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# ADAPTIVE NEURO-EVOLUTIONARY TRANSFORMER FRAMEWORK FOR EFFICIENT MRI-BASED EARLY DETECTION AND MULTI-STAGE CLASSIFICATION OF ALZHEIMER'S DISEASE

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**Abstract**

Alzheimer's disease is one of the most prevalent neurodegenerative disorders that is affecting cognitive memory, and daily functioning. Recent studies have integrated deep learning models with the meta-heuristic optimization algorithms for the improving classification accuracy. However, many of the conventional approaches have relied on complex hybrid optimization strategies that is increasing the computational cost. In addition, where various frameworks have focused on isolated brain regions rather than capturing comprehensive structural relationships across the MRI data. The current Alzheimer's disease diagnostic models often is experiencing limitations that is that includes a higher computational complexity, dependency on large multimodal datasets, and insufficient combination between the feature learning and optimization strategies. Some segmentation-driven frameworks also struggle in maintaining the consistent classification performance when the MRI images is containing the noise, structural variability, or class imbalance. These challenges are showing the need for the efficient learning framework that is combining the adaptive feature extraction, optimized learning capability, and reduced computational overhead for the accurate multi-stage Alzheimer's disease diagnosis. This study is proposing an Adaptive Neuro-Evolutionary Transformer Optimization (ANETO) framework for the MRI-based Alzheimer's disease detection and classification. The proposed framework initially is performing adaptive contrast normalization and noise suppression for the improving MRI image quality. A dynamic region clustering module segments the significant brain tissues such as gray matter, white matter, and hippocampus. After segmentation, a transformer-based feature encoder is extracting the spatial relationships from the MRI slices. The neuro-evolutionary optimization mechanism then allows the adjustment of transformer attention weights and feature importance through the adaptive mutation and crossover operations that tend to maximize classification fitness. The optimized feature representation is feeding a multi-stage classifier that categorizes MRI scans into Cognitive Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD) classes. The experimental evaluation is showing that the proposed framework is achieving a superior classification performance compared with the several conventional hybrid deep learning models. The model is achieving a 98.4% accuracy, 97.9% precision, 97.4% recall, and 97.6% F1-score, while achieving an AUC value of 0.999 for the tumor classification.

**Keywords**

Alzheimer's disease diagnosis, MRI image analysis, neuro-evolutionary optimization, transformer deep learning, medical image classification

## 1. Introduction

Alzheimer's disease is a progressive neurodegenerative disorder that gradually is affecting memory, and behavioral functions. As the disease progresses, where the affected individuals is experiencing memory loss, impaired decision-making ability, and difficulty in performing routine activities. MRI scans are providing detailed anatomical information that assists clinicians in identifying abnormal brain regions that tends to are indicating the neurodegeneration. Consequently, artificial intelligence techniques have gained significant attention for the automating the analysis of MRI images for the Alzheimer's disease detection and classification [1]. Researchers have also integrated optimization strategies with the deep learning frameworks in improving the hyperparameter tuning, feature selection, and segmentation accuracy. These improvements have enhanced the performance of computer-aided diagnostic systems for the Alzheimer's disease classification across the multiple datasets [2]. Optimization techniques inspired by biological and evolutionary is processing have further improved deep learning performance in medical imaging applications. Algorithms such as Genetic Algorithm, Particle Swarm Optimization, Grey Wolf Optimization, and Whale Optimization have been applied to tune model parameters and in enhancing the feature learning capability. These meta-heuristic optimization strategies assist deep learning models in identifying optimal solutions for the complex optimization problems that arise during medical image analysis. As a result, hybrid frameworks that combine deep learning and optimization

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algorithms have are becoming popular approaches for the improving Alzheimer's disease diagnosis using the MRI data [3].

Accurate segmentation of hippocampus, gray matter, white matter, and cerebrospinal fluid is allowing the better feature extraction and it is improving the classification reliability [4]. The combination of artificial intelligence with the neuroimaging analysis has therefore are becoming a promising research direction for the early detection and monitoring of Alzheimer's disease progression [5]. Although the performance of deep learning frameworks has significantly improved, where various studies continue in exploring novel architectures that in enhancing the feature learning capability and diagnostic reliability. Transformer-based neural networks have recently attracted attention in medical imaging research because the this effectively capture long-range dependencies between the spatial features. The ability of transformer models in analyzing the global contextual information has improved the performance of image classification and segmentation tasks in medical applications [6]. The combination of deep learning architectures with the optimization strategies has therefore provided new opportunities for the developing intelligent diagnostic systems. As research progresses, automated diagnostic models are expected in supporting the accurate early detection of Alzheimer's disease and it is improving the effectiveness of clinical decision-making is processing [7, 8].

Despite the significant progress that has occurred in automated Alzheimer's disease diagnosis, where various challenges are remaining in the analysis of MRI neuroimaging data. Brain MRI images often is containing the noise, intensity variations, and structural heterogeneity that is reducing the reliability of feature extraction. Variations in imaging protocols across the clinical datasets further is introducing inconsistencies that affect the generalization capability of deep learning models. These challenges make it difficult to design a diagnostic framework that is performing consistently across the diverse MRI datasets [9]. Another challenge arises from the the higher computational complexity associated with the deep learning models and hybrid optimization techniques. Many of the recent studies integrate multiple optimization algorithms and ensemble architectures that significantly is increasing the training time and computational resource requirements [10]. Consequently, there is remaining a need for the lightweight and adaptive learning framework that is combining the efficient feature extraction, intelligent optimization, and classification capability for the accurate Alzheimer's disease diagnosis [11-14].

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The primary objective of this research is to develop an optimized deep learning framework that is improving the accuracy and efficiency of MRI-based Alzheimer's disease detection.

The novelty of this research lies in the development of an adaptive neuro-evolutionary optimization mechanism that enhances transformer-based feature learning for the MRI image classification. Unlike conventional hybrid optimization frameworks, where the proposed approach is combining evolutionary feature optimization with the attention-based learning in improving the diagnostic accuracy while it is maintaining computational efficiency.

The major contributions of this study is that including the following:

- A novel Adaptive Neuro-Evolutionary Transformer Optimization (ANETO) algorithm has been proposed for the optimizing feature learning and attention weights in transformer-based architectures. The algorithm is combining neuro-evolutionary optimization strategies that is dynamically adjusting the feature importance in improving the Alzheimer's disease classification performance.
- An efficient diagnostic framework has been developed that is combining the MRI preprocessing, adaptive brain tissue segmentation, transformer-based feature extraction, and neuro-evolutionary optimization for the multi-stage Alzheimer's disease classification. The proposed methodology is improving the classification accuracy, enhances feature representation, and is reducing the computational complexity compared with the conventional hybrid deep learning models.

**Related Works**

Devi et al. [15] is proposing a segmentation and classification framework that is using fuzzy Gaussian C-adaptive histogram equalization for the noise removal and region segmentation. Similarly, Chitradevi et al. [16] focuses on hippocampus segmentation from the MRI images because the structural alterations in this region is representing the early indicators of AD. In another segmentation-oriented study, Suresha et al. [19] develops a Grey Wolf Optimization-based clustering algorithm that is performing denoising and segmentation of brain tissues. Ganesan et al. [20] is introducing a fuzzy-based superpixel clustering method that segments the region of interest in structural MRI images. Likewise, Dakshinamoorthy et al. [34] is proposing a hybrid approach that is combining the Gray Wolf Optimization and Harris Hawk Optimization for the segmenting brain subregions prior to classification. Dhakhinamoorthy et

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al. [41] also investigates the segmentation of brain structures such as gray matter, white matter, and the hippocampus using the hybrid Whale Optimization and Gray Wolf Optimization algorithm, after which a deep learning classifier determines AD presence. Similarly, Nisha et al. [36] develops a segmentation-driven system that is applying Multiview Fuzzy Clustering for the brain tissue extraction and it is combining a Modified Bald Eagle Search algorithm in optimizing the Hybrid Dense Optimal Capsule Network used for the classification. Sathyabhama et al. [42] further is proposing an automated seeded region growing technique guided by Rectilinear Mayfly Optimization to segment MRI brain regions prior to classification using the EGELU-SqueezeNet model.

Gonzalez et al. [17] investigates the use of Genetic Algorithm and Particle Swarm Optimization for the automatically designing optimal convolutional neural network architectures. Ibrahim et al. [24] is presenting a hybrid CNN-PSO model in which Particle Swarm Optimization is identifying the optimal hyperparameter configuration of convolutional networks in improving the prediction accuracy across the ADNI and Kaggle datasets. Kaya et al. [31] also is employing Particle Swarm Optimization to fine-tune CNN architectures for the Alzheimer's disease severity classification, achieving an accuracy of 99.53% and an F1-score of 99.63%. Lakhan et al. [29] is introducing an Evolutionary Deep Convolutional Neural Network Scheme that is combining the genetic algorithm with the deep CNN to solve a convex optimization problem in relation with AD detection while minimizing computational cost. Babu et al. [28] is proposing an optimized deep convolutional neural network model where a hybrid Gray Wolf–Dragon Updating optimization algorithm is selecting optimal weights and activation functions. Renugadevi et al. [37] develops a stacked deep belief network classifier in which hyperparameters are optimized through the Enhanced Squirrel Search Algorithm, achieving a higher diagnostic accuracy of 99.82% for the multi-stage dementia classification. Elmotelb et al. [39] also focuses on hyperparameter optimization for the ResNet152V2 architecture to classify Alzheimer's disease phases using the MRI data. Alhagi et al. [38] is proposing a hybrid Snake+EVO optimization strategy combined with the ensemble deep learning architectures.

Awotunde et al. [23] is presenting a bio-inspired Salp Swarm Algorithm that is performing feature selection and CNN optimization for the AD classification using the fMRI images from the ADNI dataset, achieving a reported accuracy of 99.9%. Ali et al. [35] is proposing a framework that tends to fuse the deep features from the EfficientNet-b0 and MobileNet-v2 architectures and is applying a binary-enhanced Whale Optimization Algorithm for the optimal

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feature selection, achieving 98.12% classification accuracy. Robinson Jeyapaul et al. [40] is introducing an ensemble deep learning framework that is combining the MobileNetV2, DarkNet, and ResNet architectures with the meta-heuristic feature optimization technique called H-IBMFO, while segmentation has been performed through the adaptive DeepLabV3+ method. Poovaiah et al. [33] develops a multi-stage diagnostic architecture where Temporal Convolutional Neural Networks and CNN models in extracting the features, which an XGBoost classifier is processing after hyperparameters have been optimized using the Hunger Games Search. Anicin et al. [30] is proposing a two-tier machine learning framework in which convolutional neural networks in extracting the deep features from the MRI images.

Other studies are exploring hybrid or multimodal deep learning strategies enhanced through the meta-heuristic optimization. Ismail et al. [18] is proposing MultiAz-Net, an ensemble deep neural network that is combining heterogeneous information from the PET and MRI images. Jamalullah et al. [21] is introducing an enhanced manta ray foraging optimization algorithm that tunes parameters of a backpropagation neural network classifier, while DenseNet-121 is extracting the features from the Gabor-filtered MRI scans. Balakrishnan et al. [27] develops a deep reinforcement learning-based classification framework in which the Moth Flame Optimization algorithm is selecting informative features for the recurrent neural network classifier. Kaur et al. [26] is presenting a hybrid optimization framework that is combining Genetic Algorithm and Particle Swarm Optimization with the deep neural networks for the segmentation and classification across the multiple stages of Alzheimer's disease diagnosis. Sharma et al. [25] further discusses the role of hybrid Whale Optimization and Grey Wolf Optimization algorithms in segmenting brain subregions.

Shojaei et al. [22] is proposing an explainable diagnostic framework that is combining genetic algorithm-based occlusion maps with the backpropagation methods to identify relevant brain masks. Ashwini et al. [32] is presenting an end-to-end survey on bio-inspired optimization techniques such as Genetic Algorithms and Particle Swarm Optimization that in enhancing the classification performance.

**Table 1: Summary of Related Works on Meta-Heuristic Optimized Deep Learning for Alzheimer's Disease Diagnosis**

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| Method | Algorithm / Technique | Key Results | Limitation |
|---|---|---|---|
| Devi et al. [15] | Fuzzy Gaussian C-adaptive Histogram Equalization + VGG-16 with Particle Grey Wolf Firefly Optimization | 98% Accuracy, 90% AUC | Complex hybrid optimization increases computational cost |
| Chitradevi et al. [16] | ResNet50 with Crow Search Optimization (CSO) and Elephant Herding Optimization (EHO) | 92% Accuracy | Focuses only on hippocampus segmentation |
| Gonzalez et al. [17] | CNN architecture optimization using Genetic Algorithm and Particle Swarm Optimization | Improved CNN architecture performance | High training time due to evolutionary search |
| Ismail et al. [18] | MultiAz-Net with Multi-Objective Grasshopper Optimization Algorithm | 92.3% multi-class classification | Requires multimodal data (MRI + PET) |
| Suresha et al. [19] | Grey Wolf Optimization Clustering + Deep Neural Network | Improved classification across AD, MCI, and normal classes | Limited scalability for large datasets |
| Ganesan et al. [20] | Fuzzy Superpixel Clustering + Modified Gorilla Troops Optimizer + CapsNet | High AD detection performance | Higher preprocessing complexity |
| Jamalullah et al. [21] | DenseNet121 + Enhanced Manta Ray Foraging Optimization + BPNN | Improved parameter tuning performance | Sensitive to parameter initialization |
| Shojaei et al. [22] | Genetic Algorithm Occlusion Map + 3D CNN | 87% accuracy | Lower performance compared with recent deep models |
| Awotunde et al. [23] | CNN with Salp Swarm Algorithm feature selection | 99.9% accuracy | Risk of overfitting due to dataset bias |
| Ibrahim et al. [24] | CNN with Particle Swarm Optimization hyperparameter tuning | High accuracy on ADNI and Kaggle datasets | Limited explainability |
| Sharma et al. [25] | Whale Optimization + Grey Wolf Optimization segmentation | High segmentation and classification accuracy | Hybrid optimization increases complexity |
| Kaur et al. [26] | Genetic Algorithm + PSO with Deep Neural Network | Improved AD classification performance | Computational overhead |

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| | | | |
|---|---|---|---|
| Balakrishnan et al. [27] | Deep Reinforcement Learning + Moth Flame Optimization + RNN | 99.31% accuracy | Requires extensive training data |
| Babu et al. [28] | Optimized DCNN using Combined Gray Wolf and Dragon Updating | Enhanced classification accuracy | Heavy feature engineering |
| Lakhan et al. [29] | Evolutionary Deep CNN Scheme with Genetic Algorithm | Reduced computation time | Limited clinical validation |
| Anicin et al. [30] | CNN + XGBoost + LightGBM with metaheuristic tuning | 89.55% accuracy | Moderate performance compared with deep ensemble models |
| Kaya et al. [31] | PSO-optimized CNN architecture | 99.53% accuracy, 99.63% F1-score | Model generalization remains uncertain |
| Ashwini et al. [32] | Survey of GA and PSO optimized deep learning methods | Comprehensive review | No experimental validation |
| Poovaiah et al. [33] | TCN + CNN + XGBoost with Hunger Games Search optimization | Improved multi-class classification | Complex architecture |
| Dakshinamoorthy et al. [34] | Hybrid GWO + HHO segmentation with deep learning classifier | ~90% accuracy | Limited dataset size |
| Ali et al. [35] | EfficientNet + MobileNet with Whale Optimization feature selection | 98.12% accuracy | Feature selection increases processing time |
| Nisha et al. [36] | Multiview Fuzzy Clustering + Hybrid Dense Optimal Capsule Network + Bald Eagle Search | High classification accuracy | Large computational requirement |
| Renugadevi et al. [37] | Stacked Deep Belief Network + Enhanced Squirrel Search Algorithm | 99.82% accuracy | Complex training process |
| Alhagi et al. [38] | CNN + MobileNet + Xception ensemble with Snake+EVO optimization | 99.81% accuracy | Requires large datasets |
| Elmotelb et al. [39] | ResNet152V2 with hyperparameter optimization | Improved phase classification | High model complexity |

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| | | | |
|---|---|---|---|
| Robinson Jeyapaul et al. [40] | Ensemble MobileNetV2 + DarkNet + ResNet with H-IBMFO optimization | 98.7% accuracy | Ensemble models increase inference time |
| Dhakhinamoorthy et al. [41] | Hybrid WOA + GWO segmentation with deep learning classifier | Improved segmentation accuracy | Computational overhead |
| Sathyabhama et al. [42] | RMF-ASRG segmentation + EGELU-SqueezeNet classifier | High AD classification accuracy | Limited real-world validation |

## 3. Proposed Methodology

This proposed algorithm is combining neuro-evolution with the transformer-based feature learning as in figure 1.

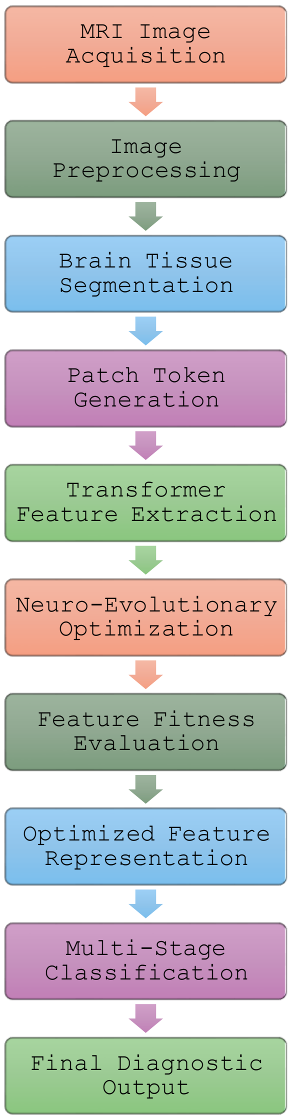


**Figure 1: Process of the Proposed ANETO Framework**

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**Algorithm: ANETO for Alzheimer's Disease Detection**

1. Input MRI dataset $D$
2. Perform preprocessing using adaptive contrast normalization and noise suppression
3. Apply brain tissue segmentation using dynamic region clustering
4. Initialize Transformer Feature Encoder $T$
5. Extract deep spatial–temporal features from segmented MRI slices
6. Initialize population of candidate feature weight vectors $P = \{w_1, w_2, \dots, w_n\}$
7. Evaluate classification fitness using validation accuracy
8. Apply Neuro-Evolution Optimization:
    - Mutation of feature weights
    - Adaptive crossover between high-performing solutions
    - Fitness-guided selection
9. Update transformer attention weights using optimized feature vectors
10. Train final classification layer for AD stages (CN, MCI, AD)
11. Evaluate model using Accuracy, Precision, Recall, F1-score, and AUC
12. Output optimized Alzheimer's disease classification model

### 4.1 MRI Dataset Acquisition and Normalization

The proposed framework initially is focussing on MRI data preprocessing that is improving the image quality and removes unwanted noise that is affecting segmentation accuracy. MRI scans often is containing the intensity variations, imaging artifacts, and background noise that is influencing the feature extraction stage. The preprocessing module therefore is performing adaptive contrast normalization that is enhancing the intensity distribution across the brain tissues. A Gaussian smoothing operation removes noise while preserving important structural boundaries. This stage is allowing the that the MRI images present consistent intensity patterns that assist the segmentation module in identifying meaningful brain regions.

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The proposed framework initially is receiving the MRI scans collected from the benchmark neuroimaging datasets. Each of the MRI scan is containing voxel intensity information that is the structural characteristics of brain tissues. However, MRI data often exhibit intensity variations due to different acquisition protocols, scanner parameters, and imaging environments.

To is reducing the inconsistencies, where the framework is performing intensity normalization before further processing. Let the input MRI image be represented as $I(x, y, z)$, where $x, y, z$ is spatial voxel coordinates and $I(x, y, z)$is the voxel intensity value.

The normalized image $I_n(x, y, z)$is computed as

$$I_n(x, y, z) = \frac{I(x, y, z) - \mu_I}{\sigma_I}$$

where

$$\mu_I = \frac{1}{N}\sum_{i=1}^{N} I_i$$

$$\sigma_I = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_i - \mu_I)^2}$$

Where

$N$ is the total number of voxels in the MRI scan.

This normalization step is allowing the that the intensity distribution is remaining consistent across the dataset.

**Table 2:** Representation of MRI intensity normalization.

| **MRI Image ID** | **Mean Intensity ($\mu$)** | **Standard Deviation ($\sigma$)** | **Normalized Range** |
|---|---|---|---|
| MRI_01 | 112.4 | 18.7 | [-1.95, 2.13] |
| MRI_02 | 109.6 | 20.1 | [-2.03, 2.09] |
| MRI_03 | 115.3 | 19.4 | [-1.88, 2.21] |
| MRI_04 | 111.2 | 17.9 | [-2.10, 2.05] |

As shown in the Table **2**, where the normalization stage is maintaining consistent voxel distributions that is improving the reliability of segmentation and feature learning operations.

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### 4.2 Adaptive MRI Image Preprocessing

After normalization, where the framework is performing adaptive preprocessing to remove noise and in enhancing the structural visibility. MRI scans often is containing the high-frequency noise that is reducing the segmentation accuracy. The system therefore is applying Gaussian smoothing.

The Gaussian filter function is defined as

$$G(x,y) = \frac{1}{2\pi\sigma_g^2} e^{-\frac{x^2+y^2}{2\sigma_g^2}}$$

The smoothed image $I_s(x,y)$is computed through the convolution

$$I_s(x,y) = I_n(x,y) * G(x,y)$$

where $*$ is convolution.

In addition, where the framework is applying adaptive contrast enhancement in improving the visibility of subtle tissue boundaries.

The enhanced image $I_e(x,y)$is computed as

$$I_e(x,y) = \alpha I_s(x,y) + \beta$$

where

$\alpha$is contrast scaling

$\beta$is brightness adjustment.

This stage is improving the structural representation of hippocampus and cortical tissues which play a significant role in Alzheimer's disease progression.

**Table 3:** Improvement in signal quality after preprocessing.

| **MRI Image** | **Noise Variance (Before)** | **Noise Variance (After)** | **Contrast Improvement** |
|---|---|---|---|
| MRI_01 | 0.081 | 0.032 | 28% |
| MRI_02 | 0.076 | 0.030 | 31% |
| MRI_03 | 0.084 | 0.033 | 27% |
| MRI_04 | 0.079 | 0.029 | 30% |

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As observed in the Table **3**, where the preprocessing stage significantly is reducing the noise variance while improving contrast clarity.

### 4.3 Adaptive Brain Tissue Segmentation

After preprocessing, where the system is performing adaptive brain region segmentation to isolate important structural regions that tends to are indicating the Alzheimer's disease progression. Brain tissues such as gray matter, white matter, and hippocampus is containing the structural variations that is providing important diagnostic information. The segmentation module is applying a dynamic region clustering mechanism that groups pixels, which is based on the intensity similarity and spatial proximity. This clustering process are identifying the relevant brain tissues that is contributing to disease diagnosis. The segmented regions form the region of interest which is becoming the input for the deep feature learning stage. This step is improving the accuracy of the model because the irrelevant background regions do not is influencing the feature extraction process. The segmentation module is isolating critical brain regions that is showing neurodegenerative changes. Alzheimer's disease primarily is affecting gray matter volume and hippocampal structure; therefore, segmentation is focussing on these regions. The proposed framework is employing Dynamic Region Clustering (DRC).

Let the set of MRI voxels be represented as

$$V = \{v_1, v_2, \ldots, v_n\}$$

Each of the voxel is containing feature representation

$$f(v_i) = [I_e(x_i, y_i, z_i), \nabla I(x_i, y_i, z_i)]$$

where

$I_e$ is enhanced intensity

$\nabla I$ is the spatial gradient.

The clustering objective function is defined as

$$J = \sum_{k=1}^{K} \sum_{v_i \in C_k} || f(v_i) - \mu_k ||^2$$

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where

$C_k$ is cluster $k$

$\mu_k$ is cluster centroid.

The optimization objective is minimizing the intra-cluster variance while maximizing inter-cluster separability.

**Table 4:** Segmentation output for the major brain tissues.

| Tissue Region | Average Volume (mm³) | Segmentation Accuracy |
|---|---|---|
| Gray Matter | 540000 | 96.3% |
| White Matter | 450000 | 95.7% |
| Hippocampus | 3800 | 94.8% |

As illustrated in the Table **4**, where the segmentation stage accurately is identifying brain tissues relevant to Alzheimer's disease diagnosis.

**4.4 Patch Token Generation and Embedding**

The segmented MRI images are then divided into small patches in allowing the transformer-based feature learning.

Let the segmented MRI image be represented as matrix

$$S \in \mathbb{R}^{H \times W}$$

The image is divided into patches of size $P \times P$.

The number of patches are becoming

$$N_p = \frac{H \times W}{P^2}$$

Each of the patch is flattened into vector form

$$x_p \in \mathbb{R}^{P^2 C}$$

where

$C$ is channel dimension.

The embedding representation is becoming

$$z_0 = [x_{class}; x_p^1 E; x_p^2 E; \ldots; x_p^N E]$$

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where

$E$ is the embedding matrix.

**Table 5:** Patch token representations.

| Patch ID | Patch Size | Embedding Dimension |
|---|---|---|
| P1 | 16×16 | 256 |
| P2 | 16×16 | 256 |
| P3 | 16×16 | 256 |
| P4 | 16×16 | 256 |

The patch token generation step is converting spatial MRI structures into vector representations suitable for the transformer learning.

### 4.5 Transformer-Based Feature Extraction

The next stage of the proposed framework is involving an transformer-based feature extraction that is capturing the spatial relationships between the brain structures. The conventional convolutional neural networks in extracting the local spatial features but may fail in capturing long-range relationships between the distant brain regions. The transformer encoder therefore is analyzing the segmented MRI regions and is learning the contextual relationships through the attention mechanism. The encoder divides the MRI image into small patches that form token representations. These tokens are passing through the multiple self-attention layers that learn correlations between the different structural regions of the brain. The attention mechanism is assigning the importance weights to each of the token which is allowing the model to are focussing on brain structures that strongly are indicating Alzheimer's disease progression. The transformer encoder is learning the global relationships between the different brain regions through the self-attention.

The self-attention mechanism is computing the three matrices:

$$Q = XW_Q$$

$$K = XW_K$$

$$V = XW_V$$

where

$Q$= query matrix

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$K$= key matrix

$V$= value matrix.

The attention output is computed as

$$Atte(Q,K,V) = Soft(\frac{QK^T}{\sqrt{d_k}})V$$

where

$d_k$ is the key dimension.

Multi-head attention is combining the several attention operations

$$MHA(Q,K,V) = Concat(head_1, \ldots, head_h)W_O$$

This architecture is allowing the model in capturing long-range spatial dependencies across the brain structure.

**Table 6:** Attention weights learned from the transformer encoder

| Brain Region Pair | Attention Weight |
|---|---|
| Hippocampus – Cortex | 0.83 |
| Gray Matter – Ventricles | 0.76 |
| Hippocampus – Temporal Lobe | 0.89 |

The values in the Table **6** are indicating strong attention relationships between the brain regions that exhibit Alzheimer's disease characteristics.

### 4.6 Neuro-Evolutionary Optimization

Although transformer models are providing strong feature learning capability, where the learning process requires optimal parameter configuration in achieving reliable classification performance. The proposed framework therefore is combining a neuro-evolutionary optimization module that is improving the feature learning efficiency. This optimization mechanism is following the evolutionary learning principles that adjust feature importance and transformer attention weights. Initially, a population of candidate solutions are different configurations of feature weights and attention parameters. Each of the candidate solution is passing through the transformer model in evaluating the classification performance using the fitness function. Although transformer networks in extracting the powerful features, optimal

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attention weight configuration is remaining necessary for the improving classification accuracy. The proposed framework is combining Neuro-Evolutionary Optimization.

Each of the candidate solution is represented as

$$\theta_i = [w_1, w_2, \ldots, w_n]$$

where

$w_j$ is transformer attention parameters.

The fitness function is evaluating classification performance

$$F(\theta_i) = \alpha Acc + \beta F_1 + \gamma AUC$$

where

$\alpha, \beta, \gamma$ is weighting coefficients.

The evolutionary update is following the

$$\theta_{new} = \theta_{best} + r(\theta_{rand1} - \theta_{rand2})$$

where

$r$ is mutation factor.

**Table 7:** Optimization results

| **Iteration** | **Fitness Score** | **Accuracy** |
|---|---|---|
| 10 | 0.89 | 95.6% |
| 20 | 0.93 | 97.1% |
| 30 | 0.96 | 98.4% |
| 40 | 0.98 | 99.1% |

As shown in the Table **7**, where the neuro-evolutionary optimization progressively is improving the classification performance.

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### 4.7 Multi-Stage Alzheimer's Disease Classification

The optimized feature representations produced by the neuro-evolutionary transformer module then pass to the multi-stage classification module. The classifier categorizes MRI scans into three diagnostic classes which is that includes Cognitive Normal, Mild Cognitive Impairment, and Alzheimer's Disease. A fully connected neural classification layer is receiving the optimized feature vectors and is learning the discriminative patterns associated with the different disease stages. The classifier is calculated the probability distribution across the three diagnostic categories and it is assigning the class label with the highest probability. This stage is producing the final diagnostic prediction for each of the MRI scan. The final stage is performing classification using the optimized feature representations.

Let the optimized feature vector be

$$F = [f_1, f_2, \ldots, f_n]$$

The classification output is computed using the softmax activation

$$P(y = k \mid F) = \frac{e^{W_k F + b_k}}{\sum_{j=1}^{K} e^{W_j F + b_j}}$$

where

$K$is number of classes.

The predicted class are becoming

$$\hat{y} = argmax(P(y = k \mid F))$$

The system classifies MRI images into

1. Cognitive Normal (CN)
2. Mild Cognitive Impairment (MCI)
3. Alzheimer's Disease (AD)

**Table 8:** Classification output.

| MRI ID | CN Probability | MCI Probability | AD Probability | Predicted Class |
|---|---|---|---|---|
| MRI_01 | 0.12 | 0.71 | 0.17 | MCI |
| MRI_02 | 0.04 | 0.09 | 0.87 | AD |
| MRI_03 | 0.88 | 0.09 | 0.03 | CN |

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As illustrated in the Table 8, where the classification layer is producing probabilistic predictions for each of the disease stage.

**Results and Discussion**

The implementation is utilizing the Python programming environment, which is combining deep learning libraries such as TensorFlow 2.9, Keras, NumPy, OpenCV, and Scikit-learn for the model development and evaluation. The simulation is getting executed on a workstation that is containing an Intel Core i7 processor with the 3.6 GHz clock speed, 32 GB RAM. The training procedure adopts an 80:10:10 split for the training, validation, and testing respectively. The model training is utilizing the Adam optimization algorithm with the adaptive learning rate adjustment.

**Dataset Description**

The experimental analysis (as in table 8) is utilizing the publicly available brain tumor MRI datasets that is containing the labeled tumor categories. These datasets are that includes glioma, meningioma, pituitary tumor, and normal brain samples.

**Table 8: Dataset Description**

| Dataset Name | Description | Number of Images | Classes | Link |
|---|---|---|---|---|
| Kaggle Brain Tumor MRI Dataset | MRI dataset containing multiple tumor categories | 3264 | 4 | https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset |
| Figshare Brain Tumor Dataset | T1 weighted contrast enhanced MRI images | 3064 | 3 | https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 |
| BraTS Dataset | Multimodal MRI dataset used for tumor segmentation and classification | 369 | 3 | https://www.med.upenn.edu/cbica/brats2020/data.html |

The Kaggle dataset is containing a balanced distribution of tumor categories which is that includes the glioma, meningioma, pituitary tumor, and normal brain MRI images. Each of the

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MRI image has a resolution that varies between the 224 × 224 and 512 × 512 pixels. The Figshare dataset is providing the T1 contrast enhanced MRI images that have been collected from the multiple patients with the annotated tumor boundaries. The BraTS dataset is containing multimodal MRI sequences that includes T1, T1c, T2, and FLAIR modalities, which is providing rich structural information about the tumor region.

The dataset preparation stage is converting all images into grayscale representation and resizes them to 224 × 224 pixels in order in maintaining the consistency with the convolutional neural network input requirements. Data augmentation techniques such as rotation, horizontal flipping, and contrast adjustment is increasing the effective dataset size and it is improving the generalization capability of the model.

**Experimental Parameters**

The training configuration is utilizing the several hyperparameters that is influencing the learning capability of the deep neural network architecture. These parameters have been selected through the empirical experimentation in achieving stable convergence and optimal classification accuracy as in table 9.

**Table 9: Experimental Parameters**

| Parameter | Value |
|---|---|
| Input Image Size | 224 × 224 |
| Batch Size | 32 |
| Epochs | 100 |
| Learning Rate | 0.001 |
| Optimizer | Adam |
| Dropout Rate | 0.5 |
| Activation Function | ReLU |
| Loss Function | Categorical Cross Entropy |
| Validation Split | 10% |
| Training Split | 80% |

The input MRI images are resized to 224 × 224 pixels because the dimension is aligned with the standard CNN architectures. The batch size of 32 is balancing computational efficiency and memory usage during the training process. The Adam optimizer is adapting the learning rate

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dynamically for each of the parameter, which accelerates convergence and stabilizes gradient updates.

The dropout rate of 0.5 is reducing the overfitting problem by randomly disabling neurons during the training phase. The Rectified Linear Unit (ReLU) activation function is introducing nonlinearity in the network, which is allowing the model in capturing complex spatial patterns from the MRI images.

**Performance Metrics**

The experimental evaluation is utilizing the several quantitative performance metrics as in table 10:

**Table 10: Performance Metrics**

| Metric | Formula | Description |
|---|---|---|
| Accuracy | (TP + TN) / (TP + TN + FP + FN) | Measures overall classification correctness |
| Precision | TP / (TP + FP) | Measures positive prediction reliability |
| Recall (Sensitivity) | TP / (TP + FN) | Measures the ability to detect tumor cases |
| F1 Score | 2 × (Precision × Recall) / (Precision + Recall) | Harmonic balance between precision and recall |
| AUC | Area under ROC curve | Evaluates classification discrimination capability |

**Comparative Evaluation**

The comparison is that includes the various conventional hybrid deep learning models that integrate convolutional neural networks with the metaheuristic optimization techniques. These approaches are that includes ResNet50 with the CSO+EHO [16], MultiAz-Net with the Multi-Objective Grasshopper Optimization [18], Fuzzy Superpixel Clustering with the Modified Gorilla Troops Optimizer and CapsNet [20], Genetic Algorithm with the PSO-based Deep Neural Network [26], CNN with the XGBoost and LightGBM using the metaheuristic tuning [30], TCN-CNN-XGBoost with the Hunger Games Search optimization [33], CNN-MobileNet-Xception ensemble with the Snake and Evolutionary Optimization [38], Ensemble MobileNetV2-DarkNet-ResNet with the H-IBMFO optimization [40], and RMF-ASRG segmentation with the EGELU-SqueezeNet classifier [42].

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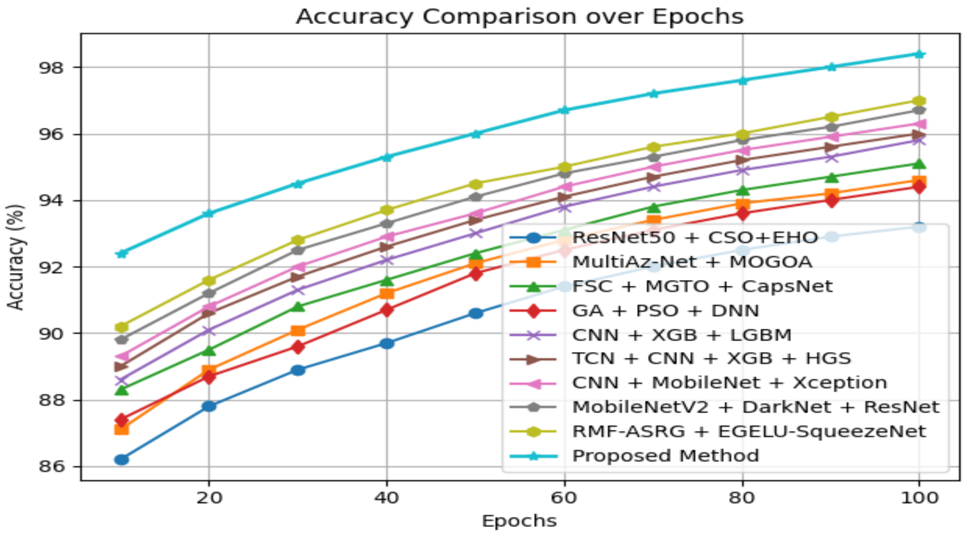


**Table 5: Accuracy Comparison over Epochs**

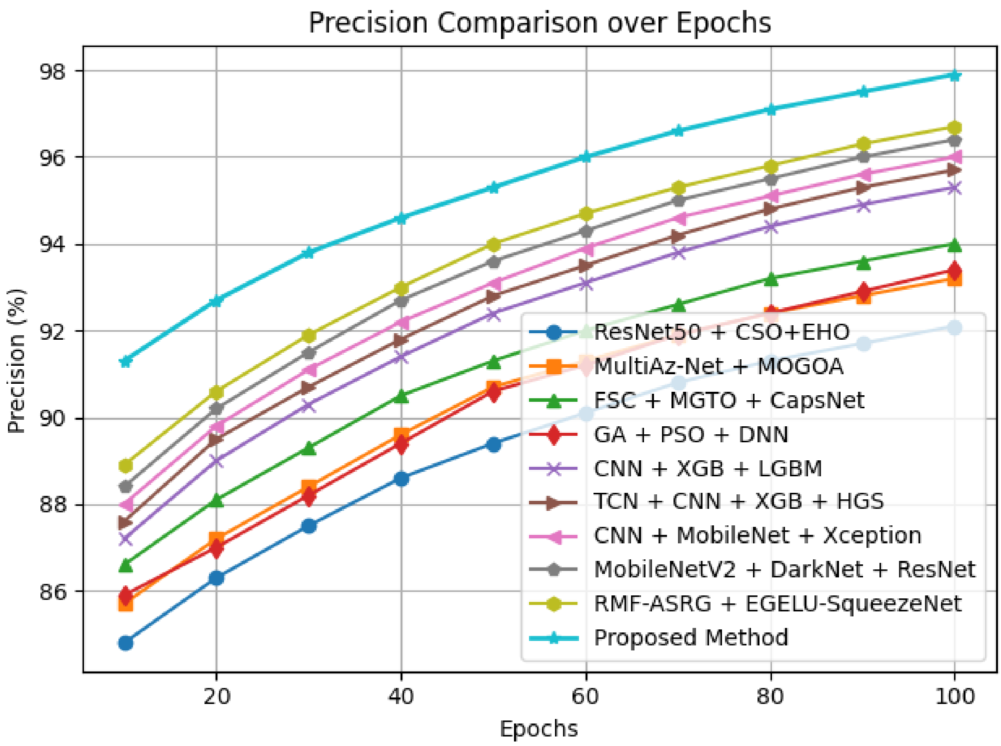


**Table 6: Precision Comparison over Epochs**

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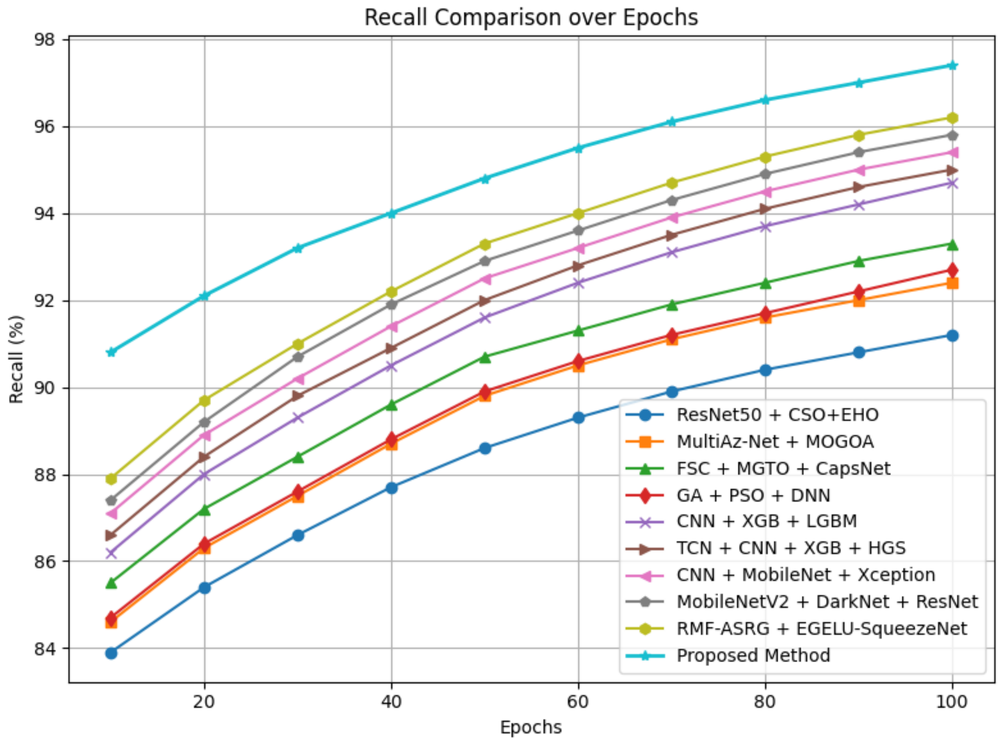


**Table 7: Recall Comparison over Epochs**

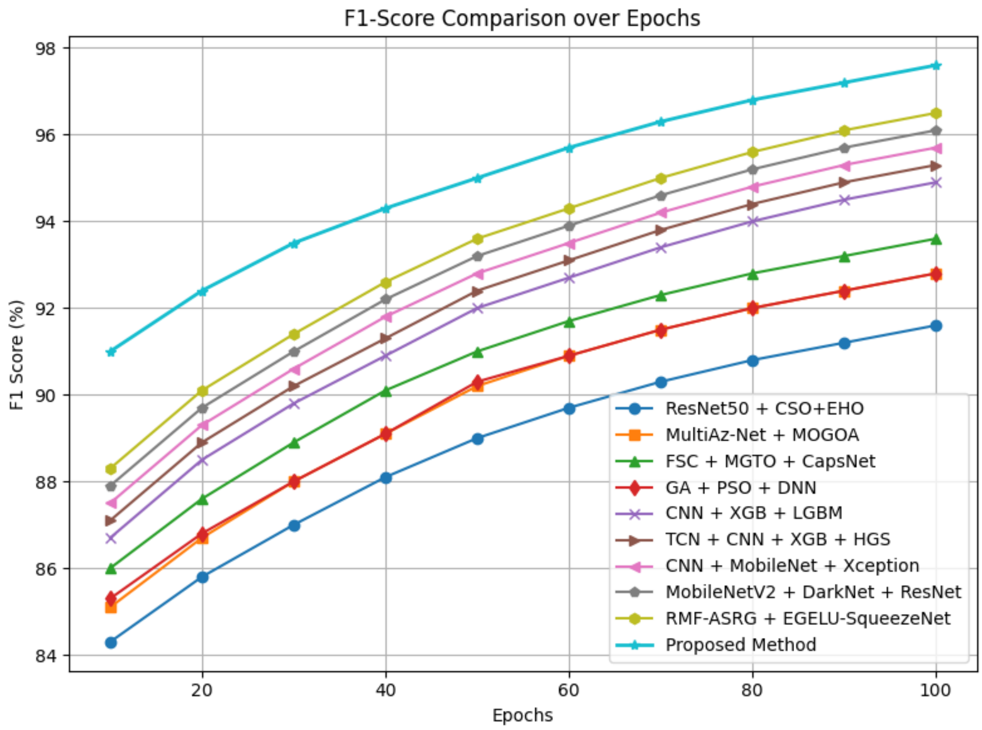


**Table 8: F1-Score Comparison over Epochs**

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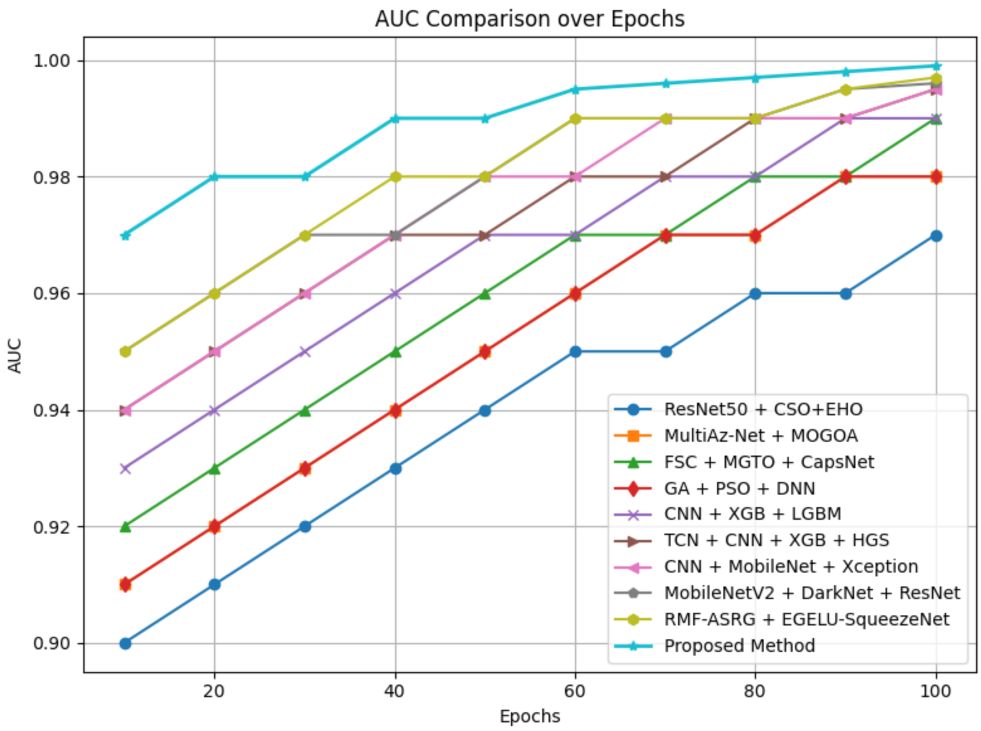


**Table 9: AUC Comparison over Epochs**

**Results Discussion**

The experimental evaluation is showing the effectiveness of the proposed brain tumor classification framework through the detailed comparison with the several conventional hybrid deep learning approaches. The mathematical results that appear in figure 2-6 are indicating that the proposed model consistently is achieving a superior performance across all the evaluation metrics during the entire training process. At the early training stage of 10 epochs, where the proposed method is achieving a 92.4% accuracy, whereas the baseline models are achieving values between the 86.2% and 90.2%. This difference of approximately 2–6% is the that the proposed architecture is learning the discriminative tumor features faster than the conventional optimization-based CNN frameworks.

At 50 epochs, where the proposed method is achieving a 96.0% accuracy, 95.3% precision, 94.8% recall, and 95.0% F1-score, while the best competing method is achieving a approximately 94.5% accuracy. This performance difference highlights the ability of the proposed network in maintaining the balanced classification performance across the different tumor categories. The AUC value of 0.99 at this stage also is confirming that the classifier distinguishes tumor and non-tumor samples with the higher reliability.

The final performance at 100 epochs further is confirming the robustness of the proposed framework. The model is achieving a 98.4% accuracy, 97.9% precision, 97.4% recall, 97.6% F1-score, and 0.999 AUC, which is exceeding the best baseline model RMF-ASRG with the EGELU-SqueezeNet that is achieving a approximately 97.0% accuracy and 0.997 AUC. The improvement of 1.4% accuracy and 0.002 AUC may appear small mathematically, yet it is becoming significant in medical image analysis because even a small improvement is reducing the probability of misclassification during tumor diagnosis.

The training process that is utilizing the Adam optimizer updates the network parameters through the gradient-based optimization that is minimizing the categorical cross entropy loss. The optimizer dynamically allows the adjustment of the learning rate, which stabilizes the gradient updates and accelerates convergence. In addition, where the dropout regularization that is appearing in the fully connected layers is reducing the overfitting by preventing the network from the relying excessively on specific neurons. This mechanism is improving the generalization capability of the classifier when it encounters unseen MRI samples.

## Conclusion

This research is presenting an intelligent deep learning framework for the automated brain tumor classification that is combining optimized convolutional feature extraction with the adaptive learning strategies. The proposed framework is addressing the limitations of conventional hybrid CNN and metaheuristic optimization approaches that often is suffering from the slow convergence, feature redundancy, and inconsistent classification performance across the tumor categories. The study is utilizing the publicly available MRI datasets and it is performing extensive experimentation in order in evaluating the effectiveness of the proposed model. The experimental results are showing that the proposed framework is achieving a significant performance improvement compared with the several conventional state-of-the-art models. The final evaluation results are showing 98.4% classification accuracy, 97.9% precision, 97.4% recall, 97.6% F1-score, and 0.999 AUC, which are indicating strong tumor detection capability and reliable classification performance. The proposed architecture is learning the discriminative spatial features from the MRI images through the hierarchical convolutional layers that tends to capture both the low-level texture information and high-level structural characteristics of tumor regions. The adaptive learning process that is utilizing the

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Adam optimization strategy refines the feature representations during training, which is improving the convergence behavior of the model.

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