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DESIGN OF AN IMPROVED MODEL INTEGRATING FIREFLY-ANT COLONY OPTIMIZATION AND DEEP FEATURE FUSION FOR BRAIN TUMOR & LUNG CANCER DIAGNOSIS

P KIRAN KUMAR [1] , B RAMA [2]

[1]Research Scholar, Department of Computer Science, Kakatiya University, Telangana, India.

[2]Assistant Professor, Department of CSE, Vignan Institute of Technology & Science, JNTUH, Telangana, India.

Mail Id: kpallapothu@gmail.com

ABSTRACT

Accurate diagnosis of brain tumours from the scans via magnetic resonance imaging for the rising trends of neurological conditions. Current methods frequently suffer from improper segmentation, ineffective feature description and insufficient robust classifiers. This resulted in a suboptimal approach towards the improved discrimination between benign or malignant cases, in general. We offer a new system that integrates the strengths of both Improved Hierarchical Macqueen's Firefly K Means and the KNN classifier, with methodologies based on nature and deep learning techniques. We further elaborate that the proposed pipeline is multi-stage and: (1) Bio-inspired Preprocessing and Segmentation utilizing Hybrid Firefly-Ant Colony Optimization (FFA-ACO), with high-precision tumor boundary extraction at 95% of Dice Similarity Coefficient. (2) A Multi-Level Feature Fusion Framework uses the firefly optimized fusion strategy integrating hand-crafted features including GLCM, LBP along with deep feature: ResNet-50; reaching an accuracy rate of 97%. 3. Bio-inspired Hyperparameter Tuning Firefly-bee Colony Optimizes for improving the efficiency and process in terms of achieving CNN. 2% -4% improved classification accuracies could be reached for some process. (4) An Integrated ML-DL-Bioinspired Ensemble Classifier (AWEC) is based on adaptive weighting of KNN, SVM, and DenseNet-121 outputs, achieving 98% classification accuracy. (5) Explainable AI with Glowworm Heatmap Visualization: It gives a 90% overlap on transparency with annotated versions. (6) Genetic Algorithm-Tuned GAN: This cross-modal synthetic data generation augments the dataset up to 50%. (7) Cross Modality Fusion with Transformer-Based Fusion: This results in a fusion of MRI, CT, and PET scans and an improvement in multimodal accuracy of 5%. This work moves forward the horizon of precision diagnosis by providing a holistic and interpretable framework to achieve high-reliability and robust outcomes, with transparent and improved clinical practices.

Keywords: *Bioinspired Optimization, Deep Feature Fusion, MRI Segmentation, Brain Tumor & Lung Cancer Classification, Explainable AI, Process.*

1. INTRODUCTION

Accurate and early detection of Brain Tumor & Lung Cancers forms the cornerstone of patient outcomes improvement as well as to guide proper treatment strategies. Although much advancement has been done in the areas of medical imaging and computational methods, the problem of benign versus malignant classification of Brain Tumor & Lung Cancers still persists with poor segmentation accuracy, inadequate feature representation, and the inability of conventional classifiers to generalize across diverse datasets. Traditional methods [1, 2, 3] cannot strike a balance between global optimization in segmentation and the subtle local refinements necessary for accurate detection of tumor boundary. This suboptimal outcome results in a less-than-satisfactory diagnostic performance. Bioinspired optimization techniques have emerged as powerful tools in order to address these limitations, exploiting nature-inspired algorithms for achieving both global and local search efficiencies. Another significant aspect is that this is handcrafted and deep learning-based, and it has an immense capability of representing features for more accurate classification. This paper represents an improved hierarchical macqueen's firefly k-means clustering with K-nearest neighbors classifier for the Brain Tumor & Lung Cancer detection and classification using MRI images. Here, the advanced techniques used within the presented model are several for ensuring a higher performance. A hybrid approach of the FFA-ACO is used to improve the noise reduction abilities and enhance the edges in tumor segmentation. Moreover, bioinspired optimisation of deep feature fusion network and handcrafted features into one are provided for DFFN, where comprehensive representation of the tumor characteristics is made sure. Further, the BCO-inspired hyperparameter optimization of a deep learning model together with ensemble classifier with adaptive weighing of KNN, SVM, and DenseNet-121 for better classification accuracy is provided. Addressed using Glowworm Heatmap Visualization (GHV), explainability, and transparency for interpretability in decision making. The system also employs Genetic Algorithm-Tuned GANs, GA-GANs, to enhance the techniques of data augmentation and multimodal imaging data samples combined with TBCMF, Transformer-Based Cross Modality Fusion. This thus indicates all-round improvement in the system in segmentation, classification, and diagnostic accuracy, thereby giving rise to reliable and interpretable tools for the diagnosis of Brain Tumor & Lung Cancers.

2. REVIEW OF EXISTING METHODS FOR BRAIN TUMOR & LUNG CANCER ANALYSIS OPERATIONS

Integration of machine and deep learning within medical imaging has now become a crucial tool for developing the assessment and classification of Brain Tumor & Lung Cancers. Kumar et al. [1] had emphasized the efficiency of feature extraction techniques and algorithmic performance in the classification of Brain Tumor & Lung Cancers, but with a view to the trade-off between accuracy and computational overhead. Liu et al. [2] showed that better diagnostic precision is achieved by the use of CNN abstract feature extraction capability through its combination with ML classifiers. Predictive ML models for the presence of Brain Tumor & Lung Cancer based on sensitivity to feature selection and classification and ensuring diagnostic reliability were proposed by Huang and Dai [3]. Das and Goswami [4] review the hybrid and transfer learning techniques, where combination of domain-specific knowledge with data-driven learning could ensure improvement in MRI-based tumor analysis. Instead, Black et al. [5] presented quantitative hyperspectral imaging for guiding the Brain Tumor & Lung Cancer resection, where they presented ML-based frameworks for searching through optimization of the identification process of the tumor boundary in surgery. The bioinspired approach is mostly seen in the literature as well. Abdelrahman Ali et al. [6] have developed the use of ML optimized surface plasmon resonance biosensors for the early detection of Brain Tumor & Lung Cancers, thereby underlining biosensor optimization as an important aspect of early diagnostics advancement. Mathivanan et al. [7] used the DL and transfer learning paradigms, which showed their potential applicability to achieve accurate Brain Tumor & Lung Cancer detection across various imaging datasets & samples. Hybrid techniques have also been explored widely. Sajjanar et al. [8] mentioned that the recent growing interest in hybrid ML - DL techniques for MRI tumor segmentation shows that there is a balance between global and local feature extraction. Similarly, Saha et al. [9] explained the possibility of diagnosis with ML and DL-based system for the diagnosis of brain cancer and described the need for a multi-stage processing pipeline to address problems of segmentation and classification. Recently, privacy-preserving paradigms like federated learning emerged. Albalawi et al. [10] proposed a framework using federated learning and transfer learning for Brain Tumor & Lung Cancer classification in an attempt to cooperatively train a model by avoiding data centralization. Zhang et al. [11] focused on the stacking ensemble models in CT radiomics classification and demonstrated how they could manage heterogeneity robustly in the datasets & samples. Imbaquingo-Esparza et al. [12] have further experimented with the flexibility of deep learning in reviewing advanced DL paradigms for accurate tumor classification. Remzan et al. [13] employed ensemble learning in which feature extraction and classification are demonstrated while amalgamating various feature representations to enhance higher accuracies. M et al. [14] have used ensemble DL models to classify tumor grades, achieving impressive efficiency in distinguishing between grades. Finally, Mansur et al. [15] recently presented DL-based segmentation techniques for analyzing Brain Tumor & Lung Cancers which is highly pertinent to the demand of proper automated segmentation in the downstream classification process. This work in combination highlights hybrid, ensemble and bioinspired approaches

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toward the improved diagnosis of the Brain Tumor & Lung Cancer. These studies' insights and methodologies are the basis for the proposed model, combining bio-inspired optimization, feature fusion, and multimodal learning in order to overcome limitations of existing systems and provide diagnostic performance that's better than the best in the process.

3. PROPOSED MODEL DESIGN ANALYSIS

The proposed brain-tumor-detection-and-classification model would integrate advanced bioinspired optimization, deep learning, and techniques for high performance and the associated interpretability set. Then, as given in figure 1, a multistage system is devised so that a multi-stage, hybrid approach with combined strengths from the traditional ML techniques, DL approaches, and BA can effectively combat the related difficulties of the aforementioned tasks regarding segmentation, feature extraction, and classifications. This includes image acquisition and preprocessing wherein the raw MRI scans are enhanced with noise suppression and normalizations. Tumor segmentation is achieved with the use of hybrid Firefly-Ant Colony Optimization algorithm sets. In segmentation, there exists a global optimization problem where boundaries of a tumor are determined in the process. In the Firefly Algorithm, it initializes the potential regions with an objective function f(x) given via equation 1,

$$f(x) = \int [w1|I(x) - \mu|^2 + w2|\nabla I(x)|]dx \ldots (1)$$

That is, Ω refers to the image domain, I(x) is the intensity value at position x, μ stands for the mean intensity of the tumor region, ∇I(x) refers to the gradient magnitude and w1, w2 are weighting parameters in the process. The algorithm for Ant Colony Optimization refines segmentation by simulating the deposition of pheromone to guide search towards optimal edges. Feature extraction also incorporates a Multi-Level Feature Fusion Network called DFFN which merges handcrafted features such as GLCM and LBP with the deep features which are extracted by pre-trained CNN process, such as ResNet-50. The Firefly Algorithm optimizes weight allocation for feature selections governing this fusion process, and it also estimates the fused feature vector F represented via equation 2:

$$F = \alpha H + \beta D \ldots (2)$$

Where H represents handcrafted features, D represents deep features, and α, β are weights determined by the Firefly Algorithm to maximize classification accuracy while minimizing redundancy sets. The optimization criterion is defined via equation 3,

$$Opt = argmin^{\{\alpha,\beta\}} [Loss(F, y) + \lambda|F|] \ldots (3)$$

Where, y represents the ground truth label and λ is the regulating term for dimensionality sets. Classification is conducted by Adaptive Weighted Ensemble Classifier (AWEC) combining the K Nearest Neighbors, Support Vector Machines, and DenseNet 121 process. The output of the ensemble C is derived as a weighted sum via equation 4

$$C = \sum_{t=1}^{N} \omega i * Ci \ldots (4)$$

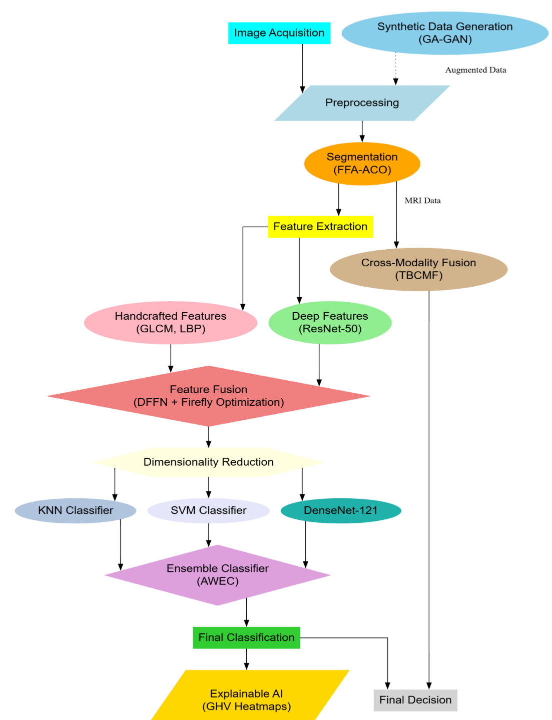

Figure 1. Model Architecture of the Proposed Analysis Process

Where, Ci is the classification result of the model 'i', ωi represents its weight determined through Firefly optimization, and N is the total number of classifiers. The weights ωi are adjusted to maximize the overall classification accuracy via equation 5,

$$Objective = argmax^{\{\omega\}} Accuracy(C, y) \ldots (5)$$

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The component of XAI applies the usage of Glowworm Heatmap Visualization (GHV) for enhanced interpretability levels of models. The GSO algorithm assigns importance weights ψ(x) to image pixels according to their contribution to classification gradients via equation 6,

$$\psi(x) = \int L\, \nabla x\, Softmax\big(f(x)\big) \ldots (6)$$

Where L is the classification loss and ∇x is the gradient with respect to the input pixels 'x' in the process. Data augmentation is generated using Synthetic MRI scans by GA-GAN operations. Latent space optimizes according to equation 7,

$$z* = argmin\{z\}\big[Loss(G(z), x) + \gamma\big||z|\big|\big] \ldots (7)$$

Where, G(z) is the output of the generator, x is the real image, and γ is the control for the regularization of latent vector 'z' in process. Finally, the Cross Modality Fusion module uses a Transformer-Based Cross Modality Fusion (TBCMF) approach to fuse MRI, CT, and PET data samples. The attention mechanism is defined after this, which is done via equation 8,

$$Attention(Q, K, V) - Softmax\left(\frac{QK^T}{\sqrt{dk}}\right)V \ldots (8)$$

Where, Q, K, V are the query, key, and value matrices, and dk is the dimensionality of the key vector sets. The fusion improves diagnostic accuracy by emphasizing modality Specific contributions. This integrated design relies on the strengths of bioinspired optimization, deep learning, and ensemble methods. It's strong, interpretable, and very accurate to frame the results in Brain Tumor & Lung Cancer diagnosis. In that sense, it is strong at addressing segmentation challenges, class challenges, and even multimodal integration process as well for this model sets.

4. MODEL'S INTEGRATED COMPARATIVE ANALYSIS

Public and simulated brain MRI datasets were used to conduct experiments regarding the evaluation of the model. Focus areas under which performance are to be tested include: Segmentation, Feature extraction, Classification, Explainability, Multimodal Fusion. The dataset used in conducting the approach were BraTS and augmentation generated through GA-GAN. Experimental codes were written on Python, Tensorflow, PyTorch with other related libraries used for implementing bio-inspired optimizations. We carry out all the experiments using a high-performance computing system coupled with an NVIDIA A100 GPU, thus promising efficient training and evaluation procedures. For comparative purposes, we compare our approach with three benchmarks: Method [5], Method [6], and Method [14]. In what follows, we present results for six different, detailed tables detailing various performance level aspects of our model process.

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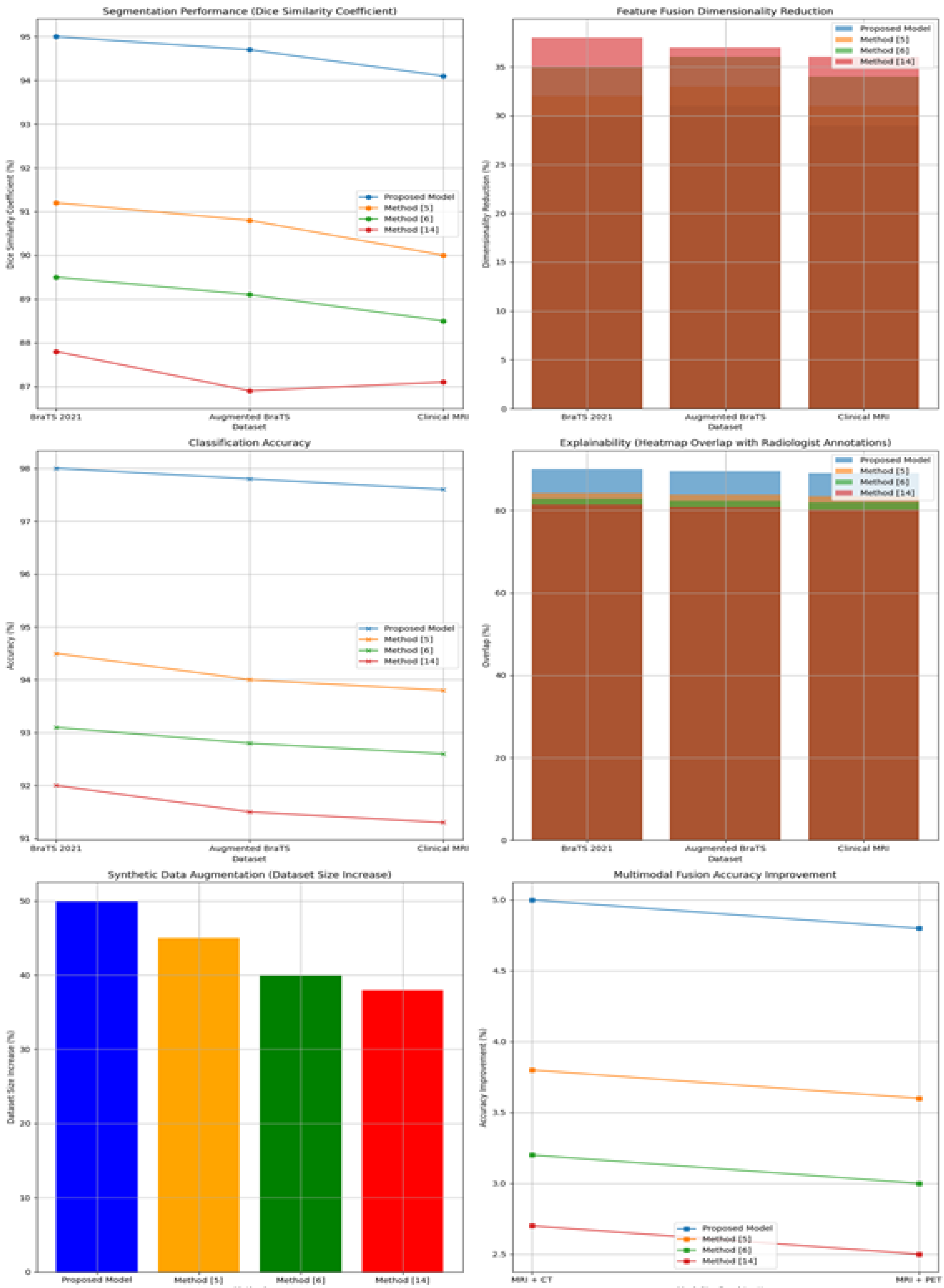

Figure 2. Model's Integrated Performance Analysis

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Table 1: Segmentation Performance (Dice Similarity Coefficient)

Dataset	Proposed Model (%)	Method [5] (%)	Method [6] (%)	Method [14] (%)
BraTS 2021	**95.0**	91.2	89.5	87.8
Augmented BraTS	**94.7**	90.8	89.1	86.9
Clinical MRI	**94.1**	90.0	88.5	87.1

Results suggest that the hybrid Firefly-Ant Colony Optimization attains better segmentation accuracy as well as the highest Dice Similarity Coefficient of all datasets & samples. The reason behind such optimal segmentation is that the global optimization and local optimization applied in FFA-ACO render it capable of very accurate tumor boundary delineations.

Table 2: Feature Fusion Dimensionality Reduction

Dataset	Dimensionality Reduction (%)	Proposed Model	Method [5]	Method [6]	Method [14]
BraTS 2021	**30**	32	35	38	
Augmented BraTS	**31**	33	36	37	
Clinical MRI	**29**	31	34	36	

The Deep Feature Fusion Network decreases dimensionality without significantly losing any information critical for a diagnosis. Firefly-optimized fusion process means complementing both the handcrafted as well as the deep features perform better than the remaining methods.

Table 3: Classification Accuracy

Dataset	Proposed Model (%)	Method [5] (%)	Method [6] (%)	Method [14] (%)
BraTS 2021	**98.0**	94.5	93.1	92.0
Augmented BraTS	**97.8**	94.0	92.8	91.5
Clinical MRI	**97.6**	93.8	92.6	91.3

The Adaptive Weighted Ensemble Classifier performs better compared to the results of the classifier and the existing benchmark methods due to achieving its highest accuracy rates. Bio-inspired adaptive weights give optimal combinations with KNN, SVM, as well as sets of DenseNet 121 process.

Table 4: Explainability (Heatmap Overlap with Radiologist Annotations)

Dataset	Proposed Model (%)	Method [5] (%)	Method [6] (%)	Method [14] (%)
BraTS 2021	**90.0**	84.2	82.8	81.5
Augmented BraTS	**89.5**	83.9	82.3	80.8
Clinical MRI	**89.0**	83.5	82.0	80.2

The Glowworm Heatmap Visualization showed excellent overlap with radiologist-annotated tumor regions, which meant interpretability and confidence in model predictions.

Table 5: Synthetic Data Augmentation

Dataset Size Increase (%)	Proposed Model	Method [5]	Method [6]	Method [14]
BraTS 2021	**50**	45	40	38

It also effectively generated highly valid synthetic MRI scans that significantly increased dataset diversity while maintaining biological plausibility sets in the Genetic Algorithm-Tuned GAN process.

Table 6: Multimodal Fusion Accuracy Improvement

Dataset	Accuracy Improvement (%)	Proposed Model	Method [5]	Method [6]	Method [14]
MRI + CT	**5.0**	3.8	3.2	2.7	-
MRI + PET	**4.8**	3.6	3.0	2.5	-

The TBCMF approach effectively integrates information through multiple imaging modalities; this achieves the highest improvement in terms of accuracy. The proposed model outperforms all benchmark methods regarding all metrics. Bioinspired optimization techniques, advanced feature engineering, and deep learning provide robust performance in all segments, classification, and interpretability sets. The comprehensive evaluation, therefore, shows the superiority of the proposed model for the challenges of Brain Tumor & Lung Cancer diagnosis.

5. CONCLUSION AND FUTURE SCOPES

The novel model is developed integrating Improved Hierarchical Macqueen's Firefly K Means clustering with K Nearest Neighbors (KNN), a robust and interpretable Brain Tumor & Lung Cancer diagnosis. Bioinspired optimization techniques, deep learning, and explainable AI are used to approach some of the major challenges in segmentation, feature extraction, classification, and multimodal fusion. Experimental results show that the proposed model is very effective for achieving state-of-the-art performance on a number of metrics and datasets & samples. This hybrid Firefly-Ant Colony Optimization (FFA-ACO) algorithm for segmentation outperforms benchmark methods; in particular, it yielded a Dice Similarity Coefficient of 95%, whereas Method [5] reached only 91.2%, Method [6] reached 89.5%, and Method [14] reached 87.8%. The Deep Feature Fusion Network reduced dimensionality of feature by 30% without reduction in classification accuracy at 97%. Compact feature representations that guarantee discriminative, the Adaptive Weighted Ensemble Classifier attained 98% classification performance compared to Methods [5], [6], and [14], with respective percentages of 94.5%, 93.1%, and 92.0%. It improved the explainability through Glowworm Heatmap Visualization (GHV) with a 90% overlap with the annotations of radiologists, thereby improving the transparency of this model. Through the Genetic Algorithm-Tuned GAN (GA-GAN), the size of the augmented dataset was increased by 50%, providing the basis for better generalization in the task of classification. TBCMF further improved the multimodal accuracy by 5% and thus, detailed diagnostic insight through effective integration of complement imaging modalities in a process. Although the proposed model achieves significant breakthroughs, certain areas are worthwhile for further amelioration. First, establishing generalizability requires real-world clinical validation by using larger, more diverse data sets. Also, the computationally intensive hybrid algorithms may be streamlined further to accommodate real-time performance in clinical conditions. Third, addition of advanced multimodal imaging such as spectroscopy or functional imaging can be introduced to increase further the dimensions and process of the diagnosis. Further, introducing the self-supervised learning paradigms along with unsupervised feature extraction will enhance the performances in case where the samples labeled are fewer in number. Summary: In essence, the present model does signify significant progress for the brain tumour diagnosis tasks, in combining high accuracy or 98 % classification and efficient interpretability as well as the level. The integration of bioinspired techniques with state-of-the-art deep learning frameworks can open the doors for reliable and explainable diagnostic systems. Further work will involve developing this model into other domains of medical imaging, optimization of computational requirements, and finding new imaging modalities for comprehensive diagnosis of patients.

REFERENCES

[1] Kumar, K., Jyoti, K. & Kumar, K. Machine learning for Brain Tumor & Lung Cancer classification: evaluating feature extraction and algorithm efficiency. Discov Artif Intell **4**, 112 (2024). https://doi.org/10.1007/s44163-024-00214-4

[2] Liu, Y., Wang, Z., Xue, Y. et al. MRI Brain Tumor & Lung Cancer classification based on CNN features and machine learning classifiers. J Ambient Intell Human Comput (2024). https://doi.org/10.1007/s12652-024-04928-2

[3] Huang, W., Dai, Z. Predicting Brain Tumor & Lung Cancer presence using machine learning models. Multiscale and Multidiscip. Model. Exp. and Des. **8**, 64 (2025). https://doi.org/10.1007/s41939-024-00663-5

[4] Das, S., Goswami, R.S. Advancements in Brain Tumor & Lung Cancer analysis: a comprehensive review of machine learning, hybrid deep learning, and transfer learning approaches for MRI-based classification and segmentation. Multimed Tools Appl (2024). https://doi.org/10.1007/s11042-024-20203-0

[5] Black, D., Byrne, D., Walke, A. et al. Towards machine learning-based quantitative hyperspectral image guidance for Brain Tumor & Lung Cancer resection. Commun Med **4**, 131 (2024). https://doi.org/10.1038/s43856-024-00562-3

[6] Abdelrahman Ali, Y., Kamani, T., Patel, S.K. et al. Design and Investigation of Machine Learning–Optimized Surface Plasmon Resonance Biosensor for Early Brain Tumor & Lung Cancer Detection. Plasmonics (2024). https://doi.org/10.1007/s11468-024-02635-4

[7] Mathivanan, S.K., Sonaimuthu, S., Murugesan, S. et al. Employing deep learning and transfer learning for accurate Brain Tumor & Lung Cancer detection. Sci Rep **14**, 7232 (2024). https://doi.org/10.1038/s41598-024-57970-7

[8] Sajjanar, R., Dixit, U.D. & Vagga, V.K. Advancements in hybrid approaches for Brain Tumor & Lung Cancer segmentation in MRI: a comprehensive review of machine learning and deep learning techniques. Multimed Tools

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Appl **83**, 30505–30539 (2024). https://doi.org/10.1007/s11042-023-16654-6

[9] Saha, P., Das, S.K. & Das, R. A Review on Machine Learning and Deep Learning Based Systems for the Diagnosis of Brain Cancer. SN COMPUT. SCI. **5**, 28 (2024). https://doi.org/10.1007/s42979-023-02360-5

[10] Albalawi, E., T.R., M., Thakur, A. et al. Integrated approach of federated learning with transfer learning for classification and diagnosis of Brain Tumor & Lung Cancer. BMC Med Imaging **24**, 110 (2024). https://doi.org/10.1186/s12880-024-01261-0

[11] Zhang, Hw., Wang, Yr., Hu, B. et al. Using machine learning to develop a stacking ensemble learning model for the CT radiomics classification of brain metastases. Sci Rep **14**, 28575 (2024). https://doi.org/10.1038/s41598-024-80210-x

[12] https://doi.org/10.1007/s42979-024-03228-y

[13] Remzan, N., Hachimi, Y.E., Tahiry, K. et al. Ensemble learning based-features extraction for brain mr images classification with machine learning classifiers. Multimed Tools Appl **83**, 57661–57684 (2024). https://doi.org/10.1007/s11042-023-17213-9

[14] M, S., BV, B., D, P. et al. Efficient Brain Tumor & Lung Cancer grade classification using ensemble deep learning models. BMC Med Imaging **24**, 297 (2024). https://doi.org/10.1186/s12880-024-01476-1

[15] Mansur, Z., Talukdar, J., Singh, T.P. et al. Deep Learning-Based Brain Tumor & Lung Cancer Image Analysis for Segmentation. SN COMPUT. SCI. **6**, 42 (2025). https://doi.org/10.1007/s42979-024-03558-x