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BREAKTHROUGH IN BRAIN TUMOR DIAGNOSIS: A CUTTING-EDGE HYBRID DEPTHWISE-DIRECT ACYCLIC GRAPH NETWORK FOR MRI IMAGE CLASSIFICATION

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ABSTRACT
Both adults and children are at risk of dying from brain tumors. On the other hand, prompt and precise detection can save lives. Early detection is necessary for a proper diagnosis of a brain tumor, and magnetic resonance imaging (MRI) is often used in this context. To assist in the early diagnosis of sickness, neuro-oncologists have used Computer-Aided Diagnosis (CAD) in a number of ways. In this study, proposed a hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET)-based deep learning was developed to distinguish between cancers and non-tumors. Three processes make up this method: pre-processing, classification, and feature extraction. Pre-processing methods used in this study included contrast enhancement and image shrinking. The MRI picture is processed to get the wavelet and texture properties and used to build a classifier. Using MRI scans, the proposed hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model classifies two types of brain tumors: tumor and non-tumor. Performance criteria such as accuracy (ACC), specificity (SP), and sensitivity (SE) are used to assess the suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model. Based on 850 images, the studies yielded a 99.54% categorization accuracy demonstrate that the suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model beats the most advanced methods.

Keywords: *Brain tumor, Detection, Depthwise-Direct Acyclic Graph Network, Deep learning, Computer-Aided Diagnosis.*

1. Introduction

Brain tumor identification has been a common cause in the world of medicine these days. An unusual mass of tissue with rapidly and uncontrollably expanding cells is called a brain tumor; in other words, the growth of the cells cannot be stopped (Hemanth et al., 2019). Brain cancer originates from glial cells, a subset of abnormal cells that are present in the brain. Brain cancer cases have grown over time in direct proportion to the aging population, raising concerns for global health (Zaw et al., 2019). A growth that grows unevenly in the brain and has an immediate impact on a brain tumor is an enlargement of a person's life.

The tissues in the vicinity of the brain or skull induce this tumor to develop on its own. In general, surgical techniques are favored when treating brain tumors (Toğaçar et al,, 2020). For successful treatment of brain tumors, early detection and correct diagnosis are essential. Better medications could be developed and lives could be saved with early detection. The development of computer-aided diagnosis and biomedical informatics offers many benefits for neuro-oncologists (Choudhury et al., 2020). Early brain tumor diagnosis is a highly demanding endeavor for radiologists. A brain tumor can grow quickly; in just 25 days, its typical size can double. If the patient receives inappropriate care, their half-year survival rate is normal. It may soon lead to death. For this reason, using an automated approach is necessary for early brain tumor diagnosis (Amin et al., 2020). One of the abnormalities of the brain that can develop for a number of reasons is a brain tumor (BT). The rates of morbidity and death will rise because to undiagnosed and untreated BT. The bio-imaging method is typically used for a widely used method: is the clinical level assessment of BT. along with MRI-assisted brain screening (Rajinikanth et al., 2020). Since brain tumors can have a wide range of shapes, appearances, and sizes, diagnosing them can be difficult. This publication uses a deep learning network to forecast input slices as either healthy or unhealthy tumors (Amin et al., 2020). (Tazeen et al., 2021) an ensembled feature extraction and classification method utilizing CNN is suggested for brain tumor detection and classification.

The following are the proposed models' main contributions.

- The Kaggle image dataset and TCIA (The Cancer picture Archive) picture datasets are also utilized to assess the proposed approaches.
- Several pre-processing methods, including contrast enhancement and image scaling, are applied to the MRI images.
- The self-organizing map is utilized in conjunction with the extraction of the two independent texture and wavelet feature sets to determine the proper center selection.
- The suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) divides the endoscopic pictures into two categories: tumor and non-tumor.
- For the purpose of measuring the model's diagnostic efficacy, calculations were made of its F1-score, accuracy, Youden's index, specificity, AUC, and sensitivity.

2. Literature Review

(Sadad et al., 2021), reported employing Unet architecture to segment With ResNet50 as the backbone, With ResNet50 as the backbone, the Figshare data set, yielding an intersection over union (IoU) level of 0.9504. In an effort to improve the categorization rate, preprocessing and data augmentation were proposed. Two methods for classifying that rely on deep learning and identifying brain cancers have been proposed by (Dipu et al., 2021). These techniques make use of the deep learning library FastAi with the state-of-the-art object identification framework YOLO (You Only Look Once). In this research, a portion of the 1,992 Brain MRI pictures from the BRATS 2018 dataset was employed. The methods for detecting brain cancers using machine learning and deep learning have been published by (Brindha et al., 2021). Patients can receive therapy more quickly and with greater precision when these algorithms are used to predict brain tumors using MRI scans. (Gull & Akbar, 2021), examined computer-aided methods with increased accuracy are essential for early brain tumor identification. (Ghassemi et al., 2020) have discussed in order to extract robust features and understand the structure of MR images, several datasets of MR images would be used to pre-train a deep neural network as a discriminator in a generative adversarial network (GAN) throughout its convolutional layers. The accessibility of multi-model images makes the classification of brain tumors increasingly intriguing. (Majib et al., 2021) state that in order to categorize the brain tumor photos without the need for human input, a variety of conventional and hybrid machine learning algorithms were developed and thoroughly examined. Furthermore, a study including sixteen different transfer learning models was carried out to ascertain which model would work best for neural network-based brain cancer classification. The application of transfer learning in combination with the VGG16 architecture and the reflection of our suggested "23 layers CNN" design has been described by (Khan et al., 2022), as a solution to this problem.

(Shah et al., 2022), have proposed layers that use a deep convolutional neural network (CNN) EfficientNet-B0 base model to increase the efficiency of brain tumor photo classification and detection. Using image enhancement techniques, several filters are applied to the photographs to improve their quality. According to (Tiwari et al., 2022), there has been a notable advancement in picture classification technology in recent times. CNN is the most popular and effective approach that is regarded as the best in this industry, which is why it is employed in this research to address the problem of classifying brain tumors. (Maqsood et al., 2022), chose the most effective features by controlling the entropy level and employing a multiclass support vector machine (M-SVM). The application of M-SVM for brain tumor classification allows for the identification of the meningioma, glioma, and pituitary images. (Saeed et al. 2022), addresses picture correctness, suggests that missing k-NN hybrid values are valuable, and creates an investigation method for applying tools for 4D imaging light field analysis to discriminate between non-tumor and cancer-damaged areas. Furthermore, we suggest a novel method for early detection of brain cancers or cerebrospinal fluid (CSF) growth. (Ullah et al., 2024) proposed the Deep Explainable Brain Tumor Deep Network (DeepEBTDNet), a novel deep learning model for binary classification of brain MRIs as tumorous or normal. (Abdusalomov et al., 2023), examined the findings were obtained when our deep learning model correctly detected the existence and exact location of brain malignancies in MRI images. The suggested methodology yielded a noteworthy 99.5% accuracy in our analysis, surpassing the accuracy of conventional methods. In order to overcome the over-fitting problem, in order to extract local and global features from the two parallel phases of a parallel deep convolutional neural network (PDCNN), (Rahman & Islam, 2023) have suggested a novel design that combines batch normalization with a dropout regularize. (Gumaei et al., 2019) have introduced a current, distilled set of significant features from the original GIST features that prevents overfitting and preserves the classification step. The GIST features from the brain images are computed using the PCA-NGIST method. (Jia & Chen, 2020) have trained Brain tumor detection and segmentation utilizing a Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM). (Xu et al., 2024) have developed a new method for MRI image segmentation and brain tumor detection that combines active contouring with a texture-based decision metric. (Asiri et al., 2024) have proposed, a new automated technology improves the speed and accuracy of detecting brain tumors.

This is due to CNN's tendency to collect data at random without understanding local and global features, which causes overfitting issues. (Khan et al., 2023), have suggested an automated approach for deep learning feature optimization and saliency map-based identifying and categorizing brain tumors. The suggested structure was put into practice gradually. The first stage of the suggested framework suggests a fusion-based method for contrast enhancement.

(Zhou et al., 2024), have proposed a novel method for classifying medical images that uses Federated Learning (FL) to solve the problems of effective illness diagnosis and data privacy. Because patient data is sensitive, traditional centralized machine learning models, however widely used in medical imaging for tasks like illness diagnosis, give rise to serious privacy concerns. (Ramanagiri et al., 2024), have proposed ResNet-50 as a feature extractor to brain magnetic resonance imaging (MRI) data in order to extract complex spatial hierarchies. Following the extraction of these features, a customized CNN designed for accurate tumor classification is fed these features, and its performance is evaluated on an independent test dataset. On the test dataset, the modified ResNet50 models obtained a 90.04% accuracy rate, which is good demonstrating exceptional performance in brain tumor classification.

3. Research Methods

The experimental setup utilized to carry out the inquiry is described in this section. After providing an overview of the dataset retrieval process, the hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) models that were employed to classify the various brain tumor subtypes are described. The following describes the general architecture of the suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET).

The flowchart for the suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) for classifying brain tumors is displayed in Fig. 1. Pre-processing (image scaling and contrast) and feature extraction (texture and wavelet characteristics) are used to identify tumors and non-tumors in MRI images. The classification of two categories of brain tumors—tumor and non-tumor—using sophisticated hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) designs is the subject of our proposed work.

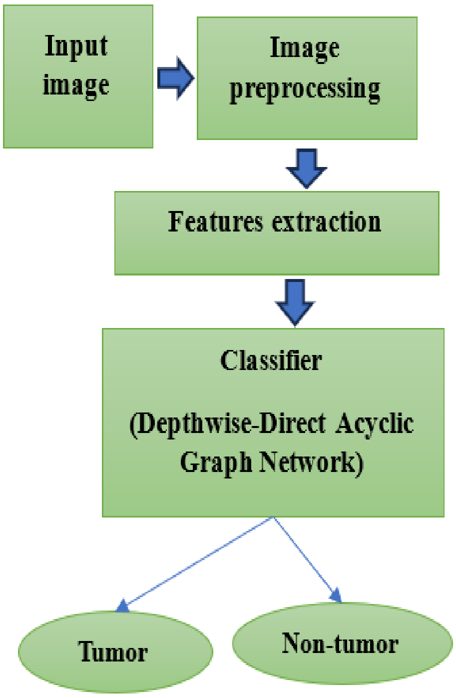

Fig. 1. Flow diagram for the hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) that is being suggested for classifying brain tumors

3.1 Datasets

Brain tumor photos from TCIA (The Cancer Image Archive) and Kaggle datasets were used to build the dataset used in this research. Access to a wide range of brain tumor photographs from different people and organizations throughout the world was made possible via the Kaggle and TCIA (The Cancer Image Archive) datasets, guaranteeing a comprehensive representation of tumor types and features. To guarantee the correctness and dependability of the dataset, the extraction procedure comprised painstaking curation and quality control, which included professional annotation and verification.

3.2 Image Pre processing

Depending on why the data is being processed, pre-processing techniques can be categorized into two groups: image resizing, which includes sizes like 512*512, 256*256, and 128*128. Second, using the "unsharp masking" filter in conjunction with the "fspecial" function successfully sharpens the image's edges and fine features. Applying this filter to a photo requires using the "imfilter" function in tandem with the "replicate" Boundary Choice. According to this choice, values that are furthest from the array's boundary are equal to values that are closest to it.

Algorithm: Filtering and pre-processing with unsharp

```
Step:1 Examine the input image (X).
Step: 2 Use Y = imresize (X, [512*512]).
Step 3 To produce a fresh color filter with the same features as the image that was input, use an unsharp masking filter.
Step 4 Utilize the line option in the replicate filter method on s. All three separate RGB planes should be combined into one.
Step 5 Make one plane out of the three.
Step 6 Output (Y)
```

It demonstrates how these actions enhance image quality and establish a starting point for appropriate feature extraction.

3.2.1 Features Extraction

In the proposed approach, wavelet and texture-related features are retrieved. The section that follows goes over these features' specifics.

i) Wavelet characteristics: In a retinal image, a wavelet transform is used to make the blood vessels stand out against the background. In this piece of work, the retinal image is divided into three layers using the Haar transform: the backdrop itself, the background-representing vessel, and the low contrast vessels. The coefficients are dispersed throughout the interval [-1,1]. Given that the amplitude of coefficients appears to be correlated with both the number of coefficients and the brain tumor, an indirect connection between the two appears to exist in different categories of MRI pictures is not unique.

ii) Texture features: These attributes are connected to how the values of pixels are arranged spatially in a picture. Gaussian noise is eliminated by applying the mean filter after the top-bottom hat transform has been applied to enhance the contrast between the drop back and the vessel.

- These are the properties related to how the values of the pixels are arranged spatially in an image.
- The top-bottom hat transformation is done to accentuate the contrast between the vessel and the backdrop, and then the mean filter is employed to remove Gaussian noise.

3.3 Proposed Hybrid depthwise- direct Acyclic Graph Network (D-DAGNET)

The hybrid D-DAGNet design improves the discrimination abilities of deep neural networks by allowing layers to communicate and effectively use the knowledge they have learnt to anticipate the output class label. Feature level fusion is problematic because feature vectors are so big. The magnitude of the feature learned from the inter in CNN can result in large learned features, and merging these features could cause dimensionality problems. To get around this feature level fusion, average pooling is applied to the learnt features of some layers using marginal activation computations. Our method is multi-scale, sending the output to a classifier and replacing feature-level fusion with the D-DAGNet framework. This section covers the network's detailed structure and training procedure. Various information levels may be automatically identified, combined, and the output label can be predicted by our D-DAGNet model. Because of the way the MobileNet framework is designed, computationally costly convolutional layers can be replaced with depthwise separable convolutions, which are crucial for computer vision applications. Laurent Sifre originally created depth-wise separable convolution for application in data classification and detection. Depth-wise convolution has been used in many studies for various real-time applications. Unlike conventional convolution, which applies the whole convolution depth all at once, DC applies to just one input channel. DC is used to address the overfitting problem because it drastically lowers the number of learnable parameters, which would have increased the computing cost of the prototype. Fig. 2, depicts the D-DAGNet's whole architecture.

3.3.1 Depth wise Convolutional, ReLU and Max-Pooling layers

The D-DAGNet consists of six depth-wise convolutional blocks. The structure of the framework's input social network Bigdataset is a 200×200×3 matrix, and the bias and weights of each convolution layer are set to sensible values. The features are estimated by running the input data through several convolutional layers with the proper weights. The input feature maps are grouped and convolved by the use of filters with various kernel sizes into multi-scale fine-grained feature maps. Through the depthwise convolutional and max-pooling layers, the input layer passes through with success. The use of such high kernel sizes has been discontinued due to the huge increase in training time and cost. The feature maps that come after DC are connected to the final feature maps at the subsequent level. (Methil, 2021) have described an innovative approach to imagine manipulation that makes use of image processing methods to help our CNN model differentiate between images that are benign and images that are malignant. To refine this task, more training was conducted on ResNet101v2, and transfer learning was also utilized as a pre-trained model. (Rizwan et al., 2022) a method for employing Gaussian Convolutional Neural Networks (GCNN) on two datasets to identify unique BT kinds.

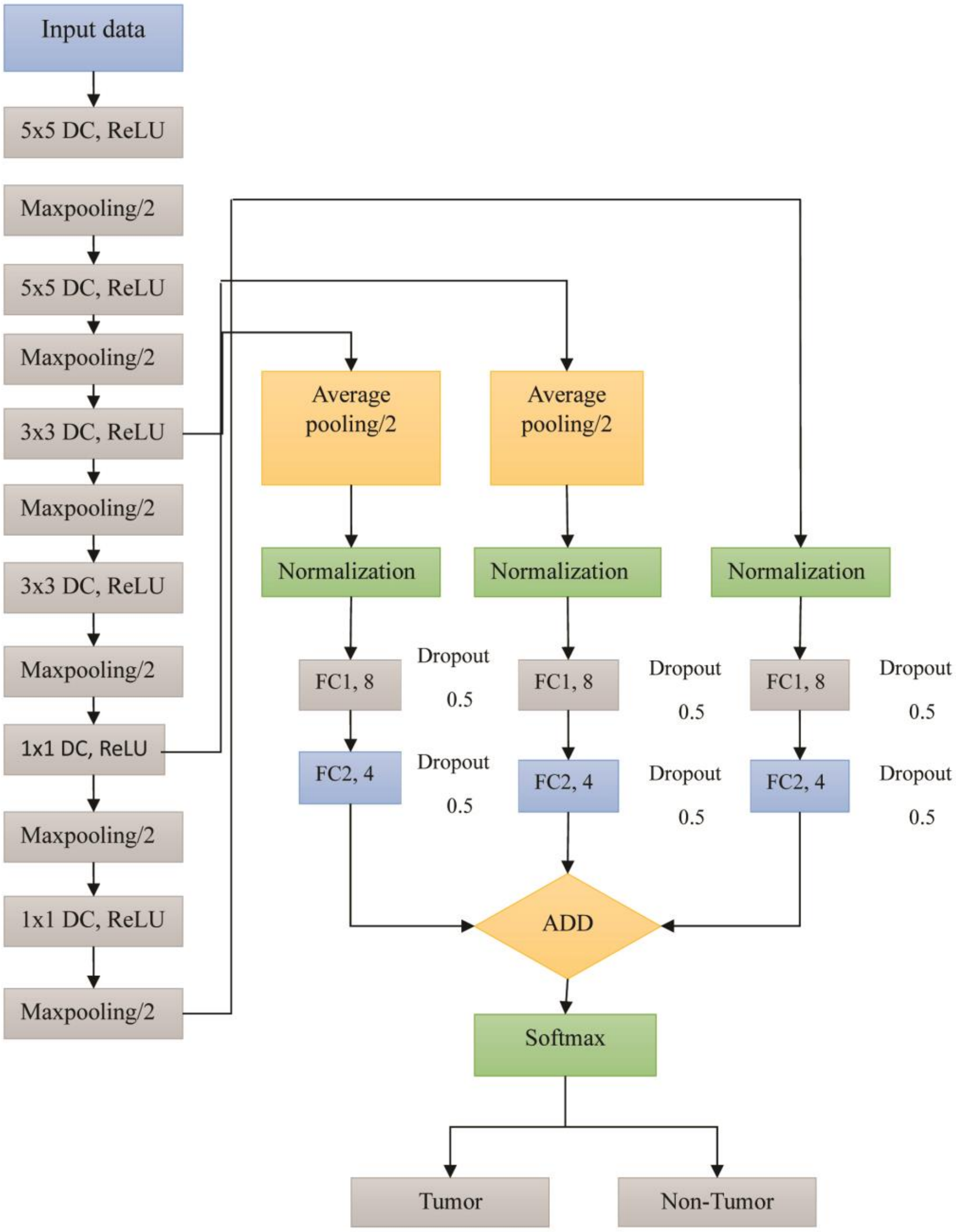

Fig. 2. The D-DAGNET framework is a hybrid depth-wise direct acyclic graph network.

Tumors are classified as meningioma, glioma, or pituitary using one of the databases. (Solanki et al., 2023) CNN has demonstrated to be fairly accurate for classification, despite the usage of several ML and deep learning techniques. CNN is frequently used to divide brain tumors into two groups: abnormal and normal. (Suryawanshi & Patil, 2024) an extensive strategy that makes use of VGG19, CNN, and the Convolutional Neural Network-Support Vector Machines (CNN-SVM) for the multiclass classification of brain MRI.

After then, the procedure is carried out repeatedly until each output feature map at every level has been handled at the next stage. To lower the dimensionality, average pooling is coupled to intermediate links from ReLU.

3.3.2 Normalization

The retrieved characteristics are normalized to enable faster training. By reducing the dependencies between gradients and the model's gradient flow, batch normalization also enhances the model's parameters or starting values. Once something is standardized, divergence is less likely. Trial and error are used to select smaller kernels, it improves decision-making by introducing large non-linearity and significantly reducing learnable parameters. Small kernel sizes result in back propagation weights and lower computational and weight sharing expenses. Weights are regularly adjusted to determine which spatial information among the supplied data is the most trustworthy. They work with the greatest feature values that may be obtained from every feature map produced by the convolutional layer before it. Max-pooling solves the overfitting problem by decreasing the dimensionality of the CNN output.

Due to its quick computation and lack of vanishing or bursting issues, ReLU is one of the most often used activation functions. By rescaling every scalar feature inside a mini-batch, batch normalization layers seek to improve performance by reducing the number of training epochs required to learn the deep network. By limiting the perimeter of feature maps to merely include the most important features, pooling layers seek to alleviate the issue of the massive number of parameters and the computational complexity of the network. The goal of max-pooling is to create output feature maps by combining all of the selected feature maps. To benefit the j^{th} feature map $\left(1 \leq j^{th} \leq T\right)$, the max-pooling process is as follows:

$$F(j,u,v) = max\left[\Psi_{q0\times q}\left(T'(j, s_0 \times u, s_1 \times v)\right)\right] \qquad u = 1,2,\dots.U; v = 1,2,\dots V \tag{1}$$

The neighbourhood operator is represented by $\Psi_{q0\times q1}(.)$, with q_0 and q_1 denoting the kernel sizes for the width dimension. s_0 and s_1 stand for the strides along the width and height directions of the max-pooling operator, respectively, the operator's height, and T, the number of channels. In order to reduce load calculation, non-maximal value processing is prohibited from the subsequent layers during max-pooling. Reducing the input space while maintaining the receptive filters allows max-pooling to achieve translational invariance. After every convolutional layer, which produces twice as many kernels as the preceding layer, max-pooling is used to preserve the information. The pooling layer of the subsampling layers gradually reduces the number of parameters by down sampling along the spatial dimensions. However, employ max pooling layers following every depth-wise convolutional layer in this investigation. This increases efficiency by facilitating the adoption of dominating invariant features via max-pooling at a higher rate of convergence. Fully connected layers consist of many neurons; the activation layer comes after each dense layer, where neurons and classes are equal. The output of the last dense layer is applied with the ReLU function in a fundamentally different way from that of the earlier dense layers, which typically employed the SoftMax function. The SoftMax function assigns a decimal probability to each class, having the greatest likelihood for the aim class. Deep neural networks can achieve greater classification capacity and accuracy by combining the SoftMax and binary entropy loss functions.

$$f(s)_i = \frac{e^{s_i}}{\sum_i^c e^{s_i}} \tag{2}$$

where C is the number of classes and s_i is the feature channel activation, and the output probability of the i^{th} neuron is $f(s)_i$. The max-pooled filter answers are fed to the SoftMax classifier, which uses them to compute the class probabilities and produce the final predictions. The output layer's two neurons determine the probability of binary classifications, such as tweets with and without depression.

3.3.3 Dropout

A well-known regularization method called dropout is required to reduce overfitting and improve generalization performance in dense layers. Through the use of dropout backpropagation, the network was adjusted. Neurons do not contribute anything to forward transfer or network backpropagation once they are dropped. A random group of hidden neurons is eliminated each time the network compression is trained. Dropouts have a negative impact on learning rates as well as performance and momentum.

3.3.4 Softmax classifier

After that, all feature maps are aggregated and submitted to the SoftMax, which separates the input data into groups like individuals with and without tumors. Data from many feature map layers, each constructed at a different depth with a distinct kernel size for each path, are integrated into the combined features. Layers are vital to the network's general functioning because they perform two functions: two passes one forward that takes inputs and computes results, and the other backward that assesses gradients and adjusts layer parameters as necessary.

4. Results and Discussions

In this section, we use our suggested technique to comparative experimental research to categorize the seven fundamental human face expressions. The datasets used in this study's approach studies were Kaggle and TCIA. Three categories were used to group this dataset: testing, validation, and training. Each training, testing set and validation had four categories of photos: meningiomas, pituitary tumors, glioma tumors, and no tumor. The dataset included 595 patients' 512*512-pixel MRI scans. For this study, select pictures are found in the axial and coronal planes. For the purposes of the performance evaluation procedure, there are four classes: no tumor, tumor, and no tumor. (Sultan, Salem, & Al-Atabany, 2019) A DL model based on a convolutional neural network is proposed to classify different brain tumor types using two publicly available datasets. Fig. 3 displays examples of different tumor types in different sites.

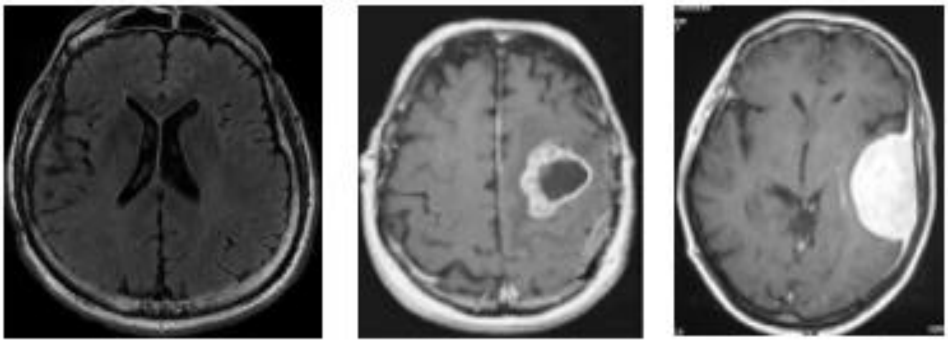

Fig. 3. Input Image

(i) Image pre-processing

The MRI pictures undergo a number of pre-processing procedures, such as contrast enhancement and picture reduction. like 128 * 128, 512 * 512, and 256 * 256. After applying the preprocessing step, the resulting images of each type of brain tumor are provided in Fig. 4 using the "unsharp masking" filter and the "fspecial" function. It demonstrates how these actions enhance image quality and provide a baseline for suitable feature extraction.

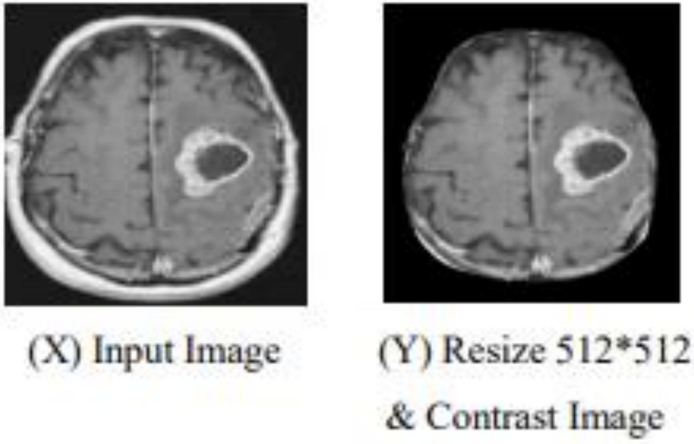

Fig. 4. Preprocessing result output image

(ii) Feature extraction

Fig. 5, displays the approximated Haar wavelet level 3 decomposition together with the three orientation details (horizontal, vertical, and diagonal). Since the coefficient amplitudes in different MRI picture categories are similar, there seems to be an indirect relationship between the number of coefficients and the severity of brain tumors.

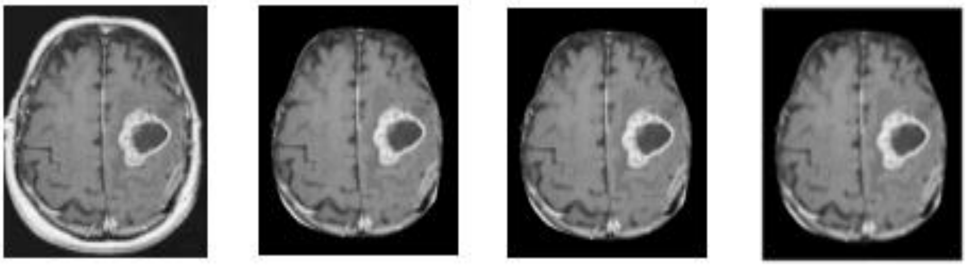

Fig. 5. Coefficient distribution of the three normal images orientations obtained from the Haar Wavelet Level-3 Transformation.

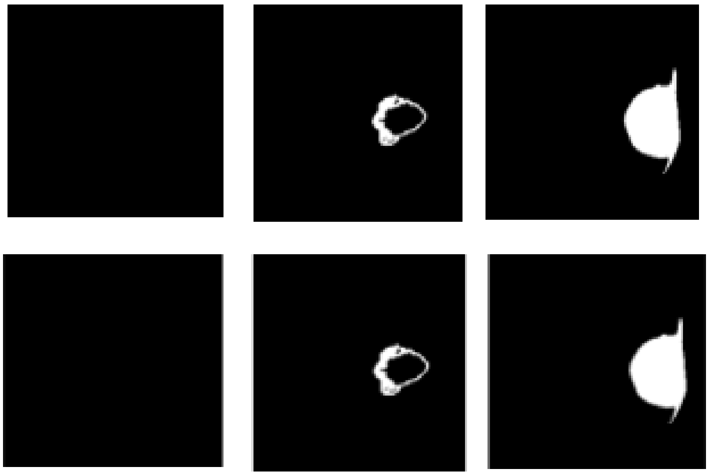

Fig. 6. The adjusted images following the top-bottom hat transformation, and the photographs following the mean filter operation.

As illustrated in Fig. 6, Gaussian noise is removed using the mean filter after the top-bottom hat transformation has been applied to improve the contrast between the vessel and backdrop. Ultimately, the MRI picture is represented by extracting the texture features associated with brightness and grey level co-occurrence matrix (GLCM). (Anaraki et al., 2019) have introduced a method utilizing genetic algorithms (GA) and convolutional neural networks (CNNs) for noninvasively categorizing various glioma classifications using magnetic resonance imaging (MRI).

(iii) Quantitative Evaluation

The performance metrics specificity (Sp), sensitivity (Se), and accuracy (ACC) were used to evaluate the suggested method's performance and make a quantitative comparison with baseline techniques.

$$Sepecificity = \frac{TP}{TP+FP} \tag{3}$$

$$sensitivity(recall) = \frac{TP}{TP+FN} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

where True positive, False negative, True negative, and False positive are denoted by the terms TP, FN, TN, and FP. Every type of brain tumor was subjected to calculations of specificity (Sp), sensitivity (Se), and accuracy (ACC) using the Kaggle and TCIA dataset.

Tables 1 show that for both tumor and no-tumor scenarios, the Hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model has 100% accuracy.

The discovery of brain tumor subtypes using the Hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model. Table. 1, displays the total mean-average specificity (Sp), sensitivity (Se), and accuracy (ACC). The results show that for three groups of tumor types, specificity is 0.99%, sensitivity is 0.995%, and accuracy is 0.9985% for precision. The suggested techniques exhibit higher classification recall capabilities for the modified Hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model. However, the specificity of classification results using the suggested methods is much reduced. In this instance, the Hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) models' average values are 99.85%. The ROC curves for the proposed hybrid Depthwise-Direct Acyclic Graph Network model are displayed in Fig. 7, respectively.

Table 1 - Performance of the Hybrid Depthwise- Direct Acyclic Graph Network (D-DAGNET) model for classifying brain tumor subtypes

	Tumor	Non-tumor	Average
Specificity	0.99	0.99	0.99
Sensitivity	0.99	1.00	0.995
Accuracy	0.997	1.00	0.9985

The modified hybrid D-DAGNET model's performances are contrasted with those of four cutting-edge techniques, designated as EfficientNet-B7 (Modiya & Vahora, 2022) Resnet-50 (Saxena, Maheshwari, & Maheshwari, 2020), and MobileNet-V2 (Arbane et al., 2021).

Table 2 - Results are summarized

Model	Accuracy
MobileNet-V2(Arbane et al., 2021)	98.25%
Resnet-50(Saxena et al., 2020)	95%
EfficientNet-B7 (Modiya & Vahora, 2022)	80%
Proposed hybrid D-DAGNET	99.85%

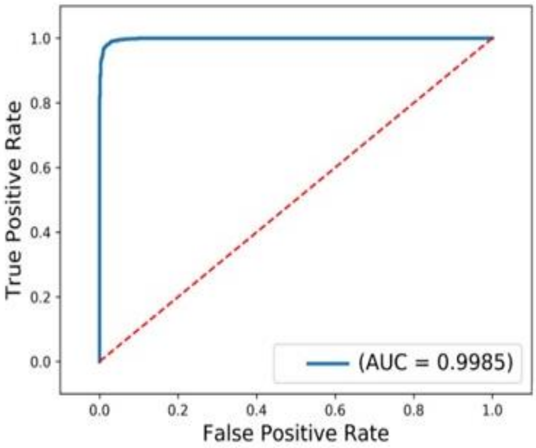

Fig. 7. ROC curve for the proposed hybrid Depthwise- Direct Acyclic Graph Network model.

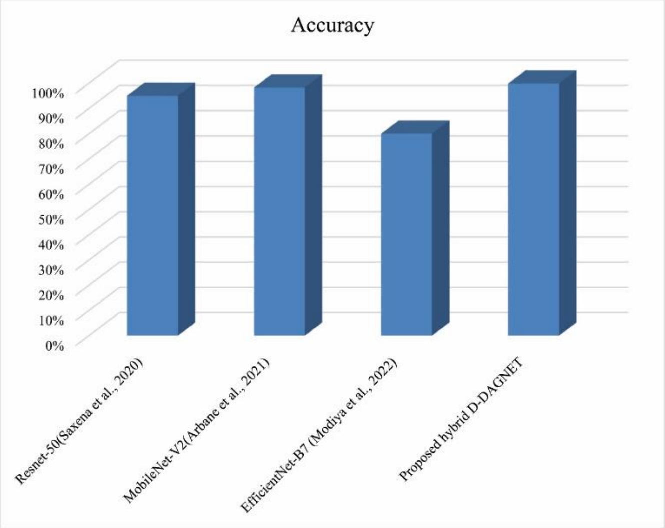

Fig. 8. Comparing the suggested hybrid D-DAGNET method with other cutting-edge techniques.

(Jabbar et al., 2024) have suggested model provided the greatest degree of efficacy and the best performance with respect to accuracy, specificity, and sensitivity. In particular, using the Brats20 dataset, the hybrid model that was presented achieved an accuracy of 0.99, a specificity of 0.99, and a sensitivity of 0.98. (Muis et al., 2024) have proposed for convolutional neural networks, the Google Net and AlexNet designs were used. The study yielded 98% accuracy for the AlexNet architecture and 96% accuracy for GoogleNet. (Nassar et al., 2024) have proposed technique significantly improved outcomes, achieving an overall accuracy of 99.31%.

A detailed comparison of the accuracy of the models proposed with previous approaches is given in Table 3. As Fig. 8, shows the recommended models perform better than the earlier methods, with hybrid D-DAGNET showing an average accuracy of 99.85%.

5. Conclusion

The proposed hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) model in this study uses MRI data from Kaggle and TCIA to classify two brain tumor subtypes: tumor and non-tumor. Brain tumor diagnosis is made using the hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) models. The MRI images undergo a number of pre-processing steps, such as contrast enhancement and picture reduction. In the proposed study, wavelet and texture-related features are extracted following preprocessing. With an accuracy of 99.85%, the suggested hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) method outperforms the current classification techniques. The classification performance is compared with other approaches, such as Resnet-50, MobileNet-V2, EfficientNet-B7, and hybrid D-DAGNET. The results of the experiment show that, with regard to accuracy and other performance metrics, the hybrid Depthwise-Direct Acyclic Graph Network (D-DAGNET) approach has surpassed traditional techniques. Findings include the division of brain tumors into different subgroups in order to attain improved outcomes. Subsequent writers can't wait to prove this accuracy in further ways. To make improvements in the future, more datasets should be tested. As datasets get bigger, more precise models must be built.

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