A Dual-Branch Lightweight Model for Extracting Characteristics to Classify Brain Tumors

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***Abstract*—Brain tumors present a significant challenge in healthcare, necessitating prompt and accurate detection for effective treatment. Pre-trained models were utilized to classify brain tumors without segmentation. Traditional pre-trained architectures like VGG16, VGG19, and ResNet, despite their accuracy, suffer from slow processing speed which leads to use them impractical for rapid diagnosis. Some of the other pre-trained models like Mobile Net and Efficient Net offer fast processing but overfitting problems occur in the small image dataset. To overcome these challenges a two-branch neural network model has been proposed which is lightweight feature extraction and multi-class classification of brain tumors. The proposed two-branch architecture begins with refining the size of the input images, then extraction of robust features, and concludes with a neural network classifier. The proposed model is also evaluated in the presence of image distortions including Gaussian, Poisson, and Speckle noise to ensure the robustness of the proposed solution. Experimental results state that the proposed model is capable of maintaining high accuracy in tumor classification when compared to the other pre-trained models with limited datasets and noise interferences.**

***Keywords*—two-branch feature extraction, Magnetic resonance imaging (MRI), brain tumor, Convolutional Neural Network (CNN), VGG16, efficient net, mobile net, DenseNet21**

I. Introduction

Secondary brain tumors are cancers that have spread to the brain from other parts of the body. The recovery rate for these tumors is still complicated but at the same time, it is increasing quickly. Advanced medical imaging tools help doctors detect these tumors early, which can make treatment and possible removal easier when the tumor is still small. However, there is a challenge that Magnetic Resonance Imaging (MRI) scans sometimes fail to correctly identify or classify the tumor. This can lead to serious problems, including difficulties with movement or even paralysis [1]. Brain cancer is sorted into four types: gliomas, meningiomas, non-tumorous conditions, and pituitary tumors. These tumors can lead to complications such as physical disabilities, requiring patients to undergo intense and often painful treatments to mitigate or diagnose these disabilities. Additionally, the impact of brain tumors on brain function varies greatly, depending on the tumor's size, location, and type [2].

A brain tumor can make a patient unable to move if it presses on the part of the brain that controls movement [3]. The most common types of brain cancer are meningioma, glioma, and pituitary adenomas. Meningioma is a tumor that begins in the meninges, the protective membranes around the brain and spinal cord. Symptoms of meningioma often start slowly and can be subtle, making them easy to overlook in the early stages. Glioma is a type of tumor that can grow in the brain and spinal cord. It starts in the glial cells, which are the supportive cells around nerve cells, helping them function. Symptoms of a-glioma include imbalance, headache, nausea or vomiting, confusion or reduced brain function, memory loss, changes in behavior or mood, trouble controlling urination, vision problems like blurry vision, double vision, or loss of side vision, difficulty speaking, and seizures, especially in someone who has never had seizures before. The symptoms of a tumor depend on where it is in the brain or, less commonly, the spine. These symptoms can include vision changes like double vision or blurriness, headaches that are worse in the morning, hearing issues or ringing in the ears, memory loss, seizures, and weakness in the arms or legs. Pituitary brain tumors are abnormal growths in the pituitary gland. Sometimes, pituitary tumors can lead to less hormone production by the pituitary gland. The most common type of pituitary tumor is a benign adenoma, which is a non-cancerous growth.

Tumors often grow without showing any symptoms and are usually not found until the disease has become advanced which makes early detection difficult. Therefore, there's a need to develop automated systems to help radiologists diagnose brain tumors more accurately. Pre-trained Convolutional Neural Network (CNN) models like VGG19 and Efficient Net B4, adapt their parameters for classifying different types of brain tumors The aim is to understand how far the tumor has

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spread and to plan the appropriate treatment. Experts believe that Magnetic Resonance Imaging (MRI) is effective in creating detailed images of organs using magnetic fields and computers. MRI images are crucial for determining the condition of brain tumors.

However, interpreting MRI images takes a lot of time and requires much expertise from doctors. Deep learning, a type of machine learning, works by learning to recognize patterns at multiple levels. It does this by building features hierarchically, where simple features form the basis for more complex ones. CNN is a deep learning technique that's particularly good at categorizing image data. CNNs learn, recognize, and classify objects by using layers that include convolutional, pooling, and fully connected layers. These layers transform 2D features into 1D vectors for classification.

To address these challenges, a two-branch neural network model has been proposed, focusing on lightweight feature extraction and multi-class classification of brain tumors. The primary objectives of the proposed framework are: (i) To extract robust features with a neural network classifier based on the lightweight, efficient two-branch architecture that has been designed for the multi-class classification of brain tumors. (ii) To develop a deep learning-based system for the identification and classification of brain tumors that can accurately detect the presence of tumors and determine their types; (iii) To evaluate the proposed model performance and robustness in the presence of image distortions, including Gaussian, Poisson, and Speckle noise, ensuring the model reliability under various conditions and its ability to maintain high accuracy in tumor classification compared to other pre-trained models, especially with limited datasets and in the face of noise interferences.

This article is divided into five parts, Section II deals with a literature analysis, and Section III describes the proposed methodology, collection, and description of the. Section IV discusses the findings, and their implications for the evaluation methods are explained. Finally, the study concludes with a summary and recommendations for future research in Section V.

II. Literature Review

This section explores the content and themes typically addressed in the literature on brain tumor classification using deep learning, then focuses on how these innovative technologies are advancing diagnostic accuracy and treatment strategies. In Discrete Wavelet Transform (DWT) feature extraction and a probabilistic neural network classifier to recognize and categorize MRI images of brain tumors [1]. To improve performance in the future, the researchers recommend using several classifiers and integrating more effective segmentation and feature extraction approaches with actual and clinical-based instances using a big dataset [4]. A multi-path adaptive fusion network was designed for the segmentation of multimodal brain tumors. Initially, it captures basic visual features and combines them with advanced semantic information [2]. This method maintains and transfers basic visual features using skip connections from ResNets to a dense block. It employs continuous memory by connecting the outcomes of previous dense blocks to all layers of the current dense block. During the upsampling process, a multi-path adaptive fusion dense block is utilized to dynamically adjust basic visual features and integrate them with complex semantic details. This innovative approach sets a new standard on the BRATS2015 dataset and requires fewer parameters compared to existing methods [5]. A Bayesian Optimization-based efficient hyperparameter optimization approach for CNN in the classification of brain cancers using MRI Images [3]. This technique is intended to improve accuracy with the limited amount of training data [6].

In Ref. [5], CNN-based Brain Tumor Classification Model (BCM-CNN) employing Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer (ADSCFGWO) was developed and it includes adjusting hyperparameters and training Inception-ResnetV2 models. Amou *et al*. [6] employed a deep transfer learning strategy and a pre-trained Google Net model to solve a 3-class classification issue distinguishing between glioma, meningioma, and pituitary cancers. In Ref. [7], deep Convolutional Neural Network (CNN) model is dubbed EfficientNet-B0, which is optimized with extra layers to recognize and categorize pictures of brain tumors. Brain tumor diagnosis is improved by pre-trained models that produce a binary categorization of normal or malignant. The BCM-CNN was 99.98% accurate on BRaTS 2021 Task 1 [8]. The method uses established classifier models to categorize the characteristics retrieved from brain MRI scans [9]. To enhance MRI pictures, several different filters are used in image enhancement methods. The suggested technique makes use of transfer learning and fine-tuning to train and optimize DL algorithms using a wide range of hyperparameters [10]. To identify brain tumors, the authors combine the K-means clustering method with the Fuzzy C-means algorithm, then use thresholding and level set segmentation. This method computation is higher with the result of the K-means clustering method and the preciseness of the Fuzzy C-means algorithm and combines them [8, 11].

The effectiveness of ten distinct gradient descent-based optimizers that are state-of-the-art, including Adagrad, AdaDelta, SGD, Adam, CLR, Adamax, RMS Prop, Nadam, and NAG, to assess their performance in enhancing the accuracy of CNN segmentation. Additionally, the necessity of optimizer selection techniques to verify the use of a single optimizer in decision problems associated with segmentation or classification tasks [9, 12]. The CELLO2 machine learning model as well as the discovery of MYC as a predictor of glioma evolution and temozolomide resistance. In addition to this, the work sheds light on the molecular pathways that are at play in gliomas that undergo hypermutation. The researchers concluded that MYC gain or MYC-target activation at the time of diagnosis was related to treatment-induced hypermutation at the time of recurrence in all glioma subtypes [10, 13].

In Ref. [11], the three pre-trained convolutional neural network (CNN) architectures, VGG-16, Inception-v3, and ResNet50, was utilized to classify brain tumor. Based on convolution layer outputs and modified dense layer technique was used to classify the brain tumor from MRI images [14]. With the help of transfer learning to compare their CNN model against pre-trained VGG-16, ResNet-50, and Inception-v3 models [12]. Deep learning is used to enhance brain tumor classification in MRI images for medical imaging diagnosis [15]. In Ref. [13], a 2D CNN is suggested to identify brain cancers using MRI data. Little mispredictions were caused by inertial noise from patient movement during the scan. The model accuracy and recall were constant across training and testing data folds in 10-fold cross-validation on the whole dataset to determine its generalizability [16]. A two-stage feature ensemble of deep CNN was utilized for the classification of brain cancers using MRI datasets. With an average accuracy of 99.13%, the suggested model can distinguish between normal brain tissue and images with meningioma, glioma, or pituitary tumors. This framework paradigm is used to develop a User Interface (UI) for real-time testing [17].

Deep learning approaches, metaheuristic techniques, and hybridizations were all part of the research that was undertaken to conduct a comprehensive literature review on strategies for the segmentation of brain tumors and the categorization of abnormality and normalcy from MRI images. A technique for the automated segmentation of brain tumors based on three incremental deep convolutional neural networks (2CNet, 3CNet, and Ensemble Net) has been suggested. This approach makes use of Ensemble Learning and limited hyper-parameters to speed up the training process [15, 18] and discussed the importance of medical imaging for early disease treatment. Tumors are often identified by radiologists using imaging techniques like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans. However, this method of diagnosing tumors is time-consuming, prone to mistakes, and heavily depends on the radiologist's expertise and knowledge [19]. Jalali and Kaur [20] focused on brain tumor detection and the challenges associated with it. The study compares various automatic brain tumor detection techniques using medical imaging. Techniques include machine learning, soft computing, and deep learning-based classifiers that analyze these techniques based on accuracy, sensitivity, and specificity. A study of GAN-based image denoising segmentation and classification was discussed in [21]. Table I describes the summary of segmentation and classification approaches for brain tumor detection.

Table II summarizes the medical image analysis by various studies, showcasing remarkable brain tumor detection. These developments underscore the potential of machine learning in revolutionizing medical diagnostics and patient care. Table III summarizes various approaches for brain cancer detection, including ensemble classification using fine-tuned models, segmentation and classification with transfer learning, feature extraction employing hierarchical methods, and hyperpermutation forecasting after treatment. These methods achieve accuracies ranging from 93.5% to 98.3%, indicating promising outcomes in brain cancer diagnostics and prognosis.

TABLE I. SUMMARY OF SEGMENTATION AND CLASSIFICATION APPROACHES FOR BRAIN TUMOR DETECTION

Ref. No	Inferences
[22]	Multi Atlas Algorithm segmentation and Cascade CNN-based classification
[23]	Brain tumor segmentation, optimization, and recognition framework.
[24]	Segmentation based on VAE 3D U-Net, Densenet, and Resnet Based Classification

TABLE II. LITERATURE SUMMARY OF DATASET, ALGORITHMS, AND RESULTS

Ref. No	Dataset	Algorithms	Results
[19]	MPII human pose dataset	VGG16 transfer learning algorithm, CNN and Multilayer Perceptron (MLP)	Accuracy of 90.2%, 87.5 % and 89.9 using VGG16, CNN And MLP
[25]	–	EfficientNet	Accuracy 97.5%
[26]	–	Exemplar deep features algorithm	Accuracy 92.5%
[27]	–	U-Net and 3D CNN	Precision 98.35%
[7]	Customized Dataset of 3264 with four tumor classes such as Glioma, Meningioma, Pituitary, and No Tumor	CNN	Accuracy is 96%
[12]	BraTS2015 dataset	Gradient descent-based optimizers for CNN	Accuracy 99.2 %
[28]	fMRI datasets	Densenet Based SNN	Accuracy 98.46 %
[29]	BRATS and FigShare 2020	SCAO with Densenet	Accuracy 93 %
[30]	FigShare	Modified Xception	Accuracy 96 %
[31]	FIgshare Brain MRI dataset	SGD, SVM, Naïve Bayes	Accuracy 94.9%, 96.8%, 92.9%

TABLE III. SUMMARY OF BRAIN CANCER DETECTION APPROACHES AND ASSOCIATED ACCURACIES

Ref. No	Inferences	Accuracy
[32]	Fine-Tuned Inception-v3 and Fine-Tuned Xception Model-based Ensemble classification for four classes of brain cancer	93.79 %
[33]	Mask RCNN with transfer learning approach of Densnet-41 based segmentation and classification	98.3 %
[34]	Dual path parallel Hierarchical-based Feature extraction, Dual input + No features, Pathomorphological features	93.5 %
[35]	CELLO2, ML model Forecast hyper permutation after the treatment	94.2 %

Pascal [36] developed a scaled Swin model for brain MRI image classification, introducing the Hybrid Shifted Windows Self Attention module and replacing the MLP with a Residual-based MLP for enhanced accuracy and efficiency, achieving improved accuracy and demonstrating superior performance over existing models in brain tumor detection.

A new MRI-based model for tumor multiclassification was developed [37], tested across four individual and two combined datasets against five existing models, and includes a feature for generating masks from MRIs, which improves but slightly outperforms traditional segmentation-first methods. In Ref. [38], discussed the combination of convolutional neural network with an SVM classifier, achieving approximately 99% accuracy on two brain MRI datasets, surpassing previous models while also improving sensitivity, specificity, and precision with significantly fewer training parameters. In Ref. [39] CNN with meticulously adjusted hyperparameters such as filter characteristics and learning specifics, which significantly enhances performance and model reliability across typical medical imaging benchmarks. This approach surpasses traditional methods in accuracy and diagnostic metrics, confirming its superiority in brain tumor detection. Sandhiya *et al.* [40] developed unique feature extraction, filtering, and hybrid deep learning techniques, tested on two major datasets, yielding superior performance across multiple metrics and surpassing existing methods in tumor detection accuracy.

III. Proposed Methodology

This section provides details of the thorough classification system for brain tumors. The proposed architecture has been designed for efficient computation and effective feature extraction, which is particularly important for medical imaging tasks where precision is critical. The steps are as follows: dataset description, preprocessing, and Robust features extraction model and classifier. Fig. 1 represents the general block diagram of the proposed work. The process begins with a dataset that undergoes image preprocessing to prepare the images for input into the network.

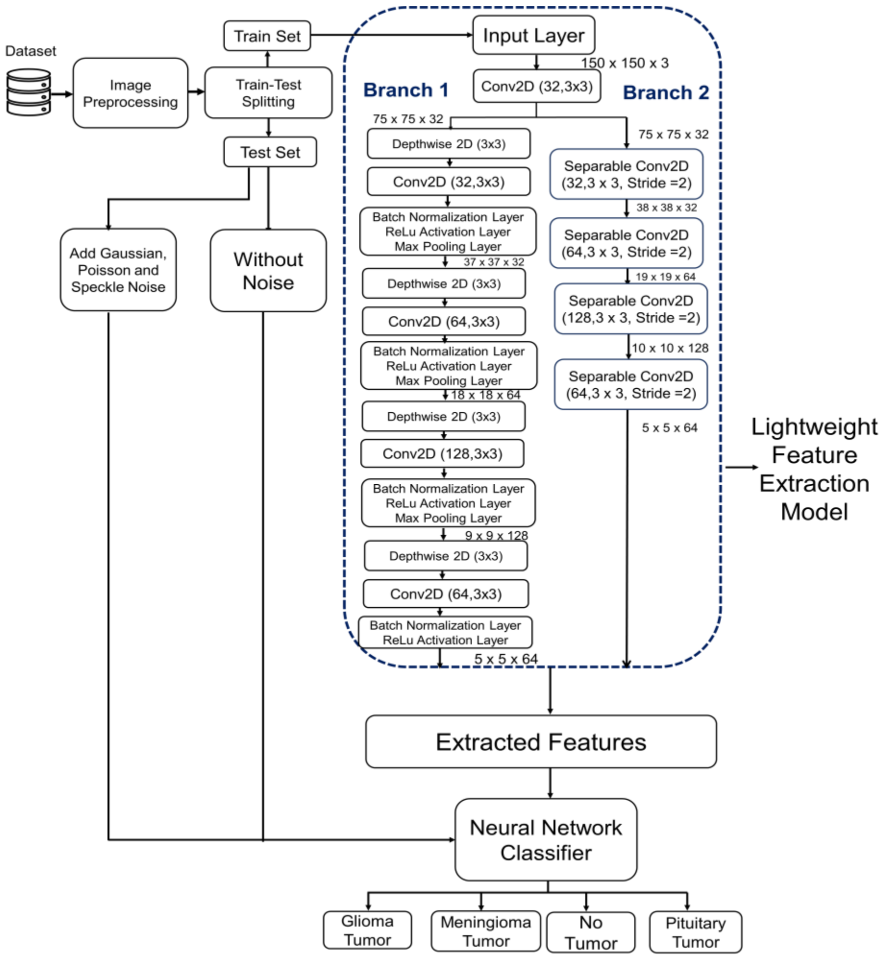
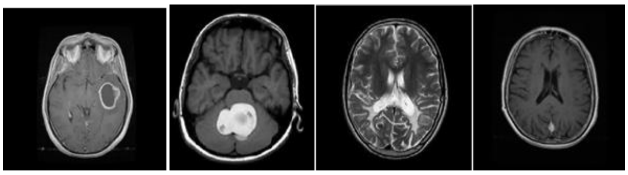


Fig. 1. General block diagram of proposed framework.

Kaggle and SRM College datasets were combined, and all images were resized to 150×150×3 pixels. Following that, the dataset was divided into training and testing groups with a 70:30 ratio. After preprocessing, the data is split into two sets: a training set for teaching the model and a test set for evaluating its performance. The test set is further processed by adding Gaussian, Poisson, and Speckle noise, simulating real-world conditions to test the robustness of the model. Finally, the extracted features were loaded into a Neutral network classifier for performance classification (see Fig. 2).



(a) (b) (c) (d)

Fig. 2. Datasets from left to right, (a). glioma tumor, (b). Meningioma tumor, (c). No tumor, (d). pituitary tumor.

A. Dataset Details

The brain tumor dataset was compiled from two sources: Kaggle and SRM Medical College. The Kaggle dataset is preprocessed into separate folders for training and testing, with each folder further categorized into four classes based on tumor type No tumor, Glioma tumor, Meningioma tumor, and Pituitary tumor. The training folder contains 826 glioma images, 822 meningioma images, 395 images without tumors, and 827 pituitary tumor images. The testing folder includes 100 glioma images, 115 meningioma images, 150 images without tumors, and 74 pituitary tumor images. Relative to other online databases, the Kaggle dataset is comparatively small. This dataset has been augmented with additional images obtained from SRM Medical College, enhancing the diversity and volume of data available for analysis is tabulated in Table IV.

TABLE IV. DISTRIBUTION OF BRAIN TUMOR IMAGES IN KAGGLE DATASET AND SRM MEDICAL COLLEGE

Tumor	Source	Dataset	
		Training	Testing
Glioma	Kaggle	826	100
Meningioma	Kaggle	822	115
No Tumor	Kaggle	395	150
Pituitary	Kaggle	827	74
Glioma	ARM	30	10
Meningioma	SRM	30	10
No Tumor	SRM	30	10
Pituitary	ARM	30	10

B. Image Preprocessing

In the proposed study a model is designed for robust feature extraction to enhance performance. Consequently, there are many operations such as image scaling, image rotating, image sheering, and image resizing to emphasize the preprocessing stage. But in the proposed architecture the input images are simply resized to dimensions of 150×150×3. Following the preprocessing, the images are fed into the robust feature extraction model and SoftMax classifier.

C. Feature Extraction

A robust feature extraction model named the Two-Branch Lightweight CNN Architecture (TBLWFE). As stated in the literature various pre-trained models have been utilized for brain tumor classification. High-density architectures like VGG16, VGG19, and the ResNet result in excellent performance but require substantial training time. On the other hand, low-density architectures such as MobileNet, EfficientNet, and DenseNet have fewer parameters, resulting in shorter training times but causing overfitting problems with small datasets. To overcome this issue, low-density architectures primarily use depthwise convolution layers instead of standard convolution layers to reduce the number of parameters. In many instances, low-density architectures have achieved performance comparable to high-density architectures. However, they may face overfitting issues with small datasets as they tend to focus less on capturing spatial features. To enhance performance using the proposed two-branch Lightweight Feature Extraction Model (TBLWFE) to extract precise features from images. This model is intentionally designed with two branches, each specializing in different aspects of feature extraction. One branch focuses on capturing spatial features within and across channels, emphasizing higher-level and complex patterns. The other branch is dedicated to extracting low-level features, contributing to a thorough representation of spatial information. This dual-branch approach allows the model to effectively gather a wide range of variables, balancing complexity and flexibility.

1) Branch 1: Extraction of complex spatial patterns and cross-channel dependencies

Branch 1 has been designed to focus on capturing higher-level features and relationships within and between channels. This branch consists of four blocks, each comprising a Depthwise Convolution 2D layer followed by a Convolution 2D layer. The first block employs 32 filters with a 3×3 kernel size to capture initial spatial information while reducing dimensionality. Instead of using strides in the convolutional layers with the help of a max pooling layer at the end of each block to further process the data. The layout remains consistent across successive blocks, same time the number of filters increases: the second block uses 64 filters, the third block 128 filters, and the fourth block returns to 64 filters. This hierarchical design allows Branch 1 to extract more complex and higher-level spatial information effectively, with a spatial down-sampling effect, thereby enhancing the model's overall feature extraction capability.

2) Branch 2: Extraction of low-level features and efficient spatial and cross-channel representations

Branch 2 is focused on extracting basic details and patterns in a lightweight and flexible manner. It comprises four blocks, each featuring a Separable Convolution layer. The first block utilizes 32 filters with a 3×3 kernel size and a stride of 2, aimed at efficiently capturing spatial features. Subsequent blocks maintain a similar configuration but increase the number of filters: 64 in the second block, 128 in the third block, and 64 in the fourth block again. This setup is intended to efficiently and adaptably capture spatial and cross-channel information, resulting in a lightweight effective feature extraction approach within the model.

The integration of both branches strengthens better feature extraction. Branch 1 is tasked with capturing high-level characteristics, such as complex patterns and relationships across channels, while Branch 2 focuses on the efficient extraction of low-level features. Together, they simultaneously capture hierarchical features, offering a comprehensive representation of the input data.

This strategy not only enhances speed by detailing intricate patterns but also minimizes the number of parameters, boosting the model's overall efficiency. The proposed methodology outcomes performance analysis has been compared with benchmarked existing methods such as EfficientNet, MobileNet, and DenseNet121. To verify our methodology's robustness, employed a rigorous training regimen using noise-free images. For testing purposes, various types of noise into the images, including Gaussian, Poisson, and speckle noise. This extensive evaluation process allows us to assess the model's performance across different scenarios, shedding light on its ability to manage noisy data and demonstrating its resilience against various noise types. basic details and patterns in a lightweight and flexible manner. It comprises four blocks, each featuring a Separable Convolution layer. The first block utilizes 32 filters with a 3×3 kernel size and a stride of 2, aimed at efficiently capturing spatial features. Subsequent blocks maintain a similar configuration but increase the number of filters: 64 in the second block, 128 in the third block, and 64 in the fourth block again. This setup is intended to efficiently and adaptably capture spatial and cross-channel information, resulting in a lightweight effective feature extraction approach within the model.

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D. Classifier Model

Following feature extraction, they are fed into a neural network classifier for classification. Three dense layers are used in this classifier. The first layer is made up of 1028 concealed units that are activated by a ReLU. The second layer contains 128 hidden units, each of which has a ReLU activation. The last layer employs four hidden units with SoftMax activation.

E. Pre-trained Models

1) MobileNet

MobileNet is a lightweight architecture designed for image categorization on mobile and embedded devices in real time. Its suitability for resource-constrained environments stems from its speed and efficiency in terms of parameters. By employing depthwise separable convolutions, MobileNet significantly reduces computational requirements. It has been refined across versions, including MobileNetV1, V2, and V3, to enhance efficiency and accuracy. The architecture consists of depthwise separable blocks, downsampling layers, and bottleneck layers, focusing on the balance between model size and performance. MobileNet's versatility and rapid inference capabilities make it an excellent choice for mobile applications and edge devices for tasks such as image recognition and object detection. However, the limited discriminative power of MobileNet may affect its ability to recognize detailed patterns, and its reliance on depthwise separable convolutions could restrict its capacity to capture complex dependencies.

2) EfficientNet

EfficientNet is an advanced neural network architecture engineered to deliver high accuracy while utilizing fewer parameters, enhancing computational efficiency. It introduces a compound scaling strategy that uniformly scales the model's depth, width, and resolution, leading to improved performance across diverse workloads. This design strikingly achieves a balance between model size and accuracy, rendering it exceptionally suitable for resource-constrained applications.

3) DenseNet-121

DenseNet-121, a variant of the DenseNet architecture, comprises 121 layers. DenseNet, short for Densely Connected Convolutional Networks, features a unique connection pattern where each layer receives inputs from not just the preceding layer but from all prior layers. This architecture promotes feature reuse, addresses the vanishing gradient problem, and enhances the efficiency of model training. During validation, we introduced different types of noise into the testing images to assess the adaptability of the feature extraction model.

IV. Result and Discussion

This study evaluates the proposed TBLWFE-NN classifier against predefined models, highlighting its better accuracy and resilience to noise in brain tumor classification. In this analysis performance comparison of the proposed TBLWFE-NN classifier with three standard classifiers such as EfficientNetB4, MobileNetV1, and DenseNet121. This comparative study aimed to evaluate the effectiveness and superiority of the proposed model against these well-established models. We utilized various metrics for comparison, including accuracy, precision, recall, kappa, F1–Score, number of parameters, and execution time, to comprehensively understand each classifier's strengths and weaknesses in brain tumor classification. To test the robustness of our proposed approach, three noises such as Gaussian, Poisson, and Speckle imposed on the test images. The objective is to observe how the proposed TBLWFE-NN classifier would perform under challenging conditions, simulating real-world scenarios with visual distortions or noise. This thorough examination aimed to assess the durability of our strategy and its ability to deliver consistent performance amidst different types of noise.

TABLE V. TEST PERFORMANCE ANALYSIS OF PROPOSED FEATURES EXTRACTION MODEL WITH OTHER MODELS—WITHOUT NOISE

Algorithms	EfficientNet B4	DesnseNet 121	MobileNet V1	TBLWFE -NN
Accuracy	95.10	95.61	97.65	**98.14**
Precision	95.24	96.39	97.70	**98.04**
Recall	95.54	95.19	97.79	**97.56**
Kappa	93.39	94.04	96.81	**96.89**
F1 Score	95.32	95.66	97.74	**97.47**

Table V presents the test classification performance for images without noise. In noise-free conditions during the validation phase, our model achieved the highest performance with an accuracy of 98.14%. In comparison, MobileNetV1 achieved 97.65% accuracy, EfficientNetB4 attained 95.10% accuracy, and DenseNet121 reached 95.65% accuracy. These findings highlight the superior performance of our proposed feature extraction model and neural network in noise-free conditions, outperforming both the baseline models and our proposed model. evaluates the proposed TBLWFE-NN classifier against predefined models, highlighting its better accuracy and resilience to noise in brain tumor classification. In this analysis performance comparison of the proposed TBLWFE-NN classifier with three standard classifiers such as EfficientNetB4, MobileNetV1, and DenseNet121. This comparative study aimed to evaluate the effectiveness and superiority of the proposed model against these well-established models. We utilized various metrics for comparison, including accuracy, precision, recall, kappa, F1−Score, number of parameters, and execution time, to comprehensively understand each classifier's strengths and weaknesses in brain tumor classification. To test the robustness of our proposed approach, three noises such as Gaussian, Poisson, and Speckle imposed on the test images. The objective is to observe how the proposed TBLWFE-NN classifier would perform under challenging conditions, simulating real-world scenarios with visual distortions or noise. This thorough examination aimed to assess the durability of our strategy and its ability to deliver consistent performance amidst different types of noise.

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Table VI presents the test performance of images with noise, including Gaussian, Poisson, and speckle noise. While all models demonstrate good performance in noise-free conditions, their robustness varies in the presence of noise. The proposed feature extraction model excels, particularly considering its minimal computational cost. However, it exhibits sensitivity to speckle noise tabulated in Table VII. The proposed model proves to be the most robust against all types of noise, maintaining high accuracy in the presence of Gaussian, Poisson, and Speckle noise. MobileNet, however, maintains optimal accuracy only for Gaussian and Poisson noise but struggles with speckle noise, which is often considered more challenging and visually disruptive. Fig. 3 illustrates the performance comparison of different neural network models. Fig. 4 illustrates the test accuracy performance with and without noise.

TABLE VI. TEST PERFORMANCE ANALYSIS OF PROPOSED FEATURES EXTRACTION MODEL WITH OTHER MODELS—WITH NOISE

Metrics	Gaussian EfficientB4/ DenseNet121/ MobileNetV1/ TBLWFE-NN	Poisson EfficientB4/ DenseNet121/ MobileNetV1/ TBLWFE-NN	Speckle EfficientB4/ DenseNet121/ MobileNetV1/ TBLWFE-NN
Accuracy	85.61/ 91.22/ 97.04/ **97.45**	95/ 95.91/ 97.24/ **97.32**	15.61/ 78.57/ 24.48/ **89.78**
Precision	88.79/ 92.34/ 97.17/ **97.24**	95.10/ 96.57 /97.28/ **97.21**	13.23/ 80.73/ 60.30/ **88.78**
Recall	86.72/ 90.31/ 97.20/ **97.78**	95.40/ 95.53/ 97.44/ **97.74**	25.09/ 79.30/ 33.13/ **89.89**
Kappa	80.66/ 88.10/ 95.98/ **96.78**	93.26/ 94.47/ 96.26/ **96.41**	19/ 71.25/ 0.9/ **85.14**
F1−Score	86.45/ 91.01/ 97.16/ **97.89**	95.22/ 95.95/ 97.35/ **97.45**	7.1/ 77.44/ 21.45/ **88.14**

TABLE VII. PERFORMANCE ANALYSIS OF PROPOSED FEATURES EXTRACTION MODEL WITH OTHER MODELS

Methods	Without Noise	With Noise		
		Gaussian	Poisson	Speckle
EfficientnetB4	95.10	85.61	95.00	15.61
DenseNet121	95.61	91.22	95.91	78.57
MobileNetV1	97.65	97.04	97.24	24.48
TBLWFE	**98.14**	**97.45**	**97.32**	**89.78**

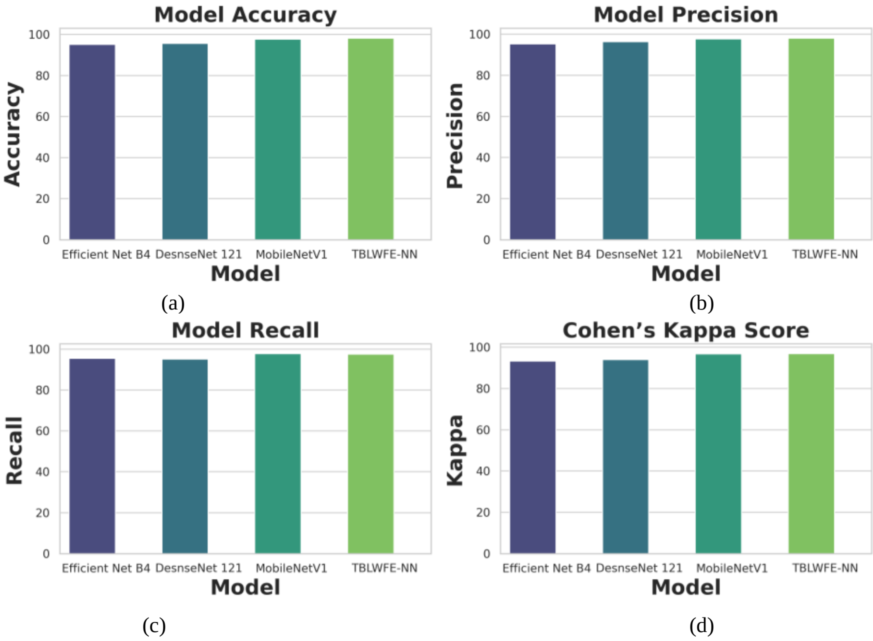


Fig. 3. Performance comparison of different neural network models, (a) Accuracy; (b) Precision, (C) Recall, (d) Kappa.

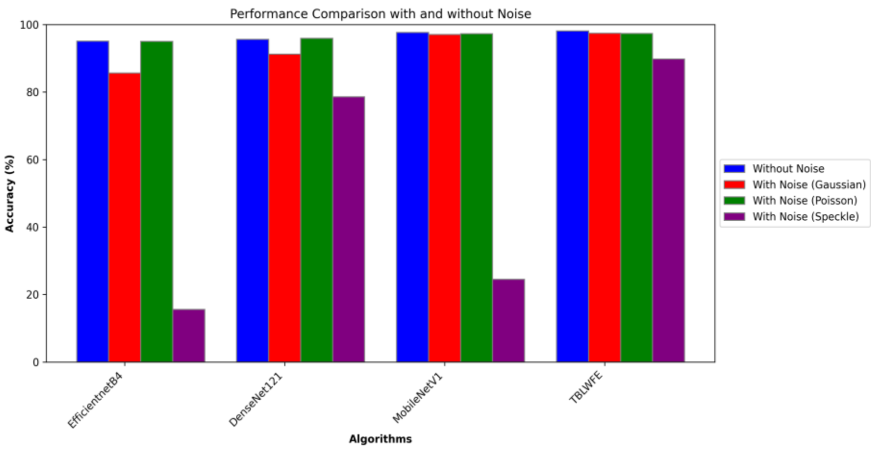


Fig. 4. Performance analysis of proposed features extraction model with other models

In the test dataset involving speckle noise, the proposed model achieves a 12.72% higher accuracy compared to DenseNet121. Both MobileNet and EfficientNet exhibit lower performance in handling speckle noise. Fig. 5 shows the model accuracy under different noise conditions.

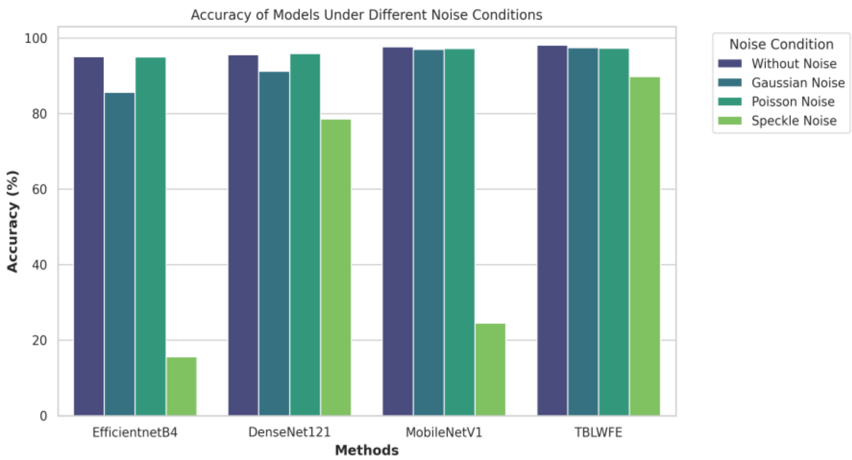


Fig. 5. Model accuracy under different noise conditions.

Table VIII and Fig. 6 show the average execution time per epoch. The proposed model stands out by significantly reducing training time, underscoring its efficiency compared to other established models. Specifically, it shows a 68.27% reduction in time compared to MobileNet, an 87.47% reduction compared to DenseNet121, and a remarkable 92.5% reduction compared to EfficientNet.

TABLE VIII. NO OF PARAMETERS VS TIME CONSUMPTION

Metrics	EfficientNet B4	DesnseNet 121	MobileNet V1	TBLWFE-NN
No of Total Parameters	17680995	7041604	3232964	214980
Average training execution time per epoch	990 ms	618 ms	244.2 ms	77.4 ms

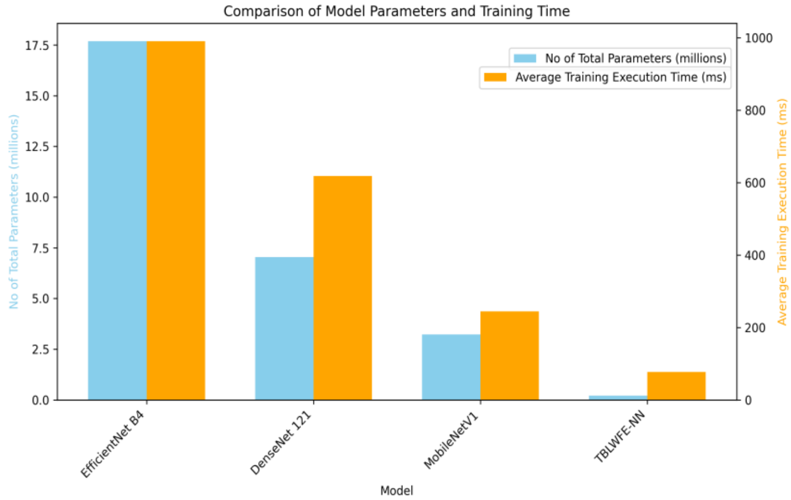


Fig. 6. Average execution time taken per epoch (in ms).

Fig. 7 depicts the confusion matrix of the proposed TBLWFE-NN classifier with and without noise. Fig. 8 depicts the ROC curves for various classifiers. The curves reveal that, compared to other types of noise, speckle noise significantly impacts the performance of EfficientNet, DenseNet, and MobileNet. During this investigation found that the proposed model maintains commendable accuracy, even in the presence of speckle noise.

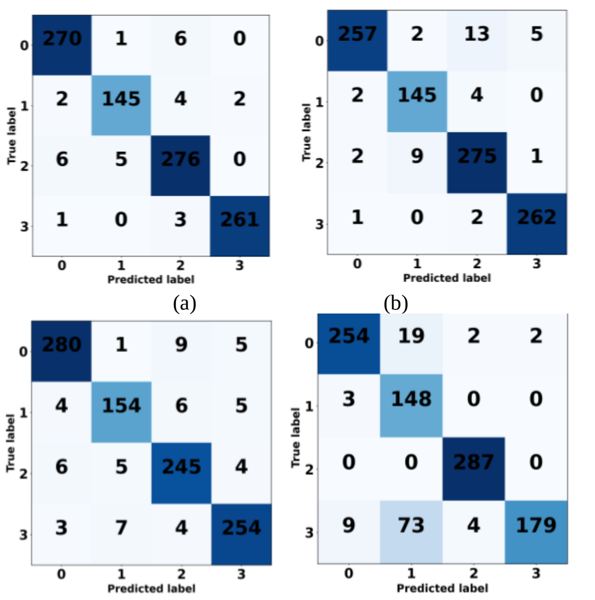
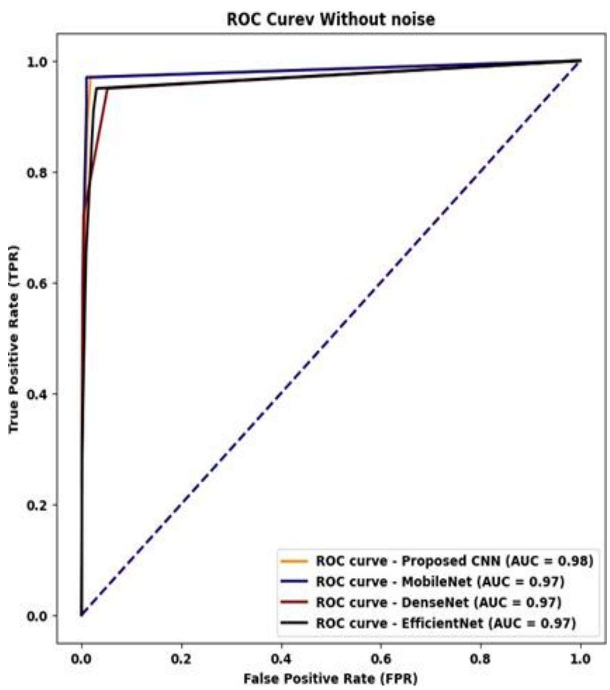
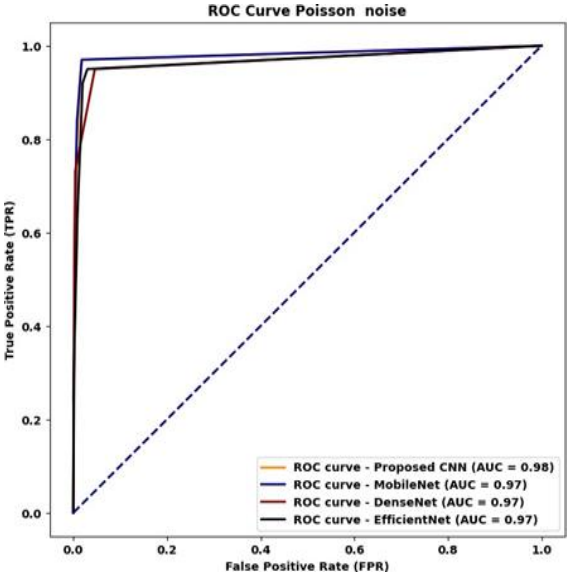


Fig. 7. Proposed features model confusion matrix (a). Without noise, (b). Gaussian noise, (c). Poisson noise, (d). Speckle noise.

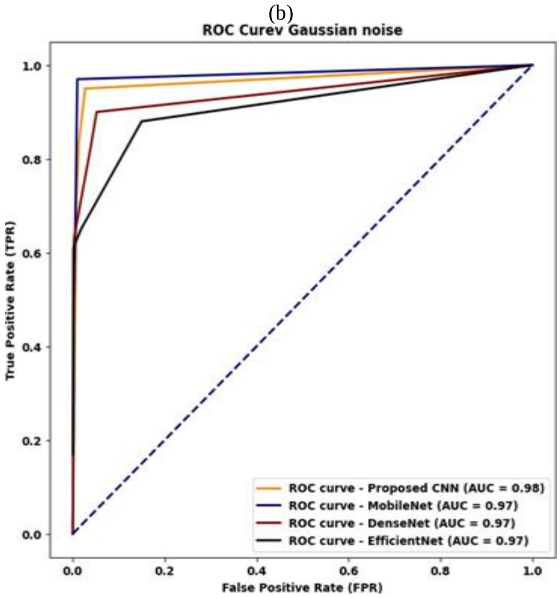
This research aims to achieve high accuracy amidst noise while reducing model complexity. Our model excels in challenging conditions involving speckle noise, offering superior accuracy with a streamlined architecture that requires fewer parameters than its competitors. Additionally, it boasts a significantly reduced average execution time per epoch (77.4 ms), demonstrating efficient computational resource use.



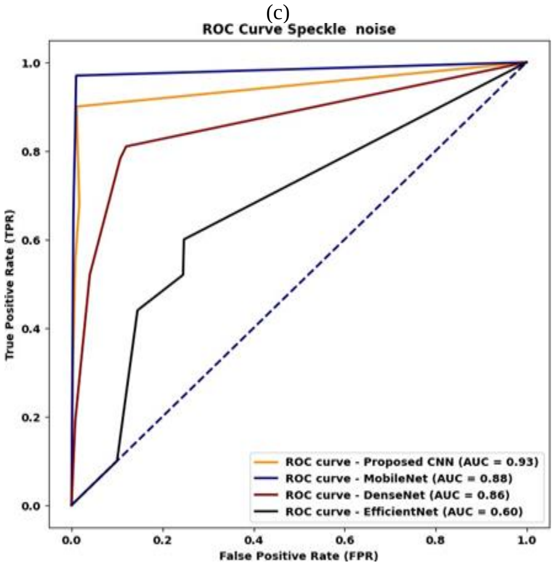
(a)



(b)



(c)



(d)

Fig. 8. Proposed features extraction model ROC Curve, (a). without noise, (b). Gaussian noise, (c). Poisson Noise, (d). Speckle noise.

This efficiency makes the proposed approach an attractive option for applications demanding both precision and speed. The robustness of the proposed model, especially against speckle noise, underscores its suitability for real-world applications. Overall, our method balances accuracy, parameter efficiency, and training speed, marking a valuable advancement in noise-tolerant image classification. Table IX showcases the performance of various fall detection methods, including the proposed TBLWFE-NN model, alongside other established algorithms and neural network architectures, illustrating their respective accuracies in percentage

TABLE IX. COMPARATIVE ANALYSIS OF MODEL ACCURACIES

Methods	Accuracy (%)
Proposed TBLWFE-NN	98.14
ADSCFGWO [8]	92.66
VGG 16 [13]	96
DWT with PNN [4]	96
Inception-V3–Ensemble [24]	94.34
Xception–Ensemble [24]	93.79

V. CONCLUSION

In this research, a novel TBLWFE-NN, a dual-branch feature extraction neural network classifier, demonstrates outstanding performance in brain tumor classification under noisy conditions. This innovative architecture leads to a substantial decrease in both model complexity and training duration, achieving a reduction in training time by over 68% relative to MobileNet, 87% compared to DenseNet121, and more than 92% when benchmarked against EfficientNet. Its robustness to noise is particularly evident in the presence of speckle noise, where it surpasses the aforementioned models. By delivering high accuracy and computational efficiency, the TBLWFE-NN stands out as a significant contribution to medical image analysis, especially in scenarios with limited computational resources. Further investigations will expand upon this work, exploring the resilience of the model against a variety of noise disruptions and leveraging advanced methodologies such as transfer learning, attention mechanisms, and ensemble models to enhance performance in real-world clinical settings, where noise and image quality can vary significantly. The goal is to ensure that the model not only maintains its classification integrity in diverse and challenging environments but also facilitates quicker and more reliable medical diagnoses.

DATA AVAILABLITY STATEMENT

The raw/processed data required to reproduce the above findings cannot be shared at this time due to legal/ethical reasons.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Sangeetha G. conducted the research work, collected the data, and wrote the paper. Vadivu G. supervised the work and approved the final version, Sundara Raja Perumal R. have Contributed to collect the Real Time Data and all authors had approved the final version.

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REFERENCES

[1] A. Saleh, R. Sukaik, and S. S. A. Naser, "Brain tumor classification using deep learning," in *Proc. 2020 International Conference on Assistive and Rehabilitation Technologies*, 2020, pp. 131–136.

[2] D. R. Nayak *et al*., "Brain tumor classification using dense efficient- net," *Axioms*, vol. 11, no. 1, 34, 2022.

[3] I. S. Rajput *et al*., "A transfer learning-based brain tumor classification using magnetic resonance images," *Multimedia Tools and Applications*, pp. 1–20, 2023.

[4] N. V. Shree and T. N. R. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network," *Brain Informatics*, vol. 5, no. 1, pp. 23–30, 2018.

[5] Y. Ding *et al*., "A multi-path adaptive fusion network for multimodal brain tumor segmentation," *Neurocomputing*, vol. 412, pp. 19–30, 2020.

[6] A. M. Amou *et al*., "A novel MRI diagnosis method for brain tumor classification based on CNN and Bayesian optimization," *Healthcare*, vol. 10, no. 3, 494, 2022.

[7] A. E. Minarno, M. H. C. Mandiri, and Y. Munarko, and H. Hariyady, "Convolutional neural network with hyperparameter tuning for brain tumor classification. Kinetik: Game technology, information system," *Computer Network, Computing, Electronics, and Control*, vol. 6, no. 2, 2021.

[8] H. Z. Eldin, S. A. Gamel, E. S. M. E. Kenawy, A. H. Alharbi, D. S. Khafaga, A. Ibrahim, and F. M. Talaat, "Brain tumor detection and classification using deep learning and sine-cosine fitness grey wolf optimization," *Bioengineering*, vol. 10, no. 1, 18, 2022.

[9] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Computers in Biology and Medicine*, vol. 111, 2019.

[10] H. A. Shah, F. Saeed, S. Yun, J. H. Park, A. Paul, and J. M. Kang, "A robust approach for brain tumor detection in magnetic resonance images using finetuned efficient net," *IEEE Access*, vol. 10, 2022.

[11] E. A. Maksoud, M. Elmogy, and R. A. Awadi, "Brain tumor segmentation based on a hybrid clustering technique," *Egyptian Informatics Journal*, vol. 16, no. 1, pp. 71–81, 2015.

[12] M. Yaqub *et al.*, "State-of-the-art CNN optimizer for brain tumor segmentation in magnetic resonance images," *Brain Sciences*, vol. 10, no. 7, 427, 2020.

[13] C. Srinivas *et al*., "Deep transfer learning approaches in performance analysis of brain tumor classification using MRI images," *Journal of Healthcare Engineering*, 3264367, 2022.

[14] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, "Brain tumor classification in MRI image using convolutional neural network," *Mathematical Biosciences and Engineering*, vol. 17, no. 5, 2021.

[15] N. F. Aurna *et al*., "A classification of MRI brain tumor based on two-stage feature level ensemble of deep CNN models," *Computers in Biology and Medicine*, vol. 146, 2022.

[16] A. Tiwari, S. Srivastava, and M. Pant, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019," *Pattern Recognition Letters*, vol. 131, pp. 244–260, 2020.

[17] S. E. Nassar, I. Yasser, H. M. Amer, and M. A. Mohamed, "A robust MRI-based brain tumor classification via a hybrid deep learning technique," *The Journal of Supercomputing*, pp. 1–25, 2023.

[18] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for brain tumor classification," *Neural Processing Letters*, vol. 53, pp. 671–700, 2021.

[19] R. O. Ogundokun, R. Maskeliūnas, and R. Damaševičius, "Human posture detection using image augmentation and hyperparameter-optimized transfer learning algorithms," *Applied Sciences*, vo. 12, no. 19, 2022.

[20] V. Jalali and D. Kaur, "A study of classification and feature extraction techniques for brain tumor detection," *International Journal of Multimedia Information Retrieval*, vol. 9, no. 4, pp. 271–290, 2020.

[21] S. P. Porkodi *et al*., "Generic image application using GANs: A review," *Evolving Systems*, vol. 14, pp. 903–917, 2023.

[22] M. Havaei, A. Davy, D. W. Farley, A. Biard, A. Courville, Y. Bengio, and H. Larochelle, "Brain tumor segmentation with deep neural networks," *Medical Image Analysis*, vol. 35, pp. 18–31, 2017.

[23] H. M. Balaha and A. E. S. Hassan, "A variate brain tumor segmentation, optimization, and recognition framework," *Artificial Intelligence Review*, vol. 56, no. 7, pp. 7403–7456, 2023.

[24] S. Dasanayaka, V. Shantha, S. Silva, D. Meedeniya, and T. Ambegoda, "Interpretable machine learning for brain tumor analysis using MRI and whole slide images," *Software Impacts*, vol. 13, 2022.

[25] F. Zulfiqar, U. I. Bajwa, and Y. Mehmood, "Multi-class classification of brain tumor types from MR images using EfficientNets," *Biomedical Signal Processing and Control*, vol. 84, 104777, 2023.

[26] A. K. Poyraz, S. Dogan, E. Akbal, and T. Tuncer, "Automated brain disease classification using exemplar deep features," *Biomedical Signal Processing and Control*, vol. 73, 103448, 2022.

[27] S. Rajagopal, T. Thanarajan, Y. Alotaibi, and S. Alghamdi, "Brain tumor: Hybrid feature extraction based on UNet and 3DCNN," *Computer Systems Science and Engineering*, vol. 45, no. 2, 2023.

[28] Z. Zhu *et al.*, "DSNN: A DenseNet-based SNN for explainable brain disease classification," *Frontiers in Systems Neuroscience*, vol. 16, 2022.

[29] M. Geetha, V. Srinadh, J. Janet, and S. Sumathi, "Hybrid archimedes sine cosine optimization enabled deep learning for multilevel brain tumor classification using MRI images," *Biomedical Signal Processing and Control*, vol. 87, 2024.

[30] Y. P. Singh and D. K. Lobiyal, "A comparative analysis and classification of cancerous brain tumors detection based on classical machine learning and deep transfer learning models," *Multimedia Tools and Applications*, pp. 1–26, 2023.

[31] S. A. S. Souza *et al.*, "Texture analysis: A potential tool to differentiate primary brain tumors and solitary brain metastasis," *Multimedia Tools and Applications*, pp. 1–13, 2023.

[32] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, and M. O. Alassafi, "Brain tumor classification based on fine-tuned models and the ensemble method," *Computers, Materials and Continua*, vol. 67, no. 3, 2021.

[33] M. Masood, T. Nazir, M. Nawaz, A. Mehmood, J. Rashid, H. Y. Kwon, and A. Hussain, "A novel deep learning method for recognition and classification of brain tumors from MRI images," *Diagnostics*, vol. 11, no. 5, 744, 2021.

[34] L. Fang and Y. Jiang, "Dual-path parallel hierarchical diagnostic model of glioma based on pathomorphological feature," *Biomedical Signal Processing and Control*, vol. 87, 2024.

[35] Q. Mu *et al*., "Identifying predictors of glioma evolution from longitudinal sequencing," *Science Translational Medicine*, vol. 15, no. 716, 2023.

[36] I. Pacal, "A novel Swin transformer approach utilizing residual multi-layer perceptron for diagnosing brain tumors in MRI images," *Int. J. Mach. Learn. and Cyber*, pp. 1–19, 2024.

[37] A. Akter *et al*., "Robust clinical applicable CNN and U-Net based algorithm for MRI classification and segmentation for brain tumor," *Expert Systems with Applications*, vol. 238, 2024.
[38] S. Khoramipour, G. Mojtaba, and M. Shakiba, "Enhancement of brain tumor classification from MRI images using multi-path convolutional neural network with SVM classifier," *Biomedical Signal Processing and Control*, vol. 93, 2024.
[39] A. A. Abdullah *et al*., "Enhancing brain tumor diagnosis: an optimized CNN hyperparameter model for improved accuracy and reliability," *Peer J. Computer Science*, vol. 10, 2024.
[40] B. Sandhiya and S. K. S. Raja, "Deep learning and optimized learning machine for brain tumor classification," *Biomedical Signal Processing and Control*, vol. 89, 2024.