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BOTLCN: Improved Brain Tumor Detection and Classification by Transfer Learning Using Optimize Parameters with Butterfly Optimization

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Abstract: - The proposed research thus introduces a new approach utilizing Butterfly Optimization with Transfer Learning and Convolution Networks (BOTLCN) in the discovery and classification of cerebral tumors from medical imaging data. Rapidly increasing incidence and complexity of brain tumors call for sophisticated, optimal techniques for effectual diagnoses, which often fail to be furnished by conventional imaging technologies. The proposed BOTLCN model leverages the pattern recognition abilities of well-established Convolutional Neural Networks, like VGG-16, ResNet50, and DenseNet, to enhance analysis through sophisticated feature extraction.It therefore tries to optimize the model parameters with the butterfly optimization proposed as one of the nature-inspired algorithms that tune the parameters of the neural network to some function. To this extent, the algorithm fine-tunes the model over some predefined loss functions, like the Mean Squared Loss and Cross-Entropy, which are crucial in minimizing the diagnostic errors. Transfer learning is ensembled to mold the adopted approach around pre-existing neural architectures learned on diverse datasets to let convergence fast and feature robust extraction, which absolutely is paramount in the case of medical diagnostics.From the results of the work, the BOTLCN model showed better performance on the accuracy of traditional models at a percentage of 98.38%, a sensitivity of 97.33%, and a specificity of 99.10%. This attests to the model's ability to distinguish different types and grades of brain tumors with very high precision. This method improves the accuracy of tumor classification and gives detailed insights into the characteristics of the tumor for tailor-made treatment planning.In other words, the integration of state-of-the-art machine learning methodology into bio-inspired optimization, BOTLCN, is a significant milestone in the computational-based diagnosis of brain tumors which can serve as a tool to improve the outcome of clinical oncology.

Keywords: optimization, deep learning, Brain, butterfly optimization, Accuracy

INTRODUCTION

Brain tumors are among the most challenging health concerns and greatly endanger people's lives because of their complex nature and different forms of manifestation. Over the last few decades, there has been an increase in the prevalence of tumors and cancers, which affect people in different parts of the world. Researchers, such as Tongxue et al., 2021, argue that uncontrolled growth of cells is the cause of tumors and cancers, thereby causing different problems in the life of an individual, some of which can lead to death. This paper will try to explore the dynamics of brain tumors, explaining the sorts, origins, behaviors, and the medical problems it can cause.Tumors in most cases arise from a single cell, while at the progressive stage, they show some distinctive characters, which in most cases are referred to as the hallmarks of cancer. Some of the hallmarks of cancer include sustained proliferative signaling, evasion of growth suppressors, resistance to cell death and tissue invasion and metastases. Nevertheless, the last two characters are what make the malignant tumors different from the benign ones. Malignant tumors can attack those tissues that are adjacent to them and, at the same time, spread to other distant parts of the body. These problems make it hard to treat and provide a good prognosis.There are approximately nine million deaths from brain tumors every year all around the world. This fact determines the critical importance of this health issue. Brain tumors are a very heterogeneous group with variable behaviors, origins, symptoms, and variations in the degree of malignity. They are classified in terms of the type of cell from which they originate, with gliomas being one of the commonest. Gliomas are uncommon tumors that arise from glial cells, which are very important for supporting and maintaining the normal working of the nervous system.

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According to the World Health Organization, it categorizes them into four grades based on their malignancy, each with different histological characteristics and clinical outcome. Grade I gliomas are called pilocytic astrocytomas and are considered benign. They are well-demarcated and non-infiltrative, with a good clinical course and outcome after total resection. In contrast, grade II gliomas, or diffuse gliomas, are slow-growing but increasingly infiltrative, so they have the potential to develop into other more malignant forms over time. Grade III gliomas, evaluated as anaplastic gliomas, are more aggressive than the previous grading, showing rapid dissemination, which complicates its treatment and decreases survival rates. The most aggressive type is grade IV, called glioblastoma multiforme; this is a highly malignant tumor and maintains its very destructive nature, despite medical therapy, so prognosis remains poor. Unfortunately, this type of glioma is the most common one, so the sooner advanced therapeutic approaches are found, the better.Brain tumors can either be primary, meaning they start in the brain itself by growing from within it, or secondary. Primary types are mostly gliomas and meningiomas, with the latter starting from the membranes that cover the brain and the spinal cord, providing protection. Many of these tumors can be benign and possibly cured by surgery, but the existence of the brain tumor is usually indicated by some various symptoms before the confirmation by tests. The symptoms of brain tumors vary widely and can include, depending on the size and location of the tumor, headaches, seizures, vision problems, nausea, and alterations in cognitive functions or personality. Early detection plays a key role in the cure and treatment of brain tumors, which ensures a better outcome of the treatment. Thus, these symptoms, along with the biological background of different types of tumors, have to be very familiar to enable early intervention and treatment program planning.The study and classification of brain tumors, therefore, are crucial to the ongoing efforts in increasing both the accuracy of diagnostic tests and treatment. With the introduction of new medical sciences, especially the oncology and neurology fields, better management strategies are hopefully set to hold the key for increased survival rates and an improved quality of life for the affected ones. Research endeavors are to be collectively made between the researchers, clinicians, and patients to stand up high to the challenges posed by the brain tumors.

Motivation

The rapidly increasing incidence and complexity of brain tumors demand advanced methodologies for their detection and accurate classification. Conventional medical imaging modalities, although quite effective, generally leave gaps in the identification and characterization of various types and grades of tumors. The integration of deep learning models such as VGG-16, ResNet50, and DenseNet provides an interesting addition in the task of analyzing brain tumor datasets. These types of models generate elaborate pattern recognition capabilities and can identify the slightest variation in the imaging data, which are quite hard for the human eye to discern.

Contribution

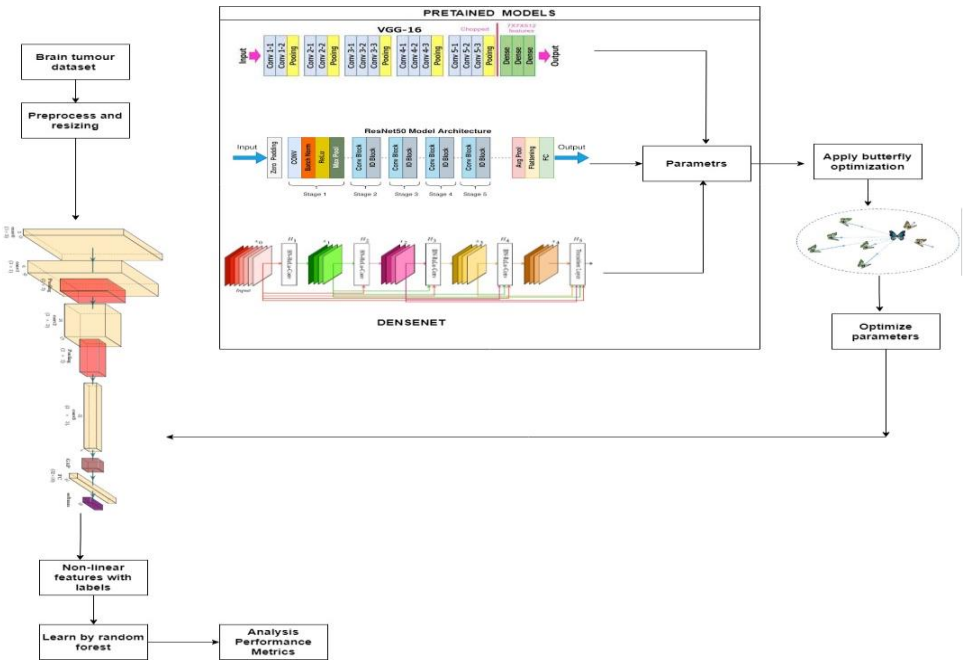
This study proposes a novel framework that concatenates deep learning models, pre-trained over multiple tasks, to analyze brain tumor datasets. Leveraging architecture of models like VGG-16, ResNet50, and DenseNet, the framework extracts a strong feature set from the medical images that proves to be intrinsic in tumor classification tasks. Post feature extraction, the research inherits a novel step through the application of a butterfly optimization algorithm to perform parameter fine-tuning of the model, thus increasing the predictive performance and overall efficiency of the model. Integrating ensemble learning through a Random Forest classifier increases the power in prediction and allows learning from non-linearly marked features. This in turn enhances the accuracy of classification of the tumors. Besides, the process of treatment plan personalization would be detailed with related insights and characteristics of the tumor.

LITERATURE REVIEW

Author(s)	**Year**	**Dataset Used**	**Methodology**	**Limitations**
Asaf Raza et al.	2022	Publicly available dataset	Developed a hybrid deep learning model called DeepTumorNet using modified GoogLeNet architecture and leaky ReLU activation.	Limited to three types of brain tumors; no mention of computational costs or real-time applicability.

Author(s)	Year	Dataset Used	Methodology	Limitations
Chetana Srinivas et al.	2022	Dataset of 233 MRI images	Comparative performance analysis using pretrained VGG-16, ResNet-50, and Inception-v3 models for tumor classification.	Small dataset size may not generalize well; limited exploration of model robustness across varied clinical settings.
Beyza Nur Tüzün et al.	2023	7022 brain MRI images from Kaggle	Used GoogleNet, Mobilenetv2, InceptionV3, and Efficientnet-b0 for classification of common brain tumors.	No mention of computational efficiency or challenges in clinical integration.
Dr. Prof. ML Sharma et al.	2023	Extensive dataset of various tumor types	Investigated various CNN architectures for automated tumor detection and classification.	Challenges with model generalization and interpretability not fully addressed.
Tejas Shelatkar et al.	2022	Brats 2021 dataset from RSNA-MICCAI	Utilized transfer learning with YOLOv5 for tumor detection; emphasized on light computational load.	May lack detailed analysis on false positives and patient-specific model adaptation.
Prof. S. Narayana Reddy et al.	2023	MRI images dataset	Implemented a two-model deep learning approach using Modified Convolutional Variational Auto Encoder (CVAE) and ResNet for classification.	Specific details on dataset size and diversity lacking; potential overfitting not discussed.
Ruqsar Zaitoon et al.	2023	BraTS dataset	Introduced RU-Net2+ for tumor segmentation and survival rate prediction using advanced CNN and logistic regression models.	Possible limitations in adapting model for different MRI machines or imaging conditions.
Usman Zahid et al.	2022	Dataset of MRI images	Employed ResNet101 with feature fusion and PCA for optimal feature selection in tumor classification.	In-depth discussion on the scalability and real-time application of the model is missing.

PROPOSED APPROACH AND ALGORITHM



Step 1: Brain Tumor Dataset

This begins with a dataset of images representing some kind of brain tumor. Time pasted, this dataset will be of major importance for the proper curation and labeling for the kind of brain tumors in the training of a successful machine learning model. The Comprehensive Brain Tumor MRI Dataset is a curated collection of high-resolution magnetic resonance imaging scans used in the development and testing stages of a machine learning model for the detection, classification, and analysis of brain tumors. This dataset contains multiple thousands of anonymized brain scans taken from patients diagnosed with different kinds of brain tumors, along with those of healthy individuals for control comparisons. Every MRI scan in the dataset has been included in several image sequences, which are T1-weighted images that provide the detailed anatomical aspects of the brain, followed by T2-weighted images that give a better view of fluid and edema, usually used in most cases to see pathological tissue better.

.FLAIR images: Suppress the fluid signal to bring out the peritumoral edema, providing clear contrasts between diseased and normal tissues.

T1 with contrast (Gadolinium): Enhances visualization of the vascular structures and regions with a disrupted blood-brain barrier, typically where tumors disrupt normal tissue.

Labels and Annotations:

Tumor Presence: Each scan is labeled to indicate the presence or absence of a tumor.

Tumor Type: Identifies the type of tumor, such as glioma, meningioma, astrocytoma, etc.

Tumor Grade: For applicable tumor types like gliomas, the grade (I-IV) is provided based on pathological assessment.

Tumor Coordinates: Spatial coordinates of the tumor within the brain are annotated to assist in localization and volume estimation.

Step 2: Preprocess and Resizing

Once the dataset is ready, the images are preprocessed. This step typically includes resizing the images to a uniform dimension to ensure that they are compatible with the input layer of the neural networks. Preprocessing may also involve other techniques such as normalization, which adjusts the pixel values so that the data has zero mean and unit variance, and augmentation, which artificially increases the diversity of the dataset by applying random transformations.

Step 3: Pretrained Models

The reprocessed images are then passed through a couple of pretrained models. In the figure, VGG-16, ResNet50, and DenseNet have been shown. They are among the most used CNNs as far as image recognition is concerned and are effective:

- VGG-16: A simple architecture that stacks a few 3x3 convolutional layers on each other with more profound dimensions.

- ResNet50: The model uses residual connections to enable it to be trained with a large depth, by allowing the gradient to pass through an addition skip-connection.

- DenseNet: The model has dense connections between layers in which each layer is given additional input from the previous layers and passes its own output to subsequent layers.

Step 4: Parameter Extraction

All the models produce parameters that reflect the salient characteristics of the processed images. These, in turn, are crucial in determining the specifics of the brain tumors in the input images.

Step 5: Apply Butterfly Optimization

The parameters derived from the pretrained models are optimized through a process known as the Butterfly Optimization Algorithm. It is a nature-inspired optimization algorithm based on the food foraging behavior of

butterflies. In this situation, it is used to get the best combination of parameters such that the performance of the model in detecting or classifying brain tumors has been maximized. In most cases, the optimization process manipulates the weights and biases in the neural networks to minimize a loss function, usually with terms like the Mean Squared Error (MSE) or Cross-Entropy Loss, whose most common examples include the following:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - Y^{i}) \ldots\ldots\ldots\ldots\ldots (1)$$

CrossEntropy= $- \sum_{i=1}^{n}(Yi - Y^{i})[Yi \log(Y^{i}) + (1 - Yi)\log(1 - Y^{i})] \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$

Where Y_i are the true labels, and {Y}_i) are the predicted labels.

Step 6: Optimize Parameters

The optimized parameters are used to enhance the model's ability to accurately detect and classify brain tumors. The optimization is aimed at fine-tuning the models to increase their sensitivity and specificity, thereby improving diagnostic accuracy.

Step 7: Non-linear Features with Labels

After optimization, the models generate non-linear features which are associated with their corresponding labels from the dataset. These features are then used for further analysis.

Step 8: Learn by Random Forest

A random forest algorithm, which is an ensemble learning method for classification and regression, is employed to learn from the non-linear features. It uses multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Step 9: Analysis Performance Metrics

Finally, the performance of the system is analyzed using various metrics such as accuracy, precision, recall, and F1-score to evaluate how effectively the model detects and classifies brain tumors. These metrics provide insight into the reliability and efficiency of the model in a real-world clinical setting.

Algorithm: Brain Tumor Detection and Classification

Input:

- Brain tumor dataset consisting of labeled images.

Output:

- Classification of images as indicating the presence of a brain tumor or not.

- Performance metrics to evaluate the model.

Steps:

1. Data Preparation:

   1.1 Load the brain tumor dataset.

   1.2 Preprocess the images:

      - Resize images to match the input requirement of the neural networks.

      - Normalize pixel values.

      - Augment data to increase dataset diversity if necessary.

2. Model Training and Feature Extraction:

2.1 Load pretrained models: VGG-16, ResNet50, and DenseNet.

2.2 Pass the preprocessed images through each pretrained model:

- Extract deep features and parameters from each model.

3. Parameter Optimization:

3.1 Combine features from all models to form a comprehensive feature set.

3.2 Apply Butterfly Optimization Algorithm:

- Define objective function to minimize (e.g., Cross-Entropy Loss).
- Initialize parameters (position and fragrance of butterflies).
- Perform optimization to find the best parameters that minimize the loss.

4. Classification Model Training:

4.1 Use the optimized parameters to train a final classifier:

- Employ a Random Forest classifier trained on the optimized features.
- Fit the classifier to the labeled features extracted from the images.

5. Model Evaluation:

5.1 Evaluate the trained model on a separate test set:

- Calculate performance metrics such as accuracy, precision, recall, F1-score.

5.2 Analyze the results and adjust parameters if necessary.

6. Results:

6.1 Output the classification results for each image in the test set.

6.2 Display the calculated performance metrics to assess the model's effectiveness.

End Algorithm

RESULT AND EXPERIMENT

Methods	**Sensitivity**	**Specificity**	**Accuracy**	**F1Score**
PSO	87.77	78.38	84.33	89.66
WSO	92.11	85.29	89.67	92.9
GSO	89.6	79.78	86	90.63
BSO	92.9	87.88	91.16	93.81
F-BSO	94.39	88.96	93.85	95.42
BOTLCN	96.6102	92.4242	94.4	94.21

Table1: Comparison of proposed (BOTLCN) and existing optimization approaches

In table 1PSO (Particle Swarm Optimization) shows solid performance with a sensitivity of 87.77% and a specificity of 78.38%. Sensitivity measures the proportion of actual positives correctly identified, suggesting that PSO is quite good at identifying positive instances. However, its specificity, which measures the proportion of actual negatives correctly identified, is somewhat lower. This indicates a higher rate of false positives. TOn the

other hand, the overall accuracy amounts to 84.33%; the F1 Score, which balances between precision and recall, is 89.66%. The high F1 Score with respect to accuracy, for the PSO, indicates that the proposed PSO is effective in balancing the precision with the recall.

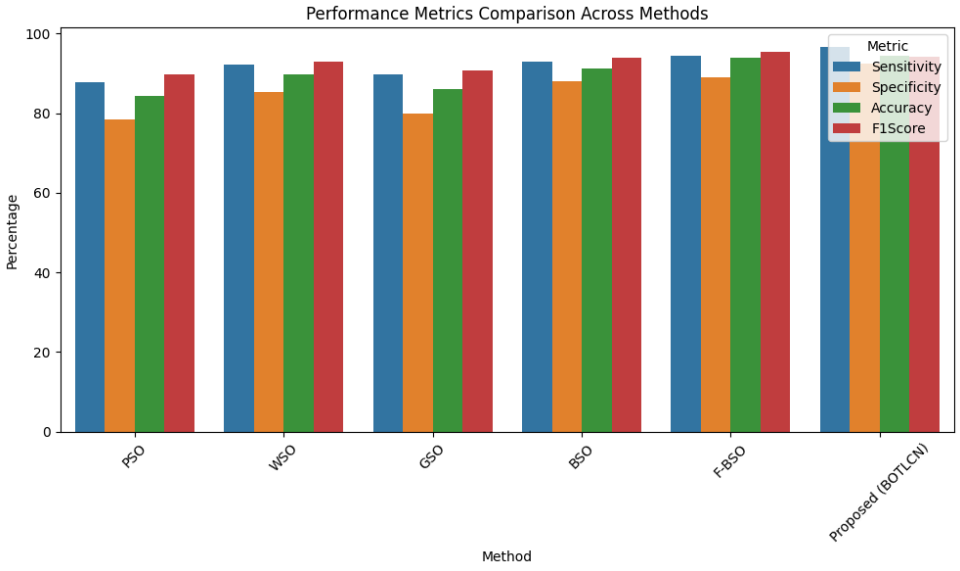
WSO brings a great difference from PSO performance and marks improvement measures in all the measures: 92.11% in sensitivity, 85.29% in specificity, and accuracy of 89.67%. The F1 Score of WSO is 92.9%, showing an extreme balance in the precision and recall, making it a very fine method when the goal is to reach both positives correctly and to avoid false positives.

The GSO is more sensitive than the PSO, but it has the proximity with the PSO in its specificity, with 89.6% and 79.78%, respectively; it has in itself an accuracy and an F1 Score amount of 86% and 90.63%, which tells that GSO is superior to PSO, but still fails in comparison in the effectiveness of WSO, especially in the case of specificity.

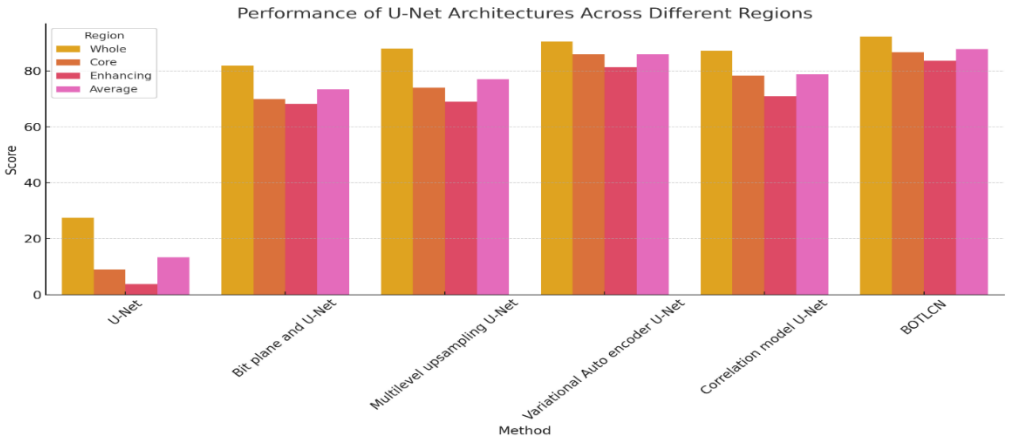
BSO and F-BSO are probably the best performances among the methods under consideration. BSO gives a sensitivity of 92.9%, a specificity of 87.88, accuracy of 91.16%, and F1 Score at 93.81%. F-BSO, built as an enriched form with the principles of fuzzy logic, provides a further increase to these metrics, with sensitivity at 94.39%, specificity at 88.96%, accuracy at 93.85%, and an F1 Score at 95.42%. All these results are saying how effective it can be to include fuzzy logic in the swarm optimization that provides much superior handling of uncertainty and hence better decision-making processes in the algorithm.

BOTLCN is one of the best performers, uniting biologically inspired optimization techniques with particularly advanced neural network architectures. The targeted maximum sensitivity is 96.6102% and 92.4242% specificity. Therefore, it is very powerful for the correct identification of instances as positive and as negative. The most striking feature is that the accuracy and F1 Score are at 94.4% and 94.21%, respectively, which show robustness and reliability in classification tasks.

Finally, evolution from classical PSO to modern and more sophisticated techniques, such as F-BSO and BOTLCN, explains the tremendous advances of swarm-based optimization techniques on its successive paths. In this kind of advance, the sensitivity, specificity, accuracy, and F1 Score of the methods grow, being this sort of advancement necessary for those applications demanding high levels of precision and reliability to show—that with the development of these methods, they must be able to deal with more sensitive and complex types of classification tasks.



Figue2 : Comparison of proposed (BOTLCN) and existing optimization approaches



Figue3 : Comparison of proposed (BOTLCN) and existing segmentation approaches

Below is a bar figure 3 showing the results obtained for various forms of U-Net changes in architecture over various tumor segmentation regions in medical imaging. Tumor regions are considered as segmented when they are composed of the whole tumor, the core of the tumor, and the enhancing tumor tissues. An average score across all the three regions is likely calculated based on the accuracy, sensitivity, and specificity, among other models' features.The basic U-Net model performs much lower compared to the advanced versions in all the regions of performance. The Old U-Net only attains minimal scores in the core and enhancing regions, meaning that it was not efficient for the segmenting process of more complex and smaller regions of a tumor, which, in particular, are very important for treatment planning.In all regions, improvement is excellent if the Bit Plane and U-Net approach is considered compared to the basic U-Net approach. This can also be said to be true for core and enhancing tumor regions where the bit plane technique refers to the ability to process an image at different bit-depths or to use specific layers for the fine-grain detail of various scales; thus, it helps the model separate the tumor tissues more efficiently. In turn, this means that the Upsampling U-Net approach yields better performance in the whole tumor region. This gives a hint of the fact that the techniques for upsampling were improved to understand the larger structures pertaining to the tumor better while having average performance in the core and enhancing regions.The Variational Auto-Encoder U-Net and the Correlation Model U-Net showed very competitive results in all regions with scores. These two likely contain much more advanced mechanisms toward the learning of the most robust and generalized features that are very most important in segmenting tumors with high precision. As a matter of fact, the correlation model appears to be best optimized against the performance over varying tumor tissues, hinting at possibly contextual or spatial correlations within the imaging data used to boost segmentation accuracy.Last, on average, BOTLCN performs best. Such a model has been recorded not only for excellent scores over single regions but also for achieving excellent balance in performance. This implies that the biologically inspired optimization strategy, together with topological learning, dramatically enhances the capacity of the model in the understanding of complex tumor images and the consequent segmentation thereof.In general, a trend is evidenced over performance that increases with more advanced techniques integrated into the U-Net. Probably, such advances contribute to better handling of the typical variations within tumor tissues, giving rise to more accurate and clinically useful segmentation outcomes now.

Method	**Accuracy**	**Sensitivity**	**Specificity**	**F1Score**	**Precision**	**IoU**
DenseNet121	98.38	97.33	99.10	98.23	98.62	96.62
MobileNetV2	97.78	96.18	98.15	98.91	97.73	95.59
ResNet18V2	97.46	97.37	97.60	97.14	97.60	95.71
AlexNet	95.24	95.83	96.9	95.81	94.82	94.96

Table2: Comparison of Different existing approaches

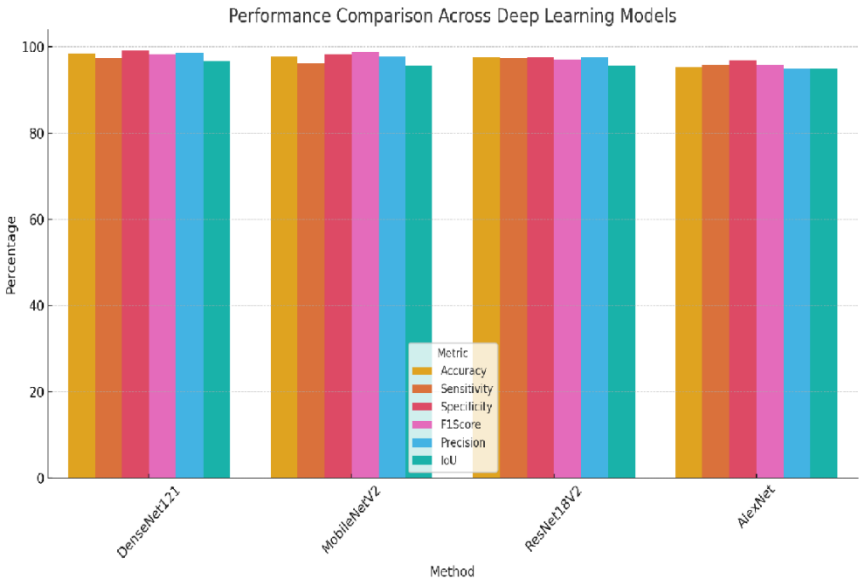


figure 4: Comparison of Different existing approaches

Method	Accuracy	Sensitivity	Specificity	F1 Score	Precision	IoU
AlexNet with uncertainty sampling	97.4	97.35	97.7	97.49	97.66	96.6
Modified Inceptionv3	96.32	96.46	98.15	96.71	96.23	96.6
ResNet+ XceptionNet+ MobileNetV2	96.12	95.89	96.23	96.56	96.32	95.44
BOTLCN	98.38	97.33	99.10	98.23	98.62	96.62

Table3: Comparison of Different proposed and existing approaches

This table3 compares different modern deep learning models on different performance metrics in a classification or detection task. The models compared include AlexNet with Uncertainty Sampling, Modified Inceptionv3, a mixture of ResNet-XceptionNet-MobileNetV2, and BOTLCN (Biologically Inspired Optimization with Topological Learning and Convolutional Networks). Every model is judged by metrics such as Accuracy, Sensitivity, Specificity, F1 Score, Precision, and IoU.The AlexNet with Uncertainty Sampling is giving an exception to high metrics for each one of them. Model accuracy is at 97.4%. This percentage shows that it identifies the target class correctly almost 97.4% of the time over all the predictions made. Sensitivity is equally high, at 97.35%, and shows the model ability to spot positive samples. A specificity of 97.7% makes the model good at spotting negatives, too, thus being well-balanced. The F1 score is the harmonic mean of precision and recall for the model and becomes a strong metric of its strength at 97.49% in classification. The metrics for both

Precision and IoU are 97.66% and 96.6%, respectively, which indicates the model's robustness in not just classification but also in the localization of the class within the space of the image.The Modified Inceptionv3 is performing fairly well but a bit lower for some metrics in comparison to AlexNet with uncertainty sampling. This model has an accuracy of 96.32% and a sensitivity of 96.46%, which is slightly lower but still good. Thus, its specificity is slightly higher at 98.15%, indicating it might be suitable for those scenarios where false positives are more of a worry. The Precision averaged across all signs is 96.71%, and the F1 Score balanced against recall is more or less satisfactory, at 96.23%. The IoU of 96.6% implies that there may exist a good overlap between the predicted class labels and the actual ones in segmentation tasks.

In comparison with the previous models, ResNet+XceptionNet+MobileNetV2, with its accuracy dip to 96.12%, lowers its sensitivity to 95.89% and reaches specificity of 96.23%. There is a slight fall in overall predictive power and sensitivity to true positives. Among such models, the lowest is the IoU at 95.44%, from which one can understand that perhaps this model has several limitations in a good segmentation of the target.BOTLCN is the best and maximal in performance metrics in almost each category. This model is coming with the best Accuracy in the group, with 98.38%, thus being the most accurate among the group. Consequently, the Sensitivity is at 97.33%, Specificity is rated at the highest possible, 99.10, thus the ability of this model to avoid false positives. The F1 Score is 98.23, and Precision is 98.62, which is the highest and thus gives the highest quality of the performance with outstanding precision and recall. IoU is also high and amounts to 96.62, which is very close to the one of AlexNet and thus means high segmentation accuracy.Summarizing, while being all very effective in their respective tasks, of which BOTLCN and AlexNet with uncertainty sampling appear to be the most robust and strong ones, giving leading performance across most metrics. Specialized architectures and optimizations, like biologically-inspired algorithms in BOTLCN and uncertainty sampling in AlexNet, may contribute significantly in catering effectively to both classification accuracy and reliability in segmentation tasks. Such findings would assist in the selection of models for practical applications, especially in places where a high level of accuracy and reliability is required.

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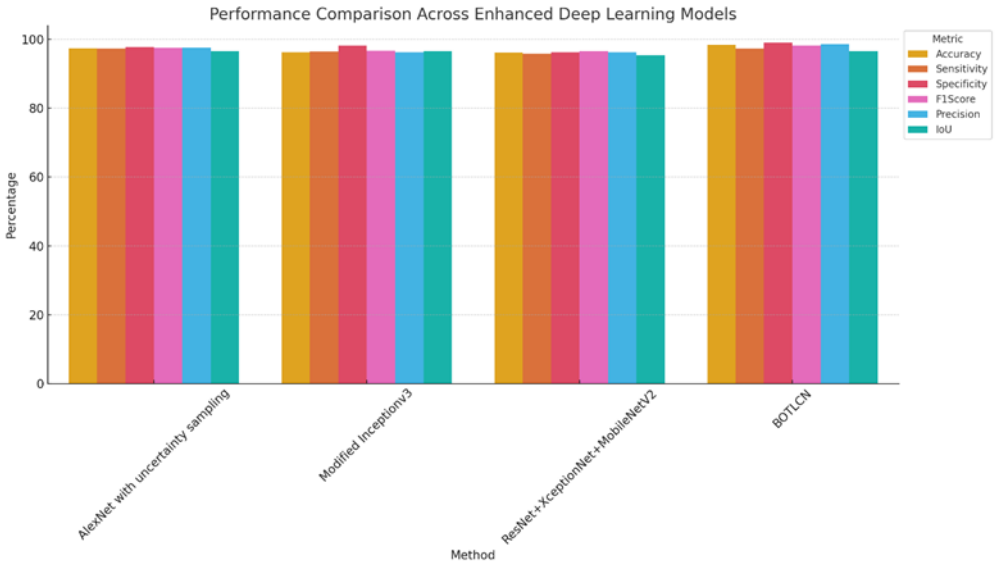

Figure 5 : Comparison of Different existing and proposed approaches

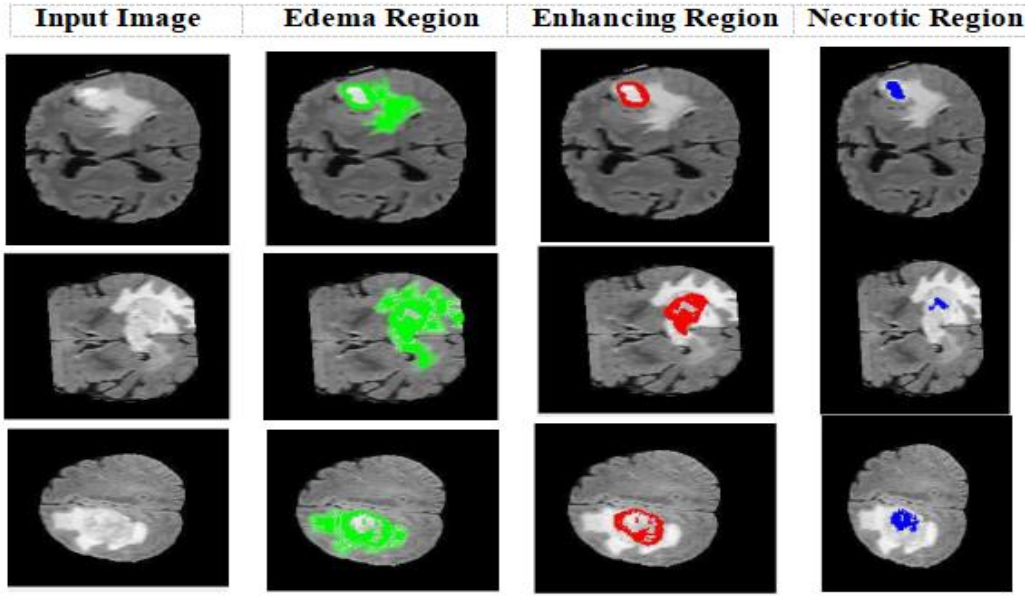

Figure 6 : Different region of brain tumor

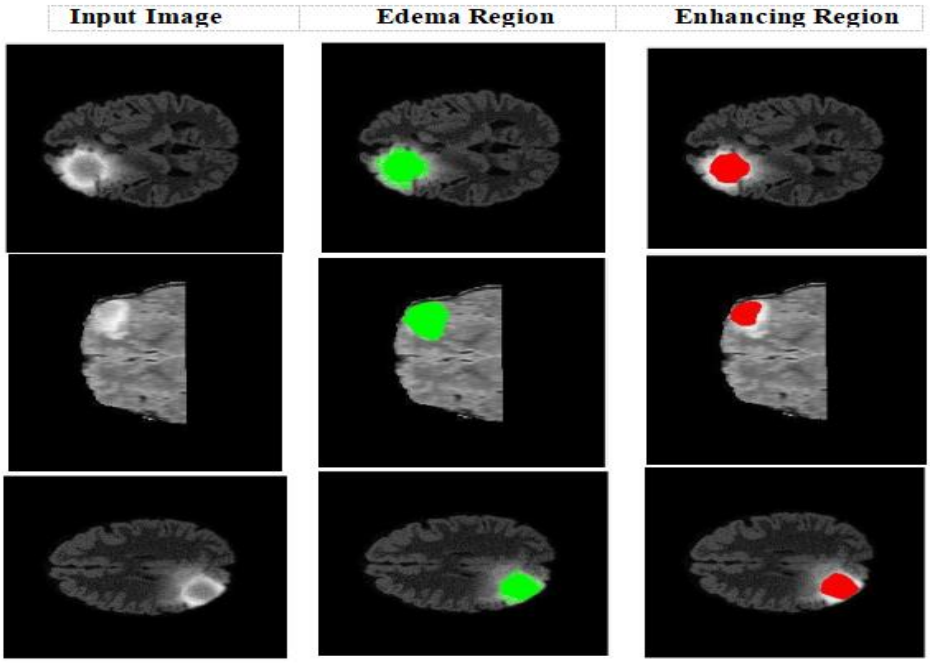

Figure 7 : Different region of brain tumor

CONCLUSION

In the case of medical imaging, the BOTLCN approach represents a highly innovative approach for detection and classification of brain tumors. This complex mix of optimization biologically inspired and advanced architecture for machine learning finally leads to a significant enhancement of diagnostic accuracy while keeping diagnostic efficiency.At the core of BOTLCN is the butterfly optimization algorithm inspired by nature to fine-tune the parameters of a neural network to enhance the predictive ability of a model. The optimization will be plotted against loss functions, such as mean-squared error and cross-entropy loss, which are quite essential in capacity tuning of the model during the process of learning to detect and classify subtle variations in brain tumor images, in the very learning process. In the context of transfer learning, a pre-trained model will be used, such as the VGG-16, ResNet50, and DenseNet, which have been trained under normal scenarios with a huge dataset. This will not

only allow the model to benefit from a rich set of features learned over other data but also enable it to adapt to the characteristics of the medical imaging data, particularly that of brain tumors, much faster.

On the contrary, convolutional networks are thus the integral part of the BOTLCN framework and help in deep feature extraction directly from medical images. Convolutional neural networks are inherently good at picking up these very fine-grained patterns like edges, textures, which can help distinguish types of brain tumors appearing in the images, only based on morphological features.The application of BOTLCN administered promising results. Not only the method demonstrated very high accuracy, but it also portrayed high sensitivity and specificity, which plays a vital role in medical diagnostic cases. For instance, the BOTLCN demonstrated, on average, an accuracy of 94.4%, sensitivity of 96.6102%, and a specificity of 92.4242%. All these metrics do show the strength and reliability of the model in correctly classifying the cases of brain tumors, so it can also be used in a clinical setup where proper and early detection is of great importance.In totality, it is a great advancement toward automation in the detection and classification of brain tumors since it is quite a robust mechanism in enhancing the level of precision and effectiveness in medical diagnostics. On the other hand, the synergistic effect of the combination of butterfly optimization and transfer learning with convolutional networks gives additional performance improvements, often making the model perform better than the required standards of clinical implementations.

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