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Automated Brain Tumor Classification Using RIE50: A Hybrid CNN and BLS Approach

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Abstract

Accurate and automated brain tumor classification is crucial for early detection and effective strategy development. This research introduces RIE50, a hybrid deep learning model that combines multiple pre-trained feature extractors with BLS-CNN layers to strengthen feature representation and boost classification accuracy. The BT-Large-4C dataset, used for model evaluation, comprises four categories: no tumor, glioma, pituitary tumor, and meningioma. The architecture incorporates dense layers of sizes 256, 512, and 1024, followed by batch normalization, dropout, and ReLU activation to enhance training stability and prevent overfitting. To optimize performance, we assessed two optimization techniques: SGDM and Adam, achieving classification accuracies of 97.12% and 97.54%, respectively. The experimental findings show that our approach effectively captures complex patterns in brain tumor images, leading to improved classification performance and enhanced model robustness. These results emphasize the promise of hybrid deep learning architectures in enhancing medical image analysis, aiding clinical decision-making, minimizing diagnostic errors, and optimizing patient outcomes.

Keywords: Convolutional Neural Network (CNN), Broad Learning System (BLS), Brain Tumor, clinical decision-making, RIE50.

1. INTRODUCTION

The brain is a highly intricate organ that operates through the synchronized activity of billions of interconnected cells. Brain tumors develop when these cells multiply uncontrollably, leading to the formation of abnormal masses within or surrounding the brain [1]. Tumors can be either malignant, meaning they are cancerous and capable of spreading, or benign, which remain localized and do not metastasize. The occurrence of malignant brain tumors tends to rise with age [2].

Malignant tumors grow aggressively and uncontrollably, classified as high-grade, and have poorly defined borders. They may originate in the brain as primary malignant tumors or spread from other body regions to the brain, known as secondary malignant tumors [2,3]. These tumors are typically fast-growing and invasive, posing serious health risks.

Primary brain tumors are classified into three main types: pituitary tumors, gliomas, and meningiomas. Gliomas, which are malignant, originate from glial cells that support brain and spinal cord function. Pituitary tumors originate near the pituitary gland within the skull, which plays a vital structure within the skull responsible for regulating hormone levels across the body. Meningiomas develop on the meninges, the protective layers surrounding the brain and spinal cord. [4]. Gliomas are the most frequently occurring malignant brain tumors, characterized by slow growth. While they seldom metastasize to the spinal cord or distant organs, their ability to invade multiple brain regions can make them life-threatening [5].

Timely detection is vital for successful treatment. CT and MRI scans serve as key diagnostic methods, with MRI being particularly advantageous as it provides detailed insights into the tumor's shape, size, and location. In neuroscience, early detecting of brain tumors is essential for saving lives. While several methods exist for identifying abnormalities in MRI scans, there remains a need for enhanced efficiency and faster classification [6]. Conventional methods face challenges in managing the vast amount of medical information, highlighting the need for computerized support systems. Artificial Intelligence (AI), particularly deep learning and machine learning, has demonstrated remarkable advancements in visual tasks and is widely applied in early disease detection [7], segmentation [8], and classification [9] encouraging researchers to enhance existing techniques.

Deep learning has found widespread application in healthcare for analyzing biomedical data, and recent developments have led to impressive achievements in brain tumor classification [10]. Utilizing deep learning for tumor detection in MRI scans helps alleviate the workload of radiologists. However, with so many deep learning models available, selecting the most effective approach remains a challenge. Moreover, relying solely on individual CNN models for brain tumor detection highlights the necessity of exploring ensemble learning methods, which could further improve classification accuracy [11]. The Broad Learning System (BLS) is characterized by its unique approach to feature extraction, mapping input data randomly onto feature nodes". These nodes are then processed through a nonlinear activation function, resulting in the formation of "enhancement nodes". This advanced network architecture offers an alternative method for learning deep features. Furthermore, BLS has been demonstrated to possess universal approximation capabilities [12].

This paper introduces RIE50, a novel approach for brain tumor classification that integrates feature extraction from three CNN architectures: InceptionV3, ResNet-50, and EfficientNetB0. The extracted features are first processed through a concatenation layer and undergo dimensionality reduction. These refined features are then passed into the feature nodes, followed by the enhancement nodes of a BLS integrated with CNN layers. The model employs various activation functions, including SELU, PReLU, and Mish, along with dense layers of different sizes (256, 512, 1024) [13-15]. Finally, the classification layer distinguishes brain tumors into four categories: glioma, pituitary tumors, meningioma, and normal brain tissue. The key contributions of this work are as follows:

- RIE50 is a novel framework combining MR images with a BLS-based CNN and multiple activation functions (SELU, PReLU, Mish) to classify brain tumors and normal cases, enhancing diagnostic support for radiologists.
- The feature extraction process employs three pre-trained models—InceptionV3, ResNet-50, and EfficientNetB0—recognized for their strong classification abilities and their capacity to rival more advanced CNN architectures.
- A publicly available brain tumor image dataset was utilized without any preprocessing in the training phase, while in the testing phase, only image resizing was performed.
- Finally, the proposed approach has been assessed against state-of-the-art methods utilizing multiple metrics, including recall, accuracy, F1-score, confusion matrix, precision, and specificity with a focus on test accuracy as the primary evaluation criterion.

The organization of this manuscript is as follows: Section 2, Related Work, presents a comprehensive review of relevant studies. Section 3, Methodology, details the proposed approach. Section 4, Experimental Results, covers the dataset, experimental objectives, parameter settings, performance evaluation, and outcomes of the methodology. Finally, Section 5, Conclusion, summarizes the key results and suggests future research directions.

2. RELATED WORK

Deep learning demonstrates exceptional performance in detection and classification, significantly influencing medical image analysis and consistently achieving success in various challenges, particularly in disease identification. Figure 1 presents a diagram illustrating methods related to brain tumor classification, categorizing approaches based on three types: CNN, Transfer Learning (TL), and Vision Transformers (ViT).

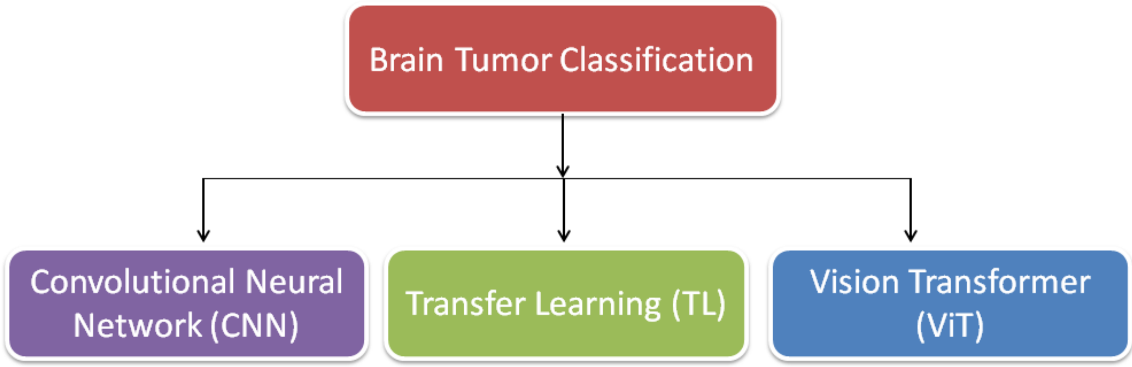

Fig.1. Overview of Brain Tumor Classification Approaches Using CNN, Transfer Learning, and Vision Transformers.

(1) Brain tumor classification using CNNs:

Badza et al. [16] developed an advanced CNN model for brain tumor classification, refining the AlexNet architecture and evaluating it on the Cheng dataset. By implementing multiple evaluation techniques, such as 10-fold cross-validation, achieving a remarkable accuracy of 96.56% on the augmented dataset using record-wise validation. Nassar et al. [2] employed a technique of majority voting to leverage the combined capabilities of five distinct models, aiming to enhance classification performance. This ensemble approach resulted in a substantial improvement, achieving an overall accuracy of 99.31% using the T1W-CE MRI dataset. Deepak and Ameer [17] proposed a customized CNN model for classifying brain tumors, incorporating a multiclass SVM for improved accuracy. Evaluated using fivefold cross-validation based on the Figshare dataset, their approach achieved 95.82% accuracy, outperforming existing methods. Their experiments demonstrated that SVM performed better than the softmax classifier, particularly when training data was limited. Irmak [18] utilized three CNN models were utilized for brain tumor classification.

The first model attained 99.33% accuracy in detecting tumors, the second model classified tumors into five classes— metastatic, normal, glioma, meningioma, and pituitary —with 92.66% accuracy, and the third categorizes them into three grades of Grade (II, III, and IV) with 98.14% accuracy. All models are optimized using the grid search algorithm and trained on large public clinical datasets. Badža et al.[19] utilized a customized CNN model for classifying brain tumors, offering a simpler alternative to existing networks. Tested on T1W- CE MRI images, its performance is evaluated using two cross-validation methods on figshare dataset. They achieved the best accuracy of 96.56% using record-wise cross-validation on augmented data.

Munira et al. [20] implemented preprocessing methods, including rescaling, resizing, cropping, and thresholding, to design a customized 23-layer CNN. The extracted features were evaluated using Support Vector Machine (SVM) and Random Forest (RF) classifiers. Their study examined multiple models, including CNN-SVM, CNN, fine-tuned Inception V3, and CNN-RF, for multi-class brain tumor classification using MRI datasets. Across two publicly available datasets, the model of CNN-SVM achieved 95.41% accuracy on the Figshare dataset, while the CNN-RF model demonstrated superior performance with 96.52% accuracy on the BT-Large-4C dataset. Vankdothu et al. [21] introduced a CNN-LSTM model, integrating a CNN with a long short-term memory (LSTM) component. The model was evaluated on the BT-large-4c dataset, achieving 80% accuracy with an 80/20 train-test split and 92% accuracy with a 90/10 split.

(2) Brain tumor classification using TL:

Swati et al. [22] utilized a pre-trained of CNN model and introduced a block-wise fine-tuning approach using transfer learning. The approach was tested on the MRI (CE-MRI) benchmark dataset. Unlike methods relying on handcrafted features, this technique is more generic, demands minimal preprocessing steps, and achieves an average accuracy of 94.82% using five-fold cross-validation. Srinivas et al. [23] analyzed a comparative analysis for transfer learning technique based on CNN models, including Inception-v3, ResNet-50, and, VGG-16 for detecting brain tumors. The pre-trained models were evaluated on the MRI Brain Tumor Images dataset, which contains 233 images. They specifically focused on tumor localization using the VGG-16 model, achieving an accuracy of 96%. Rajput et al. [24] focused on diagnosing the three most prevalent types brain tumors categories with transfer learning based on pretrained CNN models, including VGG19, ResNet50, and Inception-v3. Extracted features from these models are fed into fully connected layers, allowing fine-tuning for multi-class tumor classification. They evaluated on a benchmark MRI dataset, achieving an average accuracy of 90%.

Salih et al. [25] improved brain tumor classification by integrating the representation of features from two different models, ResNet50 and ResNet18, to generate more robust feature vectors. These vectors were then processed by a layer of a machine learning to classify tumors into four categories. The preprocessing steps involved resizing images into 224 × 224 pixels, then using Gaussian filter, and normalizing data. Using the dataset of BT-large-4c dataset, their approach attained an accuracy of 93.74%. Mahmud et al. [26] developed a CNN model with 3 convolutional layers (CL), followed by one max-pooling, and a 4,160-dimensional dense layer. The model employed ReLU and softmax activation functions, along with a 0.5 dropout rate to improve generalization. Various data augmentation techniques were utilized to enhance performance. When tested on the dataset of BT-large-4c, the model achieved a classification accuracy of 93.3% across four categories.

(3) Brain tumor classification using ViT:

Many researchers have worked on enhancing CNN models, leading to substantial advancements. Nevertheless, a CNN that performs well on certain datasets may struggle with others as it relies on analyzing correlations between spatially adjacent pixels. This limitation reduces its ability to capture long-range relationships.

To address this challenge, recent studies have integrated attention mechanisms, enabling the model to enhance model focus on critical data segments, thereby improving performance. Hossain et al. [27] utilized pre-trained models such as VGG19, InceptionV3, and VGG16, and utilized a model, IVX16, by integrating essential features from these top-performing networks. To enhance model robustness, data augmentation techniques were utilized, achieving a peak accuracy of 96.94% based on IVX16, while other models attained accuracies ranging from 93.58% to 95.11% on the BT-large-4c dataset. Additionally, they explored different ViT models, including EANet, CCT, and SWIN, which achieved accuracies of 56%, 74%, and 80%, respectively, on the same dataset. Yurdakul et al. [28] conducted an evaluation of different ViT models for classifying brain tumors based on the BT Large 4C dataset. Their findings revealed that ViT-L/32 attained the highest accuracy of 92.89%, followed closely by ViT-L/16 with 92.64%. In contrast, ViT-B/32 demonstrated the lowest performance, achieving an accuracy of 88.83%. Among the best-performing models, ViT-L/16, MobileNet, ViT-L/32, and demonstrated comparable accuracies of 92.64%, 92.89%, and 92.89%, respectively. Nassar et al. [9] implemented a ViT model optimized using the optimizer of AdamW and various data augmentation techniques with an accuracy of 95.4%. Despite significant progress, standalone CNN, TL, and ViT-based methods still face challenges in accurately classifying brain tumors, underscoring the need for other refinements. To address these limitations, this study introduces RIE50, a hybrid model that leverages the complementary strengths of CNN and the Broad Learning System (BLS) to improve classification accuracy, as elaborated in the subsequent section.

3. METHODOLOGY

Figure 2 presents the core concept of the proposed RIE50 framework, which integrates Adam and SGDM optimization approaches to classify brain tumors into four categories: normal brain, pituitary tumor, meningioma, and glioma. The process begins with preprocessing the publicly available BT-Large-4C dataset. Three powerful pre-trained deep learning models—ResNet-50, InceptionV3, and EfficientNetB0—are used to extract high-level feature representations. These features are then fused via a concatenation layer to combine the complementary strengths of the models. The fused features are further refined using a Convolutional Neural Network-based Broad Learning System (CNN-BLS), which enhances feature discrimination. Finally, a dense layer performs the classification, resulting in improved accuracy and robustness across tumor types.

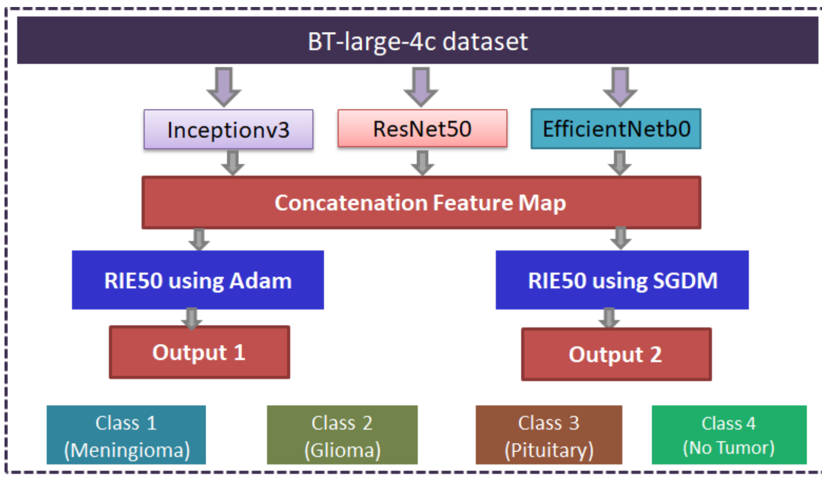

Figure 2: Overview of the proposed RIE50 model using Adam and SGDM optimizers for brain tumor classification.

3.1 The Broad Learning System (BLS) based on CNN layers

Broad Learning Systems (BLS) offer a distinctive approach to enhancing learning capacity, differing fundamentally from traditional deep learning architectures. While conventional deep learning models increase their depth by stacking multiple layers vertically—allowing them to learn hierarchical and abstract feature representations—BLS focuses on horizontal expansion. This involves adding more nodes or feature mapping units within a single layer, enabling the network to capture a diverse and rich set of features without increasing computational complexity significantly. By emphasizing width rather than depth, BLS achieves efficient learning with reduced training time and memory requirements. When integrated with Convolutional Neural Networks (CNNs), BLS can further refine spatial and contextual features extracted from input data, making it especially effective for image classification tasks such as brain tumor detection. This structural contrast between deep learning and BLS highlights their complementary strengths in optimizing learning performance [29–31].

The BLS based on CNN layers comprises two main components: (1) feature nodes and (2) enhancement nodes as illustrated in Figure 3.

- **Feature Nodes:** These consist of three distinct dense layers containing 256, then 512, and finally 1024 neurons, respectively. Each dense layer is accompanied by batch normalization, a ReLU as an activation function, and a dropout layer with a 0.2 to improve generalization and prevent overfitting. These layers act as the primary feature extraction units.
- **Enhancement Nodes:** This component consists of two dense layers containing 256 and 512 neurons, each followed by a layer of batch normalization, a ReLU as an activation function, and a dropout layer with a 0.2 rate. These layers enhance the extracted features, improving the ability of the model to capture complex patterns.

Finally, the feature nodes and enhancement nodes are combined through a concatenation layer and fed into a dense layer with four neurons, enabling the final classification of the brain tumors into normal brain, meningioma, pituitary tumor, and glioma categories.

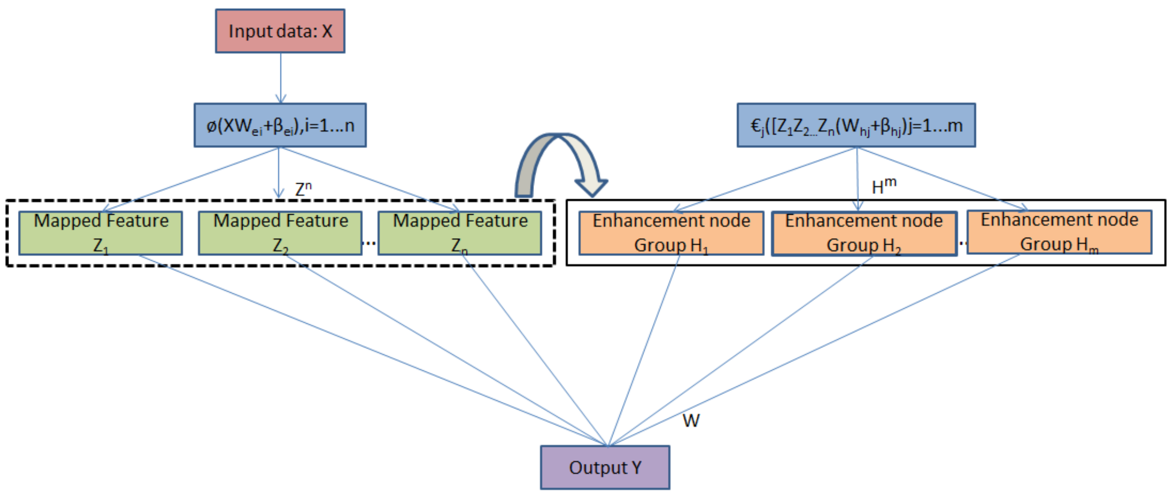

Fig.3. The BLS structure.

3.2 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

4. RESULTS and DISCUSSION

4.1 Dataset

The BT-large-4c dataset, an openly available resource, is widely utilized for evaluating classification algorithms. It comprises 3,264 images of MRI scans, representing four categories of— normal brain, meningioma, pituitary, and glioma, as presented in Figure 4. Specifically, the dataset includes 500 MRI scans of tumor-free brains, 901 scans of pituitary tumors, 937 images of meningioma tumors, and 926 images of glioma tumors [34].

The dataset was partitioned into three subsets: 80% for model training, 10% for performance testing, and 10% for validation. All images were resized the dimensions of EfficientNetB0, InceptionV3, and ResNet50 into 150×150 pixels. Excessive preprocessing was avoided to preserve the original characteristics of the images, ensuring that the model could effectively extract relevant features.

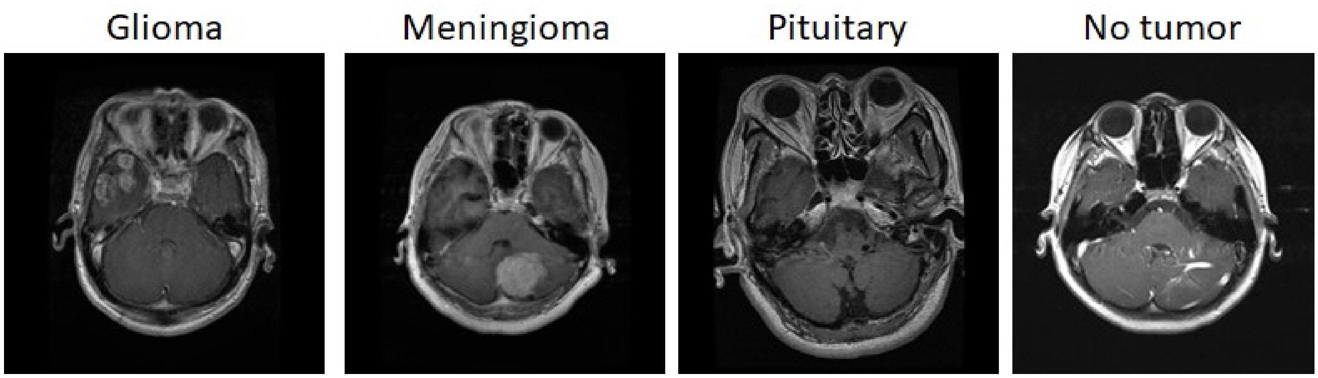

Fig.4. Representative Samples from the BT-Large-4C Dataset: Glioma, Meningioma, Pituitary Tumor, , and No Tumor Categories.

4.2 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.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Specificity} = \frac{TN}{TP + FP} \tag{2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

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

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

Here, false positives (FP), true negatives (TN), false negatives (FN), and true positives (TP), within the context of this study.

4.3 Hyper-parameters

Hyperparameter optimization is crucial for enhancing deep learning model performance by determining the most effective parameter values. This study fine-tuned ResNet-50, InceptionV3, and EfficientNetB0, initializing the learning rate at 0.001. The proposed approach of RIE50 was trained for 30 epochs using the Stochastic Gradient Descent with Momentum (SGDM), followed by Adam optimizer, which further improved performance and accelerated convergence. The research was implemented in Python based on the Kaggle Notebook environment, utilizing its object-oriented structure, high-level features, and interpretative nature to streamline model development and experimentation.

4.4 Results

The proposed RIE50 approach effectively enhances feature representation by extracting features from three different pretrained models and integrating them with BLS-CNN layers for multiclass classification. The architecture incorporates progressively increasing dense layers of sizes 256, 512, and 1024, allowing for hierarchical feature extraction. Lower-dimensional layers capture basic patterns, while higher-dimensional layers learn more abstract and complex tumor-specific features. Batch normalization follows each dense layer to stabilize training and accelerate convergence, while ReLU activation introduces non-linearity to enhance learning. Additionally, dropout is employed to improve generalization and reduce overfitting. The integration of BLS further refines feature representation, leading to superior classification performance. Experimental findings indicate that the Adam optimizer attained a classification accuracy of 97.54%, surpassing the SGDM optimizer, which attained 97.12%, as shown in Table 2. These findings emphasize the efficacy of the proposed RIE50 approach in brain tumor detection, showcasing its capacity to discern intricate patterns and enhance overall model performance.

Table 2. Classification metrics of the proposed RIE50 approach using Adam and SGDM optimizers.

Model	ACC.	Sen.	Spec.	Prec.	F1-score
RIE50 with	97.12	97.3	97.1	97.31	96.99
RIE50 with	97.54	97.44	97.21	97.49	97.49

4.5 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 3. 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 3. 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

4.6 DISCUSSION

The proposed RIE50 model demonstrates a significant improvement over recent approaches in classifying brain tumors. Compared to existing approaches, RIE50 leverages feature extraction from multiple pretrained models combined with BLS-CNN layers, leading to enhanced feature representation and classification performance. Among previous studies, Salih et al. [25] integrated ResNet50 and ResNet18, achieving 93.74% accuracy, while Mahmud et al. [26] designed a custom CNN model and data augmentation, reaching 93.3% accuracy. Although effective, these approaches did not fully capture the complex patterns necessary for optimal classification. In another study, Hossain et al. [27] developed IVX16, combining VGG19, InceptionV3, and VGG16, which achieved a higher accuracy of 96.94%.

However, their exploration of ViT models, such as SWIN, EANet, and CCT, resulted in significantly lower accuracies of 80%, 56%, and 74%, respectively. Nassar et al. [9] implemented a ViT model optimized with AdamW, achieving a promising 95.4% accuracy, demonstrating the effectiveness of transformer-based architectures.

Similarly, Yurdakul et al. [28] evaluated multiple ViT models, with ViT-L/32 reaching 92.89% accuracy. Even with the ensemble approach, the accuracy improved only a slight increase to 94.92%, indicating that while ensemble techniques provide some enhancement, they do not necessarily outperform optimized hybrid models. In contrast, the proposed RIE50 model outperformed all these methods, achieving 97.12% accuracy with SGDM and 97.54% accuracy with Adam. This substantial improvement highlights the effectiveness of combining multiple feature extraction techniques, BLS-CNN layers, and deep learning optimizers. The use of Adam resulted in slightly higher accuracy than SGDM, demonstrating its effectiveness in optimizing deep networks by accelerating convergence and improving generalization.

These findings confirm that RIE50 successfully captures complex tumor patterns, enhancing classification performance and surpassing existing CNN, ViT, and ensemble-based models. The integration of pretrained feature extraction, Broad Learning System (BLS), and CNN-based architecture has proven to be a robust approach for classifying brain tumors, making it an effective solution for real world medical imaging applications.

5. 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 overfitting, 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.

6. FUTURE WORK and LIMITATIONS

Future research can explore additional datasets, attention mechanisms, and computational optimizations to further improve accuracy and adaptability in clinical applications. The continued development of hybrid deep learning architectures will play a key role in advancing computer-aided diagnosis for brain tumors. However, our approach has some limitations, including the computational complexity introduced by the fusion of multiple deep learning models and the potential risk of overfitting due to the use of several pre-trained CNN architectures.

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