Score = 2 * \frac{Precision}{Precision + Recall} \quad (4)$$

E. The Area Under the Curve (AUC)

AUC represents the degree or measure of separability achieved by the model. It tells how much the model is capable of distinguishing between classes, higher AUC values indicate better model performance.

Interpretation of AUC:

AUC = 0.5

- The model has no discrimination capacity to distinguish between positive and negative class.

0.5 < AUC < 1.0

- The model is better at predicting the positives from the negatives. The closer the AUC to 1, the better.

AUC = 1

- The model perfectly discriminates between all positive and all negative instances.

F. Confusion matrix

A confusion matrix, sometimes referred to as an error matrix, is a structured table used to display data about actual labels (ground truth) and predicted class assignments.

It not only provides an overall summary of the model's performance but also offers a more detailed insight into how well the model generalizes across individual classes. The layout of the confusion matrix typically positions the ground truth along the y-axis, while the predicted class labels are represented along the x-axis.

VI. Results

The transfer learning of the pre-trained EfficientNetB0 model on our dataset, consisting of four distinct classes of medical images, has shown significant improvement in classification accuracy, the pre-trained EfficientNetB0, with its top layers reconfigured and lower layers frozen, achieved a baseline accuracy of 96.44% on the validation set.

This phase involved training only the newly added top layers to prevent catastrophic forgetting of useful features learned from the ImageNet dataset. figure below shows the training and validation accuracy of our presented model

The transfer learning process not only improved accuracy but also enhanced the model’s ability to generalize, as evidenced by the performance on the unseen test set, where the model achieved an accuracy of 97.08%.

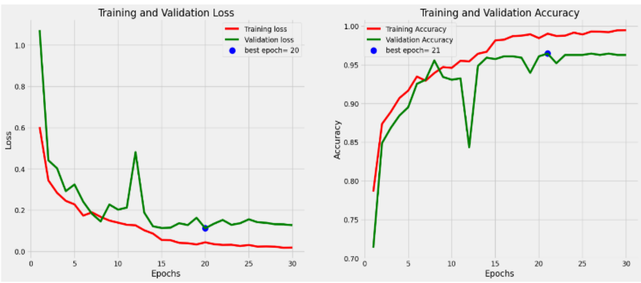

Fig.5. Performance of our Model.

Further analysis through the confusion matrix revealed high precision and recall rates across all classes, with particularly strong performance in distinguishing between glioma and meningioma tumors, which are often challenging to classify.

The precision scores were as follows: glioma (96%), meningioma (93%), no tumor (100%), and pituitary (99%). Recall scores were equally robust: glioma (94%), meningioma (96%), no tumor (99%), and pituitary (99%). F1 score: glioma(0.95), meningioma (94%), no tumor (99%), and pituitary (99%).

The AUC: (0.96501815)

The following figure illustrates the classification report metrics per class, highlighting the balanced performance across the board:

Classification Report			
Tumor type	Precision	Recall	F1 score
Glioma	0.96	0.94	0.95
Meningioma	0.93	0.96	0.94
No tumor	1.00	0.99	0.99
Pituitary	0.99	0.99	0.99

TABLE 1. Classification Report.

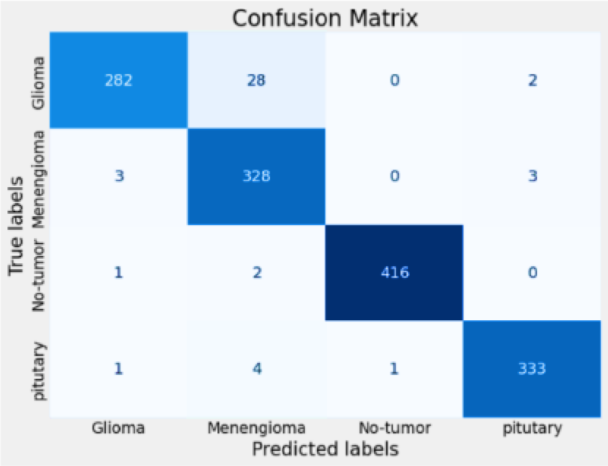

Fig.6. Confusion Matrix of Our Model.

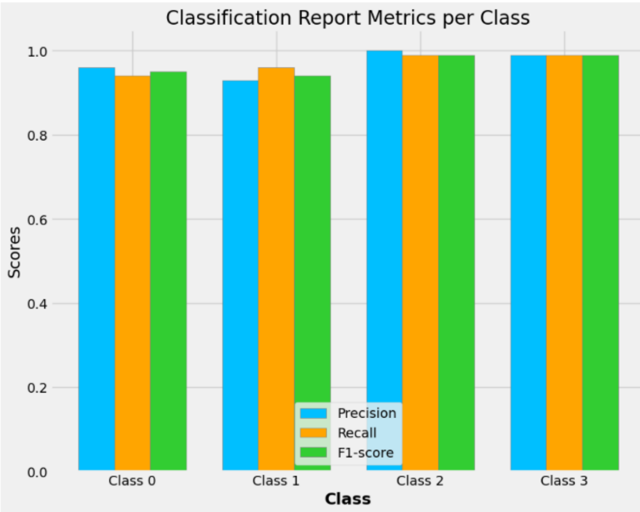

Fig.7. Classification Report Metrics Per Class.

These results underscore the efficacy of leveraging transfer learning via fine-tuning pre-trained models, particularly EfficientNet, for specialized tasks in medical image analysis, reducing the need for extensive labeled datasets and computational resources.

VII. Conclusion

This study utilizes transfer learning with pre-trained EfficientNet (EfficientNetB0) to perform multi-class classification of brain tumors using MR images of four tumor types: glioma, meningioma, no tumor, and pituitary tumor. The pre-trained ImageNet weights are loaded into the foundational model, and the architecture of EfficientNet B0 is adjusted by adding several top layers, including a convolutional base, dropout layers, batch normalization, and fully connected layers.

For the multi-class classification of brain tumor types, classifier is constructed on top of the pre-trained EfficientNet convolutional base. The model is trained using combination of MRI brain tumor dataset, with fine-tuning of the hyperparameters for EfficientNet B0. The proposed fine-tuned EfficientNet is tested in multiple trials to evaluate its performance and achieves impressive overall test accuracy of 97.08%.

VIII. Future Work

Moving forward, future research should focus on addressing several key challenges, including the need for larger datasets to train and validate deep learning models, standardization of imaging protocols and feature extraction methods, and integration of multi-modal imaging techniques for comprehensive tumor characterization. Additionally, efforts should be made to translate these advancements into clinical settings, ensuring widespread accessibility and usability of advanced imaging technologies for improved patient outcomes.

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