

A DEEP LEARNING APPROACH FOR DETECTION OF BRAIN TUMOUR USING SOFTMAX CLASSIFIER AND BACK PROPAGATION.

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ABSTRACT: Brain tumors present significant health risks due to abnormal cell growth, potentially leading to organ dysfunction and mortality in adults. Magnetic resonance imaging (MRI) is crucial for tumor classification, but limited expertise in this area necessitates advanced methods for accurate diagnosis. Deep Learning has emerged as a pivotal tool, yet gaps remain in achieving optimal accuracy. This study addresses these gaps by proposing an enhanced model for classifying meningioma, glioma, and pituitary gland tumors, thereby improving precision in brain tumor detection. Trained on a dataset of 5712 images, the model achieves exceptional accuracy (99%) in both training and validation datasets, with a focus on precision. Leveraging techniques such as data augmentation, transfer learning with ResNet50, and regularization ensures stability and generalizability. Evaluation on a 1311-image test set reveals outstanding class-specific accuracies (glioma:98.33%, meningioma:94.44%, notumor: 100.00%, pituitary:100.00%). Comprehensive metrics including precision (0.983559), recall (0.983219), F1 score (0.983140), and AUC (ROC) (0.999038) underscore the model's efficacy. This study demonstrates the potential of deep learning in early brain tumor diagnosis, surpassing conventional methods and laying a robust foundation for future research in neural network-based classification algorithms for brain tumors.

INDEX TERMS: Abnormal brain tumor comprehensive evaluation, MRI DL, segmentation, types of brain tumor, MRI.

I. INTRODUCTION

A tumor is an uncontrolled proliferation of cancer cells in any region of the body. Tumors can vary widely in type, characteristics, and treatment approaches. Currently, brain tumors are categorized into several distinct types [1]. Before delving into brain tumor segmentation methods, it is essential to introduce the MRI preprocessing operations, as they directly influence the quality of the segmentation results. Additionally, there are numerous challenges in engineering solutions for brain tumor treatment, as highlighted by Lyon et al. [2]. Malignant brain tumors are among the most devastating forms of cancer, marked by dismal survival rates that have remained largely unchanged over the past six decades. This stagnation is primarily attributed to the scarcity of available therapies capable of navigating anatomical barriers without causing harm to delicate neuronal tissue. The recent progress in cancer immunotherapies offers a promising frontier for potentially treating these otherwise inoperable brain tumors. However, despite the promising outcomes observed in other types of cancer, limited headway has been made in the case of brain tumors. The human brain constitutes a vital organ with exceptional anatomical, physiological, and immunological complexities that impede the achievement of successful treatments. These unparalleled anatomical and physiological restrictions give rise to inherent technical challenges when designing therapeutic approaches that must efficiently function within the brain and its tumor immune microenvironment. To date, engineering strategies for implementing immunotherapies in the brain, beyond merely adapting existing extraneural immunotherapies, are lacking. Nevertheless, there exist ample opportunities for innovation. Approaching therapeutic strategies from an

engineering standpoint may allow us to harness a wider array of technologies to advance tailored treatment approaches that can effectively address the specific biological constraints associated with brain cancer treatment, ultimately facilitating improved brain cancer immunotherapies. Preprocessing of raw MRI images is a fundamental step in achieving accurate brain tumor segmentation. These preprocessing operations encompass tasks such as de-noising, skull-stripping, and intensity normalization, and they directly influence the quality of brain tumor segmentation results [3]. Annotating medical images requires significant time and expertise, making the identification of a large number of images particularly challenging. Several efforts have been undertaken to address the challenges mentioned. Transfer learning models have proven to be a valuable choice, especially in scenarios with limited labeled data for training [4]. The advancement in reducing human error and lowering mortality rates relies on the development of accurate and automated classification methods. To this end, automated tumor identification systems based on deep learning have emerged, aimed at diminishing the time and effort spent by radiologists on brain tumor analysis using MRI. Recent studies indicate that automated image analysis, complemented by clinical picture assessment, holds promise as a solution to save time and deliver dependable results. Furthermore, these automated assessments can play a pivotal role in enhancing the therapeutic management of brain tumors by alleviating the burden on doctors who would otherwise manually describe tumor growth. In essence, computer algorithms have the potential to offer robust and quantitative estimations of tumor characteristics [5], [6].

noteworthy medical issue, positioned as the tenth most common cause of mortality in the United States. It is estimated that approximately 700,000 individuals are afflicted by brain tumors, with 80 percent categorized as benign and 20 percent as malignant [7]. The challenges in this domain arise from substantial variations in brain tumor attributes, encompassing size, shape, and intensity, even within the same tumor category, along with resemblances to manifestations of other diseases. Misclassifying a brain tumor can lead to severe consequences, diminishing a patient's chances of survival. As a result, there has been a growing interest in the development of automated image processing technologies to address the limitations of manual diagnosis [8], [9]. Many researchers have delved into various algorithms for the identification and categorization of brain tumors, with a strong emphasis on achieving high performance and minimizing errors. Deep learning techniques, particularly Convolutional Neural Networks (CNN), have become increasingly prevalent in the development of automated systems that enable precise classification and segmentation of brain tumors within shorter timeframes. Deep learning harnesses the power of pre-trained models, particularly for the field of medical imaging, with a specific focus on the classification of brain tumors. The proposed model extends previous research on ensemble techniques by employing a blend of pre-trained models of Resnet-50 with additional dropout layers to make it fine-tuned version and yielding a remarkable accuracy rate of 99%. Deep learning encompasses intricate multi-layered neural networks, employing the backpropagation algorithm to minimize the error between the target and actual values. As the number of network layers escalates, the development of artificial neural network models becomes progressively more intricate and demanding [10]. A variety of techniques are applied to detect brain tumors in MRI images, with deep learning methods demonstrating significant progress in this domain. This study aims to compare models utilized in the context of brain tumor detection within the realm of deep learning methods [11]. One of the remarkable strategies entails the introduction of a Convolutional Neural Network referred to as the Brain Tumor Classification Model (BCM-CNN), created by Hanaa ZainEldin. The fine-tuning of the CNN's hyperparameters was achieved through the utilization of an innovative adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) algorithm. In the series of experiments, the BCM-CNN assumed the role of a classifier, and the outcomes showcased a substantial enhancement in CNN performance subsequent to the optimization of hyperparameters. The model underwent assessment employing the BRATS2021 Task1 dataset, yielding an exceptional accuracy rate of 99.99% in the realm of brain tumor detection [12]. Furthermore, an additional investigation carried out a comparative examination of diverse editions of the BRATS2018-2020 datasets employing CNN models. The experimental findings across these three datasets unveiled peak batch accuracies of 96.50%, 97.92%, and 98.79%, coupled with nadir batch accuracies of 95%, 96.50%, and 98%, correspondingly. Within this particular methodology, precision rates of 96.50%, 97.50%,

and 98% were realized in the context of brain tumor segmentation, and 96.49%, 97.31%, and 98.79% for brain tumor categorization pertaining to the BRATS2018, BRATS2019, and BRATS2020 datasets, respectively [13]. Moreover, an examination conducted by Diker A juxtaposed pre-existing deep learning architectures, such as AlexNet, GoogleNet, and ResNet-18, in the domain of brain tumor identification. The assessment scrutinized the efficacy of these models within the study [14]. Numerous investigations have delivered substantial innovations to the domain of brain tumor categorization by harnessing deep learning frameworks. These research endeavors have concentrated on enhancing precision and responsiveness in the classification of brain tumors evident in MRI images, with the potential to offer advantages to healthcare practitioners in this specialized area [15]. Within a specific research undertaking, an intricate convolutional neural network design, founded on the architectures of VGG16 and VGG19, was crafted with the intent of distinguishing the malignancy of brain tumors observed in MRI images. The results of these experiments indicated the superiority of this methodology over alternative, more recent brain tumor classification techniques in the aspects of precision, receptiveness, and distinctiveness. The proposition arises that this strategy might hold substantial utility for healthcare experts engaged in the realm of brain tumor categorization. Furthermore, it has the potential to extend its application to the categorization of various other medical conditions, encompassing liver lesions and other types of brain tumors [15]. An alternate investigation harnessed a DenseNet21 architecture for the classification of prominent categories of brain tumors, realizing an accuracy rate of 91%. The MRI images representing brain tumors were procured from widely-recognized benchmark datasets, constituting a collection of 7023 MRI images systematically grouped into four distinct classes: 'absence of tumor,' 'glioma,' 'meningioma,' and 'pituitary.' The model underwent optimization via adaptations to the concluding layer, enabling it to prognosticate the four class designations inherent in the data set. Through out the training stage, it demonstrated an accuracy of 91%, while during the testing phase, it maintained an accuracy rate of 88% [16]. Moreover, Binju et al., a group of researchers in the artificial intelligence domain, embarked on a study incorporating an experimental dataset encompassing 7038 domainspecific illustrations to facilitate the training of a dedicated model. By conducting experiments involving six distinct machine learning algorithms, these scholars effectively discerned Glioma tumors, Meningioma tumors, and Pituitary tumors, achieving a noteworthy accuracy level of 96%. This remarkable outcome was accomplished through the implementation of the RESTNET5.0 model, integrated with a transfer learning mechanism [17]. Several scholars have formulated intricate deep learning architectures designed for the categorization of atypical brain tumors, with a specific emphasis on Convolutional Neural Networks (CNN). An exemplar scenario encompasses the binary classification of GBM brain tumors, in which a dataset inclusive of 155 MRI images originating from the REMBRANDT database was employed. The employment of transfer learning, specifically leveraging pre-existing networks such as Google Net and Alex Net, facilitated the differentiation between GBM brain tumor and standard brain tissue. The principal benefit of applying transfer learning lies in the mechanization of the segmentation and feature extraction phases, thereby mitigating potential inaccuracies inherent to manual handcrafted methodologies [18]. The categorization of brain tumors serves as an indispensable phase subsequent to tumor detection, holding a pivotal role in the formulation of an efficacious treatment strategy. Timely identification not only contributes to the enhancement of therapeutic interventions but also stands as a potentially life-saving measure. Within a specific research initiative, a dataset encompassing human brain MRI images was harnessed, encompassing a spectrum of both tumor-afflicted and non-tumor bearing brain MRI images. This dataset underwent a comprehensive preprocessing stage, which encompassed a diverse array of image manipulation techniques, including filtering, blurring, and cropping. Subsequently, the dataset was partitioned into training and testing subsets and was subjected to data augmentation involving an array of random transformations. A CNN was deployed, with the integration of pre-existing data, for the explicit purpose of ascertaining the existence of a tumor. In the event of a tumor's presence, the model further undertook the task of classifying it into one of three distinct categories: glioma tumor, meningioma tumor, or pituitary tumor [12].

A. TRANSFER LEARNING

The study at hand delves into the paramount endeavor of detecting and segmenting brain tumors, an indispensable procedure that hinges on the utilization of Magnetic Resonance Imaging (MRI) images. The inaugural phase in the detection protocol entails an exhaustive examination of both the symmetrical and asymmetrical facets of the brain, discerning anomalies and making the distinction between regular and irregular brain cells or tissues. The primary aim that propels this research is the cultivation of a method that surpasses existing practices in terms of precision and efficiency in the realm of brain tumor detection. To accomplish this objective, a comprehensive assessment is conducted by juxtaposing four distinct Keras models: ResNet50, DenseNet201, Inception V3, and MobileNet. The comparative analysis centers on ascertaining the most proficient deep learning model for the designated task. The appraisal primarily relies on their respective training accuracy, which culminates in ResNet50 achieving a remarkable 85.30%, while DenseNet201 secures a score of 78%, Inception V3 attains a commendable 78%, and MobileNet performs admirably at 77.12%. The core purpose of this investigation is to pinpoint the most apt model to enhance the precision and efficiency of brain tumor detection and segmentation through the utilization of MRI images.

TABLE 1. Comparison of proposed model with previous research.

Method	Dataset	Model	Classification Type	Accuracy %	Limitations
Khan et al [11]	1500; No, 1500; Yes	Pretrained VGG16, ResNet50, InceptionV3	Binary	96%, 89%, 75%	Multi-Class not Applicable
Srikanth et al [19]	Hospital Dataset	VGG16	Multi Class	98%	Accuracy Enhancement Required
Hanaa et al [20]	BRaTS 2021	BCM-CNN	Multi Class	99% (It may not be applicable Practically)	Long Processing Time
Akmalbek et al [21]	5000+	Yolov7	Multi Class	NA	Irregular Dataset
Proposed Method	5712	Fine-Tuned ResNet50	Multi-Class	99	Clinically not adoptable

Inception V3 attains a commendable 78%, and MobileNet performs admirably at 77.12%. The core purpose of this investigation is to pinpoint the most apt model to enhance the precision and efficiency of brain tumor detection and segmentation through the utilization of MRI images. Within this research investigation, the scholars have delved into the utilization of custom artificial neural networks and convolutional neural networks to identify brain tumors, placing considerable emphasis on the comprehensive evaluation of their effectiveness. As part of their analysis, a detailed comparison was drawn among multiple deep learning models, encompassing ResNet50, DenseNet201, MobileNet, and Inception V3. Following rigorous scrutiny, the researchers have ascertained that MobileNet stands out as the most adept model for the precise detection of brain tumors. The findings of this study hold substantial value for radiologists who depend on these predictive insights to make informed and prompt decisions [22]. The model presented within this research endeavor was meticulously trained by harnessing the capabilities of the Adam optimizer, implementing a batch size of 32 across 30 epochs. The loss function is characterized by categorical cross-entropy, and the primary metric for evaluation is accuracy. The outcomes of the training process are indeed remarkable, featuring an accuracy rate

of 0.99 and a commendably low loss value of 0.0504, signaling robust performance. Nevertheless, it remains apparent that there is potential for further refinement in achieving enhanced accuracy for the classification of individual abnormal cases [23]. Deep learning techniques find extensive applications in the extraction of features and image classification across diverse categories. In the realm of medical image analysis, particularly with MRI scans, Convolutional Neural Network (CNN) architectures serve as a prevalent choice for tasks pertaining to the recognition and categorization of medical images. The research paper introduces a transfer learning methodology that harnesses the potential of distinct pre-trained CNN architectures, such as VGG-19 and ResNet101. Additionally, the authors introduce a unique hybrid model, custom-crafted by amalgamating attributes from pre-trained Inception and ResNet architectures, denoted as InceptionResnet-v2. These model variations are meticulously examined through comparative analysis employing metrics like accuracy and AUC (Area Under the Curve). Remarkably, the Inception-Resnet-v2 based hybrid model outshines the rest, attaining an exceptional accuracy rate of 99.30% [24]. In the following approach, the study aimed to delve into various dimensions of model performance. The core objective of this investigation was to scrutinize a Convolutional Neural Network (CNN) model equipped with different kernel sizes, encompassing 5×5 and 7×7 variants, along with experimentation involving diverse batch sizes: 16, 32, and 64. Furthermore, the model underwent assessments employing an array of optimization algorithms, encompassing ADAM, SGD, RMSProp, and Adadelta. The research scrutinized and evaluated the outcomes utilizing essential metrics including Accuracy, Dice, Sensitivity, and Specificity [25]. Deep learning methodologies have the capacity to be engineered in a manner that negates the necessity for manually crafted feature extraction while still managing to attain precise classification outcomes. In a separate research manuscript, a pair of deep learning models was put forth for the identification of both binary classes (normal and abnormal) and the multiclass distinctions comprising meningioma, glioma, and pituitary brain tumors. Two openly accessible datasets were harnessed for this purpose- one encompassing 3064 MRI images, and the other, 152 MRI images. For the former dataset, a 23-layer convolutional neural network (CNN) was enlisted, owing to the abundance of training data at hand. Conversely, when confronted with the latter dataset, characterized by its limited data volume, the proposed '23-layers CNN' architecture grappled with overfitting dilemmas. To tackle this issue, the strategy of transfer learning was introduced, amalgamating the attributes of the VGG16 architecture with the adaptation of the '23 layers CNN' architecture. The core aim of this study was to devise an approach to discern and categorize anomalous brain tumors in brain scan imagery by leveraging a pre-trained Convolutional Neural Network (CNN), notably the ResNet50 model, and integrating the practices of transfer learning. The fundamental purpose was to streamline, enhance, and render judicious the process of decision-making within the pivotal realm of medical science, more specifically in the sphere of brain tumor identification and categorization. It aspired to cater to the diverse array of brain tumor types by harnessing the framework of a CNN model [26]. Despite advancements in medical imaging technologies, accurately identifying and delineating brain tumors remains.

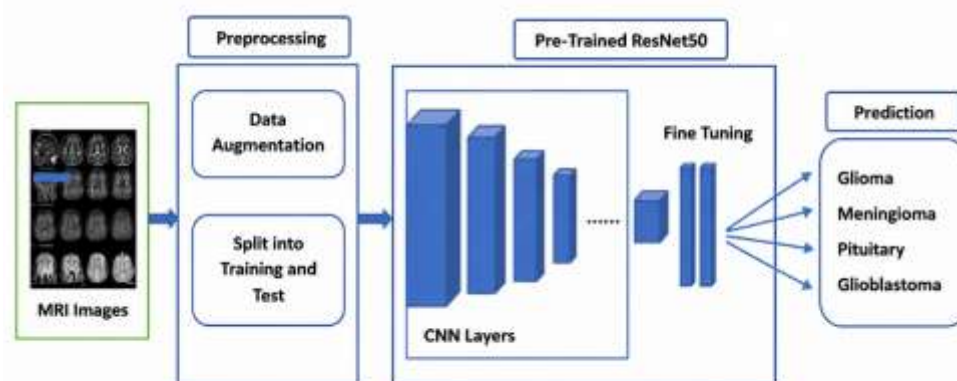


FIGURE 1. CNN fine tuning model.

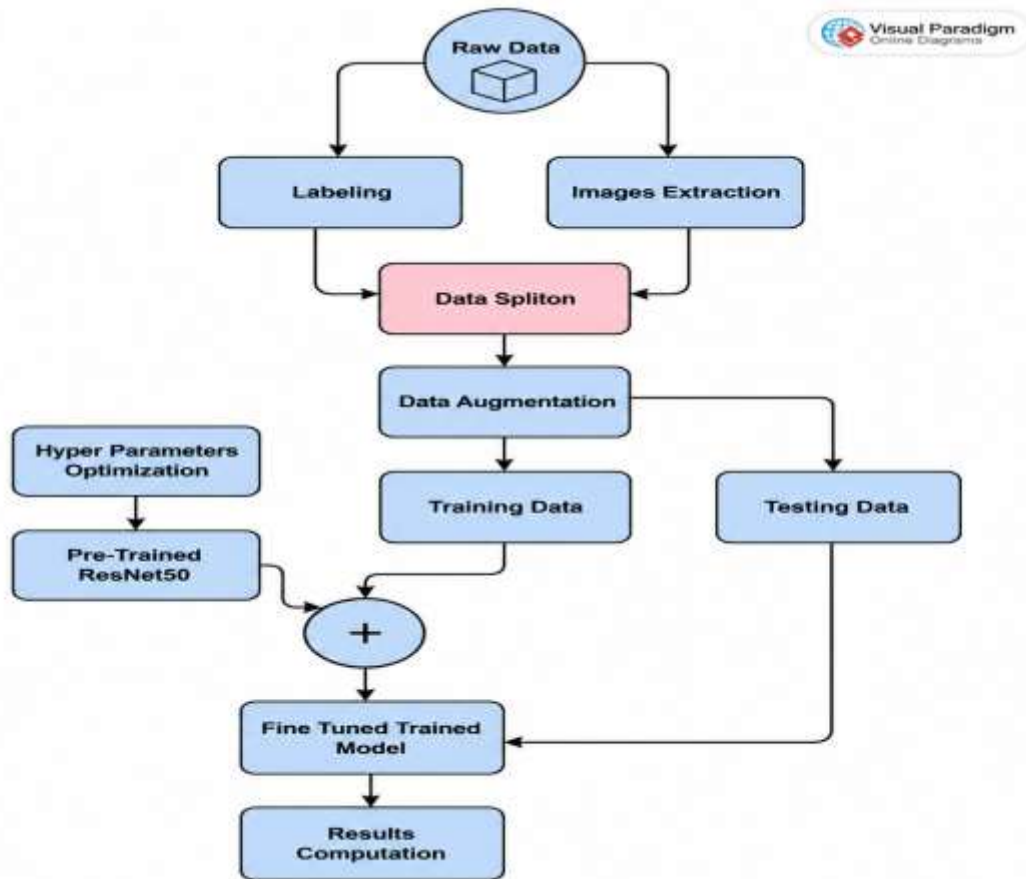


FIGURE 2. Transfer learning architecture.

challenging due to their complex and variable characteristics. While various deep learning techniques have been employed to address these challenges, there is still a gap in achieving optimal precision and efficiency in brain tumor detection and segmentation.

II. METHODS AND PROCEDURES

The field of brain tumour imaging, particularly with techniques like CT and MRI, generates a significant number of images. Brain MR imaging, for instance, produces three-dimensional anatomical representations comprised of numerous slices from an individual's brain. Manual segmentation of brain tumors from MRI images remains a substantial challenge and is a time-consuming task for medical practitioners. Moreover, the introduction of imaging artifacts has resulted in the creation of low-quality images that pose challenges in interpretation. Consequently, manually derived brain segmentations are prone to variations between different observers as well as within the same observer. To tackle these obstacles and aid radiologists, diverse automatic segmentation methods have been devised for the segmentation of brain tumors. A substantial corpus of literature adds to this field, providing answers to the issue at hand. Within this realm of research, academics have formulated automated systems for brain tumor segmentation techniques that deliver replicable and unbiased segmentation outcomes, frequently bearing a strong resemblance to manually derived segmentation results. Such automated methods can effectively mitigate the difficulties linked to manual analysis of brain tumors, leading to an enhanced pace of brain image analysis, heightened diagnostic precision, and streamlined treatment follow-up procedures involving the monitoring of tumor development [22]. The primary approach involved leveraging the pre-trained ResNet50 model as a feature extractor. By removing the top layer of the ResNet50 architecture and adding custom layers, the model was fine-tuned to tailor the learned features for the specific brain tumor classification task. This enabled the model to capture complex features effectively, which is crucial for accurate classification.

A. MATERIALS AND METHODS

This research introduces an automated approach for the detection and classification of various types of brain tumors. The transfer learning was employed to execute this task. The primary network for this task utilized the ResNet50 architecture as a pre-trained model to generate convolutional feature maps, which were subsequently utilized to classify and suggest the type of tumors. Performance evaluation was conducted based on prediction accuracy. While numerous researchers opt for development tools such as MATLAB to address brain tumor detection, our research project deliberately adopted Python programming to fulfill our project’s objectives. Several factors guided this choice, including Python’s open-source nature and its extensive availability of graphical packages in comparison to MATLAB. Python code is recognized for its precision and accuracy, affording greater control over the implementation process and enhancing visual-spatial skills. Furthermore, Python provides ease of management for various classic library versions, making it a suitable choice for our research endeavors.

B. DATASET DIVISION AND PRE-PROCESSING

The dataset used in this study consisted of a total of 7,023 images, divided into two primary sets for the purposes of training and testing. The training set comprised 5,712 images, which were categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary. These images were used to train the deep learning model, allowing it to learn the intricate features necessary for accurate tumor classification. The testing set consisted of 1,311 images, mirroring the same four tumor classes. These images were reserved for evaluating the model’s performance and assessing its ability to correctly classify brain tumors. The separation of the dataset into training and testing subsets was crucial for validating the model’s effectiveness, as it ensured that the model’s performance could be rigorously tested on unseen

TABLE 2. MRI slices distribution for model training and validation.

Brain Tumor Type	Training Images	Testing Images
glioma	1321	300
meningioma	1339	306
notumor	1595	405
pittuitary	1457	300

data. By utilizing this comprehensive dataset, the research aimed to develop and evaluate a highly capable brain tumor classification model with real-world applicability.

1) DATASET

Following the initial approach to MRI image processing, a pre-processing procedure is implemented. Notably, Convolutional Neural Networks (CNN) face challenges in adapting to the idiosyncrasies of individual classifiers, given the irregular black edges that often appear in MRI images. In the data augmentation phase, the research employed advanced augmentation techniques as a pivotal component of the model development process. These techniques encompassed a range of transformations, including rotation, shifting, shearing, zooming, and horizontal flipping. By implementing these advanced augmentations, the objective was to significantly diversify the dataset used for model training. Rotation introduced variability by altering the orientation of the images, simulating different perspectives that the model might encounter in real-world scenarios. Shifting involved displacing image content within frames, enabling the model to learn from images with varying compositions. Shearing added further diversity by distorting images along specified axes,

capturing different tumor shapes and forms. Zooming allowed the model to analyze both close-up and distant tumor details, mimicking variations in image scale. Finally, horizontal flipping introduced mirror-image variations, broadening the dataset's scope. Collectively, these augmentations played a critical role in enhancing the dataset's diversity. The diversity, in turn, enabled the deep learning model to generalize more effectively. This capacity to generalize across various image patterns and orientations was pivotal in ensuring that the model could accurately recognize and classify different tumor patterns. Through the application of these advanced data augmentation techniques, the research aimed to train a robust and adaptable model capable of handling a wide spectrum of brain tumor images, ultimately leading to improved classification accuracy and performance.

2) TRANSFER LEARNING ARCHITECTURE AND FINE TUNING

ResNet, abbreviated from Residual Network, stands as a distinct category of convolutional neural network (CNN) unveiled within the research paper published in 2015, entitled "Deep Residual Learning for Image Recognition,"

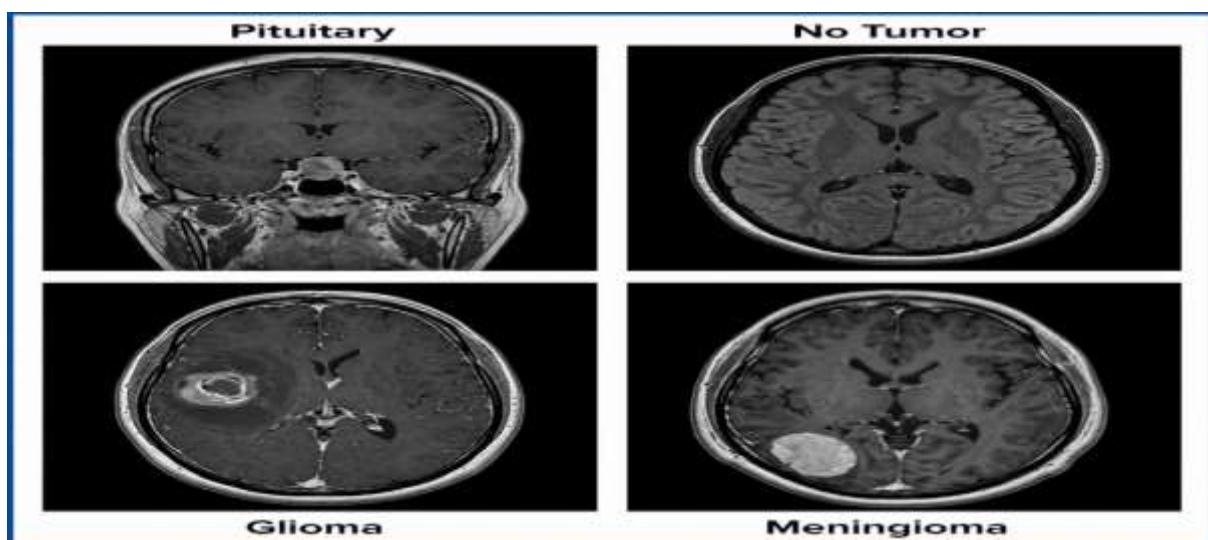


FIGURE 3. Sample MRI images with label.

He et al. [27]. Convolutional Neural Networks (CNNs) are routinely applied in numerous computer vision applications. Consider ResNet-50 for illustration, an instance of a 50-layer convolutional neural network encompassing 48 convolutional layers, a solitary MaxPool layer, and an individual mean pool layer. Residual neuronal systems, often abbreviated as ResNets, symbolize a distinct class of artificial neural networks (ANNs). They form network architectures by stacking residual blocks. Initially, the ResNet architecture emerged in the form of ResNet-34, which encompassed 34 weighted layers. This architectural approach offered an innovative method for incorporating additional convolutional layers into a CNN while evading the challenge of vanishing gradients. This advancement was accomplished through the integration of shortcut connections, which efficiently "bypass" certain layers, thereby converting a conventional network into a residual network. This design paved the way for the effective training of exceptionally deep networks, resulting in remarkable enhancements in the precision of deep learning models across diverse applications, such as image recognition and classification. The ResNet architectural design adheres to two primary design principles. Firstly, it sustains a consistent quantity of filters in each layer contingent on the dimensions of the output feature map. Secondly, when the feature map's dimensions are halved, the quantity of filters is precisely doubled to uphold the temporal complexity of every individual layer. ResNet-50, as a member of the ResNet family, upholds the previously mentioned design principles but introduces a critical distinction. The 50-layer ResNet incorporates a bottleneck design for its fundamental building blocks. Within a bottleneck residual block, there are 1×1 convolutions referred to as the "bottleneck," aimed at reducing the count of parameters and matrix multiplications. This particular design choice allows for expedited training of each layer. Rather

than the conventional two layers found in standard residual blocks, the bottleneck compasses a stack of three layers. This structural choice contributes to the network’s depth and its capacity to effectively capture intricate features. The amalgamation of these designelements



FIGURE 4. ResNet50 CNN layers architecture

Layer Name	Output Size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

results in improved training and overall performance, rendering ResNet-50 a favored selection for numerous deep learning applications. ResNet-50, a convolutional neural network renowned for its exceptional depth, encompasses a staggering 50 layers. ResNet, short for Residual Networks, stands as a foundational neural network architecture frequently adopted as the foundational framework for a diverse array of computer vision tasks. The fundamental breakthrough associated with ResNet lies in its extraordinary capacity to facilitate the training of immensely deep neural networks, even surpassing the milestone of 150 layers, a formidable challenge before the advent of this architecture. ResNet represents a pioneering neural network design crafted by the collaborative efforts of Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, elegantly introduced in their groundbreaking 2015 research paper titled “Deep Residual Learning for Image Recognition.” CNNs encounter a substantial obstacle referred to as the “Vanishing Gradient Problem” when undergoing the backpropagation process. This predicament involves a noteworthy reduction in the gradient values as they traverse backward through the neural network, resulting in exceedingly modest weight adjustments within the deeper layers. To surmount this challenge, ResNet introduces an ingenious concept termed the “skip connection,” also recognized as the “residual connection.” These connections afford a means for data to circumvent one or more intermediary layers, thereby establishing a direct route for the gradient’s smoother progression during the training process. This groundbreaking

approach profoundly bolsters the training and efficacy of exceptionally deep neural networks, rendering array of computer vision tasks.

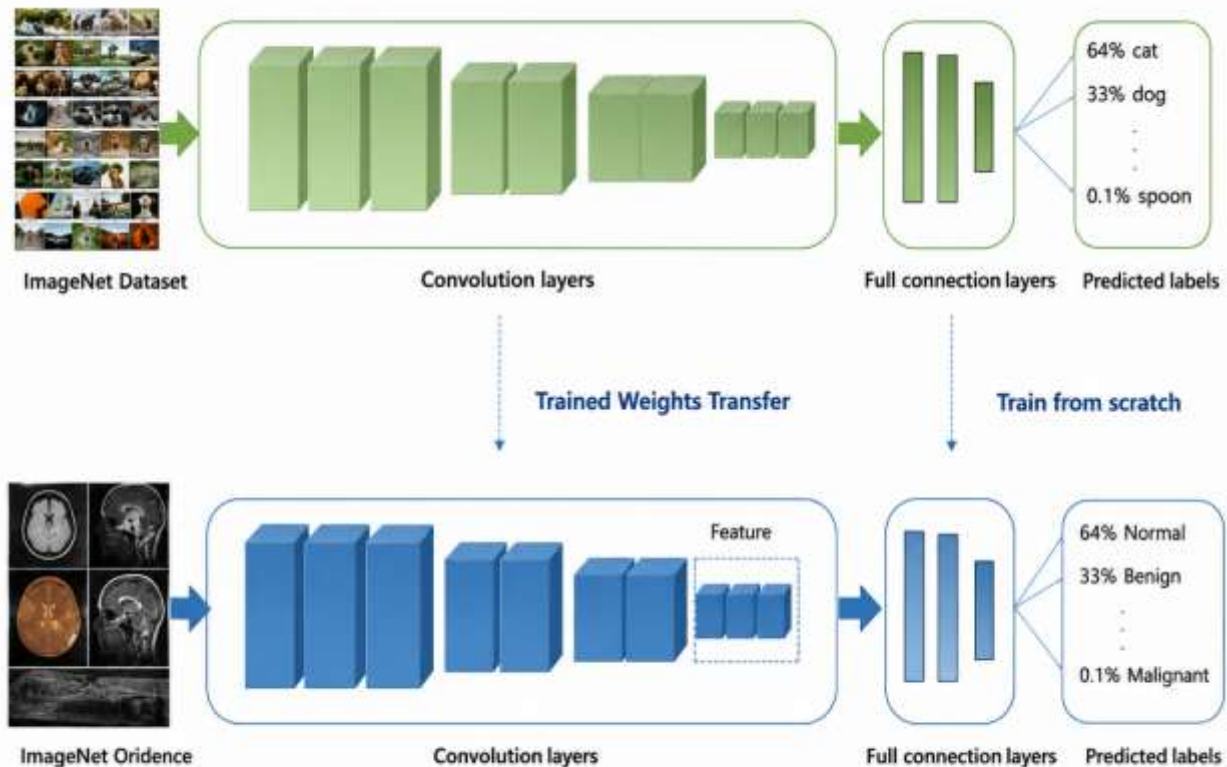


FIGURE 5. Feature extraction of CNN model.

To prevent overfitting and ensure model stability and generalizability, dropout layers were introduced with a dropout rate of 0.5. Additionally, L2 regularization with a factor of 0.01 was applied. Dropout randomly deactivates neurons during training, preventing the model from becoming overly specialized on the training data, while L2 regularization discourages overly complex weights, maintaining the model's stability and robustness. To further optimize the convergence and training process, the Reduce LR On Plateau callback was utilized. This callback dynamically adjusted the learning rate during training. In the event that the validation loss entered a state of stagnation, the learning rate underwent a proportional reduction by a factor of 0.2. This adaptive learning rate mechanism allowed the model to efficiently fine-tune its parameters, adapting to the nuances in the data and enhancing its overall performance.

3) **COMPREHENSIVE EVALUATION METRICS**

The evaluation process involved the computation of several essential evaluation metrics, which included precision, recall, and F1 score. Precision quantified the model's accuracy in classifying tumor classes correctly, while recall gauged the model's proficiency in minimizing false negatives. The F1 score served as a balanced evaluation metric, taking into account both precision and recall, thus ensuring a harmonious trade-off between false positives and false negatives. Additionally, in conjunction with the previously stated metrics, the study also computed the AUC (Area Under the Curve) score for ROC (Receiver Operating Characteristic) analysis. The AUC score served as an indicator of the model's discriminatory capacity across various tumor categories, offering valuable insights into its comprehensive classification performance.

TABLE 4. Tuned hyperparameters.

Parameter	Optimized Value
InitialLearnRate	0.0001
ExecutionEnvironment	GPU
MiniBatchSize	25
MaxEpochs	26
L2Regularization	0.01
ReduceLRonPlateau by factor	0.2
Verbose	1
Optimizer	adam

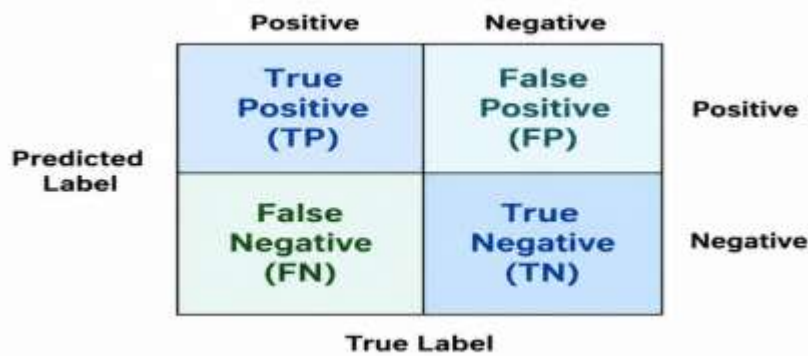


FIGURE 6. Confusion matrix.

To identify tumors, a multi-layer convolutional neural network (CNN) was designed and implemented. An input shape of $64 \times 64 \pm 3$ was defined for processing MRI scans using a convolutional layer as the initial layer. This preprocessing step standardized all images to a uniform dimension. Once the images were harmonized in terms of aspect ratio, a convolution kernel was applied to the input layer. This involved utilizing 32 convolutional filters, each with a size of 3×3 , and operated on 3-channel tensors. The composite model consisted of seven sequential layers, including hidden layers, and yielded the most accurate results for malignant conditions. Rectified Linear Unit (ReLU) was employed as an activation function. In mathematical terms, ReLU can be expressed as follows: These evaluation metrics are typically scaled from zero to one, with zero representing the poorest possible score and one indicating the highest achievable score. In practical terms, the best achievable score may be less than one because, in certain cases, the objective is to approach or emulate human performance, which can introduce ambiguity in defining correct classifications, such as in the context of sentiment analysis.

$$Precision = \frac{T_P}{T_P + F_P} \quad (1)$$

$$Recall = \frac{T_P}{T_P + T_N} \quad (2)$$

$$F_1 = \frac{\frac{2T_P}{T_P + F_P} \times \frac{T_P}{T_P + T_N}}{\frac{T_P}{T_P + F_P} + \frac{T_P}{T_P + T_N}} \quad (3)$$

III. RESULTS

The study applied ResNet50 pretrained models for brain tumor classification, yielding impressive results. Compared to prior Deep Neural Network (DNN) research, the optimized modelled moon started a significant

improvement in both training and testing accuracy, achieving a remarkable 99% accuracy rate. Precision stood at 98.35%, highlighting the model’s ability to reduce false positives, while the F1-score reached 98.31%, emphasizing its overall robustness. Detailed metrics further validated the model’s performance. Precision and recall scores of 0.983559 and 0.983219, respectively, showcased the model’s precision in making accurate positive predictions and minimizing false negatives. The F1 Score, at 0.983140, highlighted the model’s proficiency in striking a balance between false positives and false negatives. The AUC (ROC) score, an indicator of the model’s discrimination ability across tumor classes, was notably high at 0.999038, affirming its exceptional classification capabilities.

The provided confusion matrix details the model’s classification performance on various brain tumor types in the testing dataset. It reveals that Class 2 (no tumor) was perfectly classified in all 405 instances. Class 3 (pituitary tumors) was also classified accurately in all 300 cases. However, there were misclassifications observed, with Class 0 (glioma) having 5 errors, and Class 1 (meningioma) having 17 errors.

TABLE 5. Result obtained using proposed fine tuned model

Metric	Score
Precision	0.983559
Recall	0.983219
F1 Score	0.98314
AUC (ROC)	0.999038

The matrix helps identify areas for model improvement, particularly in distinguishing glioma from meningioma and mitigating their misclassifications. The study utilized ResNet50 in Python, training on open-source MRI data. It achieved high accuracy in classifying brain tumors. ‘No tumor’ and ‘pituitary’ had perfect 100% accuracy, glioma scored 98.33%, and meningioma reached 94.44%. Evaluation metrics (precision, recall, F1 Score) exceeded 0.98, and the AUC (ROC) score was 0.999, emphasizing the model’s strong performance in brain tumor classification. (1) (2) (3) The study employed transfer learning with ResNet50 in a Python environment, utilizing the Tensor framework and Colab notebook for brain tumor classification. Notably, open-source data, including MRI images from the Br35H dataset, specifically the ‘no tumor’ type, was used. The classification results indicate impressive accuracy levels. no tumor achieved a perfect accuracy score of 100%, suggesting the model’s excellence in correctly identifying non-tumor cases.

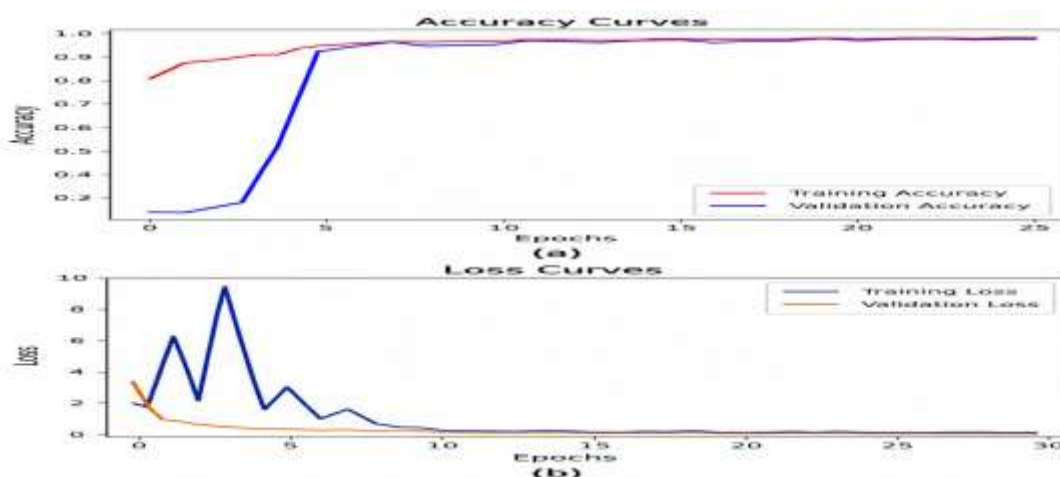


FIGURE 7. Fine tuned accuracy for model performance (a) Training & validation accuracy (b) Training & validation loss.

Furthermore, pituitary also achieved 100% accuracy, demonstrating the model’s proficiency in detecting this specific tumor type. Although glioma exhibited a slightly lower accuracy at 98.33%, it remains highly accurate. meningioma achieved a commendable accuracy of 94.44%. The evaluation metrics further underscore the model’s excellence. With precision, recall, and F1 Score all exceeding 0.98, the model demonstrates its remarkable ability to make accurate positive predictions (precision) and minimize false negatives (recall). The F1 Score, which balances precision and recall, maintains a high level, highlighting the model’s capability in achieving a balanced trade-off between false positives and false negatives. The AUC (ROC) score, an indicator of the model’s discrimination ability across tumor classes, also attains an impressive value of 0.999, affirming the model’s strong performance. Overall, the results underscore the model’s proficiency in brain tumor classification, with particularly remarkable accuracy and precision, making it a valuable tool for medical diagnosis and research.

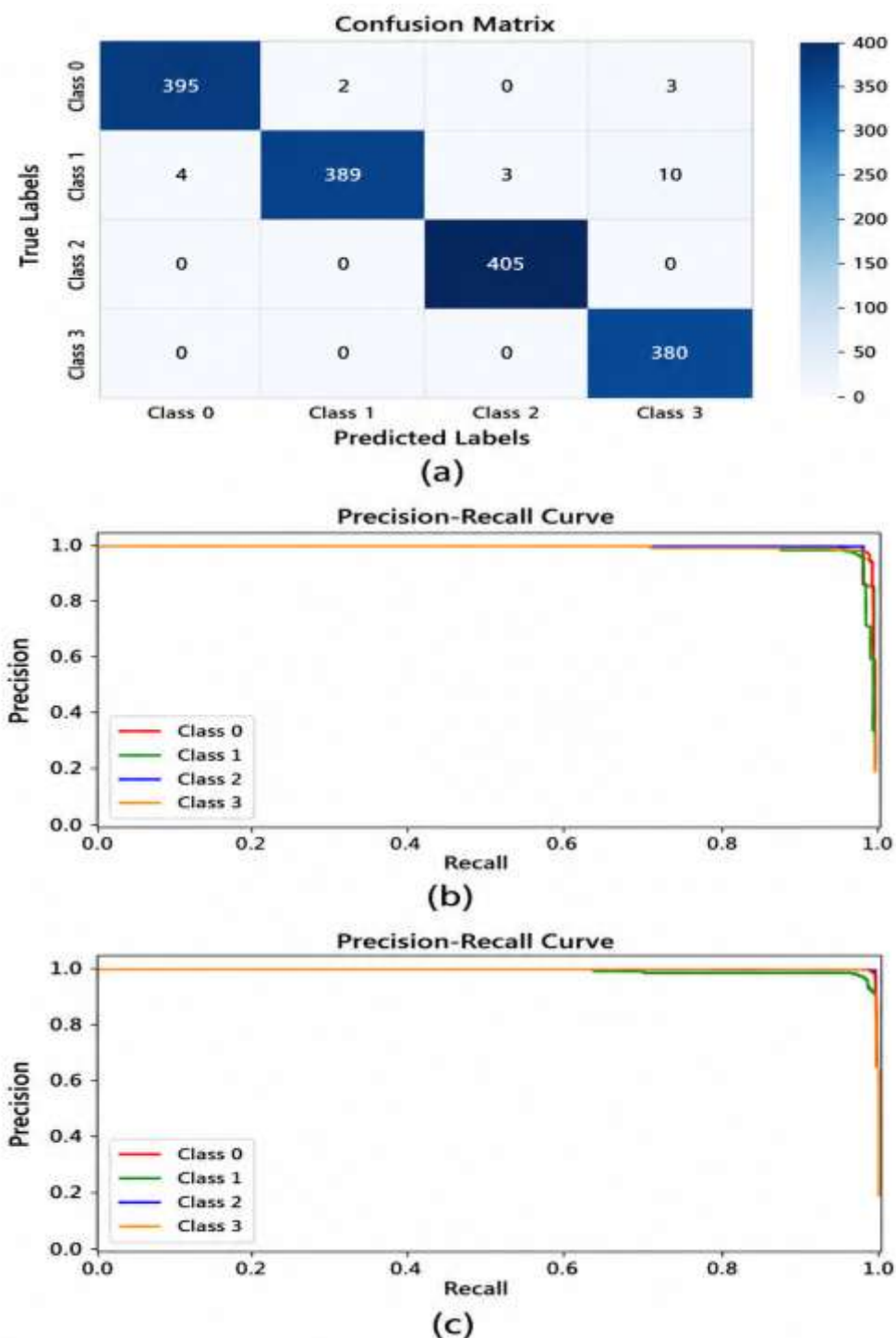


FIGURE 8. Performance model a) Confusion matrix (b)PRC curve (c) POC curve.

TABLE 6. Model evaluation score across various types of brain tumor

Model	Brain Tumor Type	Testing Accuracy	Training Accuracy	Validation Accuracy
ResNet50	glioma	98.33%	98.67%	98.32%
	meningioma	94.44%		
	notumor	100.00%		
	pituitary	100.00%		

It can be observed the performance of the model for each class of brain tumor. Class 0, representing glioma, is correctly classified as Class 0 (true positive) in 295 instances, while it is misclassified as Class 1 in 2 cases and as Class 3 in 3 cases. Similarly, Class 1, signifying meningioma, is accurately classified as Class 1 in 289 instances, but it is incorrectly predicted as Class 0 in 4 cases, Class 2 in 3 cases, and Class 3 in 10 cases. Class 2, representing no tumor, is classified perfectly as Class 2 in all 405 instances. Finally, Class 3, corresponding to pituitary tumors, is also classified correctly as Class 3 in all 300 cases. This detailed breakdown of true positive and misclassification values provides insights into the model’s performance for each specific brain tumor type. Moreover, the diagonal elements of the confusion matrix represent the true positive cases, where the model correctly predicted the class. The off-diagonal elements indicate misclassifications, and their values show how many cases were incorrectly predicted as other classes. The confusion matrix is a valuable tool for assessing the model’s performance, highlighting areas where it excels and areas where it may need improvement. In this particular case, the model demonstrates strong performance for Class 2 (no tumor) and Class 3 (pituitary), with no misclassifications. However, it exhibits some misclassifications between Classes 0 and 1 (glioma and meningioma), as well as a few between Class 1 and Class 3 (meningioma and pituitary). This analysis aids in understanding the model’s strengths and areas for refinement, ultimately contributing to its enhancement for accurate brain tumor classification.

IV. CONCLUSION Therapid growth of abnormal brain cells in tumors poses significant health risks, emphasizing the urgent need for precise and early detection. Previous Model’s of identifying brain tumor types using deep neural networks have been inefficient in accuracy, prompting our study to focus on innovative solutions in model enhancement. Motivated by the imperative for improved accuracy in abnormal brain tumor classification, our research prioritized the development of a refined model. Remarkably, our model achieved perfect accuracy rates of 100% for both “no tumor” and “pituitary tumor” classes, empowering clinicians to confidently make treatment decisions without relying on assumptions. Leveraging the power of deep learning and transfer learning with the ResNet50 model, our approach yielded impressive results. The incorporation of data augmentation, regularization, and dropout layers enhanced the model’s performance, achieving remarkable accuracy rates of 99% on both training and validation datasets. Additionally, the calculated metrics, including Kappa (≈ 0.0137), MCC (≈ 0.9038), and G-mean (≈ 0.9972), further validate the model’s effectiveness in accurately classifying brain tumor types. Despite our model’s exceptional performance, limitations persist, notably its inability to identify multiple tumors within the same MRI scan. Future research endeavors will focus on addressing this limitation to enable more accurate classification of complex cases and further enhance clinical outcomes.

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