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Brain Lesion Classification With Effincepresv2: A Hybrid Approach Combining Efficientnetv2 And Inception-Resnetv2

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Abstract – Brain lesion, whether benign or malignant, present significant health risks, making early and precise detection critical for effective treatment. This study explores the use of deep learning for brain lesion classification through MRI imaging, leveraging EfficientNetV2, Inception-ResNetV2, and a hybrid model combining the strengths of both architectures. The dataset comprises MRI scans from patients with gliomas, meningiomas, pituitary tumors, and no-tumors. Pre-processing methods like Channel Standardization, Gaussian blurring, and filtering are used to improve image quality, and data augmentation guarantees that the models will generalize more effectively. Traditional convolutional neural networks (CNNs) are improved by EfficientNetV2 using fused-MBConv layers for increased efficiency, squeeze-and-excitation blocks for adaptive feature scaling, and a progressive training approach that improves accuracy and speed. Inception-ResNetV2, on the other hand, combines ResNet's skip connections with Inception modules for multi-scale feature extraction, enhancing gradient flow and increasing performance on big datasets. The proposed hybrid model EffIncepResV2 maximizes classification accuracy while preserving computational efficiency by combining the efficiency of EfficientNetV2 with the feature extraction capabilities of Inception-ResNetV2.This method is very useful for medical imaging applications since it improves feature extraction and fortifies generalization. The results demonstrate how hybrid deep learning techniques can greatly enhance the classification of brain tumors, ultimately promoting early diagnosis and improved patient outcomes.

With an accuracy of 99.94%, precision of 99.65%, recall of 99.89%, F1-score of 99.65, and dice-coefficient of 99%, the results show that EffIncepResV2 performs better than other models. These encouraging findings demonstrate how well EffIncepResV2 can identify brain tumors from MRI pictures, making it a useful diagnostic tool.

Keywords - Brain Lesion, Magnetic Resonance Imaging (MRI), Convolutional Neural Networks (CNN), EfficientNetV2, Inception-ResNetV2, EffIncepResV2, Tumor Classification, Deep Learning.

1. INTRODUCTION

Digital medical imaging, especially Magnetic Resonance Imaging (MRI), has evolved into a vital tool for research advancement, healthcare professional education, and disease diagnosis in recent years. In 2023, the American Cancer Society reported that approximately 94,390 adults were diagnosed with a brain tumor, including both noncancerous and malignant types. More than 120 different forms of brain tumors can be either benign or malignant, making them a major cause of cancer-related fatalities globally. Rapidly growing malignant tumors have a significant chance of spreading to other areas and possibly killing people. Even while benign tumors grow more slowly, they can nevertheless cause serious neurological problems. Successful treatment and recovery depend on the prompt and precise diagnosis of brain tumors, and because of its great spatial resolution, MRI has proven indispensable in the detection and classification of these tumors [3].

Because brain structures are complicated, it is still difficult to detect and classify brain tumors, which frequently results in laborious and inaccurate manual analysis. The automation of this process has been significantly improved by recent developments in machine learning (ML) and deep learning (DL), particularly Convolutional Neural Networks (CNNs), which have increased accuracy and efficiency. In order to improve accuracy and speed up computation, the hybrid deep CNN-SVM model for brain tumor classification combines robust classification with SVM with deep feature extraction via CNN [1]. Traditional CNNs still have issues like high computational complexity and lengthy execution times, which might impede real-time applications even with deep learning's potential. Low-complexity architectures, like the Two-Channel CNN in conjunction with Region-based CNN (RCNN), have been created to address these problems by lowering computational overhead while preserving high accuracy [2].

The most prevalent and aggressive type of brain tumors, gliomas, have a median survival rate of about 12 months, which frequently results in a bad prognosis. Improving patient outcomes requires early detection by MRI. With the use of its many sequences, such as T1, T2, and post-contrast T1, MRI can capture important tumor features, leading to more precise segmentation and diagnosis [4]. However, because of tumor changes and the difficulty of distinguishing between benign and malignant types, the diagnosis and classification of brain tumors—particularly gliomas—remain complicated. By addressing tumor variance, a Deep Dense Inception Residual Network (DDIRNet) has been presented as a strategy to increase classification accuracy for tumor types as meningioma, glioma, and pituitary [5]. Despite being primarily benign, meningioma's can have serious health consequences, and their recurrence and mortality rates are higher in a typical or malignant forms. Similar to this, pituitary tumors and gliomas are significant causes of morbidity and death, hence it is imperative that they be accurately classified and detected early [9]. Deep learning-based automated classification systems are crucial for overcoming the drawbacks of labor-intensive and error-prone manual interpretation. Additionally, these technologies aid in meeting the requirement for precise tumor segmentation, which is essential for treatment planning [8]. In order to isolate tumor locations in MRI images for further investigation, image segmentation is essential. The accuracy of segmentation has been greatly enhanced by sophisticated segmentation techniques, such as hybrid approaches that blend boundary-based and region-based methodologies. Furthermore, when paired with SVM for classification, feature extraction techniques such as Dense Speeded Up Robust Features (DSURF) and Histogram of Gradients (HoG) have demonstrated significant accuracy gains, up to 90.27% [9].

Convolutional neural networks (CNNs), a recent development in deep learning, have significantly improved automated categorization by effectively extracting and evaluating characteristics from medical images [18]. One of the most popular architectures for challenging brain tumor classification tasks is EfficientNetV2, which is renowned for its high accuracy and computing efficiency [19]. Real-time clinical applications can benefit from hybrid models, like the combination of MobileNetV2 and Support Vector Machine (SVM), which have further increased classification accuracy while maintaining computational viability [20]. Nguyen et al. (2018) presented a deep CNN-based technique for classifying microscopic images that makes use of feature concatenation and transfer learning. Their model greatly increases classification accuracy by combining characteristics taken from Inception-v3, ResNet152, and Inception-ResNet-v2 [24].

The main goal is to improve health diagnosis by applying deep learning techniques, particularly Convolutional Neural Networks (CNNs). The World Health Organization (WHO) stresses the significance of a thorough diagnosis of brain tumors, which includes locating the tumor, classifying its grade, and determining its kind. For tumor detection and classification, the proposed approach makes use of a CNN-based multi-task classification system. The capacity of MRI to produce high-resolution pictures emphasizes the need of early detection in raising patient survival rates. There is potential for improving medical diagnostic and treatment procedures through the use of deep learning in brain tumor diagnosis.

The following sections comprise the remainder of the paper: A literature review of previous studies is provided in Section 2. The findings of earlier research are compiled in this section. Section 3 gives background information to help comprehend the job and explains the specifics of the suggested approach. The purpose of this part is to clearly and understandably explain important ideas and methods. The analysis and presentation of experiment results are the main topics of Section 4. At last Section 5 outlines the conclusions drawn from the data, highlights the strengths and weaknesses of the suggested work, and suggests directions for further investigation.

2. LITERATURE SURVEY

Since CNNs can automatically extract hierarchical features and achieve high accuracy in feature extraction and classification tasks, they have overtaken traditional methods that depended on handwritten features. [1] The suggested DCNN-SVM hybrid model outperformed transfer learning techniques such as AlexNet, GoogLeNet, and VGG16, achieving 96.0% accuracy after being trained on the Figshare dataset (2957 MRI images). The combination of data augmentation, adaptive histogram equalization, and anisotropic diffusion filtering produced excellent specificity, sensitivity, and precision, making it a dependable method for classifying brain tumors. CNN models' computational complexity is still an issue, though. This problem has been addressed by lightweight architectures like the Two Channel CNN, which uses smaller convolution kernels to reduce complexity [2]. Despite being computationally demanding, recurrent CNNs (RCNNs) have potential for tumor detection. Lightweight CNNs and RCNNs have been combined to increase classification speed without sacrificing accuracy [2]. The model exceeded state-of-the-art methods in terms of accuracy and processing speed by improving MRI images and using SVM for classification, making it a dependable tool for clinical brain tumor identification [3]. [4] This paper presents DeepTumorNet, a hybrid deep learning model that improves feature extraction and classification performance for pituitary, meningioma, and glioma tumors by modifying GoogLeNet by adding 15 new layers. According to the results, the suggested deep learning method is very effective and accurate at classifying brain tumors, which makes it a promising tool for clinical diagnostics.

Using MRI data, a number of deep learning-based methods have been investigated for the categorization of brain tumors. To get around vanishing gradient problems, Kumar et al. [6] developed a CNN model with Leaky ReLU activation, which produced a validation accuracy of 78.57%. Using a CNN design with tiny kernels, Seetha and Raja [11] achieved 97.5% accuracy on the BRATS 2015 dataset, demonstrating the computational efficiency of the system by fine-tuning only the last layer. By combining C2f_DySnakeConv and Efficient Multi-Scale Attention (EMA), Lin et al. [13] improved tumor diagnosis using a YOLOv8-DEC model, which markedly increased precision and recall on a sizable MRI dataset. [14] proposed a hybrid approach that used GLCM features and LS-SVM with MLP kernel, and it achieved 96.63% accuracy on both synthetic and real-time MRI images from the BraTS 2013 dataset. With an accuracy of 98.87%, EfficientNet-B0, which was refined by [15], outperformed well-known CNN designs such as VGG16 and ResNet50. Using VGG-16 in conjunction with data augmentation (flipping, rotation, and translation), Alsaif et al. [16] improved training and achieved a 96% accuracy rate on an augmented Kaggle dataset. Another important technique by [17] proposed a dual-module CNN framework integrating picture enhancement and classification, attaining 97.63% accuracy on the BraTS dataset. Zoph and Le [21] presented Neural Architecture Search (NAS) employing an RNN controller with reinforcement learning, automating neural network construction through optimized architectural hyperparameters. Using T1-weighted contrast-enhanced MRI images, Saeedi et al. [22] created a hybrid 2D CNN-autoencoder model with 8 convolutional layers that achieved 96.47% accuracy. The robustness of multi-feature extraction in brain tumor classification was lastly demonstrated by Usman and Rajpoot [23], who used wavelet-based texture features with Random Forest classifiers for multi-modality MRI classification. They achieved high Dice overlaps (88% for complete tumor, 95% for enhancing tumor).

3. RESEARCH METHODOLOGY

3.1 Data Collection

The dataset includes brain MRI images that have been taken from Kaggle website (https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset). This dataset comprises of a fusion of three distinct datasets: figshare, SARTAJ dataset, and Br35H. The dataset under discussion here is similar to one that these papers utilized in previous study [8, 20, 22]. Within this amalgamated dataset a total of 7023 images depicting human brain MRI scans are categorized into four classes : glioma, meningioma, no tumor and pituitary. The training subset of the dataset consists of 5712 images portraying brain tumors, designated for training the model. Conversely the testing subset encompasses 1311 images of brain tumors, utilized for evaluating the model’s performance.

3.2 Data Preprocessing

Any kind of processing done on raw data to get it ready for further data processing is known as data preprocessing, which is a subset of data preparation. It has always been the most crucial starting point for the data augmentation procedure. Providing unprocessed data in a form that the network can understand, preprocessing is frequently the first step in the deep learning procedure. For example, image resizing can be done to change the input image's size. Once the dataset is assembled, the MRI images will undergo data pre-processing. Here, the photographs are processed using a variety of ways. The methods include channel standardization, Gaussian Blurring, Erosion/dilation.

3.3 Data Augmentation

Data augmentation is the process of producing new data points from previously collected data in order to fictitiously increase the volume of data. The diversity and volume of the dataset were artificially boosted through a range of data enhancement approaches, which reduced the likelihood of overfitting and enhanced the model's capacity to generalize to previously unobserved data. One of the primary data augmentation techniques utilized was geometric transformations, including flipping, rotation, and scaling. In order to simulate real-world situations where patients' heads may be positioned differently during MRI scans, we can create differences in the orientation of the brain regions by flipping images either horizontally or vertically. While scaling allows us to take into consideration variations in picture resolutions and magnifications, rotation allows us to imitate variations in the angle of acquisition. It is important to keep in mind that the features of the dataset and the specific requirements of the activity at hand dictate the choice and organization of data augmentation approaches. A varied and representative dataset that successfully reflected the variability observed in clinical MRI imaging of brain tumors was produced by carefully choosing and utilizing various strategies, which eventually enhanced model performance and diagnosis accuracy. The model's capacity to precisely identify cancers can be improved by the prudent use of several augmentation strategies, which will aid in early identification and boost patient outcomes in clinical settings.

3.4 Classification Technique

For accurate brain lesion diagnosis, the Convolutional Neural Network (CNN) architectures EfficientNetV2 and Inception-ResNetV2 were selected due to their competence in MRI image processing and feature extraction. Because of its sophisticated neural network search and scaling methods, which maximize training speed and parameter efficiency, EfficientNetV2 was chosen. In the meantime, Inception-ResNetV2 was incorporated due to its special blend of ResNet concepts and Inception modules, which effectively captures multi-scale data while addressing the vanishing gradient issue. The proposed hybrid model, EffIncepResV2, improves the precision and resilience of brain lesion categorization by utilizing the advantages of both designs.

a) EfficientNetV2

EfficientNetV2 greatly increases training speed and parameter efficiency, building on the success of EfficientNet. This is accomplished by combining multi-dimensional scaling of breadth, depth and resolution with Neural Architecture Search (NAS). Enhancing computing efficiency while maintaining high accuracy is the main goal.

Fused-MBConv blocks shown in Fig. 1, which take the role of traditional MBConv layers in the network’s early phases, are a significant advancement in EfficientNetV2. By improving efficiency, this change maximizes performance. The model also uses a progressive learning approach, which training starts with images of lower resolution and progressively increases it. This method improves generalization while simultaneously speeding up convergence.

There are several variations of EfficientNetV2, including EfficientNetV2-S, M, and L, which provide a trade-off between computational cost and performance. With fewer parameters and less training time, EfficientNetV2 outperforms more conventional convolutional neural networks such as ResNet, Inception-ResNetV2. Because of these benefits, it is especially well-suited for medical image analysis, notably in the categorization of brain tumors, where high accuracy and computing efficiency are essential.

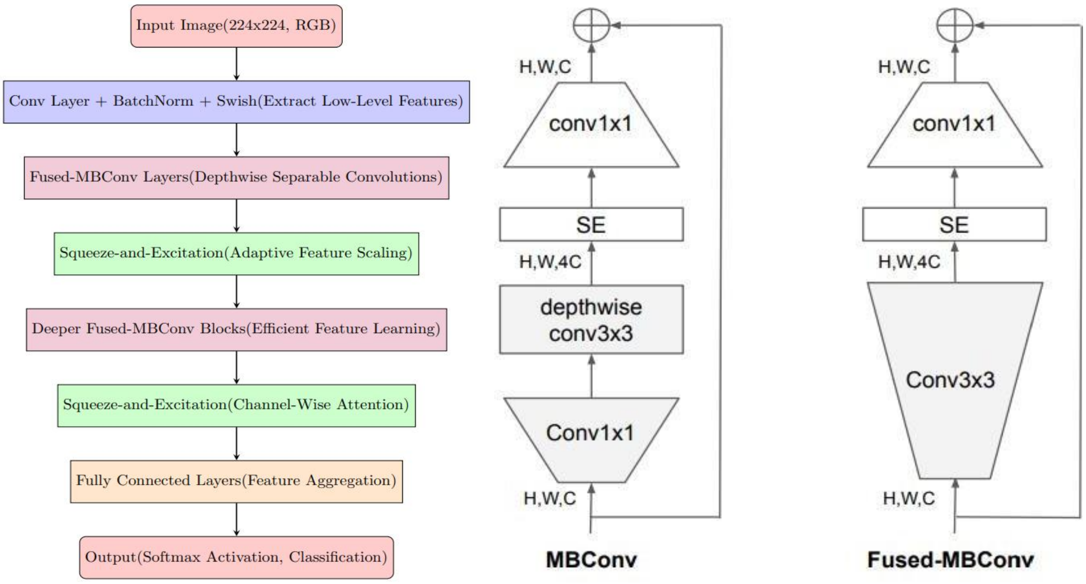

Fig. 1: An overview of EfficientNetV2 Architecture and Structure of MBConv and Fused-MBConv blocks

b) Inception-ResNetV2

A deep convolutional neural network architecture called Inception-ResNetV2 combines the ideas of Residual networks (ResNets) and Inception networks to produce state-of-arts results in an image categorization applications. While the residual connections enable fast training of deeper networks by resolving the vanishing gradient issue, the Inception module facilitates multi-scale feature extraction utilizing convolutional layers with varying kernel sizes. When compared to traditional deep networks, this combination produces faster convergence, better accuracy, and less computing complexity.

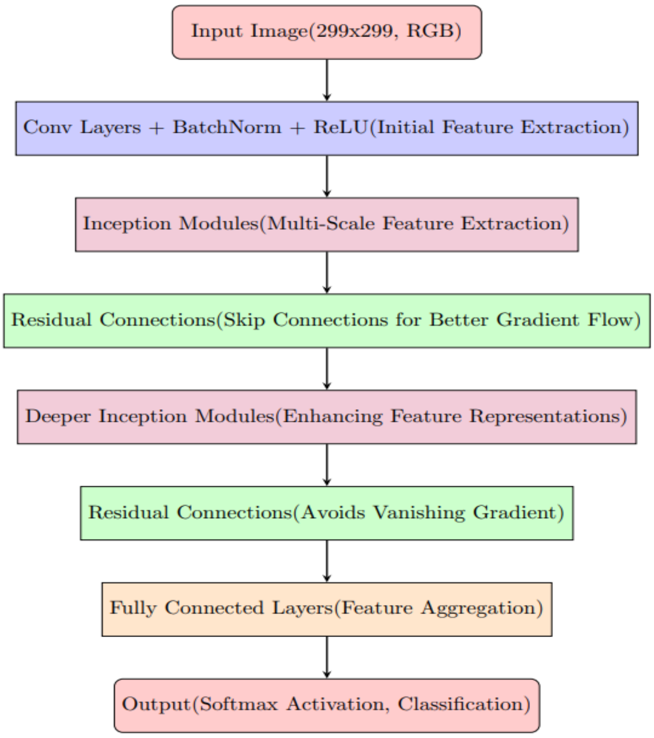

Fig. 2 Architecture of Inception-ResNetV2

As the block diagram of Fig. 2 illustrates, the Inception-ResNetV2 architecture for brain lesions categorization is made

up of several crucial parts:
i) Input Image: The network receives the raw MRI input image for preliminary processing.
ii) Convolution Layers + Batch Normalization + ReLU (Initial Feature Extraction): To process raw input images and guarantee stable training and initial feature extraction, the stem layer uses convolutional operations, batch normalization, and ReLU activation.
iii) Multi-Scale Feature Extraction Inception Modules:
Inception-ResNet-A: Allows for multi-scale feature extraction by capturing fine-grained spatial information using several tiny convolutional filters (1×1, 3×3, and 5×5).
Reduction-A: To lower computational complexity while maintaining key features, feature maps are downsampled.
iv) Residual Connections (Skip Connections for Better Gradient Flow): By enabling the network to learn residual mappings rather than direct transformations, residual learning aids in training of deeper networks. By avoiding vanishing gradients during backpropagation, this method guarantees improved gradient flow.
v) Deeper Inception Modules (Enhancing Feature Representations):
Inception-ResNet-B: Increases the network's ability to represent high-level patterns by extracting deeper and more abstract information through intricate convolutional procedures.
Reduction-B: Optimizes the network's efficiency by further downsampling feature maps while preserving a substantial amount of spatial information.
vi) Residual Connections (Avoids Vanishing Gradient):
To facilitate smoother gradient propagation and prevent gradient vanishing problems during training, the residual connection are uniformly integrated across layers.
vii) Fully Connected Layers (Feature Aggregation):
Global Average Pooling (GAP) reduces the number of parameters and minimizes overfitting by aggregating feature maps into a single vector in place of conventional fully connected layers.
viii) Output (Softmax Activation, Classification):
A softmax classifier uses the retrieved high-level feature representations to forecast the probabilities of brain lesions, completing the final classification.

c) EffIncepResV2:

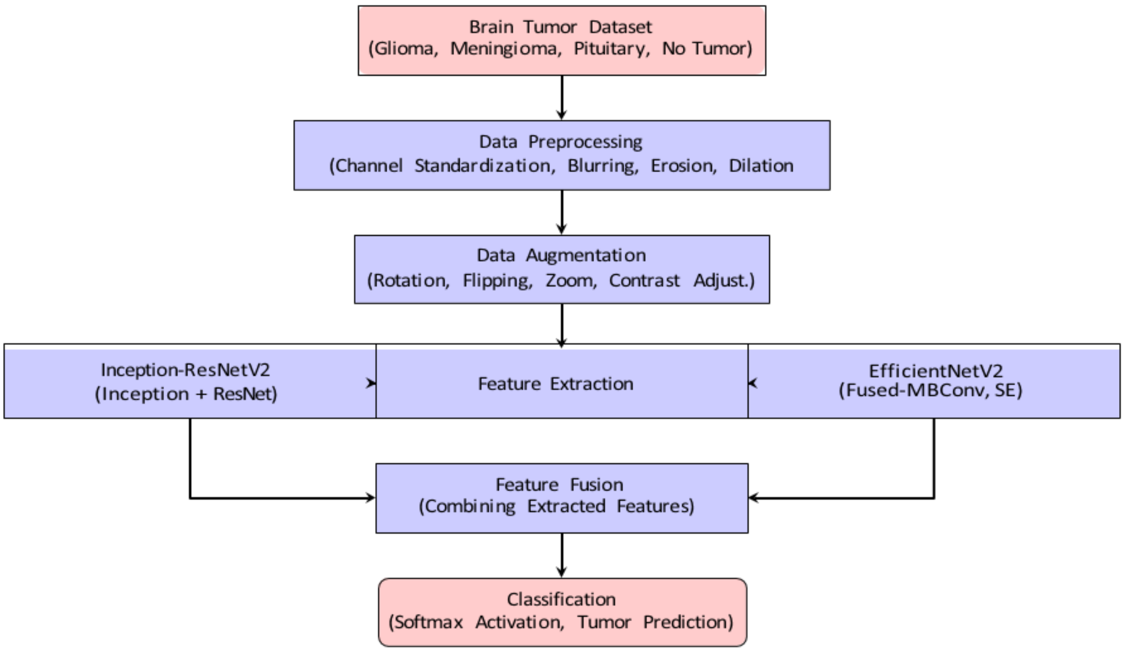

Fig. 3 Workflow of the EffIncepResV2 architecture for brain tumor classification

Key procedures such as dataset preparation, preprocessing, data augmentation, feature extraction (utilizing Inception-ResNetV2 and EfficientNetV2), feature fusion, classification, are depicted in the Fig. 3.
The EffIncepResV2 model uses a well-organized pipeline to classify brain tumors, guaranteeing a methodical approach from managing data to making final predictions. Data preparation, preprocessing, augmentation, hybrid network feature extraction, feature fusion, and tumor classification are the six main steps in the procedure. Below is a thorough explanation of every step:

1. Brain Tumor Dataset

The process begins with a dataset containing brain MRI images categorized into four distinct classes: Glioma, Meningioma, Pituitary, No Tumor. This dataset is fundamental in training the model and evaluating its accuracy in classifying tumors.

2. Data Preprocessing

To enhance image quality and reduce noise, preprocessing techniques are applied:
Channel Standardization: For consistent processing, images are converted to a standard RGB format (3 channels).
Guassian Blurring: Uses Gaussian filter to smooth out visual features and cut down on noise while keeping key structures intact.
Erosion,Dilation (Morphological operations): Improves structural features for greater clarity by eliminating noise (erosion) and strengthening important areas (dilation)

3. Data Augmentation

To prevent overfitting and improve model generalization, the dataset is augmented by applying various tranformations:
Rotation: Simulates different viewing angles of the tumor.
Flipping (Horizontal/Vertical): Enhances spatial invariance.
Zooming: Focuses on specific regions for detailed analysis.
Contrast Adjustment: Improves image visibility, making subtle features more distinguishable.

4. Feature Extraction:

The model extracts relevant features through two powerful deep-learning networks operating in parallel.
Inception-ResNetV2: Integrates Inception modules with residual connections, capturing multiscale features while mitigating vanishing gradients.
EfficientNetV2: Leverages neural architecture search and Fused-MBConv blocks for efficient and high-speed feature extraction.
The input images are processed independently by each network: EfficientNetV2 offers effective feature extraction with streamlined computations, whereas Inception-ResNetV2 uses residual connections to capture multi-scale features.

5. Feature Fusion:

Once both networks have extracted their respective features, the outputs are combined to create a richer and more comprehensive feature representation. This fusion step ensures that complementary information from both architectures is effectively utilized, enhancing classification performance.
EffIncepResV2 is a hybrid deep learning model that improves brain tumor classification by combining EfficientNetV2 and Inception-ResNetV2. It makes use of EfficientNetV2's optimized parameterization and training performance while leveraging the residual connections in Inception-ResNetV2 for multi-scale feature extraction.
Feature Fusion in EffIncepResV2:
Prior to classification, the output feature maps from Inception-ResNetV2 and EfficientNetV2 are combined and converted into a single feature representation. The fused feature representation $F_{EffIncepResV2}$ can be expressed mathematically as follows:

$F_{EffIncepResV2}=\alpha F_{EffNetV2}+\beta F_{IncepResV2}$

where:

- $F_{EffNetV2}$ represents the extracted feature maps from EfficientNetV2,
- $F_{IncepResV2}$ represents the extracted feature maps from Inception-ResNetV2,
- α,β are learnable weight parameters controlling the contribution of each model which are trainable parameters.

6. Classification

- The fused feature set must then be passed via a classification layer as the last step:
- The model then predicts one of the four potential categories: glioma, meningioma, pituitary, or no tumor (showing the absence of a tumor). Each class is given a probability value based on a Softmax activation function.

After fusion, the final classification output y is computed using:

$y=\sigma(WF_{EffIncepResV2}+b)$

where:

- W is the weight matrix,
- b is the bias term,
- σ represents the softmax activation function, mapping features to class probabilities.

When these cutting-edge methods are combined, the EffIncepResV2 model produces extremely accurate and effective tumor classification, which makes it a potent instrument for medical imaging applications.

Softmax Activation Function σ is given in equation 1:

$$\sigma(z_i) = \frac{e^{z_i}}{\left(\sum_j e^{z_j} \right)} \qquad (1)$$

Fusion Weight Constraints are defined in equation (2) and (3)
α+β=1

$$\alpha = \frac{\{e^{\{\gamma_1\}}\}}{\{e^{\{\gamma_1\}} + e^{\{\gamma_2\}}\}} \qquad (2)$$

$$\beta = \frac{\{e^{\{\gamma_2\}}\}}{\{e^{\{\gamma_1\}} + e^{\{\gamma_2\}}\}} \qquad (3)$$

Advantages of EffIncepResV2

1. Better Feature Extraction: EfficientNetV2 guarantees optimized computation, whereas Inception modules extract multi-scale features.
2. Improved Generalization: Residual connections lessen overfitting by promoting better gradient flow.
3. Computational Efficiency: The hybrid model maintains high accuracy with fewer parameters.

Proposed Algorithm: EffIncepResV2: Brain Tumor Classification
Require: Brain Tumor Dataset *D* with classes: Glioma, Meningioma, Pituitary, No Tumor
Ensure: Predicted Tumor Class *C*
Step 1: Data Preprocessing:
1: Ensure images are in RGB format (3 channels)
2: Apply blurring, erosion/dilation to reduce noise and enhance features.

Step 2: Data Augmentation:
3: Perform rotation, flipping, zooming, and contrast adjustment to generate diverse training data.

Step 3: Feature Extraction:
4: Extract multi-scale features using Inception-ResNetV2 with Inception modules and residual connections.
5: Extract efficient feature representations using EfficientNetV2 with Fused- MBConv and SE blocks.

Step 4: Feature Fusion:
6: Combine feature maps from both networks to create a unified representation.
$F_{EffIncepResV2}=\alpha F_{EffNetV2}+\beta F_{IncepResV2}$ where α, β are learnable weight parameters ensuring α+β=1

Step 5: Classification:
7: Apply a fully connected layer followed by the Softmax activation function to predict tumor class
$y=\sigma(WF_{EffIncepResV2}+b)$
where W is the weight matrix, b is the bias term, and σ is the softmax function.
8: return Predicted Tumor Class *C*

Table 1 Hyperparameters used in the model

Hyper-parameter	Value
Learning rate	0.001
Optimizer	AdamW
Batch Size	64
Number of epochs	100
Dropout Rate	0.3
Weight Decay	1e-5
Residual Scaling factor	0.2
Augmentation	Rotation, flip, zooming, contrast adjustment
Stochastic Depth	0.8
Fusion Strategy	Concatenation+SE Blocks

The proposed model's hyperparameters, which were carefully chosen to maximize performance, are shown in Table 1. Stable and effective training is ensured with the AdamW optimizer at a learning rate of 0.001. In order to balance convergence and computational efficiency, batch sizes of 64 and 100 epochs were selected. Overfitting can be avoided with regularization strategies like weight decay (1e-5) and dropout (0.3). Rotation, flipping, and brightness modulation are examples of data augmentation techniques that improve model generalization. Deep network training is further stabilized by the stochastic depth (0.8) and residual scaling factor (0.2). Furthermore, feature extraction and representation learning are enhanced by a concatenation-based fusion approach with SE (Squeeze-and-Excitation) blocks. The suggested model's strong performance and resilience are a result of these hyperparameter selections.

3.5 Performance Metrics:

We employ the following performance indicators to assess the categorization models:

Accuracy: Measures the overall percentage of correct predictions. Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision: Indicates the proportion of true positives among all predicted positives. Precision=TP/(TP+FP)

Recall: Measures the proportion of true positives among all actual positives.

Recall= TP/(TP+FN)

F1-Score: The harmonic mean of Precision and Recall.

F1-Score=2x(PrecisionxRecall)/(Precision+Recall)

Dice Coefficient: Measures the similarity between the predicted and actual positives.

Dice Coefficient=2.TP/(2.TP+FP+FN)

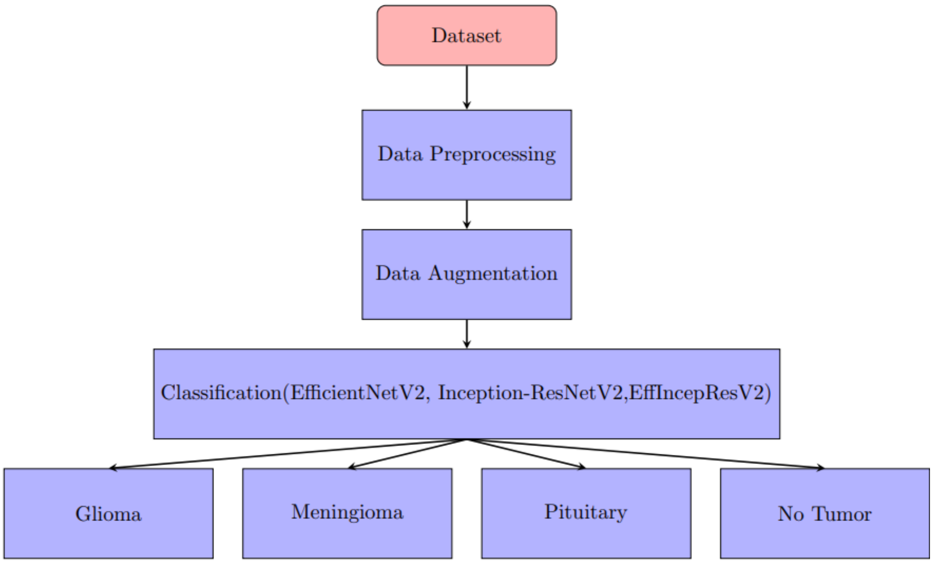

Fig. 4 Overall Architectural Diagram of the proposed System

The brain tumor classification model's workflow is depicted in the Fig. 4, beginning with dataset, data preprocessing and augmentation procedures to improve the dataset. To classify MRI scans into four groups—glioma, meningioma, pituitary, and no tumor—the classification procedure makes use of EfficientNetV2, Inception-ResNetV2, and the proposed EffIncepResV2 model.

4. RESULTS AND DISCUSSIONS

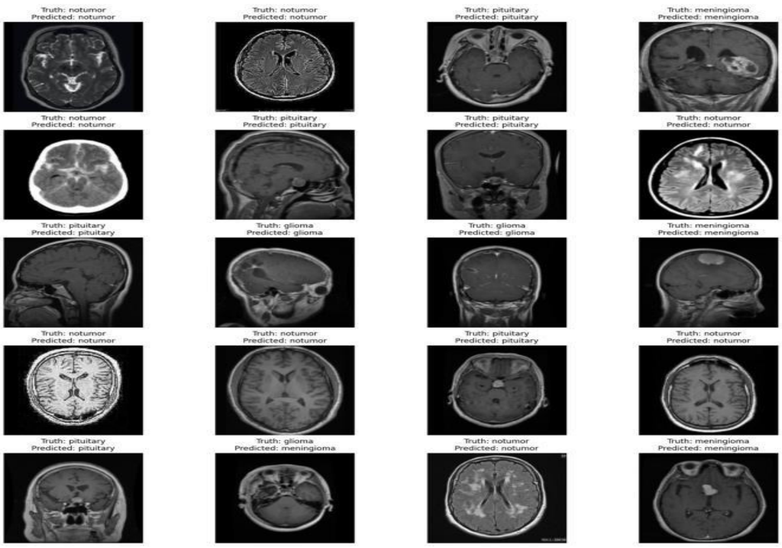

Fig. 5 Predicted Tumor Classes Using EffIncepResV2

Fig. 5,shows the classification results , clearly indicating the high prediction accuracy. EffIncepResV2, Inception-ResNetV2, EffIncepResV2 Models are trained and tested. The EffIncepResV2 model has highest accuracy of about 99.76%. Along with these models, we even trained some state-of-the-art models such as VGG16, ResNet50. Table 2 compares the five CNN models based on parameters, Accuracy, Precision, Recall, F1-Score and Dice-Coefficient.

Table 2: Comparision of Five CNN Models Accuracy

Metric	VGG	ResNet50	EfficientNetV2	Inception-ResNetV2	EffIncepResV2(Proposed Model)
Accuracy	93.00	96.38	98.72	98.00	99.94
Precision	90.50	94.80	97.50	97.00	99.65
Recall	91.20	95.20	97.90	97.40	99.89
F1-Score	90.85	95.00	97.70	97.20	99.65
Dice-Coefficient	89.50	94.00	96.80	96.50	99.00

As the architectures get more complex , the performance comparison of many deep learning models-VGG , ResNet50, EfficientNetV2, and Inception-ResNetV2 –shows notable gains in accuracy, precision , recall ,F1-Score and Dice-Coefficient as shown in Table2. The proposed EffIncepResV2 model performs better than any of the others, with the best accuracy of 99.94% and the highest precision (99.65%), recall (99.89%) and F1-Score (99.65%) values. These findings show that EffIncepResV2 is a strong option for high-accuracy deep learning applications since it efficiently improves feature extraction and classification performance.

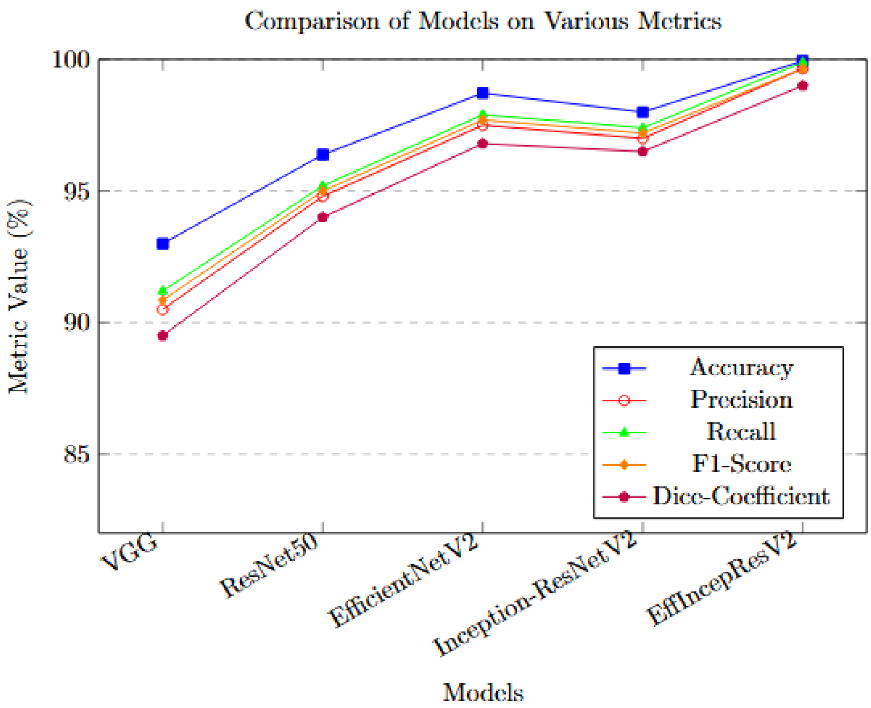

Fig. 6 Comparative Evaluation with various models.

The proposed EffIncepResV2 performs the best, with a steady improvement in all metrics with advanced architectures. The robustness and efficacy of combining EfficientNet and Inception-ResNetV2 for improved prediction accuracy are confirmed by EffIncepResV2's higher performance as depicted in Fig. 6.

Table 3: Comparison with Existing works

Metric	Ensemble Model (ResNet50 + EfficientNet -B7) [8]	MobileNetV2+SVM [20]	2DCNN[22]	EffIncepResV2(Proposed Model)

Accuracy	99.53	98.2	93.44	99.94
Precision	99.5	94.53	94.75	99.65
Recall	99.6	-	95.75	99.89
F1-Score	99.53	96.6(no tumor)	95.00	99.65

Table3 compares different deep learning models according to F1-score, Accuracy, Precision and Recall. When compared to other methods, such as the Ensemble Model (ResNet50+EfficientNetB7)[8], MobileNetV2 + SVM[20], and 2DCNN[22], the suggested EffIncepResV2 model achieves the highest accuracy (99.94%). Although the ensemble-based model (ResNet50 + EfficientNet-B7) performs competitively, it lags somewhat in terms of F1-score (99.53%) and recall (99.6%). Comparatively lower accuracy and pre-cision values are displayed by MobileNetV2 + SVM and 2DCNN. These outcomes confirm that the EffIncepResV2 model is effective in obtaining better tumor classification results.

5. CONCLUSION

Early brain tumor classification using MRI is crucial for accurate evaluation, treatment planning, and improving patient survival rates. Deep learning facilitates faster and more accurate tumor identification by processing medical images through multiple models, ultimately selecting the one with the highest accuracy. Additionally, a web-based platform is developed to enable users to access the system and make independent disease predictions. This study leverages deep learning to enhance tumor classification by integrating EfficientNetV2 and Inception-ResNetV2 into a hybrid EffIncepResV2 model, achieving improved accuracy and generalization. To maximize performance, the suggested method makes use of transfer learning, dataset augmentation, and architectural fine-tuning. Some of this approach's advantages are better feature extraction from integrated architectures, increased classification accuracy, and resilience against overfitting through regularization techniques. Nevertheless, there are certain drawbacks, including the requirement for extensive annotated datasets, significant processing costs, and possible model biases brought on by dataset imbalances. The robustness of the model can be further improved by several trials, and dependability is ensured using validation methods like cross-validation. By addressing the identified challenges and expanding the scope of experimentation, this research aims to contribute to more reliable and accessible automated brain tumor classification.

Conflicts of interest: The authors declare no conflicts of interest

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