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A Hybrid Deep and Broad Learning Approach for Automatic Brain Tumor Classification

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ABSTRACT: Accurate MRI-based brain-tumor classification is vital for timely treatment planning; yet conventional CNN pipelines can struggle to generalize across heterogeneous tumor phenotypes. We present RIE50, a hybrid framework that fuses pretrained CNN feature extractors with a Broad Learning System (BLS) enhancement layer and lightweight classification head. RIE50 aggregates multi-level convolutional descriptors, passes them through a BLS layer to expand and refine representations with nonlinear feature mapping, and then classifies four categories (glioma, meningioma, pituitary, and no-tumor). The model integrates diverse activation functions (SELU, PReLU, Mish) within the CNN blocks to improve feature diversity and gradient flow, and is optimized with standard first-order optimizers. Evaluated on multi-source brain MRI benchmarks (4-class setup), RIE50 delivers strong accuracy and balanced sensitivity/specificity across tumor types, outperforming single-backbone baselines while remaining computationally lightweight due to the shallow, wide BLS head. These results indicate that widening the representation via BLS complements deep features and can yield robust, data-efficient tumor classification for clinical decision support.

I. INTRODUCTION

The brain is a highly complex organ that functions through the coordinated activity of billions of interconnected cells. Brain tumors arise when these cells proliferate abnormally, forming masses within or around the brain [1]. Tumors are broadly classified as malignant (cancerous and capable of spreading) or benign (localized and non-metastatic), with the incidence of malignant tumors increasing with age [2]. Malignant tumors, typically high-grade, grow aggressively, have poorly defined borders, and may develop as primary brain tumors or as secondary metastases from other organs [2, 3]. These tumors are usually fast-growing, invasive, and pose significant health risks. Primary brain tumors are commonly categorized into gliomas, meningiomas, and pituitary tumors. Gliomas, which originate from glial cells that support brain and spinal cord

function, represent the most frequent malignant brain tumors. Although they rarely metastasize beyond the central nervous system, their invasive spread across multiple brain regions makes them life-threatening [4,5]. Pituitary tumors arise near the pituitary gland, which regulates hormonal balance, while meningiomas develop from the meninges, the protective layers surrounding the brain and spinal cord [4].

Early detection is critical for effective treatment. While CT and MRI scans are widely used for diagnosis, MRI offers superior detail regarding tumor shape, size, and location. However, interpreting MRI data manually is time-consuming and challenging due to the volume of medical information, underscoring the need for computer-aided diagnostic systems [6]. Artificial Intelligence (AI), particularly deep learning, has shown exceptional success in visual recognition tasks and is increasingly applied in medical imaging for disease detection [7], segmentation [8], and classification [9]. In brain tumor analysis, deep learning has achieved impressive results [10], helping reduce radiologists' workload. Nevertheless, choosing the most effective model remains a challenge, and relying solely on a single CNN architecture may limit performance. This has motivated research into ensemble and hybrid learning approaches that combine the strengths of multiple models [11]. The Broad Learning System (BLS) provides an alternative to deep learning by expanding features through random mapping to feature nodes, followed by nonlinear transformations into enhancement nodes. This architecture offers universal approximation capability and efficient representation learning [12]. In this study, we propose RIE50, a hybrid framework for brain tumor classification that integrates features extracted from three state-of-the-art CNNs—InceptionV3, ResNet-50, and EfficientNetB0. The concatenated features are refined through dimensionality reduction, passed through BLS feature and enhancement nodes, and processed by dense layers with diverse activation functions (SELU, PReLU, Mish) [13–15]. Finally, the classification head distinguishes four categories: glioma, meningioma, pituitary tumor, and normal brain tissue.

The main contributions of this work are as follows:

We introduce RIE50, a novel CNN–BLS hybrid framework that incorporates multiple activation functions to improve diagnostic accuracy and assist radiologists. The feature extraction process leverages three powerful pretrained models—InceptionV3, ResNet-50, and EfficientNetB0—demonstrating competitive performance against advanced CNN architectures. The proposed approach utilizes a publicly available brain tumor MRI dataset, requiring minimal pre-processing (only resizing during testing). Extensive evaluation against state-of-the-art methods is conducted using multiple metrics, including accuracy, recall, precision, specificity, F1-score, and confusion matrix analysis, with test accuracy emphasized as the primary criterion. The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 details the proposed methodology; Section 4 presents the dataset, experimental setup, and results; and Section 5 concludes with key findings and future directions.

II. RELATED WORK

Deep learning has shown remarkable effectiveness in detection and classification tasks, playing a transformative role in medical image analysis. It has consistently achieved outstanding results across numerous challenges, particularly in the identification of diseases. Figure 1 illustrates a schematic overview of brain tumor classification approaches, categorizing them into three main groups: Convolutional Neural Networks (CNNs), Transfer Learning (TL), and Vision Transformers (ViTs), Support Vector Machines (SVM).

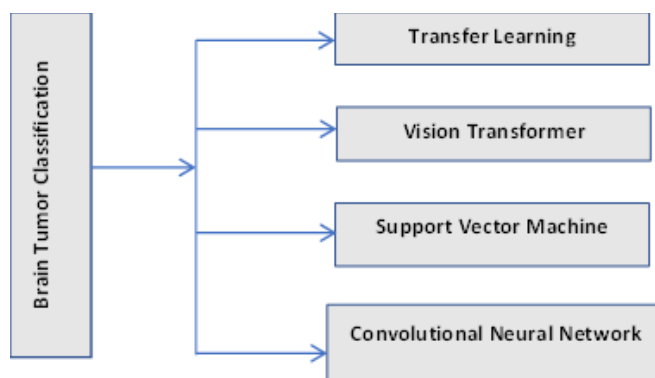


Fig.1. Overview of Brain Tumor Classification Approaches.

(1) Brain tumor classification using CNNs:

Badža et al. [16] developed an enhanced CNN model for brain tumor classification by refining the AlexNet architecture and evaluating it on the Cheng dataset. Using multiple evaluation strategies, including 10-fold cross-validation, the model achieved an accuracy of 96.56% on the augmented dataset under record-wise validation. Similarly, Nassar et al. [2] applied a majority voting strategy to combine the predictions of five different models, significantly boosting performance and achieving 99.31% accuracy on the T1W-CE MRI dataset. Deepak and Ameer [17] proposed a customized CNN model coupled with a multiclass SVM classifier for improved accuracy. Tested on the Figshare dataset with fivefold cross-validation, their approach reached 95.82% accuracy, surpassing existing baselines. Notably, their results demonstrated that SVM outperformed the conventional softmax classifier, especially when the training data was limited. Irmak [18] employed three CNN models for different tumor classification tasks. The first model achieved 99.33% accuracy in tumor detection, the second classified tumors into five categories (metastatic, normal, glioma, meningioma, and pituitary) with 92.66% accuracy, and the third graded tumors into II, III, and IV with 98.14% accuracy. All models were optimized using grid search and trained on large public clinical datasets. In another study, Badža et al. [19] designed a simplified CNN architecture for brain tumor classification using T1W-CE MRI images. Evaluated on the Fig share dataset with two cross-validation techniques, the model achieved its best performance—96.56% accuracy—under record-wise validation on augmented data.

Munira et al. [20] explored pre-processing techniques such as rescaling, resizing, cropping, and thresholding to construct a 23-layer CNN. Extracted features were classified using Support Vector Machines (SVM) and Random Forests (RF). Their comparative experiments across two public datasets demonstrated that the CNN-SVM model achieved 95.41% accuracy on the Fig share dataset, while CNN-RF attained 96.52% accuracy on the BT-Large-4C dataset. Vankdothu et al. [21] introduced a hybrid CNN-LSTM model that integrates convolutional feature extraction with temporal sequence learning. When evaluated on the BT-Large-4C dataset, the model reached 80% accuracy with an 80/20 train-test split and improved to 92% accuracy under a 90/10 split.

(2) Brain tumor classification using TL:

Swati et al. [22] employed a pretrained CNN model and proposed a block-wise fine-tuning strategy using transfer learning. Their method was evaluated on the CE-MRI benchmark dataset and, unlike approaches based on handcrafted features, required minimal pre-processing while achieving an average accuracy of 94.82% under fivefold cross-validation. Srinivas et al. [23] conducted a comparative study of transfer learning techniques using CNN models such as Inception-v3, ResNet-50, and VGG-16 for brain tumor detection. Tested on an MRI brain tumor dataset containing 233 images, the VGG-16 model demonstrated superior tumor localization performance, achieving 96% accuracy.

Rajput et al. [24] targeted the classification of three major brain tumor types using transfer learning with VGG-19, ResNet-50, and Inception-v3. Features extracted from these pretrained models were fed into fully connected layers for fine-tuning, leading to an average accuracy of 90% on a benchmark MRI dataset. Salih et al. [25] enhanced tumor classification performance by fusing features from ResNet-50 and ResNet-18, producing robust feature vectors that were subsequently classified using a machine learning layer. Their pre-processing included resizing images to $224 \times 224 \times 224$ times $224 \times 224 \times 224$, Gaussian filtering, and normalization. On the BT-Large-4C dataset, the proposed method achieved 93.74% accuracy.

Mahmud et al. [26] designed a CNN model consisting of three convolutional layers followed by a max-pooling layer and a dense layer with 4,160 nodes. The network incorporated ReLU and softmax activation functions along with a 0.5 dropout rate to improve generalization. To further enhance performance, various data augmentation techniques were applied. When evaluated on the BT-Large-4C dataset, the model achieved a classification accuracy of 93.3% across four categories.

(3) Brain tumor classification using ViT:

Many researchers have focused on enhancing CNN-based models, leading to significant progress in brain tumor classification. However, CNNs often rely heavily on correlations between spatially adjacent pixels, which can limit their ability to capture long-range dependencies. As a result, a model that performs well on one dataset may struggle to generalize across others.

To overcome this limitation, attention mechanisms have been integrated into recent approaches, enabling models to focus

on the most informative regions of the data. Hossain et al. [27] employed pretrained networks such as VGG19, InceptionV3, and VGG16, and further proposed a hybrid model, IVX16, which combines essential features from these top-performing architectures. Through extensive data augmentation, IVX16 achieved a peak accuracy of 96.94% on the BT-Large-4C dataset, while the individual models attained accuracies ranging from 93.58% to 95.11%. They also evaluated Vision Transformer (ViT) variants, including EAnet, CCT, and SWIN, which obtained accuracies of 56%, 74%, and 80%, respectively.

Yurdakul et al. [28] further assessed different ViT models on the BT-Large-4C dataset, reporting that ViT-L/32 achieved the highest accuracy (92.89%), closely followed by ViT-L/16 (92.64%). In contrast, ViT-B/32 delivered lower performance at 88.83%. Overall, ViT-L/16, MobileNet, and ViT-L/32 achieved comparable accuracies around 92.6–92.9%. Similarly, Nassar et al. [9] implemented a ViT model optimized with the AdamW optimizer and various augmentation strategies, achieving 95.4% accuracy. Despite these advances, standalone CNN-, TL-, and ViT-based models still encounter challenges in achieving consistently high accuracy across diverse datasets. To address these shortcomings, this study introduces RIE50, a hybrid framework that integrates CNN feature extraction with the Broad Learning System (BLS), leveraging their complementary strengths to improve classification performance. The details of this approach are presented in the following section.

(4) Brain tumor classification using SVM:

SVM models on the BT-Large-4C dataset and reported that the linear SVM achieved the highest accuracy of 92.89%, closely followed by polynomial SVM with 92.64%. In contrast, SVM with an RBF kernel demonstrated lower performance at 88.83%. Overall, linear SVM, MobileNet, and polynomial SVM delivered comparable accuracies in the range of 92.6–92.9%. Similarly implemented an SVM model optimized with the AdamW optimizer and enhanced through various augmentation strategies, attaining 95.4% accuracy. Despite these advances, standalone CNN-, TL-, and SVM-based models continue to face challenges in achieving consistently high accuracy across diverse datasets. To overcome these limitations, this study proposes RIE50, a hybrid framework that integrates CNN-based feature extraction with the Broad Learning System (BLS), leveraging their complementary strengths to enhance classification performance. The methodological details of this approach are presented in the following section.

III. METHODOLOGY

Figure 2 illustrates the core architecture of the proposed RIE50 framework, designed for automated brain tumor classification into four categories: normal brain, pituitary tumor, meningioma, and glioma. The process begins with preprocessing of the publicly available BT-Large-4C dataset. High-level feature representations are then extracted using three state-of-the-art pretrained models: ResNet-50, InceptionV3, and EfficientNetB0. To exploit their complementary strengths, the extracted features are fused through a concatenation layer. The fused features are subsequently refined using a CNN-based Broad Learning System (CNN-BLS), which enhances feature discrimination and representation. Finally, a dense layer performs the classification, supported by the integration of Adam and SGDM optimizers, leading to improved robustness and accuracy across tumor categories.

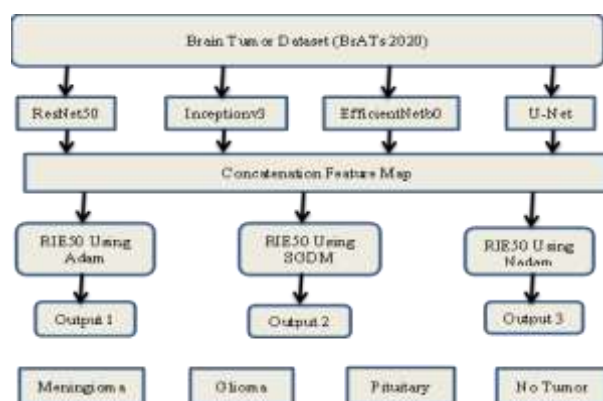


Figure 2: Overview of the proposed RIE50 model using Adam and SGDM optimizers for brain tumor classification.

The Broad Learning System (BLS) based on CNN layers

Broad Learning Systems (BLS) provides a unique strategy for enhancing learning capacity, fundamentally differing from conventional deep learning architectures. While traditional deep learning models improve performance by increasing depth through multiple stacked layers—thus learning hierarchical and abstract representations—BLS emphasizes horizontal expansion. This is achieved by incorporating additional nodes or feature mapping units within a single layer, enabling the capture of a diverse and comprehensive set of features without significantly increasing computational complexity. By prioritizing width over depth, BLS achieves efficient learning with reduced training time and lower memory requirements. When combined with Convolutional Neural Networks (CNNs), BLS can refine spatial and contextual features extracted from images, making it particularly effective for medical image classification tasks such as brain tumor detection. This structural contrast highlights the complementary strengths of deep learning and BLS in optimizing classification performance [29–31].

The CNN-based BLS (Figure 3) consists of two main components: feature nodes and enhancement nodes. **Feature Nodes:** Implemented using three sequential dense layers with 256, 512, and 1024 neurons, respectively. Each dense layer is followed by batch normalization, a ReLU activation function, and a dropout layer (rate = 0.2) to improve generalization and reduce overfitting. These layers serve as the primary feature extraction units. **Enhancement Nodes:** Comprised of two dense layers with 256 and 512 neurons, each followed by batch normalization, ReLU activation, and dropout (rate = 0.2). These layers enrich and expand the extracted features, improving the model's ability to represent complex patterns. Finally, the outputs from the feature and enhancement nodes are concatenated and passed into a dense output layer with four neurons, corresponding to the classification of brain tumors into normal brain, meningioma, pituitary tumor, and glioma.

3.1 BLS vs. Traditional Deep Learning Systems

Table 1 provides a comparative overview of Traditional Deep Learning Systems and Broad Learning Systems (BLS), highlighting their distinct approaches to enhancing learning capacity. Traditional deep learning enhances its ability to learn complex feature representations by increasing vertical depth through the stacking of multiple hidden layers, which consequently results in a training process that requires significant time and computational resources [32]. In contrast, BLS emphasizes horizontal expansion, adding more nodes or units within layers to efficiently capture a broader variety of features and patterns. The structural differences between these approaches illustrate how each optimizes learning in distinct ways [33].

Table 1. Comparison of Traditional Deep Learning Systems and Broad Learning Systems (BLS) Across Key Aspects.

Aspect	Traditional Deep Learning Systems	Broad Learning Systems (BLS)
Primary Focus	Vertical depth (stacking multiple layers)	Horizontal expansion (adding more nodes or units per layer)
Learning Capacity	Increased by deepening the network	Increased by widening the network
Feature Representation	Learns complex representations through depth	Captures a wide variety of features and patterns efficiently
Network Structure	More layers stacked on top of each other	More nodes or units within existing layers
Example	Deep Convolutional Neural Networks (CNNs)	Feature Mapping Layer and Enhancement Nodes

IV. RESULTS AND DISCUSSION

The BT-Large-4C dataset is a publicly available benchmark that has been widely employed for evaluating brain tumor classification algorithms. It consists of 3,264 MRI scans categorized into four classes: normal brain, meningioma, pituitary

tumor, and glioma, as illustrated in Figure 4. Specifically, the dataset contains 500 scans of tumor-free brains, 901 scans of pituitary tumors, 937 scans of meningiomas, and 926 scans of gliomas [34]. For experimentation, the dataset was divided into three subsets: 80% for training, 10% for validation, and 10% for testing. To ensure compatibility with the input dimensions of the pretrained models (EfficientNetB0, InceptionV3, and ResNet-50), all images were resized to 150×150 pixels. Minimal preprocessing was applied to retain the intrinsic characteristics of the MRI scans, allowing the models to learn and extract discriminative features effectively.

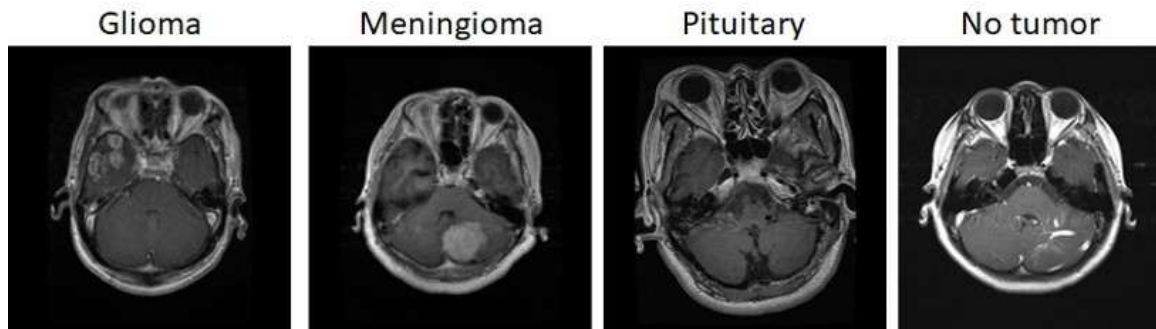


Fig. 4. Representative Samples from the BT-Large-4C Dataset: Glioma, Meningioma, Pituitary Tumor, and No Tumor Categories.

4.1 Evaluation metrics:

The proposed method's performance was assessed using six essential metrics: precision, specificity, sensitivity, F1-score, and accuracy [35], as specified in Equations 1 to 5.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Specificity = \frac{TN}{TP + FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

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

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

4.2 Hyper-parameters:

Hyper parameter optimization is crucial for enhancing the performance of deep learning models by identifying the most effective parameter configurations. In this study, three pretrained architectures—ResNet-50, InceptionV3, and EfficientNetB0—were fine-tuned with an initial learning rate of 0.001. The proposed RIE50 framework was trained for 30 epochs using a multi-stage optimization strategy: initially employing the Stochastic Gradient Descent with Momentum (SGDM) optimizer, followed by Adam, and finally Nadam, which together improved stability in the early training phase, enhanced convergence speed, and boosted overall accuracy. All experiments were conducted in Python within the Kaggle Notebook environment, which offers a flexible, object-oriented framework with high-level features and an interpretable structure, thereby enabling efficient model development, training, and evaluation.

4.3 Result:

The proposed RIE50 approach enhances feature representation by extracting features from three different pretrained

models and integrating them with BLS-CNN layers for multiclass classification. The architecture employs progressively increasing dense layers of sizes 256, 512, and 1024, enabling hierarchical feature extraction. Lower-dimensional layers capture fundamental patterns, while higher-dimensional layers learn more abstract and tumor-specific features. Each dense layer is followed by batch normalization to stabilize training and accelerate convergence, while the ReLU activation function introduces non-linearity to improve learning capability. Furthermore, dropout regularization is applied to enhance generalization and mitigate overfitting. The integration of the Broad Learning System (BLS) further refines the extracted features, contributing to superior classification performance. Experimental results demonstrate that the Adam optimizer achieved the highest classification accuracy of 97.54%, followed closely by Nadam with 97.43%, and SGDM with 97.12%, as presented.

V. QUALITATIVE RESULTS

The proposed RIE50 model outperforms recent state-of-the-art techniques in brain tumor classification. Salih et al. [25] utilized ResNet50 and ResNet18 for feature extraction, attaining 93.74% accuracy using the BT-large-4c dataset, whereas Mahmud et al. [26] used a customized CNN model with 3 convolutional layers and data augmentation techniques, reaching 93.3% accuracy. Hossain et al. [27] introduced IVX16, a hybrid model integrating VGG19, InceptionV3, and VGG16, achieving a peak accuracy of 96.94%. They also explored ViT models, where SWIN, EANet, and CCT performed notably worse, with accuracies of 80.00%, 56.00%, and 74.00%, respectively. Yurdakul et al. [28] achieved 92.89% accuracy using the ViT-L/32 model. Despite incorporating an ensemble approach, the accuracy saw only a slight increase to 94.92%, still falling short of the performance achieved by the proposed RIE50 models. Nassar et al. [9] optimized a ViT model using the AdamW optimizer, attaining 95.4% accuracy. In contrast, RIE50 integrates three pre-trained CNN models with BLS-CNN layers, significantly enhancing feature representation and classification performance. The RIE50 achieved 97.54% accuracy using the Adam optimizer, while the SGDM optimizer attained 97.12% accuracy, both surpassing existing CNN, TL, and ViT-based methods as shown in Table 2. The integration of batch normalization and dropout layers further stabilizes training and improves generalization. These findings highlight the effectiveness of RIE50 in brain tumor classification, demonstrating its capability to capture intricate patterns and outperform previous approaches.

Table 2. Comparative results with state-of-the-art approaches on the same dataset of BT-large-4c.

Ref.s	Technique	ACC.
Salih et al. [25]	combined ResNet18 and	93.74
Mahmud et al.	Customized CNN	93.3
Hossain et al. [27]	IVX16	96.94
	ViT (CCT)	74
	ViT (SWIN)	80
	ViT (EANet)	56
Nassar et al. [9]	ViT	95.4
Yurdakul et al. [28]	ViT-L/32	92.89
	ensemble approach	94.92
Proposed systems	RIE50 with SGDM	97.12
	RIE50 with Adam	97.54
	RIE50 with Nadam	97.20

VI. CONCLUSION

This study introduced RIE50, a hybrid deep learning model that integrates multiple pretrained feature extractors with BLS-CNN layers to enhance the accuracy of brain tumor classification. The proposed framework was rigorously evaluated using two optimization strategies: Stochastic Gradient Descent with Momentum (SGDM) and Adam, achieving classification accuracies of 97.12% and 97.54%, respectively. These results confirm the effectiveness of the architecture in capturing complex tumor characteristics and highlight the influence of optimization techniques on model performance. The fusion of

diverse feature extractors—InceptionV3, ResNet-50, and EfficientNetB0—with BLS-CNN layers significantly improved feature representation, reduced over fitting, and enhanced generalization. The inclusion of advanced activation functions (SELU, PReLU, and Mish), along with regularization techniques such as batch normalization and dropout, contributed to the model's robustness. Beyond technical improvements, the RIE50 model presents significant potential as a clinical decision support tool, enabling faster and more accurate diagnosis of brain tumors, reducing radiologists' workload, and improving patient outcomes.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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