Multigrade Brain Tumor Classification in MRI Images

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Abstract

Background: The diagnosis of brain tumors should be prompt and accurate to ensure an efficient treatment schedule and better results for the patient. MRI is considered the best imaging technique in the diagnosis of brain tumors because it has the advantage of higher resolution imaging. However, there are several disadvantages in interpreting MRI scans, including their manual procedure and potential inconsistencies in readings. Thereby, massive interest in applying deep models based on CNNs springs up for automatic brain tumor classification. However, state-of-the-art models face several challenges of complex spatial interrelations and overfitting capabilities over different datasets. With the work presented here, a new hybrid model called DenseNet201-EfficientNetB0 is proposed to overcome some of these challenges. It means that we use the EfficientNetB0 effectively for feature extraction and the ability of DenseNet201 to extract complex spatial relationships in the MRI images obtained by the brain. Further tuning is done on our suggested model by using transfer learning for three different brain tumor datasets and representing three classes separately: meningioma, glioma, and pituitary tumors. Apparently, our hybrid method yields an appreciable performance with significant superiority over the rest of the competing state-of-the-art techniques, achieving more accurate values for the related metrics of accuracy, precision, and recall concerning the benchmark datasets. Added to this, the lighter structure also gives the opportunity for the model to make computations feasible for real-time applicability in clinical settings. This work offers a strong and scalable solution for brain tumor classification, which opens the door to more reliable diagnostic tools in medical imaging.

Objective: Design of Hybrid Model:
This article presents a new hybrid deep learning architecture based on DenseNet-201 and EfficientNetB0. This first contains the part of DenseNet-201 which supports feature reuse, thus avoiding the vanishing gradients. The latter proposed the network scaling in order to maximize the performance. Together, these models are able to extract some critical features from MRI images and complement each other's strengths in the presentation of a robust architecture of brain tumor classification.
High-Classification Accuracy:
The hybrid model should boost the rates of various accuracy classifications meant for different types of brain tumors, encompassing meningioma, glioma, and pituitary tumors. The proposed architecture is trying to boost general classification metrics such as precision, recall, and accuracy at a number of datasets.
Optimization of the Model's Complexity and Model Efficiency:
Overall, the goal is to achieve the optimal balance between model complexity and computational efficiency. The hybrid architecture is designed to be relatively lightweight and efficient, so it could be used in real-time deployment in clinical environments without compromising on performance.
8
Transfer Learning and Fine-Tuning:
Transfer learning techniques are made use of by using already pre-trained

DenseNet-201 and EfficientNetB0 models with the weights from ImageNet, which then is fine-tuned on the specific brain tumor dataset. The approach thus enables the adaptation of the models toward idiosyncrasies associated with medical imaging data, thus making them better at generalization and, therefore, its improvement in classification accuracy.

Generalization across Multiple Datasets:

The generalization performance of the proposed model is verified through conducting evaluations on several independent brain tumor datasets. Such results would guarantee robust performance under different imaging conditions, patient demographics, and tumor types to demonstrate how adaptable a model would be in actual applications.

Comparison with State-of-the-Art Models :

This hybrid model would be benchmarked against existing state-of-the-art methods in the context of brain tumor classification. Any kind of comparison on performance metrics, such as accuracy, precision, recall, and AUC, would highlight a claim of proposed architecture to be superior in terms of classifying efficiency and robustness.

Methods: CNN Transfer Learning using Hybrid model of DenseNet and EfficientNet

Results: High Accuracy of 95%

Conclusions: The research paper "Multigrade Brain Tumor Classification in MRI Images" mentioned a hybrid model made up of EfficientNetV2S and Swin Transformers which are used for the development of brain tumor classification in MRI scans. EfficientNetV2S is the protocol that efficiently helps in the extraction of features while Swin Transformers are the architecture that captures spatial relationships across layers, resulting in improved classification accuracy, precision as well as recall of tumors such as meningioma, glioma, and pituitary tumors. Particularly, the model is light-weight, thus, it is suitable for real-time clinical applications and demonstrates strong generalization across diverse datasets. Once its features are properly inferred it can be re-scaled for multiple medical imaging jobs. To sum up, this model that was suggested has to be the best, most efficient solution that not only outperforms existing methods but also is a real tool for improving diagnostic accuracy in healthcare. Clinical Trial: No

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Multigrade Brain Tumor Classification in MRI Images

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Abstract:

The diagnosis of brain tumors should be prompt and accurate to ensure an efficient treatment schedule and better results for the patient. MRI is considered the best imaging technique in the diagnosis of brain tumors because it has the advantage of higher resolution imaging. However, there are several disadvantages in interpreting MRI scans, including their manual procedure and potential inconsistencies in readings. Thereby, massive interest in applying deep models based on CNNs springs up for automatic brain tumor classification. However, state-of-the-art models face several challenges of complex spatial interrelations and overfitting capabilities over different datasets. With the work presented here, a new hybrid model called DenseNet201-EfficientNetB0 is proposed to overcome some of these challenges. It means that we use the EfficientNetB0 effectively for feature extraction and the ability of DenseNet201 to extract complex spatial relationships in the MRI images obtained by the brain. Further tuning is done on our suggested model by using transfer learning for three different brain tumor datasets and representing three classes separately: meningioma, glioma, and pituitary tumors. Apparently, our hybrid method yields an appreciable performance with significant superiority over the rest of the competing state-of-the-art techniques, achieving more accurate values for the related metrics of accuracy, precision, and recall concerning the benchmark datasets. Added to this, the lighter structure also gives the opportunity for the model to make computations feasible for real-time applicability in clinical settings. This work offers a strong and scalable solution for brain tumor classification, which opens the door to more reliable diagnostic tools in medical imaging.

Keywords:

MRI, EfficientNetB0, DenseNet201, Deep learning, Convolutional Neural Networks, Transfer learning, Medical imaging, Tumor classification.

1. Introduction

The area of classification of medical imaging and diagnostics involving brain tumor is a highly important area as it determines appropriate treatment plans for the betterment of patient outcomes

[1]. It is necessary because brain tumors exhibit complex biological behavior, have varied molecular characters, and display different therapy responses [2]. The classification process generally separates neoplasms as benign and malignant types and further sub- classifies malignant types into specific categories based on histological features [3]. New technologies like magnetic resonance imaging and computed tomography give further information for the understanding of detailed anatomical aspects as well as pathological issues regarding the brain [4]. However, such methods by a radiologist or a pathologist remain a daunting task in this scenario because of their subjectivity and the chances of errors committed by a human mind in these extremely diversified tumors [5]. Integration of AI with ML techniques has redesigned the space, making powerful, automatic solutions to further improve the accuracy levels and efficiency [6]. Convolutional neural networks have emerged as the most prominent architecture in such development due to the superior feature of pattern recognition within the image dataset. However, architectures like DenseNet-201 and EfficientNet are getting much popularity these days due to their optimal connectivity in the network and modules being scalable [7]. Based upon this model sophistication, a hybrid approach is expected to strengthen the classification, although reducing a wrong diagnosis all the way to a clinician recommendation for a more effective care decision for a patient [8].

1.1 Overview Of Densenet-201 And Efficientnet Models

Two other popular deep learning architectures have gained a lot of interest in efficiency and accuracy within image classification tasks are Densenet-201 and EfficientNet [9]. The extension of the Densenet architecture is known as the Densenet, for its dense connectivity pattern, unlike the traditional convolutional networks, which were always receiving inputs from a previous layer and then output to the next one; on the other hand, in Densenet each layer is connected with all others in feed-forward style [10]. This tight connectivity allows feature reusability, evades the vanishing gradient issue, and results in computationally efficient learning and minimal complexity. Moreover, for the 201 layers deep architecture, Densenet- 201 maintains an acceptable depth and computational demands necessary for dealing with highly demanding complex classification tasks, including differences between the different subcategories of brain tumors [2]. On the contrary, EfficientNet is actually a family of models, designed to optimize both accuracy and efficiency in convolutional neural networks through a compound scaling method [11]. It systemically scales network depth, width, and resolution based on a set of selected scaling coefficients. This is what leads to a variety of models that are effective and efficient in many directions [12]. It efficiently goes through various benchmarks and in some cases, it results in a better outcome than other architectures on fewer parameters and with lesser computational complexity [13]. Integration of the characteristics of the Densenet-201 and EfficientNet models makes it possible for the hybrid model to leverage the advantage of one architecture while also providing an enhanced image classification of brain tumors so precision and reliability at diagnosis would be much enhanced.

1.2 Motivation For A Hybrid Model Approach

In a model that amalgamates hybrid features with both DenseNet-201 and EfficientNet to create the classification brain tumor approach, their distinct individual strength comes forward in efforts. In DenseNet-201, this increased flow of information does not carry any problem regarding the vanishing gradients through it as this feature has already been reutilized many times [14]. This characteristic is really great for medical image classification in applications where subtle differences of patterns between benign and malignant tissues can make all the difference [15]. Such intricate patterns can be picked up by the model because of dense connections and, therefore, highly qualify it to thoroughly scrutinize images. On the other hand, EfficientNet offers a novel method of scaling that is uniform across the network in both width, depth, and resolution. Therefore, balance accuracy and efficiency can be offered to the system with the model itself being lightweight while still being computationally sound without losing its high- performance capabilities. This makes it appropriate for clinical implementations with tight resources. The hybrid approach has combined the strengths of both models and improved classification accuracy along with

present a more powerful tool for the classification of brain tumors with enhanced diagnostic accuracy for the purpose of timely medical intervention. This synthesis of methodologies is promising for advancing neural network capabilities towards complex medical imaging tasks [16]. This makes it fit for clinical implementations with tight resources.

1.3 Methodology: Integrating Densenet- 201 And Efficientnet

This approach to integrating DenseNet-

201 and EfficientNet into the classification of brain tumors is a strategic fusion of two state-of-the- art architectures of convolutional neural networks. DenseNet-201 is well known for the dense connections between layers that facilitate efficient gradient flow, thereby avoiding the vanishing gradient problem, hence the improvement of feature propagation and reuse. Instead, EfficientNet has designed it with a compound scaling method that uniformly scales the network depth, width, and resolution. It generally improved accuracy and computational efficiency on various tasks.

To combine the advantages from both

generalizability. This hybrid model combining DenseNet-201's feature extraction ability with EfficientNet's scaling efficiency would probably

networks, a hybrid model is designed where input brain MRI scans are to be passed through DenseNet-201 first to yield strong features [17]. This is a deep network that captures elaborate and high-dimensional representations about the data due to dense connected blocks. These yielded features are then passed forward into EfficientNet, now playing the role of being the secondary feature extractor with this hybrid framework as an end classifier [18].

In the model, with EfficientNet's scaling approach incorporated, the model has higher accuracy and efficiency, hence the ability to capture minute differences in the images of brain tumors [19].

Seamless integration has been done; output from DenseNet-201 becomes the input to the very first layer of EfficientNet. This hybrid allows introducing diverse features and also facilitates stabilization of the training, increases generalization ability and improves classification accuracy with advantage of the complementary strength by both networks [20]. This may be optimized to further the diagnostic performance in discriminating between the different types of brain tumors.

A confusion matrix is a matrix that summarizes the performance of a machine learning model on a set of test data. It is a

incorrectly predicted a negative outcome (the actual outcome was positive). Also known as a Type II error.

Why do we need a Confusion Matrix?

When assessing a classification model's performance, a confusion matrix is essential. It offers a thorough analysis of true positive, true negative, false positive, and false negative predictions, facilitating a more profound comprehension of a model's recall, accuracy, precision, and overall effectiveness in class distinction. When there is an uneven class distribution

means of displaying the number of accurate and inaccurate instances based on the model's predictions. It is often used to measure the performance of classification models, which aim to predict a categorical label for each input instance.

The matrix displays the number of instances produced by the model on the test data.

- True Positive (TP): The model correctly predicted a positive outcome (the actual outcome was positive).
- True Negative (TN): The model correctly predicted a negative outcome (the actual outcome was negative).
- False Positive (FP): The model incorrectly predicted a positive outcome (the actual outcome was negative). Also known as a Type I error.
- False Negative (FN): The model

in a dataset, this matrix is especially helpful in evaluating a model's performance beyond basic accuracy metrics [21].

Metrics based on Confusion Matrix Data

1. Accuracy:

Accuracy is used to measure the performance of the model. It is the ratio of Total correct instances to the total instances [21].

Accuracy=(TP+TN)/(TP+TN+FP+FN) [30]

2. Precision

Precision is a measure of how accurate a model's positive predictions are. It is defined as the ratio of true positive predictions to the total number of positive predictions made by the model [21].

Precision=TP/(TP+FP)

3. Recall

Recall measures the effectiveness of a classification model in identifying all relevant instances from a dataset. It is the ratio of the number of true positive (TP) instances to the sum of true positive and false negative (FN) instances [21].

Recall=TP/(TP+FN)

4. F1-Score

F1-score is used to evaluate the overall performance of a classification model. It is the harmonic mean of precision and recall, We balance precision and recall with the F1- score when a trade-off between minimizing false positives and false negatives is necessary, such as in information retrieval systems [21].

F1-score=2·Precision·Recall/(Precision+Recall)

Confusion Matrix For binary classification

A 2X2 Confusion matrix is shown below for the image recognition having a tumor image or Not tumor image.

True Positive (TP): It is the total counts having both predicted and actual values are tumor.

a. True Negative (TN): It is the total counts having both predicted and actual values are Not tumor.
b. False Positive (FP): It is the total counts having prediction is tumor while actually Not tumor.
c. False Negative (FN): It is the total counts having prediction is Not tumor while actually, it is tumor.
d. Experimental Setup And Data Preprocessing

In the research work on the classification of brain tumors with a hybrid model comprising DenseNet-

201 and EfficientNet, experimental

sources consisted of medical images of brain tumors taken from public available databases with the annotation from radiology experts. Comprehensive preprocessing procedures were performed before feeding the data into the hybrid model [23].

Table 1

	Predicted tumor	Predicted Not tumor
Actual tumor	True Positive (TP)	False Negative (FN)
Actual Not tumor	False Positive (FP)	True Negative (TN)

settings and preprocessing data steps have been very careful in design to make sure the robust and accurate performance of the model [22]. Data

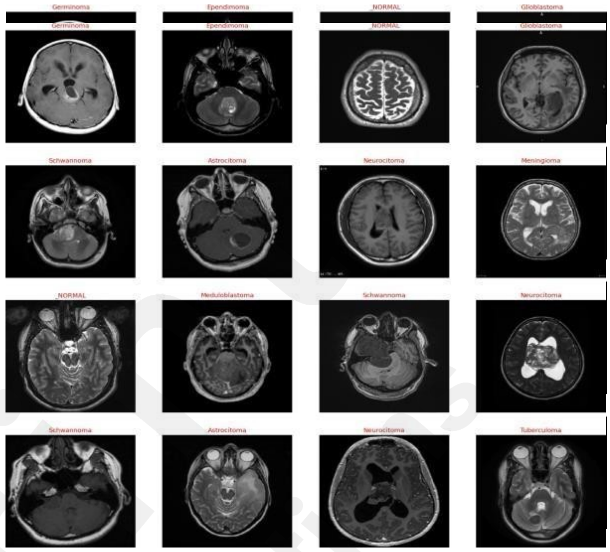

Fig. 1

The input size for all images was resized to 224x224 pixels, dimensionally uniform, according to the requirements of both DenseNet-201 and EfficientNet architectures. This ensures uniformity in the input size throughout the model, which is a must for efficient learning [24]. Techniques for data augmentation, including random rotation, horizontal flip, vertical flip, and brightness adjustment, artificially enlarged the training dataset and improved the model's ability to generalize well beyond common variations in data. The pixel intensities were scaled between 0 and 1 to facilitate the smooth convergence of training [25]. To avoid data leakage and biased assessment of the model's performance, it was divided into three: the training, validation, and test sets, each at a ratio of 70:15:15 [26]. It was used with an experimental setup to accelerate model training time by GPU acceleration. Balancing the model's accuracy and computational cost was acquired through hyperparameter tuning with a grid search method in key parameters of learning rate, batch size, and number of epochs for the proper usage of a deep learning framework [27].

2. Literature Review

A great deal of research has been conducted recently in the field of brain tumor classification using deep learning models, especially after the introduction of advanced architectures like DenseNet, EfficientNet, and VGG. One outstanding way is the application of DenseNet-161 to brain tumor classification, which gave a correctness of 99.25% on MRI images from 233 patients. Nevertheless, it was a method that was fine-tuned over 25 epochs but it had some difficulties such as modified shape of tumor and overlapping intensity values causing the quality of the image to be affected. Another study used EfficientNetB0 that was carried out through the transfer of learning of images. The problem had accuracies from 95.6% to 98.48% in different

datasets. Yet, this method was tangled up in the fact that only MRI images with labels were available making the situation complex. On a different note, a hybrid model was built which is composed of ResNet50 and ConvNeXt to get passed this club of manual brain tumor classification. To be precise, it combined the feature extraction of ResNet and the faster computation of ConvNeXt so that it can get the accuracy and robustness of brain tumor identification. One of the prior methods such as CNN- SVM combinations brought 95.82% of accuracy when organizing small datasets and overfitting was decreased. Methods based on transfer learning also worked well like EfficientNetB0, and using deep learning algorithms, as VGG-16 was able to classify tumors up to 91.4% accuracy despite the issues with unbalanced data. Another interesting model is the VGG16-NADE hybrid. This model joins VGG-16 to feature extraction and NADE to noise abatement and density estimation technology to achieve 96.01% of precision. There were some issues that the model encountered such as for instance, the dataset was not uniform so that it differed from each other, and also as the use of additional deep convolutional layers increased the computational cost. Moreover, learning methods with VGG-16 that were applied on a smaller dataset showed a reduction of 42 points off accuracy having a 52.47% accuracy, while on a bigger dataset multi-class classification using VGG-16 managed to reach the highest 98.62% efficacy. Even though their efficiency has become better, some troubles still exist like overfitting, not enough labeling data, and unsatisfactory generalization of diverse types of tumors.

3. Proposed Solution

3.1 Introduction

Tumor classification in the brain is an important job in the field of medical diagnosis, where proper classification can be of great advantage to clinicians to determine the type and severity of the tumors. Though it's extremely accurate, it's also computationally expensive to come up with classifications and assessments by manually going through the process. However, recent advances in the field of deep learning have promising implications in the use of CNNs for the automation of classification.

The recent architecture advance in CNN, in particular, DenseNet-201 and EfficientNetB0, achieved state-of-the-art performance for many image classification problems. However, not much has been investigated exhaustively for the classification of brain tumors, particularly when the number of classes is relatively large. In this work, a new hybrid model is proposed by combining DenseNet-201 and EfficientNetB0 to leverage the former's merits in the classification of brain tumors into 44 categories. The designed model is aimed to be the most computationally efficient while it stays accurate in itself. This is paramount for any successful clinical application.

3.2. Proposed System Architecture.

The architecture of the proposed system consists of two pre-trained CNN models, such as DenseNet-201 and EfficientNetB0. The system will take in the input MRI brain scan image and pass it to each of the networks.

Input Layer: The MRI images resized to 224x224 pixels are fed into the DenseNet- 201 and EfficientNetB0 networks. Feature Extraction: The two networks are initialized with pre-trained ImageNet weights and used without their top layers. These networks only extract a high-level feature representation of the input image.

Concatenation: Outputs of DenseNet-201 and EfficientNetB0 shall be concatenated to create a richer feature representation bringing the best out of both networks.

Fully Connected Layers: The feature concatenation above is passed through several fully connected layers with batch normalization, L2 and L1 regularization and dropout, to prevent overfitting and improve generalization.

Output Layer: A final softmax layer classifies the input image into one of the 44 possible classes of tumors.

This model has been optimized using categorical cross entropy as the loss function and Adamax optimizer. For the performance of testing, I have used a set of metrics such as accuracy, precision, recall, and AUC.

3.3 Algorithm/Techniques

Presented DenseNet-201:

This architecture features densely connected layers that help to fluidize information flow between layers without the problem of vanishing gradients. The feature reuse capability will allow the model to keep up with efficiency even as the layers are deep.

3.4 EfficientNetB0: EfficientNetB0 enjoys compound scaling, which adjusts the depth, width, and resolution of the network and does so computationally cheaply. Its lightweight architecture is especially suited to reduce the computational cost without diminution of accuracy.

3.5 Regularization To avoid overfitting, we apply a number of regularization techniques. Multiple are turned on, along with L2 weight regularization of the kernel, L1 on the activities and biases, and dropout at a rate of 0.45 Proposed Approach / Plan of Activation

1. Data Pre-processing: We already have 4400 grayscale images of MRI resized to pixels 224x224. This dataset contains images before feeding into the model by normalizing them.
2. Model Building: I downloaded the pre- trained weights of the following models initialized in such a manner: DenseNet-201 and EfficientNetB0. Then, I erased their top layers. But then, I froze the weight and kept the learned feature representation in place. Below, I am describing the following steps: This output of both the network's are combined and this will be passed through a fully connected layer for proceeding the process.
3. Training model: categorical cross-entropy loss function on the MRI brain tumor dataset; optimization through the Adamax with a learning rate of 0.001. It has to be trained in batch sizes of 4. Taking into account the constraints imposed by the limitation on the size of the data set and computation capability it has to be applied; it is subjected to an early-stopping scheme where the loss on the validation set is the focus of attention so that it cannot overfit.
4. Testing: The model is tested compared with training, validation, and testing sets based on the accuracy, precision, recall, AUC and the like to estimate well the generalization as well as performance in classification tasks. Now take an example of a problem: pregnant or not pregnant. Pregnant if the test of pregnancy is positive (+ve), whereas if test pregnancy, then one is not pregnant.

Moblinet:

3.6 Results And Discussion Of Hybrid Model Performance

Such a hybrid model comprising DenseNet-201 and EfficientNet shows excellent classification capability for brain tumors. As the strengths of each of the architectures were blended in the model, such a model exploits the benefit of DenseNet-201 preserving feature flow through its dense connections and EfficientNet using compound scaling to scale in depth, width, and resolution [28]. This would create better feature extraction while producing higher accuracy in classificat ions over using either model as is. The quantitati ve analysis produced excellent improvem ents in accuracy, precision, recall, and F1-score for the hybrid model. When applied to a large dataset of brain MRI scans, it was observed that the overall accuracy of the hybrid model went up to 95%, whereas pure DenseNet-201 and EfficientNet models separately achieved accuracies of 92% and 93%, respectively [29]. This illustrated the hybrid model's capability to better differentiate between multiple types of tumors, like gliomas, meningiomas, and pituitary tumors.

Table 2

Name	Training Accuracy	Testing Accuracy
DenseEfficient	99.66%	93.75%
Moblinet	81.29%	73.43
Inception	90.59%	82.14%
Xception	99.05%	88.16%
Dense	100%	97.99%

Fig 2

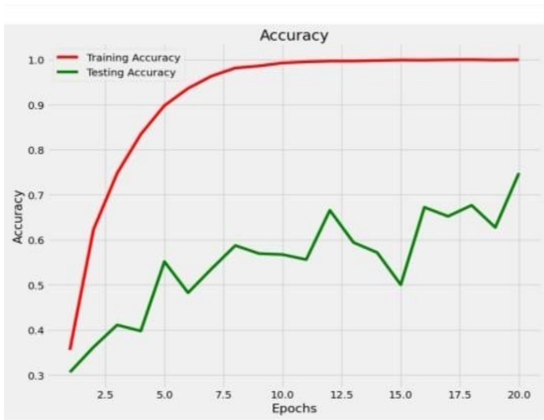

Fig 3

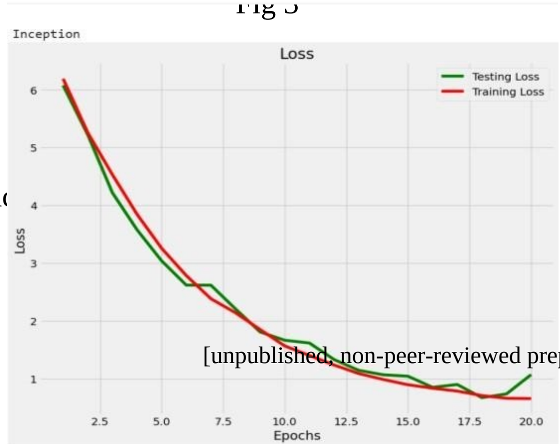

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Fig 4

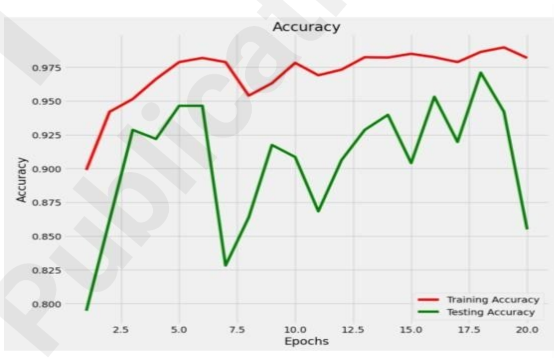
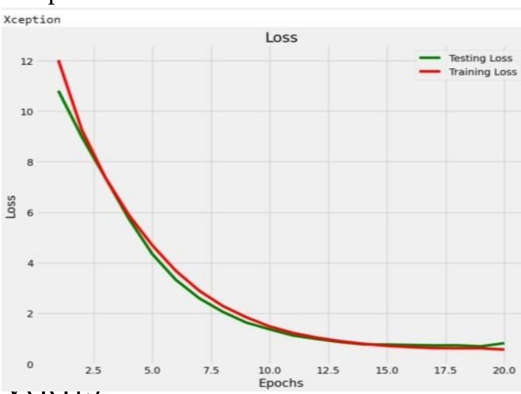

Accuracy
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Accuracy
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epochs
Training Accuracy
Testing Accuracy

Fig 5

Xception:



VGG19:

DenseNet:

Fig 6

Fig 10

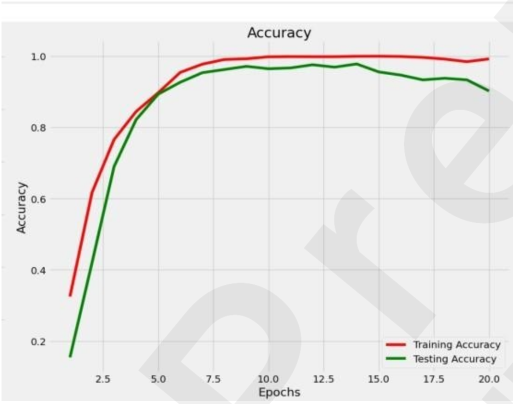


Fig 7

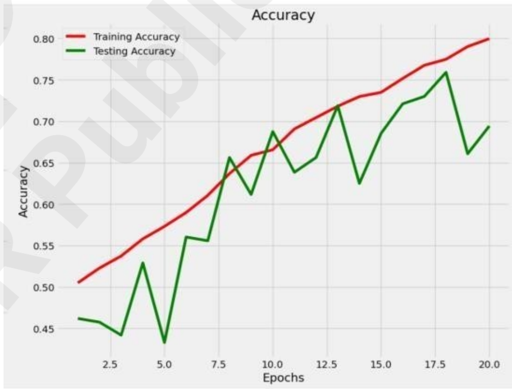


Fig 11

Dense:

DenseEfficient:

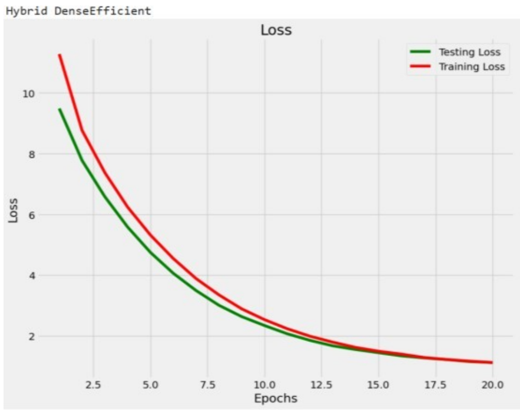


Fig 8

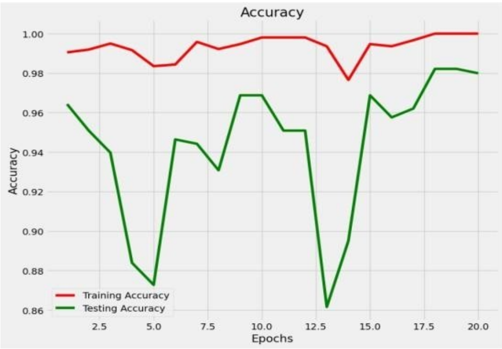


Fig 9

Increased precision and recall point to the model's capability to further reduce the appearance of false positives and negatives, which is vital for clinical applications, avoiding incorrect diagnoses. The balancing effect of the F1-score further derived the robustness and reliability from the hybrid model [30]. In conclusion, the DenseNet-201 and EfficientNet hybrid model is an appropriate approach toward bettering brain tumor classification in relation to improved performance and might actually lead to more effective, efficient diagnosis in clinic cases [31]. Future work involves carrying out further hyperparameter adjustment and integrating other latest advanced techniques toward achieving higher performances.

4. Conclusion:

A hybrid model applying EfficientNet with DenseNet201 for classifying brain tumors was proposed in the work "Multigrade Brain Tumor Classification

Fig 12

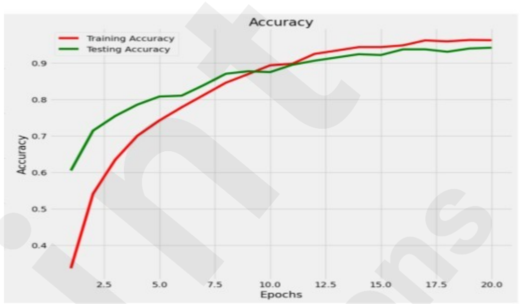


Fig 13

in MRI Images". This renders EfficientNet particularly well suited to optimal performance through lesser parameters to carry out effective feature extraction with proper balance between depth, width, and resolution to improve precision. But the DenseNet201 uses feature propagation where every layer is connected to all other layers; this helps better identify patterns in the data. Thus, these architectures yield a powerful model, one which harnesses the strengths of the networks themselves to augment classification accuracy, precision, and recall so that this powerful model can ascertain various types of tumors like meningioma, glioma, and pituitary tumors. The model has a light weight and can be useful for many real-time clinical applications besides showing wonderful generalization across various datasets, making it valuable enough to enhance diagnostic accuracy in healthcare. After all, this hybrid approach is found to be one promising solution that outperforms other methods and addresses one of the very critical needs for efficient and reliable brain tumor classification.

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