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Diagnosing Brain Tumors from MRI images through a Multi-Fused CNN with Auxiliary Layers

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Abstract: In this study, we proposed a novel Multi-Fused Residual Convolutional Neural Network (MFR-CNN) with Auxiliary Fusing Layers (AuxFL) to diagnose various types of brain tumor MRI images. The MFR-CNN was designed to handle four specific cases, namely glioma, meningioma, pituitary, and healthy brain images, obtained from reliable Kaggle databases. Our proposed model integrated three state-of-the-art models into a single feature extraction pipeline, incorporating partially frozen and truncated layers. This strategic fusion enabled the propagation of robust features and improved diagnostic performance without incurring significant computing costs, unlike most existing state-of-the-art models. Moreover, the MFR-CNN effectively mitigated overfitting and performance saturation issues, providing a notable advantage over models lacking these components. Upon evaluation, our proposed model achieved an outstanding accuracy of 94%, surpassing the efficiency and accuracy of conventionally trained DCNNs. Notably, the MFR-CNN demonstrated potential in enhancing brain tumor diagnosis more cost-efficiently than ensembles and outperforming conventional pre-trained and fine-tuned DCNNs. In conclusion, the proposed MFR-CNN with AuxFL and FuRB exhibits promising capabilities to improve the diagnosis of brain tumors, offering better cost-efficiency and accuracy compared to existing methods.

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1. Introduction

The brain, as the most vital and intricately structured part of the human body [1], is encased within the protective skull layer, making its study challenging and disease identification complex [2]. Unlike other body parts, brain diseases can arise from abnormal cell growth, leading to devastating conditions such as brain cancer [3]. The World Health Organization (WHO) reported that in 2018, approximately 9.6 million people worldwide lost their lives due to diagnosed cancer, with brain cancer accounting for 30% to 50% of primary cancer cases [4]. Among various types of cancer, brain cancer stands out as a particularly lethal one, claiming about 17,760 adult lives in 2019 [5]. Given the severity of this situation and the intricate nature of the brain, early and accurate diagnosis is imperative. Magnetic

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resonance imaging (MRI) plays a crucial role in tumor analysis, providing high-quality brain images with excellent spatial resolution and contrast determination [6].

A brain tumor is an abnormal growth of cells within the brain or the central spinal canal, which can be either benign (non-cancerous) or malignant (cancerous). Brain tumors may originate from brain tissue itself, known as primary brain tumors, or they can be secondary tumors that have spread from other parts of the body, referred to as metastatic brain tumors.

Types of Brain Tumors:

A. Primary Brain Tumors: These tumors originate from brain cells, the membranes covering the brain (meninges), nerves, or other structures within the brain. The most common types of primary brain tumors include:

- ✓ Gliomas: Gliomas are a broad category of primary brain tumors that originate from glial cells. Glial cells, also known as neuroglia or simply glia, are non-neuronal cells that provide support and protection to neurons (nerve cells) in the brain and spinal cord. They play crucial roles in maintaining the structural integrity of the nervous system, modulating the transmission of nerve signals, and regulating the brain's chemical environment.
- ✓ Meningiomas: Meningiomas are primary brain tumors that arise from the meninges, which are three protective layers of tissue that cover the brain and spinal cord. These tumors account for approximately 30% of all brain tumors and are the most common type of non-cancerous (benign) brain tumor. Meningiomas can occur in both males and females, but they are more common in women, with a female-to-male ratio of about 3:2.
- ✓ Pituitary Adenomas: Pituitary adenomas are non-cancerous (benign) tumors that arise from the pituitary gland, a small, pea-sized gland located at the base of the brain. Despite being benign, these tumors can cause significant health issues due to their location and their effect on the hormonal regulation controlled by the pituitary gland. Pituitary adenomas are one of the most common types of brain tumors, and they account for approximately 10-15% of all brain tumors.

B. Metastatic Brain Tumors: These tumors result from cancer cells that have spread (metastasized) from other parts of the body, such as the lung, breast, skin, or colon, to the brain through the bloodstream. Metastatic brain tumors are more prevalent than primary brain tumors.

Moreover, in this article, we will focus on detecting the types of primary brain tumors, because these more types are prevalent. Medical imaging techniques play a crucial role as non-invasive tools to explore the human body, aiding in treatment and diagnosis and thereby enhancing the healthcare process [7]. The diagnosis of brain tumors involves a comprehensive approach, including medical history evaluation, neurological examination, and imaging studies such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. A biopsy, where a small sample of the tumor tissue is extracted and analyzed, is performed to determine its nature, whether it is benign or malignant. Treatment options for brain tumors are determined based on factors such as the type of tumor, its size, location, and the overall health of the patient. The primary treatment modalities for brain tumors include Surgery, Radiation Therapy, and Chemotherapy. Magnetic Resonance Imaging (MRI) is a common and effective approach for detecting brain tumors in clinical practice. It provides detailed images of the brain, enabling radiologists and neurologists to identify and characterize brain abnormalities, including brain tumors.

In the realm of medical applications, Deep Learning (DL) plays a remarkable role. As a subset of machine learning, DL utilizes deep layers to analyze data. Convolutional Neural Networks (CNNs) are a type of DL that proves especially well-suited for analyzing medical images such as X-ray, CT, and MR images. CNNs are also well equipped to handle large image datasets [8].

2. Related Work

There are many studies on brain tumor MRI images, The author [13] studied classification brain tumors in three types meningioma, glioma, and pituitary tumor, there dataset depend on past work and was 3064 images. they used the VGG-16 CNNs and used two GLCM feature which are contrast and energy Image and depends in there experiment the original image with energy features which give better accuracy achieve of 96.5%. Also, the author [14] studied the classification in the same types of brain tumor, collect their dataset from government hospital on located Tirupathi and was 170 images depend in deep learning the CNN algorithm to achieve accuracy of 90%. The author [15] studied the same class to classification brain tumor. they collect dataset from two dataset public database the Figshare and the Brain MRI, which contain 233 different subjects on Figshare, and in Brain MRI 253 sample. There experiment used Mask RCNN densenet-41 and achieve accuracy of 98.34%. the author [16] studied same classification on brain tumor, there dataset collect from T1-weighted contrast-enhanced images contain 3064 images. There experiment used new CNN architecture to achieve accuracy 96.56%. The author [17] studied classification brain tumor in three types Low-grade glioma High-grade glioma and health,and they collect dataset from two different database the Brain Tumour Segmentation (BraTS) 2019 and T1-weighted contrast-enhanced images . There experiment used3D CNN with ResNet Mixed Convolution and achieve accuracy 96.98%. The author [18] studied binary classification of brain tumor with tumor or non-tumors, collect their dataset from Kaggle and was 3264 image, there experiment in three algorithm BP, U-Net, and RCNN and the best achieve accuracy was RCNN with 95.17%. the author [19] studied binary classification of brain tumor with Glioma and healthy tumor, collect the dataset from two public database the figshare and Kaggle, which contain on figshare 3064 images and Kaggle 253 images, there experiment used Low complex Two Channel CNN and achieved accuracy 98.21%. the author [20] studied binary classification of brain tumor with malignant and benign, they collect dataset from The Cancer Imaging Archive (TCIA) Public Access repository contain 696 image. There experiment on AlexNet, GoogLeNet, ResNet50, ResNet101, and SqueezeNet, and achieve the best accuracy on 99.04%. The author [21] studied multi- classification of brain tumor in first studied binary classification, second five classes which is glioma, meningioma, pituitary, normal brain and metastatic, and third glioma brain tumors into grade II, grade III and grade IV. There collect dataset from four public database was reference image database to evaluate therapy Response (RIDER), Repository of Molecular Brain Neoplasia Data (REMBRANDT), the cancer Genome atlas low-grade glioma (TCGA-LGG) , finally T1-weighted contrast-enhanced images. There experiment contain Classification-1 was 2990 images, Classification-2 was 3950 images and Classification-3 was 4570 images, they CNN algorithm, they achieved accuracy on binary 99.33%, five classes 92.66%, glioma brain 98.14%. The best accuracy on binary classification. The author [22] studied two classification of brain tumor, in first three classes which were meningioma, glioma, and pituitary and second glioma grades which were Grade II, Grade III, and Grade IV. They collect dataset from T1-weighted contrast-enhanced images was 3580 images. There experiment on CNN and achieve accuracy 96.13% and 98.7%, respectively.

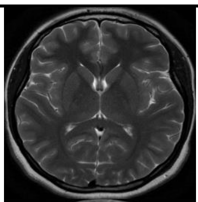
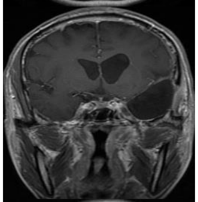
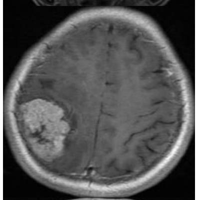
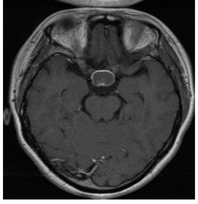
3. Proposed Method

1. Dataset

The dataset is taken from the Kaggle website. This dataset contains MRI images of brain tumors. There are four folders one of these folders represents the normal brain image and the other folders represent the three types of primary brain tumor images. Totally, there are 7023 images in these folders. **Table 1** presents the curated dataset with image samples labeled with their proper classes, quantity, and distribution. Total 2000 nontumor, 1621 glioma, 1645 meningioma, and 1757 pituitary. 5712 images for training and 1311 images for testing are taken. An automated image data generator from Keras was utilized to resize the train images to a consistent dimension of 224 × 224. This approach optimized resource allocation, accelerated training speeds, and effectively managed computing memory during experiments. However, it is important to note that the specific dimensions may vary depending on the machine's specifications.

TABLE 1.
DATASET SPECIFICATIONS.

Samples	Class	Train	Test	Total

	0_normal	405	1595	2000
	1_ glioma	300	1321	1621
	2_ meningioma	306	1339	1645
	3_ pituitary	300	1457	1757
	Total	**5712**	**1311**	**7023**

a. Input the MRI Image

The MRI image of a brain is taken to segment the tumor region, within this step, the image going to taken from a specific directory to load on our code in the Google Colab platform and pass to the next part of the code.

Pre-Processing on MRI Brain Image

In this stage, the MRI brain images undergo several essential pre-processing steps to ensure the system can interpret the input correctly and optimize image analysis. The following steps are performed:

1. Image Resizing: Considering that input images may have varying sizes in height and width, we resize each image to a fixed dimension, such as (32 × 32). This standardization enables consistent analysis across the entire dataset.

2. Skull Removal: Given the paramount importance of the brain in our analysis, this step involves using specific functions to remove the skull surrounding the brain. By eliminating the background and isolating the brain structure, we enhance the accuracy of subsequent image processing and feature extraction.

3. Image Filtration: In this stage, we apply a median filter to effectively remove noise from the MRI images. This process enhances the possibility of detecting relevant features, making it particularly valuable for both training and testing conditions of MRI images. By reducing noise interference, the filtered images provide a more accurate and reliable foundation for further analysis and feature detection.

2. Data preprocessing and augmentation

The curated data obtained from diverse resources lacked a standardized format, leading to potential inconsistencies that could adversely affect the performance of DCNN (Deep Convolutional Neural Network) models. Failure to address this issue could result in poor convergence during the training process. To mitigate this concern, the mix-max scaling equation (1) was applied in this study, rescaling all pixel values (xi) in each image to a uniform range of 1.0 / 255. This normalization ensured that all images had comparable pixel values, promoting improved consistency and enhancing the overall training process.

$$x_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \qquad (1)$$

Data augmentation, a valuable technique, was employed to generate a diverse set of variations for each sample, leading to improved results. While data augmentation encompasses numerous techniques, this study selected only a few that introduced sufficient transformations without causing significant alterations. The chosen augmentations for the images included horizontal and vertical flips, rotation, shear, zoom, height and width shifts, and brightness adjustments. **Table 2** provides the specific values used for each augmentation, resulting in the creation of additional samples that preserved essential features without compromising the integrity of the data.

TABLE 2.
DATA AUGMENTATION SETTINGS.

Augmentation	Value
Horizontal flip	True
Vertical flip	True
Rotation	45
Shear	0.1
Zoom	0.1
Height shift	0.1
Width shift	0.1
Fill mode	Constant
Brightness range	0.1 to 1.0

3. Development approach

Given the demonstrated effectiveness of DCNNs in accurately diagnosing medical images, this study embraced their adoption. However, to create a lightweight yet accurate FMR-CNN (Brain Tumor Convolutional Neural Network), only prominent models, including EfficientNetB0, MobileNetV2, and ResNet50V2, were selected. It is important to note that these models underwent extensive experimentation, as evidenced by the results presented in subsequent sections of this article.

In addition, it is important to note that other models tested for the proposed fusion to diagnose brain tumor cases did not exhibit the same level of performance and cost-efficiency as the three selected models.

Subsequently, the pre-trained, truncated, and partially frozen models were connected to their respective layers, which reshaped their outputs into similar dimensions, effectively forming a unified pipeline. Ultimately, the models were prepared and connected to the MFR component, which regulated the robustly fused features necessary for accurate diagnosis. Table 3 provides an overview of the selected models, including their initial parameters, truncated parameters after transfer learning, preserved features.

TABLE 3.
TRUNCATION SETTINGS.

Model	Initial	Features	Truncated
EfficientNetB0	4 M	192	2.9 M
ResNet50V2	23 M	512	1.1 M
MobileNetV2	2.2 M	96	558 K

Prior to commencing the actual training process, the MFR-CNN underwent the setup of hyperparameters and the selection of a suitable loss function for compilation. **Table 4** presents the specific hyperparameter values employed for the training process. To ensure smooth and efficient training, a batch size of 16 was selected, carefully adjusted according to the current machine specifications and dataset size to prevent memory exhaustion during training and validation. For swift yet effective training, the Adam optimizer was chosen, utilizing a Learning Rate (LR) of 0.00001. The adaptive and rapid nature of the Adam optimizer significantly reduced the training duration even with a low LR value, resulting in substantial convergence within 25 epochs.

TABLE 4.
HYPER-PARAMETER CONFIGURATION.

Hyper-Parameter	Value
Batch Size	8
Epochs	25

Optimizer	Adam
LR	0.00001

While feature fusion can contribute to improved performance, fusing indirectly related models with a relatively small dataset may lead to overfitting [9] [10]. To address this issue, this study proposed adopting ResNet's concept of residual learning in the form of the Fusion Residual Block (FRB), which serves as a potential solution to handle such situations effectively.

Furthermore, it is important to note that other models tested for the proposed fusion to diagnose brain tumor cases did not demonstrate as much performance and cost-efficiency as the three selected models. Moreover, using more or fewer models for fusion did not show any improvements and only increased the parameter size, contradicting the purpose of this work. **Figure 1** illustrates how the selected models were integrated to build the proposed Multi-Fused Residual Convolutional Neural Network (MFR-CNN) for diagnosing brain tumor cases in greater detail. The initial procedure involved transfer learning, where the selected models were equipped with pre-trained features from ImageNet, enhancing their ability to recognize images effectively [11]. Following transfer learning, the models' layers were truncated, reducing their trainable parameters. Additionally, their layers were frozen during training to preserve the pre-trained weights, leading to a reduction in the number of required parameters for training the proposed model [12]. Subsequently, the pre-trained, truncated, and partially frozen models were connected to their respective Auxiliary Fusing Layers (AuxFLs), reshaping their outputs into similar dimensions and forming a unified pipeline. Ultimately, the models were prepared and connected to the FRB, which effectively regulated the fused features necessary for accurate diagnosis.

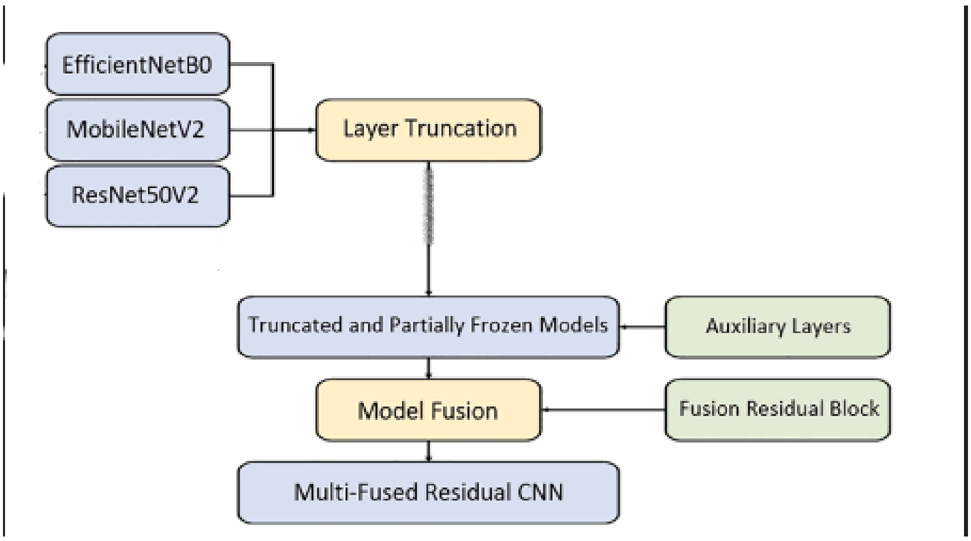


Figure 1: The proposed development framework.

Figure 2 depicts the FRB (Fused Residual Block), which closely resembles the ResNetV2 block with a slight modification. The FRB consists of two consecutive operations: Batch Normalization (BN), followed by the Scaled Exponential Linear Unit (SeLU) activation function, and then a convolutional layer with a skip connection. The original ReLU activation in the ResNetV2 block is replaced with the SeLU activation. The SeLU activation function normalizes the x features from previous layers through successive layers, maintaining a mean of 0 and a variance of 1. This normalization improves gradient stability during training, addressing the issue of the "dying ReLU" problem. Additionally, SeLU offers better memory usage due to its parameter and mini-batch independence, making it an ideal choice for our work.

Furthermore, SeLU has demonstrated numerous recent successes in outperforming the commonly used ReLU activation in enhancing the performance of Deep Learning models. Its ability to stabilize gradients, improve memory usage, and consistently outperform ReLU make SeLU a valuable activation function for our proposed FRB.

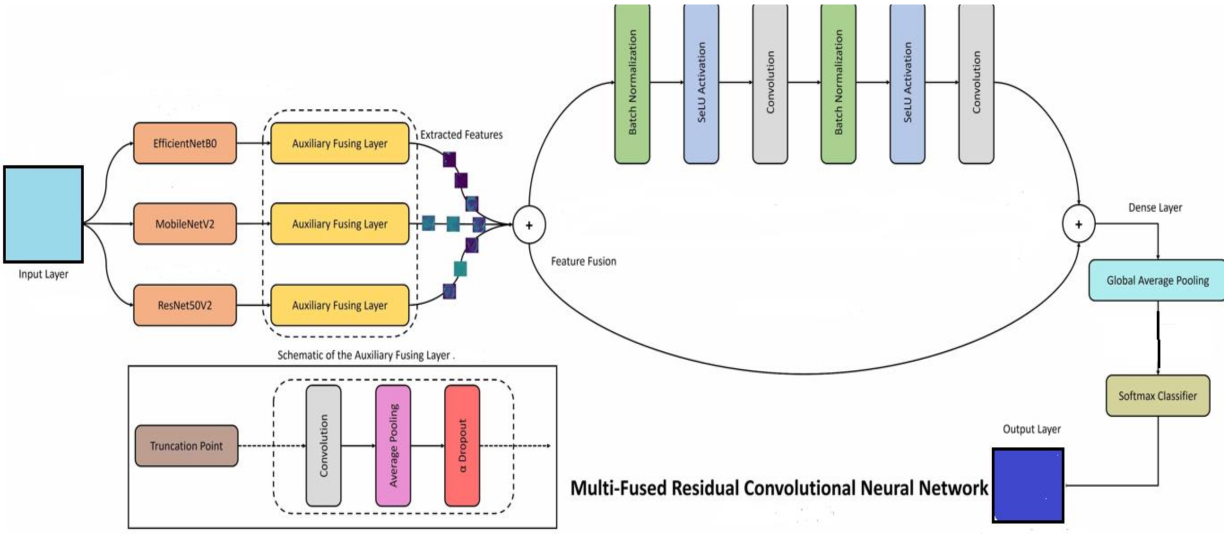


Figure 2: The Multi-Fused Residual Convolutional Neural Network.

4. Results

This section presents the evaluation of the proposed MFR-CNN based on widely used metrics in DL to provide comparable results with other models.

We have obtained an accuracy of the overall submitted model of 94%, precision 95%, recall 94%, and f1 – score 94%. For an in-depth analysis of the MFR-CNN's performance across diverse situations, this work used precision, recall, and f1−score approaches to get clear results for detecting each type of brain tumor, as **Table 5**.

TABLE 5 .
THE DIAGNOSTIC PERFORMANCE OF THE PROPOSED MODEL.

Cases	Precision	Recall	F1–score
nontumor	100%	96%	98%
Glioma	94%	85%	90%
Meningioma	86%	98%	92%
Pituitary	99%	99%	99%

To facilitate a more direct comparison of the overall performance with other state-of-the-art models, this study adopted a three-way split approach, utilizing a train, validation, and test dataset instead of conducting k-fold cross-validation for each model. The evaluation results of the proposed MFR-CNN model on the validation and test datasets are visually presented in **Figure 3**, showcasing the predictions in the form of confusion matrices.

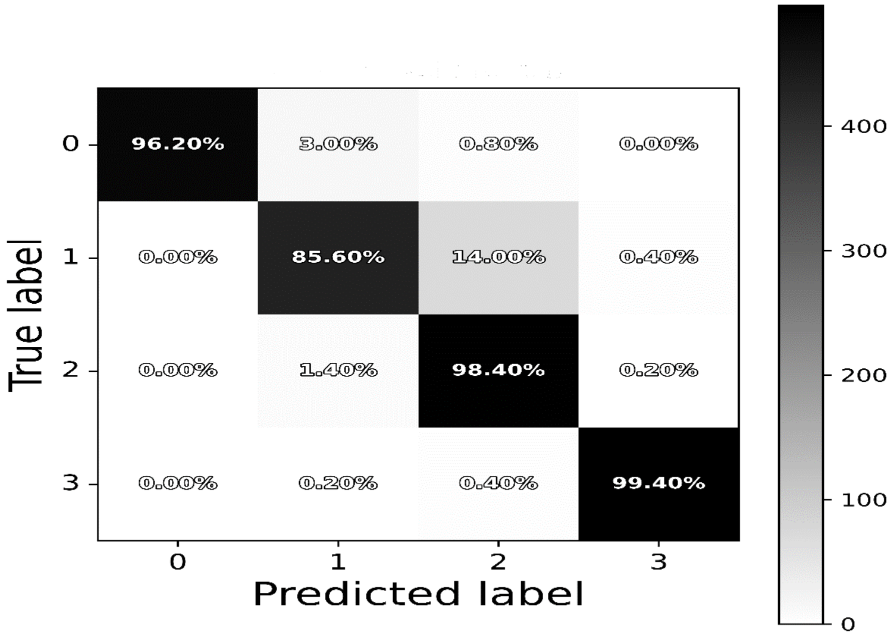


Figure 3: Confusion matrix to validation

Following the computation of values within the provided matrices, this study derived the corresponding accuracy, precision, recall, and f1-score of the MFR-CNN model using the three-way split method, as demonstrated in **Table 6**. The evaluation results indicated that the MFR-CNN exhibited outstanding performance, achieving 94% accuracy on the validation dataset and 97% on the test dataset. Moreover, the results demonstrated consistency in precision, recall, and f1-score, highlighting the efficacy of the balanced curated dataset in enhancing the model's overall performance.

TABLE 6.
THE DIAGNOSTIC PERFORMANCE OF THE PROPOSED MODEL.

Dataset	Accuracy	Precision	Recall	F1-Score
Validation	94%	96%	96%	96%
Test	97%	97%	97%	97%

5. Conclusions

Brain tumors are complex and potentially life-threatening medical conditions that require prompt diagnosis and appropriate treatment. Advances in medical imaging, such as the integration of deep learning CNNs, have significantly contributed to improving the accuracy and efficiency of brain tumor detection, assisting clinicians in making more decisions that are informed and enhancing patient outcomes. Nevertheless, ongoing research and medical advancements are essential to improve our understanding of brain tumors further and develop more effective treatment strategies. In this study, a novel MFR-CNN (Multi-Fused Residual Convolutional Neural Network) was proposed, demonstrating improved diagnostic capabilities for four brain tumor conditions while maintaining a superior cost-efficiency to performance ratio compared to conventional state-of-the-art DCNNs. The MFR-CNN design involved integrating three prominent DCNN models - EfficientNet, MobileNetV2, and ResNetV2 - into a unified pipeline.

Through comprehensive experiments and evaluations, the results showed that the proposed MFR-CNN outperformed most state-of-the-art DCNNs in diagnosing the four brain tumor cases, achieving an accuracy of 94%, precision of 95%, recall of 94%, and an f1-score of 94%.

Supplementary Materials

Not applicable.

Author Contributions

All authors contributed equally to this study.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

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