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Bio-inspired Heuristic Optimization-Based Cascaded Hybrid Network for Brain Cancer Screening

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***Abstract*—Brain cancer is among the most fatal diseases globally, requiring early detection and timely intervention to reduce mortality rates. Traditional diagnosis relies on oncologists manually examining MRI images for signs of cancer, a process that, while effective, is time-consuming and labor-intensive. Recently, artificial intelligence (AI)-driven computer vision has emerged as a practical solution for image analysis and diagnosis. However, previous AI methods often demanded high computational resources and large datasets to achieve sufficient accuracy. This paper introduces a cascaded network combining deep learning and traditional machine learning techniques, optimized using a bio-inspired heuristic algorithm, for brain cancer detection from MRI images. The proposed approach achieves a high accuracy of 99.16% using limited data and low-computation devices. The cascaded network leverages five popular CNN models for feature extraction, Bacterial Foraging Optimization (BFO) for optimal feature selection, and seven machine-learning models for cancer detection. Among these, the MobileNetV2-BFO-KNN combination proved to be the most effective. The proposed method ensures efficiency, accuracy, scalability, and robustness, offering a reliable solution for brain cancer screening.**

***Index Terms*—Deep Learning, Machine Learning, Cascaded Network, Bacterial Foraging Optimization (BFO)**

I. Introduction

Brain cancer is a life-threatening condition that disrupts normal brain function and can cause severe neurological impairments or even death if not detected and treated early. Various types of brain cancer exist, including gliomas, which originate from glial cells and are highly malignant, and meningiomas, which arise from the meninges and are generally benign but can still negatively impact the body [1]. These brain tumors disrupt essential neural functions, manifesting with symptoms such as persistent headaches, epilepsy, and dementia, which profoundly affect the well-being of patients and their families [2]. Magnetic Resonance Imaging (MRI) is the most important and effective diagnostic tool for diagnosing brain cancer together with conventional MRI due to its results in defining the structure and characteristics of brain tumors. However, the qualitative analysis of MRI is exhaustive, time-consuming, and often misleading, especially in discriminating between tumor types and grades [3]. Such a limitation entails incorporating integrated systems that enhance the exactness of the diagnosis besides minimizing the interpretation period [4]. Recently, artificial intelligence (AI)-guided computer vision approaches have been implemented successfully for many medical image analysis and diagnosis applications. AI precisely detected, segmented, and classified anomalies, including morphology analysis and molecule quantification in medical images, to provide an accurate diagnosis. Several AI methods were developed to detect brain cancer as well. There are two individual types of methods available. The first cluster in which traditional machine learning-based methods with handcrafted features were applied for brain cancer detection. The second approach used deep learning-based methods that enable automated feature extraction and selection through loss optimization. DL models, in particular, perform well because the models can extract complex features from imaging data and gain greater diagnostic results [5]. However, these models are stochastic, so they take a lot of computations and normally are trained on large datasets [6]. Conversely, ML models are light computational and give good results with a smaller number of data samples but tradeoff accuracy [7]. Currently, the world still faces the threat posed by Glioma as brain cancer, and there are over 200 subtypes of tumors [8]. About 11,700 new cases of brain tumors worldwide are registered annually [9]; thus, the global mortality rate is 69% among patients diagnosed with this disease [10]. The fact is such statistics prove the need for effective and efficient screening and treatment approaches that are available for widespread [11]. A study has indicated that the application of the automated system has shown promise in overcoming certain diagnostic difficulties with increased efficiency and accuracy for the classification of tumors that will help to make clinical decisions [12] [13]. In this study, we developed a novel method for classifying MRI images by combining machine learning and deep learning techniques into a cascaded hybrid network. The proposed approach incorporates BFO-based feature selection, balancing the lightweight efficiency of machine learning with the high accuracy of deep learning trained on large datasets. Despite using a small dataset for training, the cascaded network demonstrated high accuracy, comparable to other deep learning methods. For automatic feature extraction, five pre-trained CNN models were employed, and the extracted features underwent BFO heuristic optimization for selecting the most relevant features. Finally, traditional machine learning models utilized the optimized features for multiclass classification. Additionally, we analyzed the role of BFO in enhancing the cascaded network's performance. The major contributions of this paper are:

- This study focuses on designing and implementing a lightweight and hybrid cascaded network for brain cancer screening, integrating deep learning-based feature extraction, bio-inspired feature selection, and traditional machine learning for disease detection.
- InceptionV3, MobileNetV2, ResNet50, DenseNet201, and Xception were employed as feature extractors, while classifiers such as SVM, RF, DT, LR, GNB, XGB, and KNN were used for accurate classification.
- Additionally, the performance of bacterial foraging optimization (BFO) are analyzed to enhance the detection accuracy for brain cancer.

The study's procedures are organized into four sections as follows: Section II reviews the existing models in the literature. Section III details the proposed model, its techniques, and the underlying working concepts. Section IV highlights the key findings, comparative analyses, and their implications, supported by visuals. Lastly, Section V concludes the study, discussing its limitations and suggesting directions for future research.

II. Literature Review

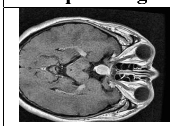
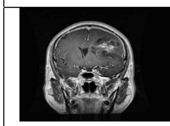
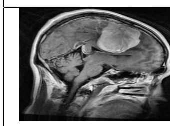
Leon et. al [14] applied in their study a ML-based hyperspectral imaging framework and achieving median macro F1-Score of 70.2 ±7.9%. Gupta et. al [15] designed a CNN architecture for classifying brain tumors using cross-validation for 10 folds. They achieved an accuracy of 96%. Mahmud et. al [16] used pre-trained CNN like ResNet-50, VGG16, and Inception V3 models and achieved 93.3% accuracy, 98.43% AUC. Saha et. al [17] applied a BCM-VEMT system that combined CNN-based deep feature extraction and a weighted average ensemble of machine learning on the multiclass dataset and achieved an overall accuracy of 98.42%. Anantharajan et. al [18] this study introduced a novel MRI brain tumor detection method using fuzzy c-means segmentation and came up with a classification with 97.93% accuracy. Saeedi et.al. [19] applied 2D CNN and a convolutional auto-encoder network to classify glioma, meningioma, pituitary gland tumors, and healthy brains. This 2D CNN achieved 96.47% training accuracy and an AUC of 0.99. Kosare et. al [20] introduce an automated approach for brain tumor detection in MRI scans using machine learning techniques, mainly neural networks, achieving about 92% accuracy. Khan et. al [21] applied DL with image preprocessing and feature selection methods to accurately classify brain tumors and achieve an impressive landmark of 96% accuracy. Khan et. al [22] Machine learning classifiers, CNN, and LSTM on MRI brain images, and their results were about 83.71% and 84.5% respectively.

III. Material and Method

A. Dataset

The MRI images used in this research work were obtained from a public domain [23] and a local cancer institute. Then, these images were reviewed by an expert oncologist to identify whether brain cancer cells were present or not in the images and scored them as 0, 1, or 2 where 2 stands for brain tumor (abnormal growth of malignant cells), 1 is for brain meningioma (typically benign tumors arising from meninges) while 0 (tumors originating from glial cells in the brain) for brain glioma. For our experiments, we used only such images for classification according to their scores. To make sure that all these images were fit for the training of machine learning models, the quality of these images was judged by the image quality assessment method proposed by Yagi et al [24] on the basis of sharpness and noise. There are about 5000 images for each three individual classes, Brain Giloma, Brain Menin, and, Brain Tumor. In Table 1, the authors provided sample images of the given dataset.

TABLE I
Sample Brain cancer Images for this Research.

Sample Images	Class Name	Class No.	Dataset Size
	Brain Glioma	0	5000
	Brain Menin	1	5000
	Brain Tumor	2	5000

The proposed system architecture is represented in Fig. 1 while Algorithm 1 shows a systemic approach to the proposed method. At first, the preprocessing technique starts with a basic function known as CLAHE (Contrast Limited Adaptive Histogram equalization) which helps in eradicating of noise of images [25]. Following that six filtering techniques, namely Average, Median, Minimum, Maximum, Bilateral,

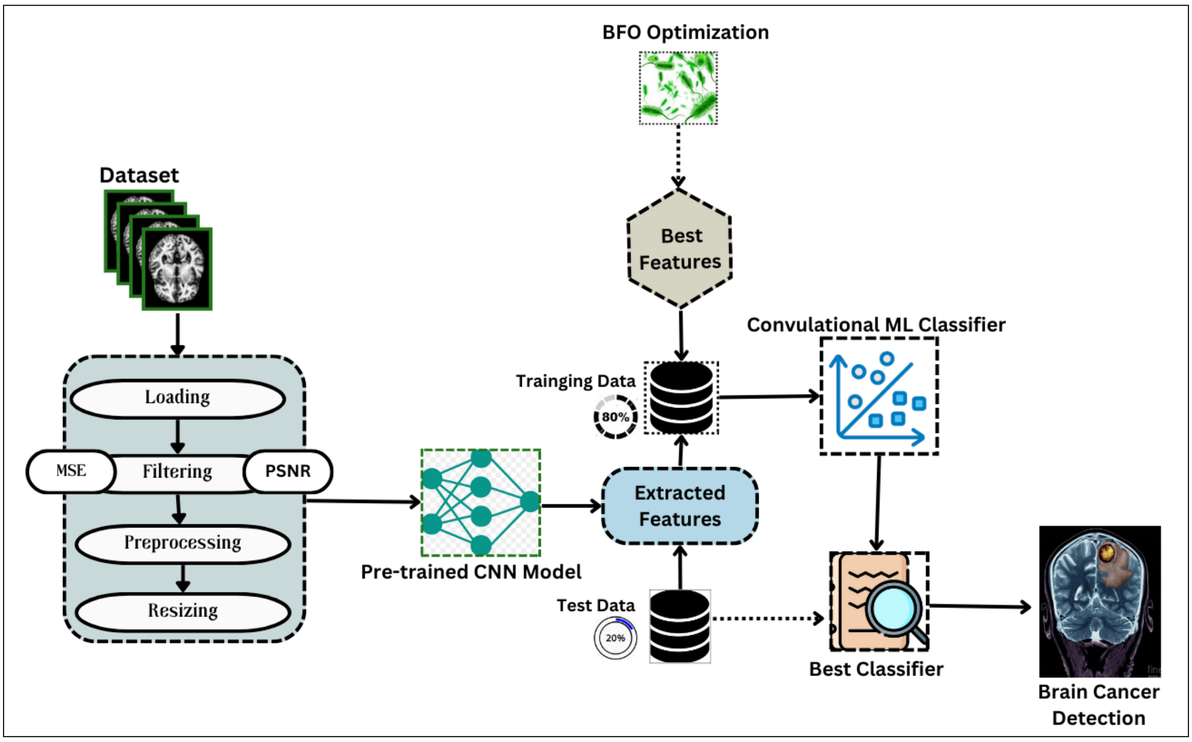


Fig. 1. Workflow Diagram of the Proposed Model.

and Gaussian Blur were used to enhance the quality of the images further. To evaluate the quality of the image, we have developed an image quality assessment cell (IQAC). The IQAC assessed the quality of the image in terms of sharpness and noise. The sharpness and noise indices of the image were calculated like the method proposed by Yagi et al. [24]. Image quality Q_i was calculated using a linear regression model with coefficients derived from regression analysis, where mean square errors served as predictors. A higher Q_i value indicated lower image quality. Images with Q_i values below the threshold Q_{ih} =10 were deemed suitable for further analysis. After that, the IQAC-approved image was transferred to sRGB space to normalize the color values. Finally, the image was resized to fit the input size of AI models. After the pre-processing, the image is processed using the pre-trained CNN model to extract features automatically. The proposed system relies on the MobileNetV2 network for feature extraction. The MobileNetV2 model was selected based on its performance and suitability for the proposed system, which is explained in the following section. Then, the BFO method processed the extracted features to select the suitable one for the classifier. Finally, the ML model utilized on the BFO-selected features to predict the output class of the image as Brain Giloma, Brain Menin and Brain Tumor. The proposed method selected the KNN model as the classifier. The following section explains how the feature extractor and classifier model were selected for the proposed method.

B. *Algorithm For the Proposed Model*

$P \leftarrow \{P_1, P_2, P_3, \ldots, P_n\}$
$B \leftarrow \{B_1, B_2, B_3, \ldots, B_n\}$
$C \leftarrow \{C_1, C_2, C_3, \ldots, C_n\}$
while $I_{\text{SRGB}} \neq I_{\text{NIL}}$
do $I_{\text{SRGB}} = I_{\text{QAC}}(I_{\text{RGB}})$
$I_R \leftarrow$ Resize(I_{SRGB} to 224×224)
FM$_i \leftarrow$ Load feature extractor MobileNetV2 with parameters P_i
$f_i \leftarrow \text{FE}_i(I_R)$
BFO$_i \leftarrow$ Load BFO with parameters B_i
$Sf_i = \text{BFO}_i(f_i)$
LDA$_i \leftarrow$ Load LDA with parameters LDA$_i$
$R_{f_i} = \text{LDA}_i(Sf_i)$
CM$_i \leftarrow$ Load classifier KNN with parameters C_i
$y = \text{CM}_i(R_{f_i})$
if $y == 0$ then
$\psi \leftarrow$ Brain-Giloma
else if $y == 0.5$ then
$\psi \leftarrow$ Brain-Menin
else
$\psi \leftarrow$ Brain-Tumor
Output: ψ

Function I$_{QAC}(I_{RGB})$*Initialization* :$\alpha, \beta, \gamma, Q_{ih}$
Load model with the n + 1 parameters α, β, γ
$Q_i = \alpha + \beta \times \text{Sharpness} + \gamma \times \text{Noise}$
Sharpness and Noise are estimated
if $Q_i < Q_{ih}$ then
return NIL

end if
if $C_{\text{linear}} \leq 0.0031$ then
$I_{\text{SRGB}} = 12.92 \times C_{\text{linear}}$
else
$I_{\text{SRGB}} = 1.0552 \times C_{\text{linear}}^{1/2.4}$
end if
return I_{SRGB}

Function BFO(F_i)
Initialization: a $\leftarrow 2A - 1,$ where $A = 1, 2, 3, 4, \ldots$
$P \leftarrow$ Input Image
$R_u \leftarrow$ Respective Feature Vector
BestFilter $\leftarrow$ applyFilter(P)
$Q_a \leftarrow$ applyFilterToImage$(P, \text{BestFilter})$
$A \leftarrow$ imageToArray(PQ_a)
for each A do Use(P, Q_a) to get $R_a \mid R_a\{V_0, V_1, \ldots, V_{14}\}$
end for
$R_u \leftarrow R_a$
$return \mathrm{R}_u$

C. Model Selection for Proposed Network

This study evaluated five prominent CNN-based models—MobileNetV2, ResNet50, InceptionV3, DenseNet201, and Xception—for feature extraction. For classification, seven leading machine learning models were explored: Support Vector Classifier (SVC), Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), Extreme Gradient Boosting (XGB), K-Nearest Neighbors (KNN), and Logistic Regression (LR). By combining the five feature extractors with the seven classifiers, 35 distinct cascaded networks were developed, each leveraging a CNN model for feature extraction and a machine learning model for classification. Additionally, a BFO-based feature selection mechanism was applied to these networks, creating 35 new optimized networks.While optimization techniques like BFO enhance model efficiency by reducing redundant features and tuning parameters, their direct impact on screening accuracy remains underexplored. This resulted in a total of 70 networks: 35 without optimization and 35 with BFO optimization. Each network was trained, validated, and tested using a dataset split into 60% for training, 20% for validation, and 20% for testing. To assess performance, four widely recognized evaluation metrics were utilized: Accuracy, Precision, Recall, and F1-Score. This comprehensive experimental design facilitated an extensive comparison of the networks, enabling the identification of the optimal configuration for the proposed system.

IV. Result Analysis and Discussion

In this study, we evaluated the performance of 70 cascaded networks trained using two distinct approaches. The first 35 networks employed CNN-based feature extraction models combined with traditional machine learning classifiers, utilizing all extracted features without applying any optimization methods. The remaining 35 networks incorporated the Bacterial Foraging Optimization (BFO) technique, which was used to eliminate unfit features from the feature set, ensuring the classifiers received optimal input. All networks were trained, validated, and tested on the same dataset, as the task involved classification. Performance was assessed using metrics such as accuracy, precision, recall, and F1-score. The experiments were conducted on a personal computer without GPU acceleration.

The performance of the study is summarized in Table II. The results indicate that the MobileNetV2-KNN model outperforms all other models, achieving 98.08% accuracy without BFO and 99.16% accuracy with BFO. Additionally, this model attained the highest precision, recall, and F1-score among all evaluated approaches. In comparison, other models showed lower performance. The InceptionV3-LR model achieved accuracy of 75.85% and 76.69% without and with BFO, respectively. ResNet50-XGB achieved 84.93% accuracy, while LR recorded 84.49%. DenseNet201-SVM achieved 91.16% and 91.78% accuracy without and with BFO, respectively. Finally, the Xception-LR model reached 91.87% accuracy without BFO and 91.98% with BFO. These results highlight the superior performance of the MobileNetV2-KNN model with BFO optimization.

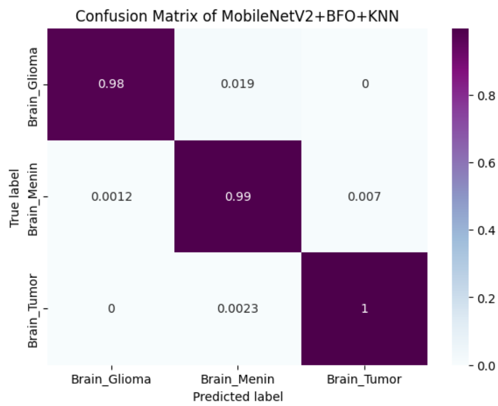


Fig. 2. Confusion Matrix of the proposed Model

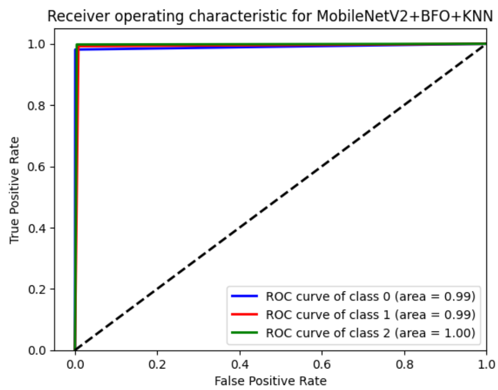


Fig. 3. ROC Curve of the Proposed Model

TABLE II

PERFORMANCE METRICS FOR DIFFERENT PRE-TRAINED MODELS AND CLASSIFIERS

Pre-trained model	**Classifier**	**Accuracy (%)**		**Precision (%)**		**Recall (%)**		**F1-Score (%)**	
		W/O BFO	**BFO**	**W/O BFO**	**BFO**	**W/O BFO**	**BFO**	**W/O BFO**	**BFO**
InceptionV3	**SVC**	70.13	61.02	69.65	60.97	70.41	61.00	69.72	60.75
	RF	68.22	71.19	67.92	70.60	68.48	71.17	68.14	70.69
	DT	58.69	59.53	58.82	59.62	58.86	59.51	58.84	59.30
	GNB	64.62	63.56	62.98	61.62	65.16	63.54	62.60	61.60
	XGB	74.15	74.36	73.97	73.98	74.37	74.35	74.08	74.00
	KNN	68.64	71.61	68.83	71.43	68.87	71.59	68.52	71.24
	LR	75.85	76.69	76.07	76.78	75.90	76.70	75.95	76.73
MobileNetV2	**SVC**	97.35	97.40	97.65	97.68	97.24	97.28	97.43	97.47
	RF	93.30	92.86	93.99	93.62	92.62	92.38	93.19	92.92
	DT	77.69	76.94	78.20	76.91	77.68	77.41	77.92	77.13
	GNB	79.63	78.84	79.07	78.26	80.44	79.63	79.21	78.39
	XGB	95.77	95.72	96.05	96.14	95.54	95.45	95.78	95.77
	KNN	**98.09**	**99.16**	**99.09**	**99.25**	**98.91**	**99.02**	**99.00**	**99.13**
	LR	96.03	95.06	96.19	95.42	96.12	95.13	96.15	95.26
ResNet50	**SVC**	78.11	81.08	79.09	82.52	73.65	76.50	75.54	78.65
	RF	79.21	80.31	80.12	82.14	74.49	74.47	76.38	76.63
	DT	66.78	66.56	64.37	63.41	64.81	63.87	64.48	63.62
	GNB	54.90	54.24	58.93	59.92	62.01	63.02	55.33	55.25
	XGB	84.93	83.83	84.56	83.86	82.98	80.84	83.69	82.06
	KNN	77.78	78.99	76.87	78.12	75.61	75.41	75.90	76.53
	LR	83.72	84.49	82.67	83.54	82.88	82.73	82.77	83.12
DenseNet201	**SVC**	91.16	91.78	45.58	45.89	50.00	50.00	47.69	47.86
	RF	88.70	89.77	45.47	45.80	48.65	48.90	47.01	47.30
	DT	86.74	86.41	54.86	51.98	53.86	51.72	54.23	51.82
	GNB	70.13	71.81	57.76	57.45	71.62	71.33	55.64	55.81
	XGB	88.65	89.43	46.55	46.95	48.91	49.03	47.48	47.73
	KNN	90.44	90.77	56.54	53.63	51.03	50.69	50.24	49.89
	LR	90.94	91.50	53.93	45.88	50.16	49.85	48.24	47.78
Xeption	**SVC**	88.98	88.75	88.33	87.32	87.01	87.38	87.60	87.35
	RF	88.75	88.08	87.85	86.50	87.06	86.80	87.43	86.64
	DT	82.52	81.51	80.66	79.16	80.70	79.44	80.68	79.30
	GNB	76.06	76.17	77.26	76.66	67.92	67.15	69.15	68.46
	XGB	90.85	91.98	90.05	90.82	90.91	91.23	91.00	91.02
	KNN	89.76	88.75	88.85	87.21	88.36	87.63	88.60	87.41
	LR	91.87	91.98	91.03	90.82	90.97	91.23	91.00	91.02

The confusion matrix and ROC curve of the proposed MobileNetV2-BFO-KNN model are presented above. fig 2 illustrates the confusion matrix, while fig 3 depicts the ROC curve.

Table III presents the deep learning models used in this study, detailing their features, parameters, MACS, and FLOPS values. MobileNetV2 emerges as the most efficient choice, retaining only 503 features after applying BFO, a significant reduction from the initial 1024 features. It also maintains the lowest parameter count (3.505M), along with minimal MACs (327.487M) and FLOPs (654.973M), making it a lightweight and optimal model compared to others.

The results presented in Table IV demonstrate that the proposed model, MobileNetV2 + BFO + KNN, outperforms other models in terms of accuracy. It achieves the highest accuracy of 99.16%, with a time complexity of 3.06 ± 0.60 seconds and a space complexity of PM: 2428 and INC: 1216.34 MIB. These findings underscore the effectiveness of the proposed method in optimizing both performance and computational efficiency.

TABLE III

FEATURE, PARAMETER, MACS & FLOPS VALUES OF DIFFERENT MODELS USED IN THIS STUDY.

Model	**Number of Features**		**Parameter**	**MACS**	**FLOPS**
	Without Opt	**BFO**			
DenseNet201	1024	509	20.014M	4.390G	8.781G
MobileNetV2	1024	503	3.505M	327.487M	654.973M
ResNet50	2048	1049	25.557M	4.134G	8.267G
InceptionV3	2048	1022	23.835M	5.749G	11.498G
Xception	2048	987	22.855M	4.146G	8.292G

V. CONCLUSION

An automated system for brain cancer screening is essential, particularly in countries like Bangladesh, where the prevalence of cancer is rising. This research addresses the need by introducing a cascaded network that integrates deep learning

TABLE IV
COMPARISON OF THE PROPOSED MODEL WITH OTHER EXISTING MODELS.

Ref.	Author	Method	Accuracy	Time Complexity	Space Complexity
[16]	Mahmud et al. [2023]	VGG16	93%	X	X
[15]	Gupta et al. [2023]	CNN	96%	X	X
[26]	S. Anantharajan et al. [2024]	Fuzzy-C	97.93%	X	X
[17]	Saha et al. [2023]	BCM-VEMT	98.43%	X	X
	Proposed Method	**MobileNetV2 + BFO + KNN**	**99.16%**	**3.06 s $\pm$ 0.60 s**	**PM: 2428.54 MiB & INC: 1216.34 MiB**

for feature extraction with machine learning for classification, fine-tuned using the BFO heuristic optimization method. The proposed system demonstrates high accuracy (99.16%) and efficiency, meeting real-world medical imaging criteria, as evidenced by complexity analysis. Deep learning models excel in feature extraction and accuracy but often require extensive datasets and significant computational resources. In contrast, machine learning models are compact, perform well with limited data, and demand fewer resources, although with lower precision compared to deep learning. A hybrid model combining the strengths of both approaches offers a balanced solution, benefiting both patients and physicians. This was achieved by leveraging BFO-based feature selection, which prioritized relevant features for brain cancer detection. The results showed that fewer but more effective features significantly enhanced the model's performance. An ablation study highlighted the critical role of BFO in improving both accuracy and speed.

However, the proposed system currently lacks real-world implementation. Future work aims of this study is to develop a functional, practical system based on the findings. In conclusion, the proposed approach represents a significant step toward creating an efficient and reliable automated system for brain cancer screening, offering a promising direction for future advancements.

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