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Research Article

Multi-Dataset Evaluation of Hybrid Models for Brain Tumor Diagnosis

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ABSTRACT

Brain tumor detection is the identification and categorization of aberrant brain tissues using methods like MRI for tumor diagnosis and tracking. This sophisticated technique uses deep learning to analyze images, resulting in precise early detection and treatment. This study uses hybrid architectures for different deep-learning applications to offer a comprehensive hybridization strategy with promising prospects for improving the diagnostic precision of images obtained for medical diagnostics. In this study, it employs three separate datasets, previously known as Brain MRI images, Br35H and BraTS, to assess several architectures, including ResNet, VGG, Inception, EfficientNet, DenseNet121, MobileNetV2, Xception, NASNetMobile, and InceptionResNetV2. For the Brain MRI dataset, the findings demonstrated that the VGG16 model had a training accuracy of 99.93% with the lowest train loss of 0.0238; on all three datasets, the InceptionV3 showed exceptional robustness, with an accuracy of 99.78%. Although hybrid models that combined architectures such as Xception, NASNetMobile, and InceptionResNetV2 performed effectively, they also appeared to overfit, with validation and test losses being comparatively larger than training accuracy. The hybrid model hybrid model (EfficientNet, DenseNet121, MobileNetV2) achieved 99.87% training accuracy using the BraTS dataset. These findings indicate the possibility of applying deep learning architectures more effectively to better diagnose brain tumors, in addition to rigorous model optimization and selection to reduce the tendency for overfitting. This study encourages hybrid DL models' application in the medical area.

Keywords: Brain MRI images, CNN, BraTS dataset, Deep learning (DL) and Brain tumor detection.

INTRODUCTION

Early brain tumor diagnosis is essential as early management greatly improves treatment outcomes. Compared to other illnesses, brain tumors are more challenging to diagnose since their size, shape, and location vary, making identification imprecise. Because MRI may detect unusual brain tissue, it is the primary method for brain tumor detection. Even with high-resolution MRI imaging, it can be difficult to determine the difference between normal and abnormal tissue, therefore, advanced computational methods are required [1].

In this study, they explore the probable hybrid deep learning (DL) models, which combine the advantages of many architectures, including Inception, VGG, ResNet, Xception, DenseNet, and others, to improve diagnosis accuracy. By training these models on a variety of datasets, including the Br35H, BraTS, and Brain MRI Images for Brain Tumor Detection datasets, they have improved feature extraction and predicted accuracy. A hybrid model combined with feature extraction using several models may provide an improved depiction of the image data and thus, enhance the potential of detecting accuracy [2]. By combining several methods of analysis, the proposed method truly intends to overcome the constraints of the current MRI-based brain tumor diagnosis.

Since most brain tumors have been difficult to diagnose with distinction, this work is significant because it may change how brain tumors are diagnosed and treated. By combining these deep learning models, the study will fill

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important gaps in the current methods for diagnosing patients with more accuracy and dependability in MRI-derived predictions. This will enhance patient care and results by improving early tumor detection. Additionally, the findings could inform future studies that could lead to more sophisticated diagnostic instruments in medical imaging and machine learning fields [3].

The objective of this study is to improve brain tumor identification by designing and testing hybrid DL models across multiple datasets using the architectures CNN, ResNet50, VGG16, InceptionV3, and other hybrid models. The research objectives are to assess these models' performance metrics in terms of improving prediction accuracy and developing a more reliable and efficient process for differentiating healthy from tumour-affected brain tissue in medical imaging.

RELATED WORK

The existing study shows the various findings with different methodologies. A. S. Musallam et al. [5] A lightweight Glioma, meningioma, and pituitary tumors can be accurately and early diagnosed with the DCNN architecture from MRI images proposed in this paper. This model has faster training, with effective weight initialization using a minimal number of convolutional and max-pooling layers.

M. S. Majib et al. [6] the study describes that the majority of fatalities are produced by untreated brain tumors, and early detection of malignant brain tumors can have a substantial effect on both medical care and survival. It is quite difficult to manually diagnose and segment tumors from MR images, and it mostly relies on the radiologists' level of experience. To do this, the researchers presented a few conventional hybrid models for ML-based tumor categorization automation. The optimal neural network model for classifying brain tumors was also determined by testing sixteen transfer learning models. Ultimately, a stacked classifier was suggested, which performed better than any of the models examined.

A.Anaya-Isaza and L. Mera-Jiménez. [7] The study describes Data augmentation methods that are employed intensively in the training of neural networks, especially when the datasets available are small. Applications also involve the medical fields where the availability of data might be limited. For example, MRI in cancer pathology scans normally requires data augmentation for model performance improvement. This work aims to explore various traditional data augmentation techniques used on the ResNet50 network specifically for brain tumor detection. They also added a novel method grounded on PCA. In the training procedure, both from-scratch networks and networks that leverage transfer learning using weights pre-trained on ImageNet are used.

Table 1: An existing study with different methodologies

Ref.	Objectives	Technology Applied	Finding / Research Gap identified
[8]	MRI brain tumors are segmented and identified, and convolution operations can be carried out using a convolutional layer to increase the recognition efficiency rate.	Principal Component Analysis (PCA)	The main characteristics of the information are extracted in the unique space and the correlation between the features. There is a possibility of information loss and the attributes become less interpretable.
[9]	Diagnosis of the tumor with Deep CNN	Deep CNN	The database collected 1258 MRI images by efficient method with an accuracy rate of 96%.
[10]	Diagnosis of brain tumor	Pretrained DL model: Inception-v3 and DensNet201	Produced 99.51%accuracy
[11]	Improve brain tumor diagnosis and classification by DL with the EfficientNet family	Deep learning: EfcientNetB3	The 3064 T1-weighted CE MRI image dataset is used which produced an accuracy rate of 99.69%.
[12]	MRI Image Diagnosis of Brain Tumors	SVM, FCM, and grey-level run-length matrices (GLRLM)	Deliver more precise and efficient outcomes to categorize MRI images of the brain. Only 24 images are used for

			testing, and 96 images are used for training.
[13]	A convolutional-block architecture for MRI scan-based multiclass brain tumor identification	CNN, novel models including DenseNet121, Xception, ResNet50, MobileNet, EfficientNet, VGG16, and VGG19	The model's exceptional diagnostic accuracy has been demonstrated by extensive tests on three different datasets and has a 97.52% accuracy percentage on average.
[14]	Brain tumors are diagnosed by MR imaging	Deep learning: CNN, VGG, ResNet, DenseNet, SqueezeNet and Machine learning methods	The limited optimization of CNN architectures for brain tumor diagnosis brings a research need.
[15]	To categorize brain tumors from brain MR images, including pituitary, meningioma, and glioma	The classification was done using CNNs, Transfer learning techniques based on CNN, Inception V3, EfficientNet B4, and VGG19.	VGG16 produced the best accuracy result, scoring 98%.

Table 2: Different available datasets.

Ref.	**Dataset**	**Description**	**Features**
[16] [17] [18] [19]	BraTS	The Brain Tumor Segmentation (BraTS) dataset spans the years 2012 to 2020 and is always focused on evaluating both new and existing techniques for brain tumor segmentation in multimodal MR images.	Conditional Random Fields (CRF) and Fully CNN, which were created in connection with the MICCAI conferences in 2012 and 2013., serve as the foundation for brain tumor segmentation.
[20] [21]	Br35H	CNN and TL, a feature of deep learning, are used to detect and classify brain tumors and to analyze the tumor's location (segmentation).	The dataset is divided into three folders: yes, no, and pred. It has 3060 brain MRI images.
[22]	Brain MRI images	For brain tumor detection, this approach pre-processes MRI images and features two DL models that have been trained and feature vectors are combined to form a hybrid vector using the PLS method.	Data from 233 patients in two Chinese hospitals (2005-2010) comprises 3,064 T1-weighted MRI scans at 512x512 pixels, 0.49x0.49 mm². The dataset includes three types of tumors: Pituitary (930 cases), Meningioma (708 cases), and Glioma (1,426 cases) in axial, coronal, and sagittal planes.

Deep learning has made substantial progress in diagnosing brain tumors., but there are numerous unresolved issues. The speed and accuracy of trains have been enhanced by lightweight architectures like those suggested by Musallam et al., but very little research has been done on how efficiently they perform on larger datasets or how effectively they adapt to different types of MRI images. Furthermore, Majib et al. proposed automated classification techniques based on hybrid models and stacked classifiers, which identically demand reliable, automated segmentation to reduce dependence on physicians but have difficulty finding a balance between interpretability and model complexity. Research on data augmentation methods by Anaya-Isaza and Mera-Jiménez demonstrates that a lack of data remains a significant constraint and frequently leads to possible overfitting. Additionally, it only uses pre-trained models like ResNet50 or EfficientNet and does not specifically modify CNN architecture for brain tumor diagnosis, which encourages more studies to maximize model performance and adaptability in medical imaging.

METHODOLOGY

The study identifies the different hybrid models, the proposed model for brain tumor diagnosis that shows the diagnosis procedure to improve prediction accuracy, and the performance metrics to assess how effectively different models perform to improve prediction accuracy.

A. *Models used for prediction*

There are seven models are used in this study for brain tumor diagnosis:

1) CNN model

The CNN model is employed to enhance brain tumor diagnosis by automatically analyzing the MRI images used in this investigation. CNNs can learn and extract intricate patterns from any number of layers involving convolution, pooling, and activation functions contributing to its high efficiency in image recognition applications. The model's method of operation will entail analyzing MRI Images to determine the key features that differentiate between brain tissue that is healthy and that has been impacted by tumors. To identify tumors based on differences in size, shape, and texture, the CNN is trained on labeled datasets. In this approach, it could precisely categorize images and make it easier and more accurate to diagnose brain tumors, a vital condition.

2) ResNet50

ResNet50 is a 50-layer DCNN, which has proven very strong in the feature extraction from the data, therefore, ResNet50 has been crucial in this study. The application of residual links addresses the dead gradients that occur routinely in such deep structures. ResNet50 is adept at identifying subtle and complex patterns and variations within MRI images concerning differences between healthy and malignant brain tissues. By adding this network to the hybrid model, it can successfully enhance its diagnostic accuracy and robustness; hence, it is heavily valued to improve results in detecting brain tumors.

3) VGG16

The hybrid deep learning model used to diagnose brain tumors included VGG16 as a key element. Convolutional layers, which are the fundamental component of the straightforward yet effective 16-layer VGG16 architecture, are good at extracting fine-grained features. While it keeps the kernel size of VGG16 at 3x3, it has been able to capture very minor changes between healthy and tumour-affected tissues. There, the hybrid model's detection accuracy is increased and its efficacy in classifying benign and malignant tumors is enhanced by including VGG16's strength.

4) InceptionV3

This study was able to diagnose brain cancers because InceptionV3 is very good at extracting very complicated features from visual data. Its unique design allows for the simultaneous recording of several spatial features by utilizing multiple convolutional filters of varying sizes inside a single layer. By detecting minute variations in shape, texture, and density, InceptionV3 facilitates the analysis of intricate MRI patterns and makes it possible to distinguish between benign and cancerous tissue. Its ability to handle high-resolution images with computing efficiency gives it an important benefit when used as a key element in the hybrid model to increase diagnostic accuracy.

5) Hybrid model1 (ResNet50, VGG16, Inceptionv3)

Hybrid Model 1 develops an integrated model for brain tumor diagnostics by combining three powerful deep architectures: ResNet50, VGG16, and InceptionV3. Each of them has a unique strength: InceptionV3 improved feature extraction from multi-scale information captured by its various inception modules, VGG16 stands on its simple yet good structure with consistently good performance in classification applications using images, and ResNet50 is better at maintaining accuracy in very deep networks. To improve feature extraction from MRI images and provide more precise and reliable predictions for differentiating between healthy and dangerous brain tissues, the hybrid model integrates and leverages the characteristics of the two models.

6) Hybrid model 2 (Xception, NASNetMobile, InceptionResNetV2)

It combines three cutting-edge deep architectures such as Xception, NASNetMobile, and InceptionResNetV2 and categorization. Xception's separable convolutions reduce computational costs while improving feature extraction. Without requiring excessive resources, NASNetMobile adjusts its model performance to a mobile device, allowing it to process without sacrificing accuracy. Using Inception and remaining links from ResNet, InceptionResNetV2 combines the greatest features of multi-scale processing. In terms of MRI data complexity, it is among the best models for identifying complicated patterns. These architectures are combined in Hybrid Model 2 to provide a strong framework that addresses the many tumor variants to improve diagnostic reliability and prediction accuracy.

7) Hybrid model 3 (EfficientNet, DenseNet121, MobileNetV2)

Hybrid Model 3 combines the architectures of EfficientNet, DenseNet121, and MobileNetV2 to provide a robust but effective framework for classifying brain tumors. Each component model has several advantages. MobileNetV2 adds lightweight yet powerful depthwise convolutions, which improves model efficiency without sacrificing accuracy. DenseNet121's dense connections allow for better feature reuse and gradient flow, while EfficientNet optimizes feature extraction to help with scale and efficiency at a low computational cost. It is appropriate for both high-performance and limited resources situations in medical image applications because, when combined, they produce a powerful hybrid model that can effectively categorize MRI data while preserving computational resources.

B. The proposed method

This study enhances the detection of brain cancers by using weighted ensemble pre-trained model selection, data preprocessing and noise reduction, brain contour extraction, and feature extraction. To improve prediction accuracy and diagnostic precision, it processes Images for training, validation, and testing using a hybrid model that integrates EfficientNet, VGG16, InceptionV3, ResNet50, DenseNet, and others. The proposed brain tumor detection model is shown in Figure 1.

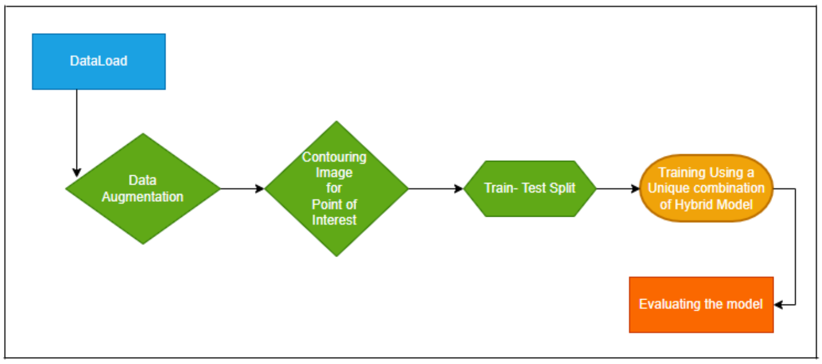


Fig 1: The proposed brain tumor detection model.

This research study aims to enhance deep learning hybrid models for diagnosing brain tumors. To identify brain tumors, the method starts by gathering MRI data from many datasets. Data augmentation is not performed only while utilizing the BraTS dataset. Here, the first pre-processing is done using data augmentation approaches to improve the dataset's robustness by reducing noise and redundant information. Each MRI scan's region of interest is a weighted ensemble of many pre-trained models that pick pertinent features, ensuring that the hybrid model only concentrates on those features necessary for a correct diagnosis. Each image is further processed into grayscale, the largest contour is found, the brain's contour is isolated using thresholding, and the image is cropped. This method successfully separates the brain area for a more focused investigation.

After pre-processing, the images were categorized into trained, validated, and tested sets and tagged. Additionally, it ensured that this dataset contained a distinct brain shape. After that, the images were adjusted in size and normalized to ensure model compatibility. To leverage the advantages of these architectures, a variety of models that have already been trained VGG16, InceptionV3, ResNet50, EfficientNet, and DenseNet as hybrid combinations are implemented. By evaluating combinations of pre-trained models like Inception, ResNet, and VGG, this hybrid technique improves feature extraction and predictive accuracy. Among many datasets, a hybrid technique like it will result in more precise and reliable brain tumor diagnoses.

C. Performance measures

Performance indicators like accuracy and loss are used to evaluate the performance of the hybrid model.

1) Accuracy: Accuracy is utilized to assess a categorization model's effectiveness. It displays the percentage of all instances that might have been anticipated with accuracy.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \times 100 \quad (1)$$

2) Loss: The amount of loss indicates how well (or poorly) the model can predict the correct classes.

- Binary Cross-Entropy for binary classification
- Cross-Entropy Loss

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}(\mathcal{Y}_i log(\mathcal{P}_i) + (1-\mathcal{Y}_i)\log(1-\mathcal{P}_i)) \quad (2)$$

Where N is the number of samples.

$\mathcal{P}i$ is the predicted probability of the i-th sample being in class 1.

$\mathcal{Y}i$ is the actual label of the i-th sample (either 0 or 1).

RESULTS

Important hybrid model architectures include ResNet, VGG, Inception, EfficientNet, DenseNet121, MobileNetV2, Xception, NASNetMobile, and Inception. Two datasets, including the Br35H dataset for brain tumor detection, brain MRI images and the BraTS dataset, are used. The anticipated accuracy and overall performance of each model, which are evaluated by analyzing these measures, decide which model is the most reliable and efficient for diagnosing brain tumors.

A. *Dataset*

Models are being evaluated using three different databases: Brain MRI Images, Br35H, and BraTS. This work also increased its diagnostic accuracy when compared to other studies. These databases all provide images of different kinds of brain tumors, each of which was selected at a varied stage and has a thorough explanation of every single one of its characteristics. It was accomplished by closely examining the capacity of the model to differentiate between cancerous and healthy tissues. To improve brain tumor accuracy and dependability diagnosis in the actual clinical setting, the project goal is to make a good prediction model that generalizes well on a variety of data sources through the model's testing and training on a variety of datasets.

B. *Experimental results*

1) Evaluation of various models using Brain MRI image dataset

Table 3 demonstrates that the VGG16 model works effectively overall, with the highest training, validation, and test accuracy of any model. While hybrid models, particularly the combination of Xception, NASNetMobile, and InceptionResNetV2, also demonstrated outstanding accuracy with minimum loss across all sets, other models, such as CNN and ResNet50, demonstrated average performance with higher losses.

Table 3: Performance of different models with a dataset of brain MRI images

Models	Validation (Loss)	Validation (Accuracy)	Training (Accuracy)	Training (Loss)	Test Loss	Test Accuracy
CNN	0.4327	80.97%	80.26%	0.3682	0.3990	85.16%
ResNet50	0.4247	80.65%	83.94%	0.4107	0.3974	83.55%
VGG16	0.0864	99.03%	99.93%	0.0238	0.0562	98.71%
InceptionV3	0.4083	92.90%	97.53%	0.0912	0.3758	90.32%
Hybrid model (ResNet50, VGG16, InceptionV3)	0.5985	70.65%	99.60%	0.2796	0.5113	75.16%
Hybrid model (Xception, NASNetMobile, InceptionResNetV2)	0.3419	98.06%	99.72%	0.0152	0.3058	98.06%
Hybrid model (EfficientNet, DenseNet121, MobileNetV2)	0.1935	93.55%	97.44%	0.0877	0.2220	92.58%

- Evaluation of CNN, ResNet50, VGG16 and InceptionV3 using Brain MRI image dataset

In this, the CNN model has an accuracy of 80.26% and a training loss of 0.3682. Figure 2 shows that the validation's accuracy was 80.97% and its loss was 0.4327. On the test set, the model yielded an accuracy of 85.16% and a loss of 0.3990. As illustrated in Figure 3(a)(b), the accuracy of the ResNet50 model is 80.65% with a loss of

0.4247 and 83.94% during training with a loss of 0.4107. It obtained an accuracy of 83.55% and a loss of 39.74% on the test set. The training loss of the VGG16 model is 0.0238 and a training accuracy of 99.93%. Test accuracy is 98.71%, test loss is 5.62%, and during validation, the loss is 0.0864 with an accuracy of 99.03%.

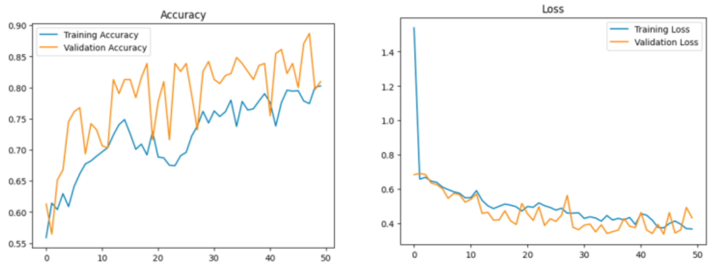
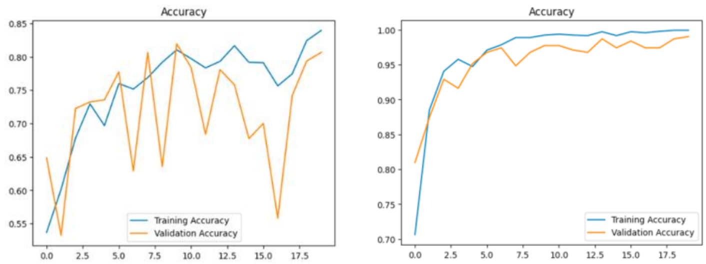


Fig 2: The Results of the CNN model.



(a) (b)

Fig 3 (a)(b): Training and validation accuracy of ResNet50 and VGG16 model.

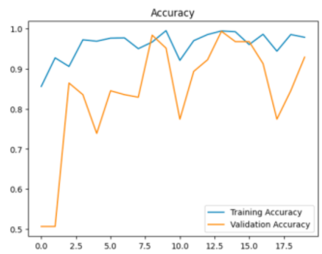


Fig 4: Validation and training accuracy of InceptionV3 model.

The InceptionV3 model has a 97.53% training accuracy and a 0.0912 training loss, as demonstrated in Figure 4. The accuracy is 92.90% and the loss is 0.4083 on the validation set. 90.32% accuracy and 37.58% loss were attained in the test set.

- Evaluation of hybrid model (ResNet50, VGG16, InceptionV3) using Brain MRI image

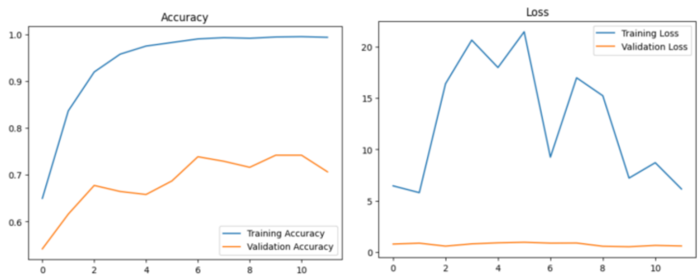


Fig 5: Training and validation loss, hybrid model accuracy (ResNet50, VGG16, InceptionV3).

The accuracy of training is 0.9960 and the loss of training is 0.2796 demonstrating the model's remarkable performance on the information used to train it, attaining nearly flawless accuracy and minimal error. On fresh, raw data, the model appears to perform worse, as indicated by the validation accuracy of 0.7065 and validation loss of 0.598. As shown in Figure 5, the model's accuracy of training is higher than its accuracy of validation even though its loss of training is less than its loss of validation. The test loss is 0.5113 and the accuracy is 75.16%.

- Evaluation of hybrid model (Xception, NASNetMobile, InceptionResNetV2) using Brain MRI image

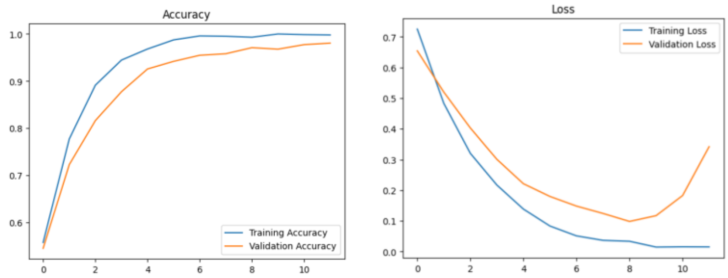


Fig 6: Validation and training accuracy and loss of hybrid model (Xception, NASNetMobile, InceptionResNetV2).

Using Xception, NASNetMobile, and InceptionResNetV2, the hybrid model demonstrated excellent performance on the training data, exhibiting high accuracy and minimal mistakes. The hybrid model, which makes use of the InceptionResNetV2, Xception, and NASNetMobile, attains an accuracy of 0.9972 and a training loss of 0.0152. With the validation accuracy being 0.9806 and the validation loss being 0.3419, the training loss is less than the validation loss, and the training accuracy is greater than the validation accuracy. Test accuracy is 98.06% and test loss is 0.3058.

- Evaluation of hybrid model (EfficientNet, DenseNet121, MobileNetV2) using Brain MRI image

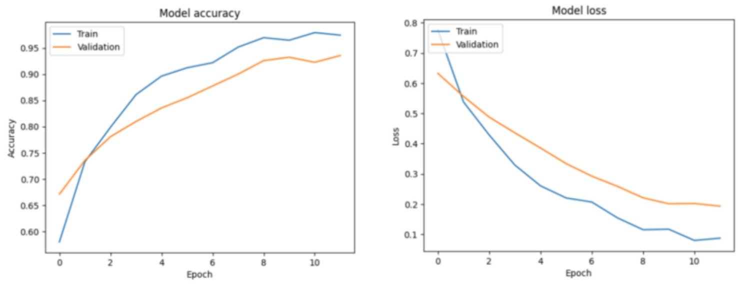


Fig 7: The Results of hybrid model (EfficientNet, DenseNet121, MobileNetV2).

The accuracy of the training exceeds that of the validation, as seen in Figure 7. loss of training is 0.0877, the accuracy of training is 0.9744, the loss of validation is 0.1935, and the accuracy of validation is 0.9355 were all achieved using the hybrid model (EfficientNet, DenseNet121, and MobileNetV2). The test loss is 0.2220 and the accuracy is 92.58%.

2) Evaluation of various models using (Br35H: Brain Tumor Detection 2020) datasets

The Br35H dataset is used to evaluate various models. 1500 patients without tumors and 1500 patients with tumors are contained in the dataset.

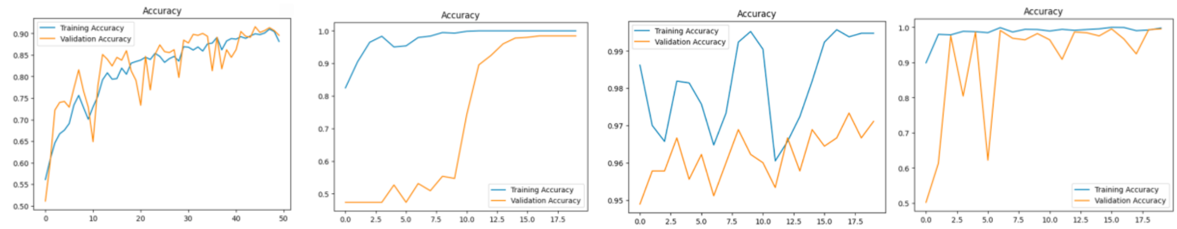
Table 4: Performance of various models using Brain MRI image dataset.

Models	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**	**Test Accuracy**	**Test Loss**
CNN	88.68%	0.2633	89.56%	0.2390	92.44%	0.2536
ResNet50	100%	1.1516	99.44%	0.0820	98.89%	0.0199
VGG16	99.74%	0.0110	97.11%	0.1295	98.71%	0.0562
InceptionV3	99.80%	0.0100	99.56%	0.0191	99.78%	0.0057
Hybrid model (ResNet50, VGG16, InceptionV3)	100%	0.0019	99.44%	0.298	91.94%	0.2330
Hybrid model (Xception, NASNetMobile, InceptionResNetV2)	98.52%	0.0472	99.39%	0.4095	98.42%	0.0631
Hybrid model (EfficientNet, DenseNet121, MobileNetV2)	99.87%	0.0141	98.45%	1.9892	93.23%	0.2356

Table 4 hybrid models that integrate MobileNetV2, DenseNet121, and EfficientNet. It demonstrates that while the InceptionV3 and ResNet50 models perform differently, each of them attains high accuracy and low loss across training, validation, and test sets. Hybrid models can overfit, as shown by higher test and validation losses, even if they usually have excellent accuracy of training.

- Evaluation of CNN, ResNet50, VGG16 and InceptionV3 using Br35H dataset

The accuracy of CNN, ResNet50, VGG16, and InceptionV3 models' training and validation are displayed in the figure below.



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

Fig 8 (a)(b)(c)(d): Training and validation accuracy of (a)CNN, (b) ResNet50, (c) VGG16 and (d) InceptionV3 model

Figure 8 demonstrates that the CNN model demonstrated strong adaptability with a test accuracy of 92.44% following 88.68% accuracy during training and 89.56% accuracy during validation. With 100% accuracy, the ResNet50 model showed perfect training performance. It also performed effectively in validation (99.44%) and testing (98.89%). The VGG16 model showed a high degree of accuracy in testing (98.71%), validation (97.11%), and training (99.74%). InceptionV3 outperformed all other models across all datasets, with training accuracy of 99.80%, validation accuracy of 99.56%, and test accuracy of 99.78%.

- Evaluation of hybrid model 1 (ResNet50, VGG16, InceptionV3) using Br35H dataset

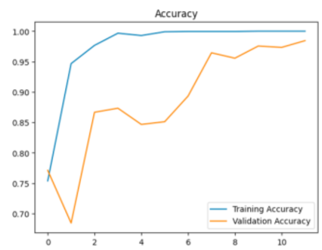


Fig 9: Accuracy of the hybrid model (InceptionV3, VGG16, and ResNet50).

The hybrid model, which combined ResNet50, VGG16, and InceptionV3, achieved little training loss and 100% accuracy. On the validation data, it performed nearly equally well, with an accuracy of 99.44% and a slightly higher loss. Test results showed a little decrease in performance, with accuracy lowering to 91.94% and loss increasing.

- Evaluation of hybrid model (Xception, NASNetMobile, InceptionResNetV2) using Br35H dataset

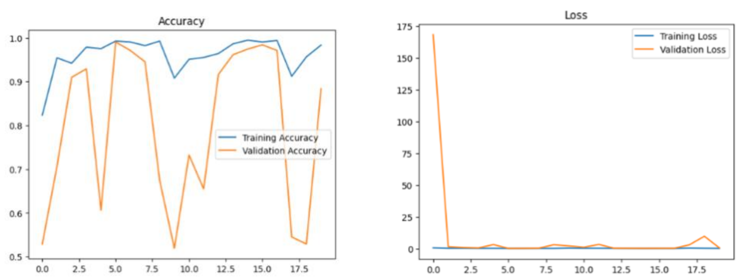


Fig 10: accuracy and loss of the hybrid model (Xception, NASNetMobile, InceptionResNetV2)

The hybrid model had a low training loss of 0.0472 and a high training accuracy of 98.52%., combining InceptionResNetV2, Xception, and NASNetMobile. A higher validation loss of 0.4095 indicated a minor overfitting issue, even with a high validation accuracy of 99.39%. With a 98.42% accuracy rate on the test set, the model is performing effectively.

- Evaluation of hybrid model (EfficientNet, DenseNet121, MobileNetV2) using Br35H dataset

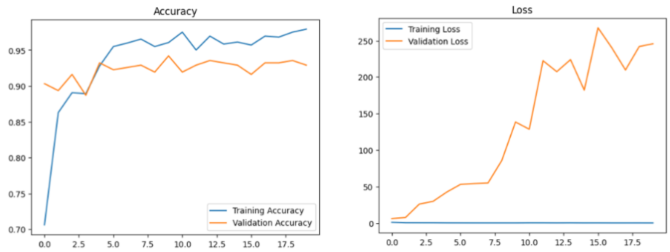


Fig 11: Loss of the hybrid model (EfficientNet, DenseNet121, MobileNetV2)

The model demonstrated exceptional performance on the training data, with a low loss of 0.0141 and a high accuracy of 99.87%. With a greater validation loss of 1.9892 and an accuracy of 98.45%, it performed somewhat worse on the validation data, indicating overfitting. It continued to perform well on test data, with an accuracy of 93.23%.

3) Evaluation of various models using (BraTS2020) datasets

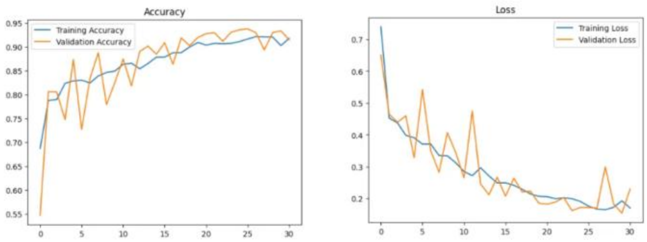
BraTS has consistently concentrated on assessing innovative methods for brain tumor segmentation in multimodal magnetic resonance imaging (MRI) data. The BraTS dataset is in RGBA format, so they are converting the 3D images to 2D to apply the models. Various models are evaluated using the BraTS dataset as shown in Table 5.

Table 5: Performance of various models using the BraTS dataset.

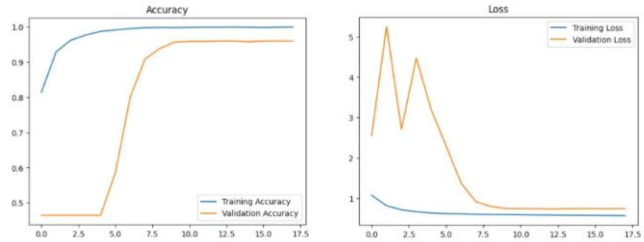
Models	**Validation Loss**	**Validation Accuracy**	**Training Accuracy**	**Training Loss**	**Test Accuracy**
CNN	0.2305	91.47%	90.48%	0.1832	93.27%
ResNet50	0.7405	95.99%	99.99%	0.5704	96.29%
VGG16	0.1747	93.18%	94%	0.1496	90.46%
InceptionV3	0.2253	93.78%	99.37%	0.0231	93.27%
Hybrid model (ResNet50, VGG16, InceptionV3)	0.0812	96.80%	98.02%	0.0452	93.60%
Hybrid model (Xception, NASNetMobile, InceptionResNetV2)	148.3094	88%	97.44%	0.0635	89.60%
Hybrid model (EfficientNet, DenseNet121, MobileNetV2)	0.2537	90.40%	86.04%	0.2642	93.60%

This study evaluates various models for detecting brain tumors. ResNet50 achieves 95.99% validation accuracy and 96.29% test accuracy. VGG16 improves test accuracy to up to 90.46% while achieving a low validation loss of 0.1747. With the lowest validation loss (0.0812), maximum validation accuracy (96.80%), and good test accuracy (93.60%), the hybrid model that integrates ResNet50, VGG16, and InceptionV3 is the best model which gives the highest detection accuracy.

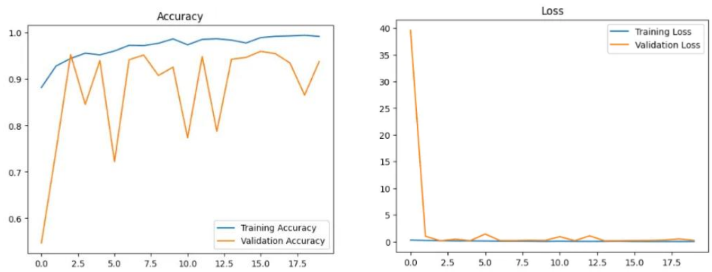
- Evaluation of CNN, ResNet50, VGG16 and InceptionV3 using BraTS dataset



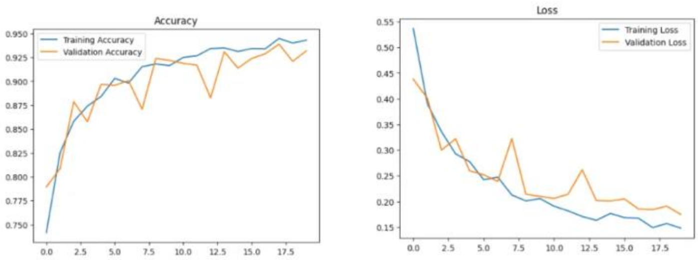
(a) The results of the CNN model.



(b) The Results of the ResNet50 model.



(c) The Results of the InceptionV3 model.



(d) The Results of the VGG16 model.

Fig 12 (a)(b)(c)(d): The outcomes of the InceptionV3, CNN, ResNet50, and VGG16 models using BraTS dataset

The CNN-based model has high performance in the diagnosis of tumor brain with a 90.48% accuracy for training and 91.47% for validation, with some loss value. The test value is a high of 93.27%, indicating great robustness in performance cross-datasets. The highest performing was the ResNet50 with a training performance of 99.99% and a test at 96.29% with no significant overfitting due to its relatively low values in training losses and validations of 0.5704 and 0.7405, respectively. This helped ensure stability in learning by having an accuracy value of 1.0e-06 on new data for identifying tumors. InceptionV3 performed quite well on both tests, achieving 99.37%, training loss of 0.0231, and validation scores of roughly 93.78%. In this study, good results of 93.27% have also been discovered when testing the case on other different datasets, thus solidifying the generalizability element of this model. With a low loss value of 0.1496, the VGG16 model obtained a 94.00% training accuracy. Its validation accuracy was 93.18%, with a slightly higher validation loss of 0.1747. With a test accuracy of 90.46%, it may have clinical utility in the categorization of brain tumors across various datasets. These findings demonstrate the superior learning capabilities of the proposed hybrid model and its efficacy in enhancing the accuracy level of brain tumor diagnosis.

- Evaluation of hybrid model 1 (ResNet, VGG, and Inceptionv3) using the BraTS dataset

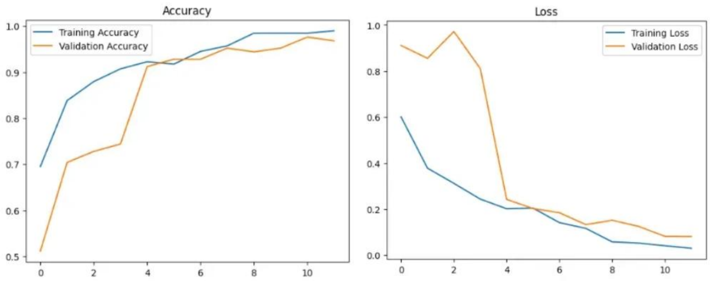


Fig 13: Accuracy and loss of hybrid model 1 (ResNet, VGG, and Inceptionv3) using the BraTS dataset

The training loss is 0.0452, and the model successfully learned with a training accuracy of 98.02%. Its accuracy with a loss value of 0.0812 after 96.80% validation points to issues with unidentified information. The accuracy is 93.60%, which makes it a strong and reliable generalization tool. These findings collectively suggest a high-performance model suitable for clinical use in brain tumor detection.

- Evaluation of hybrid model 2 (Xception, NASNetMobile, InceptionResNet) using the BraTS dataset

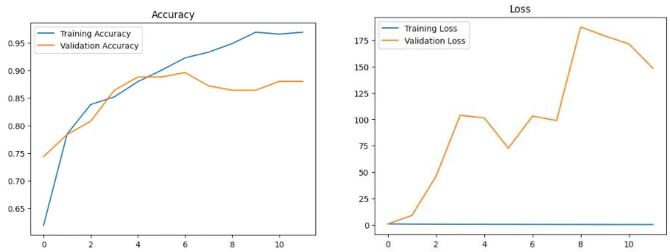


Fig 14: Accuracy and loss of hybrid model 2 (Xception, NASNetMobile, InceptionResNet) using the BraTS dataset

The hybrid model 2 (Xception, NASNetMobile, InceptionResNet) obtained a training accuracy of 97.44% with a low training loss of 0.0635, which indicated excellent performance on the training data. However, validation accuracy was 88.00% with a high validation loss of 148.3094, which indicates that the model may be overfitting. Test accuracy was 89.60%, which indicates that the model works well with new data. This further establishes that the model has great potential for the effective detection of brain tumors while ensuring that it has reasonable accuracy in the validation and testing phases.

- Evaluation of hybrid model 3 (EfficientNet, DenseNet121, MobileNetV2) using the BraTS dataset

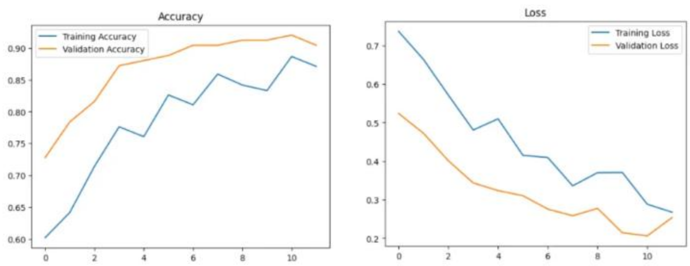


Fig 15: Accuracy and loss of hybrid model 3 (EfficientNet, DenseNet121, MobileNetV2) using the BraTS dataset

The best training accuracy of 86.04% against a training loss of 0.2642 is demonstrated in this work for hybrid deep learning models that efficiently classify brain cancers. The test accuracy is 93.60%, demonstrating strong real-world performance, and further validation accuracy is 90.40%, demonstrating appropriate generalization to new data. These measurements demonstrate the hybrid model's improved diagnostic precision and dependability in medical applications. The Br35H and BraTS databases provided the data for these investigations. VGG16 achieved the maximum training accuracy of 99.93% using brain MRI data, with a loss of 0.0238. The test accuracy for InceptionV3 was 99.78%. Although hybrid models were excellent, they overfitted the data, particularly when significant validation and test losses were involved. The findings show that these models have the potential to enhance brain tumor diagnosis.

DISCUSSION

The study demonstrates that hybrid models consistently outperform individual models in detecting brain cancers across all datasets, indicating high test accuracy and low loss. The hybrid models Xception NASNetMobile and InceptionResNetV2 have a 98.06% test accuracy in the Brain MRI dataset compared to the accuracy and stability of the corresponding individual models. To detect tumors, hybrid models appear to accurately capture complex MRI data. In comparison to its equivalents, the hybrid models which incorporate the ResNet50, VGG16, and InceptionV3 achieved 100% accuracy on the training dataset and up to 99.44% on the validation dataset while avoiding overfitting. The BraTS2020 demonstrated excellent accuracy during testing on this highly difficult multimodal dataset, with a hybrid model consisting of EfficientNet, DenseNet121, and MobileNetV2 scoring up to 98.45%, despite having a significantly larger validation loss value. Since hybrid models balanced feature extraction from complementary architectures toward improved generalization and higher diagnostic accuracy, they were usually reliable for use in healthcare.

CONCLUSION

Across many datasets, the current study showed that hybrid deep learning models significantly outperformed other models to increase brain tumor accuracy identification. The results also demonstrated that combining multiple types of architectures, such as ResNet50, VGG16, and InceptionV3, greatly improved performance because the hybrid model had the minimum validation loss and the maximum validation accuracy. Despite the high efficiency of the VGG16 and InceptionV3 individual models, the hybrid technique exhibits a greater variety of features, increasing detection accuracy and decreasing overfitting. The significance and applicability of model integration for medical imaging optimization are emphasized, as are encouraging possibilities for further research. The scope of the research is further optimised by implementing techniques such as regularization, data augmentation, fine-tuning, and making a hybrid deep learning model generalize better. The variety in the dataset and some applications in real-time can lead to robustness for these models. These hybrid models have the potential to become a valuable medical tool with improved accuracy, dependability, and efficiency in identifying brain tumors, thus enhancing the health of patients.

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