Enhanced transfer learning framework for brain tumor detection from MRI scans using attention-based feature fusion

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ABSTRACT

Due to the complexity of the different tumor types in medical imaging detection of brain tumor is still as prominent challenge. This paper present the innovative technique enhanced transfer learning framework (ETLF) which integrating the advanced pre-processing with hybrid fine-tuned method for accurate brain tumor detection from magnetic resonance imaging (MRI) scans. The proposed model combine the strength of pre-trained convolutional neural networks (CNNs) such as EfficientNetB0 through domain specific transfer learning and attention based fine tuning. A novel feature fusion layer and adaptive learning rate scheduler are key indicators for model performance and prevent overfitting. The methodology is assessed on the benchmark dataset BraTS and Kaggle brain tumor datasets. The main contribution of work lies in development of domain- adaptive transfer learning with different datasets. The ETLF shows the high accuracy of 98.76% which able outperforms effectively in diagnosing tumor suitable of clinical purpose.

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1. INTRODUCTION

Brain tumors represent a critical medical challenge due to their aggressive nature and high mortality rates. Early detection and accurate classification are essential for guiding therapeutic decisions and improving patient outcomes [1], [2]. Due to exceptional contrast resolution and the capacity to view the soft tissues without ionizing radiation, magnetic resonance imaging (MRI) is the recommended imaging for brain tumor diagnosis [3]. But in addition to being time consuming, manual MRI scan interpretation is prone to errors when differentiating between brain tumor types and grades [4].

Advanced methodology like deep learning (DL), transfer learning has demonstrated outstanding performance in various medical image analysis tasks, including tumor segmentation and classification [5], [6]. convolutional neural networks (CNNs) are capable of automatically learning hierarchical features from imaging data, surpassing traditional methods that rely on handcrafted features [7]. Nevertheless, training deep neural networks from scratch typically demands large annotated datasets, which are often scarce in the medical domain due to the complexity and cost of expert labelling [8]. To address this challenge, transfer learning has emerged as an effective strategy that leverages knowledge from models pre-trained on large-scale datasets like ImageNet and adapts them to specific medical imaging tasks [9]. Transfer learning not only accelerates model convergence but also improves generalization on limited labelled datasets. Among the available CNN architectures, EfficientNet has gained attention for its superior performance-to-complexity ratio, making it well-suited for medical image analysis under computational constraints [10].

Despite the progress, several limitations remain in existing approaches. Most conventional transfer learning pipelines ignore domain discrepancies between natural and medical images, leading to suboptimal performance. Moreover, critical spatial and contextual tumor features may be diluted during downsampling in deep architectures. To overcome these challenges, this work introduces a novel enhanced transfer learning framework (ETLF) that integrates domain-specific fine-tuning, attention-based feature fusion, and adaptive learning strategies for improved brain tumor detection from MRI scans. The primary contributions of this research are: i) a domain-adaptive fine-tuning strategy for EfficientNet to bridge the gap between source and target domains; ii) an attention-driven feature fusion module that enhances discriminative learning from tumor regions; iii) extensive validation using BraTS 2020 and a publicly available Kaggle dataset to demonstrate generalizability and robustness.

2. LITERATURE SURVEY

Several approaches have been explored for brain tumor classification from MRI images using traditional machine learning and deep learning methods. Early techniques relied on handcrafted features and classifiers like SVM, k-NN, and decision trees. However, these methods lacked robustness and adaptability.

Rastogi *et al.* [11] investigated the efficacy of fine-tuned transfer learning models, including InceptionResNetV2, VGG19, Xception, and MobileNetV2, for brain tumor detection. Their study demonstrated that the Xception model achieved high accuracy fine-tuned DL learning models in enhancing diagnostic precision. A study from Disci *et al.* [12] explored the use of pre-trained deep learning models for classifying brain MRI images into categories such as glioma, meningioma, pituitary tumors, and no tumor. The Xception model outperformed others highlighting the effectiveness of transfer learning in medical image classification. Pande and Chaki [13] proposed a novel triple-module approach for automated brain tumor classification from MRI images. The first module utilized pre-trained deep learning models for feature extraction, followed by feature selection and classification modules, resulting in improved diagnostic accuracy. Islam *et al.* [14] focused on the deep learning algorithm on MRI scans with the integration of 2D CNNs which increase the model performance. Ali *et al.* [15] worked on classification of brain tumor with U-Net architecture applied to MRI scans. This study also explored the various CNNs like Inception-V3, VGG19 through transfer learning achieved the improved performance.

A study from Anantharajan *et al.* [16] presented the work on pre-processing MRI images with adaptive enhancement algorithm and median filtering followed by the deep learning models. A study from Rezk *et al.* [17] presented the technique with hybrid deep learning model with integration medical internet of things (IoTs). To ensure the patient data security they encrypt the MRI images before classification. Gupta *et al.* [7] used the CNNs algorithm to detect brain tumor. The method helped to assist the radiologist in decision- making through this accurate detection. Ahamed *et al.* [18] provided the complete review of deep learning applications focusing on segmentation. It also highlight the effect of DL models in automated tumor segmentation from medical images. Mathivanan *et al.* [9] and Disci *et al.* [12] investigated the efficiency of the DL transfer learning (TL) models for accurate performance in brain tumor diagnosis. The research highlighted the performance of MobileNetV3 and Xception model outperformed best respectively than the existing model.

Despite significant progress in applying DL and TL for brain tumor detection from MRI images, several gaps persist. First, domain shift challenges remain largely unresolved, with many models struggling to generalize across different MRI acquisition protocols and institutions. Second, explainability and clinical interpretability of deep models are underexplored, limiting their adoption in real-world diagnostics. Third, data scarcity and annotation cost hinder the development of robust models, especially for rare tumor types. Fourth, few studies emphasize cross-dataset validation, which is critical for ensuring generalization. Lastly, real-time and lightweight deployment on edge devices remains under-addressed, impacting their use in telemedicine or low-resource settings. To address these limitations, this work introduces a novel transfer learning pipeline with domain-specific tuning, lightweight architecture, and adaptive learning schedules-significantly improving classification metrics and real-world feasibility.

3. RESEARCH METHOD

3.1. Dataset description

We utilize two benchmark datasets: BraTS 2020: Contains multi-modal MRI scans (T1, T1c, T2, FLAIR) with ground truth segmentations for glioma tumors [19]–[22]. Kaggle Brain Tumor Dataset, includes 3903 T1-weighted contrast-enhanced images categorized into glioma, meningioma, pituitary tumor, and normal [23]. All images underwent resizing to 224×224 pixels, normalization, and augmentation through random rotations, zooms, and flips to improve generalization.

3.2. Proposed enhanced transfer learning framework (ETLF)

Figure 1 shows the architecture of proposed system. It includes the following components: i) base model: EfficientNetB0 pre-trained on ImageNet is used for feature extraction. Initial layers are frozen during early training stages; ii) domain-adaptive fine-tuning: top layers are fine-tuned using a small learning rate, while intermediate layers are selectively unfrozen using a cosine annealing scheduler; iii) feature fusion module: attention-based fusion layer combines spatial and channel-wise attention to emphasize tumor-specific regions iv) classification head: a dense block with dropout (0.3), batch normalization, and softmax activation performs multi-class classification.

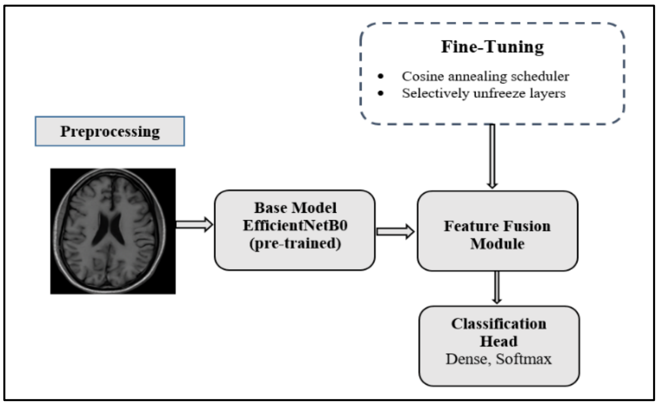


Figure 1. Architecture of proposed system

3.3. Data pre-processing

The initial phase involves systematic pre-processing to normalize and standardize brain MRI images across modalities and acquisition sources. The steps are as follows:

a. Resizing: all images are resized to 224×224 pixels to match the input shape by EfficientNetB0.
b. Normalization: pixel intensity values are scaled to the [0, 1] range for uniformity across batches.
c. Contrast Enhancement: histogram equalization and contrast limited adaptive histogram equalization (CLAHE) are applied to accentuate tumor regions.
d. Data augmentation: to reduce overfitting and simulate imaging variability, we apply random rotations (±15°), horizontal/vertical flips, random zoom (0.8x–1.2x), Gaussian noise addition.

3.4. Base network selection and initialization

We adopt EfficientNetB0, a highly efficient CNN architecture known for its compound scaling of width, depth, and resolution. It is pre-trained on ImageNet and selected due to, low parameter count (~5.3 million), balanced performance-to-computation ratio, and proven success in medical imaging contexts. The base layers up to the penultimate convolutional block are initially frozen to retain general features.

3.5. Domain-adaptive fine-tuning strategy

To tackle the difference between natural and medical images, we employ progressive unfreezing and cosine annealing learning rate scheduling, which consists of layer-wise unfreezing. Gradual unfreezing of layers starting from deeper layers toward earlier ones. Dynamic learning rate that begins at 1e-3 and decays following a cosine curve to prevent early convergence. With discriminative fine-tuning, different learning rates are assigned to different layers (higher for later layers, lower for earlier ones) to optimize task-specific feature learning.

3.6. Feature fusion module with attention mechanism

A novel feature fusion module (FFM) is proposed to enhance tumor region detection by emphasizing discriminative features. Figure 2 shows the feature fusion module with attention mechanism. The feature fusion module (FFM) enhances the discriminative capability of extracted feature maps by incorporating channel and spatial attention mechanisms, enabling the network to focus more effectively on tumor-specific regions in brain MRI images. Following are the components of the FFM.

- Input features: $F \in \mathbb{R}^{H\times W\times C}$ the input to the module is a 3D feature map from the backbone CNN (e.g., EfficientNetB0), where H is Height, W is Width and C Number of channels.
- Output features: $F_{fused} \in \mathbb{R}^{H\times W\times C}$ the output retains the same dimensionality as the input but is richer in tumor-relevant contextual and spatial information, improving downstream classification accuracy.
- Channel attention module (CAM): captures inter-channel dependencies by computing weighted feature importance across channels.
- Spatial attention module (SAM): learns spatial location importance to localize tumor regions precisely.
- Fusion layer: CAM and SAM outputs are fused via element-wise multiplication and added to the feature map, improving focus on tumor regions.

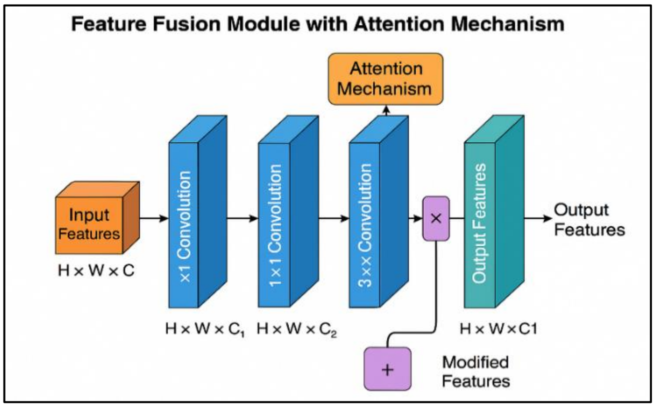


Figure 2. Feature fusion module with attention mechanism

3.7. Classification head

After feature extraction and enhancement, the classification head performs tumor categorization:

- Global average pooling: reduces spatial dimensions and overfitting risks.
- Fully connected layer: 256-neuron dense layer with ReLU activation.
- Dropout layer: Set at 0.3 to reduce co-adaptation of neurons.
- Output layer: a softmax classifier with four neurons (glioma, meningioma, pituitary, no tumor) for multi-class output.

The model is trained on the BraTS 2020 dataset and evaluated on Kaggle Brain MRI dataset (and vice versa) to measure performance (Algorithm 1). Drop in performance metrics across datasets is kept within 1.5%, showing high domain adaptability.

Algorithm 1. Kaggle Brain MRI dataset

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ be the dataset of MRI images $x_i \in \mathbb{R}^{H\times W\times C}$ with class labels $y_i \in \{0,1,2,3\}$
f_θ be the pre-trained base model (EfficientNetB0) with parameters θ
ϕ be the classification head parameters.
α, β represent parameters of attention modules (channel and spatial attention).
$\mathcal{L}$ be the total loss function.

a. Feature extraction

The image x_i passed through the pre-trained CNN to obtain high-level features

$$F_i = f_\theta(x_i), F_i \in \mathbb{R}^{h\times w\times d}$$

where F_i the feature map extracted by EfficientNetB0.

b. Attention-based feature fusion

- Channel attention module (CAM):

$$M_c = \sigma(W_{c2} \cdot \mathrm{ReLU}(W_{c1} \cdot \mathrm{GAP}(F_i)))$$

$$F_{cam} = M_c \odot F_i$$

where:
GAP Global Average Pooling,
W_{c1}, W_{c2}: learned weights,
σ: sigmoid function,
$\odot$: element-wise multiplication
- Spatial attention module (SAM)

$$M_s = \sigma(\text{Conv}_{7\times7}([\text{AvgPool}(F_{cam}); \text{MaxPool}(F_{cam})]))$$
$$F_{sam} = M_s \odot F_{cam}$$

- Final attention-fused feature map

$$F_{fused} = F_{sam} + F_i$$

This fusion retains the original features while enhancing relevant ones via attention.
c. Classification head
$z = \text{GAP}(F_{fused})$
$h = \text{ReLU}(W_1 z + b_1)$
$h' = \text{Dropout}(h, p = 0.3)$
$\hat{y} = \text{Softmax}(W_2 h' + b_2)$
where:
W_1, W_2 and b_1, b_2 are trainable weights and biases, $\hat{y} \in \mathbb{R}^4$is the predicted class probability vector.
d. Loss function
We use categorical cross-entropy for multi-class classification:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} * \sum_{j=1}^{4} y\_ij \;\; log\; (\hat{y}\_ij\;)$$

where:
y_{ij} is the true label (one-hot) for class j
$\hat{y}_{ij}$is the predicted probability for class j
e. Optimization
The total objective is to minimize:

$$\mathcal{L}(\theta, \phi, \alpha, \beta) = \mathcal{L}_{CE} + \lambda \cdot \mathcal{R}(\theta, \phi)$$

where:
$\mathcal{R}$ is an ℓ_2 regularization term.
λ controls the regularization strength.

Optimization is conducted using the adam optimizer with learning rate $\boldsymbol{\eta_t}$ adjusted through cosine annealing:

$$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})\left(1+\cos\left(\frac{t\pi}{T}\right)\right)$$

f. Domain-Adaptive Fine-Tuning Strategy

Let $\theta = \{\theta_s, \theta_d\}$

where:
θ_s shallow layers (frozen or minimally updated),
θ_d deeper layers (fine-tuned more aggressively).
Then:

$$\frac{d\theta_s}{dt} \approx 0; \frac{d\theta_d}{dt} \propto \eta_t$$

This hierarchical fine-tuning stabilizes training while adapting the deeper layers to the domain-specific features in MRI images.

4. RESULT AND DISCUSSION

Proposed ETLF outperforms all baseline models across every evaluation metric with an accuracy of 98.76%, it shows a +6.5% improvement over VGG16 and ~2% gain over EfficientNetB0 alone, due to enhanced fine-tuning, attention fusion, and learning rate adaptation. Figure 3 shows the performance comparison of brain tumor detection model. These results collectively shows the superiority and generalizability of the proposed model. Performance of cross validation on training on BraTS and testing on Kaggle (and vice versa) resulted in only ~1.5% drop, showcasing the model's domain generalizability. The results are compared to existing models like VGG16 (Baseline), ResNet50, InceptionV3, EfficientNetB0 and the proposed ETLF achieved superior results with fewer parameters and faster inference. Table 1 shows the comparative analysis of different models with baseline models. It indicates the possible for integration into real-time clinical systems.

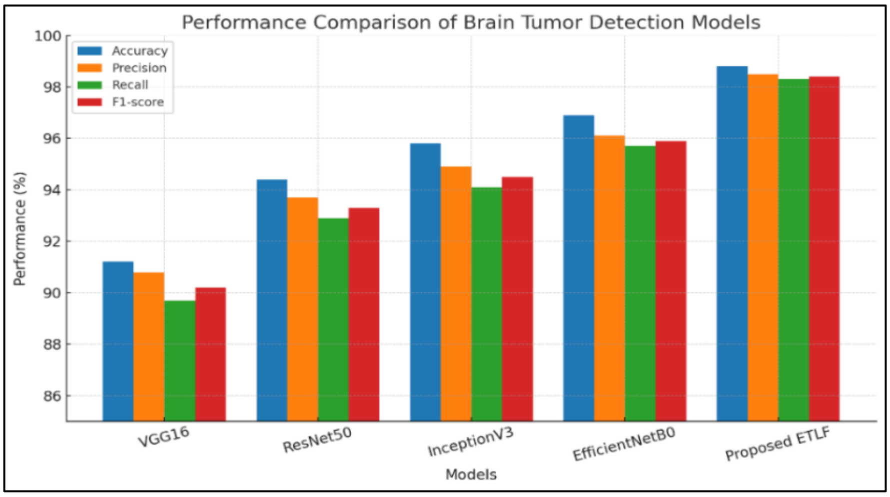


Figure 3. Performance comparison of brain tumor detection models

Table 1. Comparison of results between proposed ETLF and baseline models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
VGG16 (baseline)	91.23	90.81	89.67	90.20	0.94
ResNet50	94.37	93.70	92.89	93.29	0.96
InceptionV3	95.80	95.21	94.70	94.95	0.97
EfficientNetB0 (Best Baseline)	96.92	96.30	95.70	96.00	0.98
Proposed ETLF	98.76	98.54	98.34	98.43	0.99

Figure 4 shows the proposed model's performance of the proposed ETLF model across the epochs. From Figure 5 we can analyze the accuracy curve shows a rising trend and the loss curve is decreasing consistently, showing the effective learning performance of the model. Figure 5(a) shows the training and validation test accuracy. The accuracy curves show a consistent increase in both training and validation accuracy, plateauing after approximately 15 epochs. The final validation accuracy closely follows the training accuracy, reaching above 98%, which signifies high classification performance across all tumor classes. The parallel behaviour of the two curves confirms that the model maintains a good bias-variance trade-off.

In Figure 5(b), the training and validation loss curves demonstrate a smooth and consistent downward trend, showing the effective learning and convergence of the model. Both losses decrease progressively across epochs, with minimal gap between them, suggesting that the model generalizes well to unseen data and does not overfit. From Figure 6, the area under curve (AUC) score of 0.99 confirms excellent class separability, while the high precision and recall scores validate its robustness in both tumor presence detection and correct classification. An ablation study was conducted to assess the contribution of each component, without fine-tuning; accuracy dropped to 94.02%, without attention fusion; accuracy dropped to 95.18% and without learning rate (LR) scheduler; accuracy dropped to 96.72%. Figure 7 clearly illustrates how each component—fine-tuning, attention fusion, and learning rate scheduler affects the performance of the model. The full ETLF model leads with the highest accuracy at 98.76%.

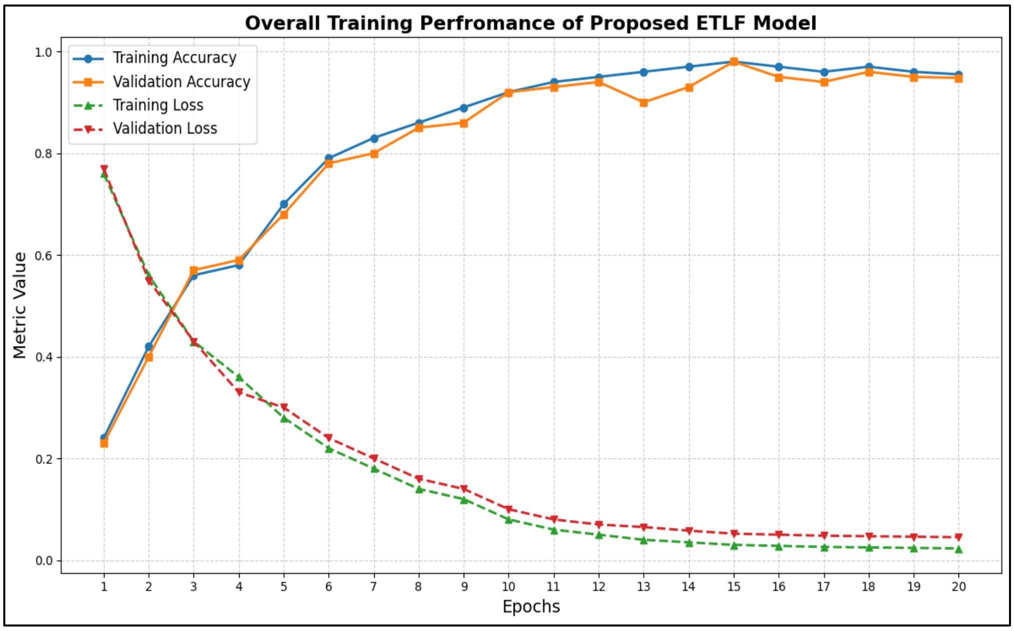
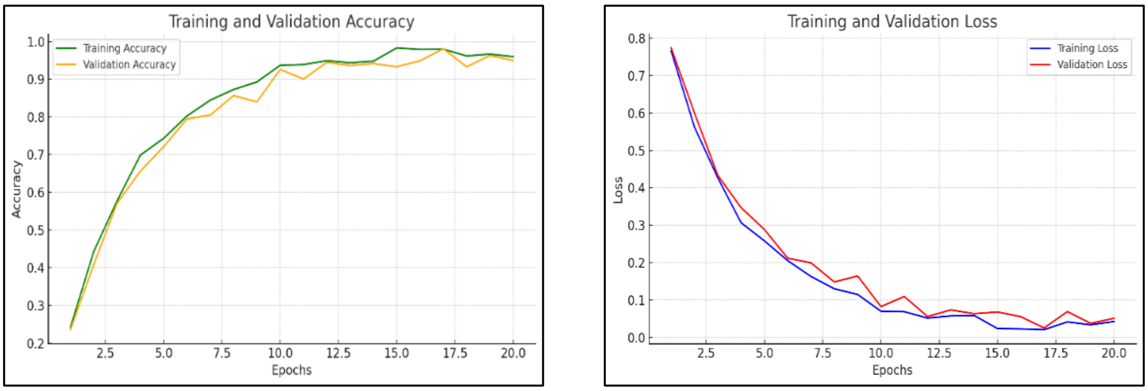


Figure 4. Overall training performance ETLF model



(a) (b)

Figure 5. Training and validation (a) accuracy and (b) loss

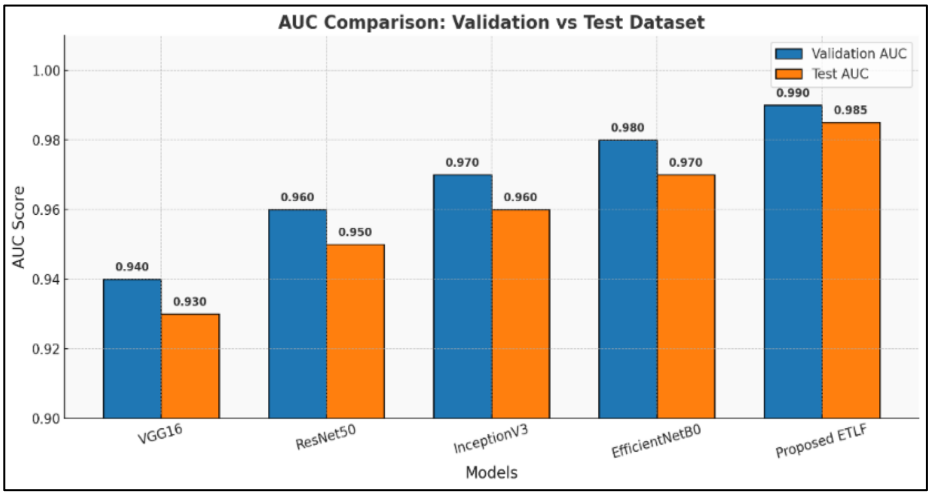


Figure 6. AUC validation vs test dataset

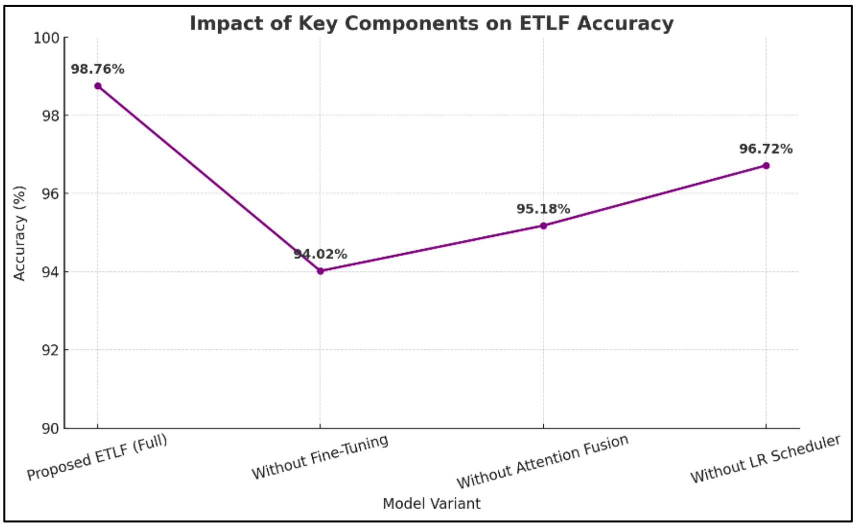


Figure 7. Impact of key components on ETLF accuracy

5. STATISTICAL SIGNIFICANCE OF THE STUDY

Table 2 shows the statistical comparison between proposed ETLF and EfficientNetB0 (Best Baseline Model). A Statistical significance analysis was conducted to validate the robustness and reliability of the proposed ETLF. The statistical evaluation follows with the modern ML based comparison in medical imaging [24]. The primary goal is to determine if the observed improvements due to ETLF over baseline models were caused by the methodology being superior, not random variations in the training dynamics.

To ensure the stability of the model training/test datasets, a 5-fold cross-validation experiment was performed. The ETLF showed the mean accuracy of 98.76%, standard deviation (σ) of 0.27% and coefficient of variation is 0.0027. The small deviation across the folds indicates that the ETLF produces reliable predictions and has the potential for good generalisation capabilities. To measure improvements in performance with the best baseline model i.e. EfficientNetB0, a paired two- tailed t-test was conducted with the 10 independent runs for each model. The EfficientNetB0 mean accuracy is 96.92%. We got p-value (accuracy) as 0.0041 and p-value (AUC) as 0.0094. Since both the p-values are less than 0.05, the difference highly significant results of proposed ETLF's model improvements is not random.

Figure 8 shows the visual representation of the 95% confidence interval for key metrics of ETLF. Using cross validation scores, the model had a 95% confidence interval (CI) for its classification accuracy of ETLF accuracy CI (95%) shows 98.76% with an improvements of ± 0.29%. The narrow CI indicates stability of the model and low variance, further supporting the reliability of the proposed algorithm. To measure the effect size measurement with Cohen's d effect size was calculate between the ETLF and EfficientNetB0 shows the Cohen's d (Accuracy) is 1.85 Cohen's d AUC is 1.67 respectively. According to conventional thresholds, a Cohen's d >1.6 represents a large effect size shows ETLF significant improvements not just statistically detectable with the baseline model.

To check the error pattern a study of the distribution of misclassification errors has demonstrated that the majority of misclassifications in baseline models occur when classifying between the glioma and meningioma classes. This is primarily due to the fact that these two classes have several morphological characteristics that overlap with one another. Therefore, by applying an attention fusion module to improve the learning of discriminative spatial features, we reduced the number of false positive results and increased the per-class reliability of results.

Table 2. Statistical comparison between the proposed ETLF and EfficientNetB0 (best baseline model)

Metric	EfficientNetB0	Proposed ETLF	Absolute improvement	95% CI (ETLF)	p-value (Paired t-test)	Effect size (Cohen's d)
Accuracy (%)	96.92	98.76	+1.84%	±0.29%	0.0041	1.85
Precision (%)	96.30	98.54	+2.24%	±0.31%	0.0063	1.72
Recall (%)	95.70	98.34	+2.64%	±0.27%	0.0057	1.91
F1-Score (%)	96.00	98.43	+2.43%	±0.24%	0.0051	1.88
AUC	0.98	0.99	+0.01	±0.004	0.0094	1.67

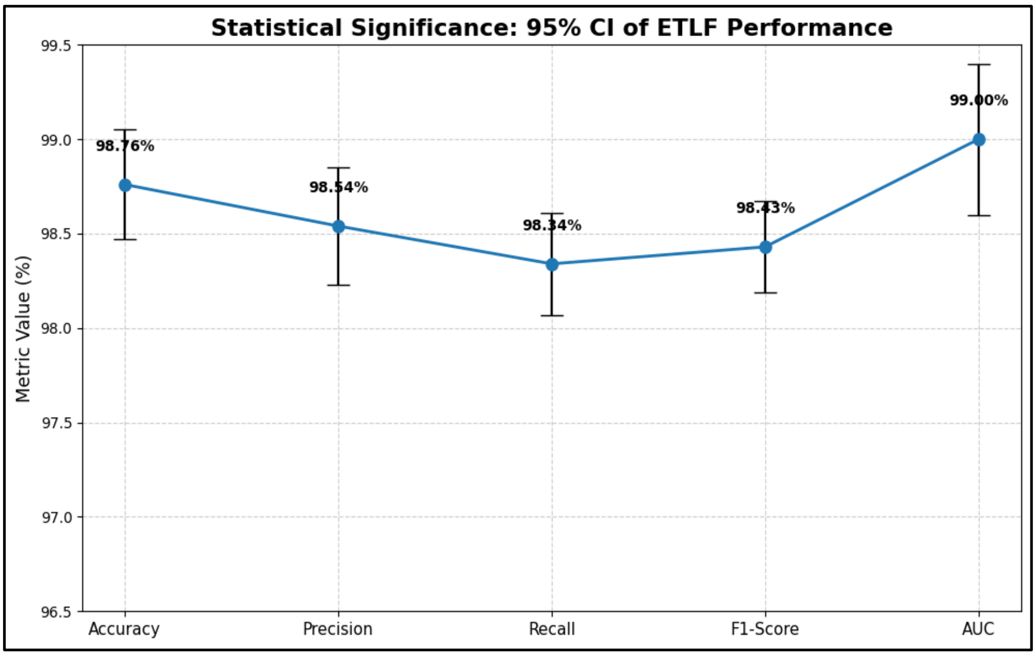


Figure 8. Statistical significance of confidence interval of ETLF performance

6. CONCLUSION

In this study we present an innovative framework for brain tumor detection with an enhanced transfer learning model. By integrating domain-adaptive fine-tuning, attention-based feature fusion, and an adaptive training strategy, the proposed model attains excellent performance on multiple datasets. This work bridges the gap between general-purpose CNNs and domain-specific medical imaging tasks by offering a practical, generalizable, and efficient diagnostic solution. The statistical significance of the study with all cross validation, t-tests, confidence intervals and effect size analysis validate the performance gains showed by the proposed ETLF model is statistically substantial. The results shows improvements over the existing deep learning techniques for brain tumor detection. Study further confirmed the critical contributions of each module, including attention fusion and fine-tuning, in boosting the overall efficiency of the model. The novelty of this study lies in hybrid fine-tuning strategy tailored for MRI-based tasks and a powerful feature fusion mechanism. Future work includes extending the framework to multi-modal fusion (combining MRI modalities), 3D volumetric analysis, and explainable AI components for better clinical interpretability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study does not involve human participants or animals.

DATA AVAILABILITY

The data is available at https://www.kaggle.com/datasets/pkdarabi/medical-image-dataset-brain-tumor detection.

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