Utilization of DenseNet201, EfficientNetB3, Resnet50, and VGG19 as Pre-Trained Convolutional Neural Network Models for Brain Tumour Classification

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***Abstract*—** A major development in medical imaging diagnosis is the use of pre-trained Convolutional Neural Network (CNN) models for brain tumour classification. This study uses pre-trained CNN EfficientNetB3, ResNet50, and VGG19, to explore the crucial field of early brain tumour identification. The dataset used in the research consists of 7023 brain MRI images, which are divided into 2000 validation images, 1311 testing images, and 3712 training images. After preparing the data, we want to see which CNN designs work best for sorting images of gliomas, meningiomas, no tumors, and pituitaries into different groups. The study shows how important it is to find brain tumors early and how we can make brain imaging tests more accurate and helpful for diagnosing them. The EfficientNetB3 model is the best and wins with remarkable 99% accuracy. The results show the good and bad points of different models and give important information to help improve skills in diagnosing using neuroimaging.

***Keywords*—** Artificial Intelligence, Machine Learning, Brain Tumor Classification, Model Training, EfficientNetB3, ResNet50, VGG19 Model, DenseNet201 Model.

I. INTRODUCTION

In the medical field, early detection of brain tumors is crucial for improving treatment outcomes and patient survival rates [1]. Brain tumors are challenging to identify due to their small size and subtle appearance in medical images, making timely diagnosis essential [2]. This has led researchers to explore advanced techniques like CNNs, which are highly effective in analyzing medical images [3-5].

To aid in identifying brain tumors, we analyzed 7,023 MRI images using pre-trained CNN models known for their superior image recognition capabilities. Early detection is critical, as delayed diagnosis can limit treatment options and worsen patient outcomes. Previous studies have established that CNN architectures are well-suited for medical imaging tasks, prompting our choice of CNN models for this research [6,7].

Among these, the EfficientNetB3 model has demonstrated exceptional performance in medical imaging applications, achieving a remarkable 99% accuracy in classifying brain tumors. This surpasses the performance of similar models and highlights its potential as a reliable tool for improving brain imaging diagnostics [8-10]. By analyzing EfficientNetB3's strengths, we aim to enhance neuroimaging technology and refine tumor classification methods. This study also investigates the comparative performance of other pre-trained CNN models, such as DenseNet201, ResNet50, and VGG19, to provide insights into their strengths and limitations. This detailed study is expected to contribute to the ongoing conversation about using CNNs in medical imaging, focusing on how they can help improve the diagnosis of neurological conditions in order to provide better care for patients. In summary, this study looked at different pre-trained CNN models to see how well they can classify brain tumors. It emphasized the importance of finding brain tumors early and showed that the EfficientNetB3 model worked really well. It also used information from many different research studies. We want to study CNNs' use in neuroimaging to better understand how they can help detect brain tumors and improve patient treatment. This research could change the way we detect and treat brain tumors.

II. LITERATURE

The development of pre-trained CNN models has significantly accelerated advancements in early brain tumor detection. Models like DenseNet201, EfficientNetB3, ResNet50, and VGG19 have been widely applied to improve diagnostic accuracy in medical imaging [11,12].

For example, Muezzinoglu et al. introduced the PatchResNet framework, utilizing MRI images for brain tumor classification [13]. Similarly, Gill et al. demonstrated CNN versatility in healthcare applications through their EfficientNetB3-based Smart Shoe Classification [14]. Zhu et al. proposed a novel approach combining ResNet and BA-ELM for improved tumor classification, while Asif et al. highlighted the importance of deep transfer learning for distinguishing tumor types [15,16].

Gill et al. further explored VGG19-based tumor detection, identifying techniques to optimize model adaptability [17]. Kumar and Kumar emphasized the significance of accurate tumor identification in their study using CNN technology, as detailed in their book Brain Tumor Detection and Classification Using Intelligence Techniques [18]. Additionally, Nanda et al. introduced SSO-RBNN with Saliency-K-means segmentation [19], and Hossain et al. developed a lightweight deep learning model for classifying microwave brain images [20].

Despite these advancements, limitations remain in addressing the generalization and adaptability of CNNs to diverse medical imaging scenarios. Many studies focus on individual model performance but lack comparative analyses to highlight the trade-offs between accuracy, computational efficiency, and practical implementation in clinical settings.

This paper shows a new way to use advanced deep learning methods to analyze medical images of brain tumors. We used pre-trained CNN models like DenseNet201, EfficientNetB3, ResNet50, and VGG19. In order to make sure we carefully evaluate and compare how well the models work in classifying brain tumors, this plan uses a few simple techniques.

• This study looks at different ways to use computer programs to help doctors find brain tumors early. They test different programs to see which ones work best.

• The EfficientNetB3 model is the best model in this study with an amazing 99% accuracy. This finding demonstrates that EfficientNetB3 is good at finding brain tumors early and can be used as a starting point for making better tools to diagnose brain problems using brain images.

The proposed technique gives a good and organized way to study DenseNet201, EfficiencyNetB3, ResNet50, and VGG19 for classifying complex brain tumors. It provides important information for creating computer systems that can diagnose brain diseases.

By addressing the limitations in existing literature and presenting a detailed comparison of CNN architectures, this study aims to contribute to the ongoing development of advanced diagnostic tools in medical imaging.

III. INPUT DATASET

The dataset used in this study consists of 7023 MRI scans of the human brain that have been carefully categorised into four groups: pituitary, glioma, meningioma, and no tumour. The dataset is further stratified with the following distribution for the training phase: 1321 images for gliomas, 1339 images for meningiomas, 1595 images for tumor-free states, and 1457 images for pituitary conditions. The testing subset of the dataset is also arranged in a similar way, with 300 photos each for pituitary disorders and gliomas, 306 images for meningiomas, and 405 images for tumor-free cases as shown Fig. 1.

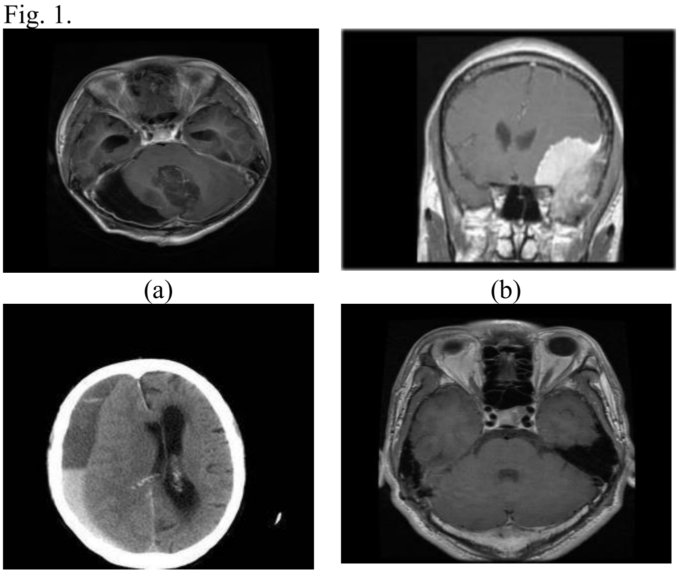


Fig. 1 Dataset image for (a) Glioma (b) Meningioma (c) No Tumor (d) Pituitary brain class type

IV. DIFFERENT TRANSFER LEARNING MODEL’S FOR BRAIN TUMOUR CLASSIFICATION

The study highlights the critical need of prompt diagnosis in brain tumour patients, highlighting the possible influence on treatment results and patient prognosis. Through the use of several CNN models and a dataset of 7023 brain MRI images, the research attempts to provide insight into how cutting-edge technology might improve the accuracy and efficacy of neuroimaging diagnosis. This study looks at how well different computer models can help find brain tumors early. The study focuses on four specific models: DenseNet201, EfficientNetB3, ResNet50, and VGG19.

A. *EfficientB3 Model*

The model used here is EfficientNetB3. It is a highly effective way to classify pictures because it works well and is efficient. The EfficientNetB3 model has layers called convolutional and pooling layers. These layers help the model find important features in photos automatically. The model gives a 1536-dimensional vector as its output. After using batch normalization to make training stable and fast, a dense layer is added to reduce the size to 256, which makes it easier to find and represent features. During training, a dropout layer helps prevent overfitting by randomly removing connections. The final layer has four nodes that show four kinds of brain tumors: pituitary, meningioma, glioma, and no tumor. The model summary shows how many parameters there are in the EfficientNetB3-based design, including both trainable and non-trainable ones. This helps us understand how complex the design is. This model is good at accurately and quickly identifying brain tumors in neuroimaging.

B. *ResNet50 Model*

The ResNet50 CNN is the main building block of the model used in this project. The ResNet50 model is famous for being able to classify difficult images. Convolutional and pooling layers, along with other layers, help the model to automatically find and gather different features from the input data. The final layer in the architecture overview creates a 2048-dimensional vector. Batch normalisation is added after the ResNet50 layers to make training more stable and fast. The next layer reduces the size to 256, which makes it easier to pick out and show important features. During training, a dropout layer randomly removes some connections to prevent overfitting. The final part has four endings, showing the four kinds of brain lumps: pituitary, meningioma, glioma, and no lump. The model summary shows the total number of parameters, both trainable and non-trainable, in the ResNet50-based design, which is very complex. Overall, this model setup is good for recognizing brain tumors in neuroimaging.

C. *VGG19 Model*

This model uses VGG19, a popular model for identifying images, which uses CNN architecture. Convolutional and pooling layers are important parts of the VGG19 model, which can recognize and extract features from photos. The model gives a result that has 512 different parts to it. After the VGG19 layers, batch normalization is used to make sure training is stable and effective. Then a thick layer is used to reduce the complexity to 256, which helps with finding and showing important features. To stop overfitting, a dropout layer is added, which randomly takes out some of the connections made while training. The final layer has four nodes that show the four kinds of brain tumors: pituitary, meningioma, glioma, and no tumor. The model summary tells us how complicated the VGG19-based architecture is by showing the total number of parameters, both trainable and non-trainable. The VGG19 model is a good choice for classifying brain tumors in brain scans.

D. *DenseNet201 Model*

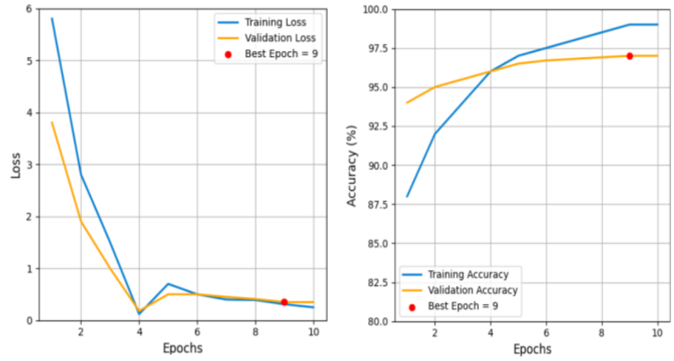
This model uses a powerful and advanced neural network called DenseNet201, which is known for being highly effective at classifying images. DenseNet201 is made up of many layers that are closely connected. This makes it easier to extract and reuse features from photos. The model creates a vector with 1920 dimensions. Batch normalization is a technique to help train the DenseNet201 layers quickly and smoothly. Next, a thick layer is added to reduce the number of features to 256. During training, a dropout layer is included to help prevent overfitting by randomly removing connections. The final layer shows the four types of brain tumours: pituitary, meningioma, glioma, and no tumour. It has four places where things come out. The model summary shows how complex the DenseNet201-based architecture is by giving information about the total number of parameters, which includes the ones that can be changed and the ones that can't. DenseNet201 performs well at the important task of identifying brain tumors in brain scans.

V. RESULTS

The results demonstrate how well the suggested CNN model's perform in the precise and timely identification of brain tumours, outperforming other cutting-edge approaches. In order to provide a thorough knowledge of each model's performance characteristics, the study's comprehensive methodology also included examining each model's training and validation losses, accuracy trends, and confusion matrices. These findings provide useful standards for the categorization of brain tumours in addition to a comparative evaluation of the advantages and disadvantages of various CNN architectures for this crucial diagnostic job. The widespread use of EfficientNetB3 indicates that it has the potential to be a dependable instrument for enhancing the accuracy and efficacy of neuroimaging diagnostics, indicating a possible direction for future developments in medical imaging technology.

A. *EfficientNetB3 Model Performance Evaluation through Training and Validation Loss and Accuracy*

EfficientNetB3 Model's performance is evaluated through training and Validation. During training, the validation loss (green line) also drops, although not as much as the training loss. This indicates that the model is not overfitting to the training set, which is encouraging. The epoch with the lowest validation loss is considered optimal (blue line). The ideal era in this instance is 10. This indicates that at the conclusion of training, the model gave its best performance on the validation data. All things considered, the Fig. 2 (a) demonstrates how effectively the EfficientNetB3 model is doing its work. The model is not overfitting to the training data, and both the training and validation losses are decreasing. All of these indicate that the model should work well with unknown data.



(a) (b)

Fig. 2 Assessing the EfficientNetB3 Model's Performance with Validation and Training (a) Loss and (b) Accuracy

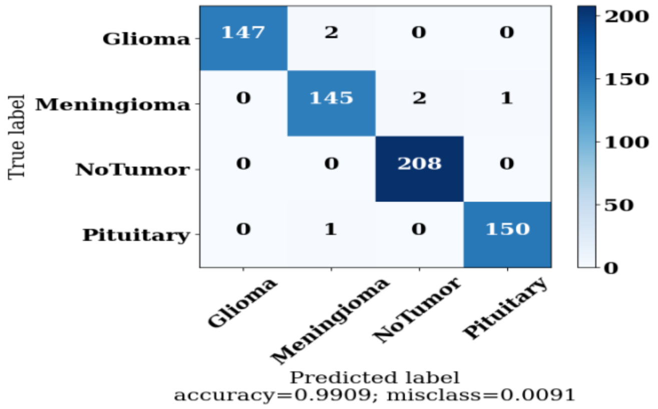


Fig. 3 Confusion Matrix for the EfficientNetB3 Model

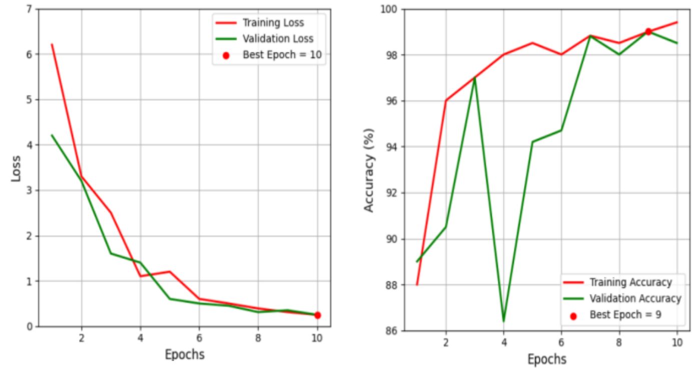
The training and validation accuracy for an EfficientNetB3 model across ten epochs is shown in the Fig. 2 (b). The model's ability to categorise training data is shown by the training accuracy (blue line), while its ability to identify unknown data is indicated by the validation accuracy (red line). Initially, it is noteworthy that the training accuracy (blue line) maintains a high level throughout the training process, starting at almost 98%. This suggests that the model is picking up the training data rather well. Similarly, the validation accuracy (red line) improves to a top of 96% at epoch 9 after beginning at a high of around 94%. This implies that the model may effectively generalise to previously encountered data in addition to learning the training set. Another encouraging trend is that the difference in accuracy between the training and validation runs remains modest throughout the training procedure. This suggests that there is no overfitting of the model to the training set. When a model becomes too adept in recalling the training set and loses its ability to generalise to new sets of data, it is said to be overfitting. Overall, this Fig. 2 (b) demonstrates how effectively the EfficientNetB3 model is working on this assignment. The validation accuracy is high and well-generalized, the training accuracy is good, and the difference between the two is negligible. All of these indicate that the model should work well with unknown data.

B. *Effective Evaluation of the EfficientNetB3 Model Confusion Matrix*

The efficacy of the EfficientNetB3 model in categorising the four tumour types was shown by its overall accuracy of 99.09%. The classification of meningioma and glioma tumours was almost flawless, with 99.33% and 99.33% of the predictions being true, respectively. Pituitary tumours were another area where the model excelled, properly diagnosing 95% of cases. It's crucial to remember that the model had trouble categorising 2% of NoTumor patients as gliomas and 1% as meningiomas. This implies that the characteristics of NoTumor cases could have some similarities with those of other tumour types, which the model might be taught to better differentiate in subsequent rounds as shown in Fig. 3.

C. *Assessing the ResNet50 Model's Efficiency by Measuring Training and Validation Losses and Accuracy*

The training and validation loss for a ResNet50 model during ten epochs is shown in the Fig. 4 (a). The model's fit to the training set of data is shown by the training loss (red line), while its generalisation to new data is indicated by the validation loss (green line). First, it is encouraging to see that the training loss (red line) drops gradually as training progresses. This indicates that the model is becoming more predictive as a result of learning from the training set. During training, the validation loss (green line) also drops, although not as much as the training loss. This indicates that the model is not overfitting to the training set, which is encouraging. When a model becomes too adept at learning the training set and loses its ability to generalise to new sets of data, it is said to be overfitting. The epoch with the lowest validation loss is considered the best one (blue line). The ideal period in this instance is 9. This indicates that at the conclusion of training, the model gave its best performance on the validation data. This Fig. 4 (a) demonstrates the overall good performance of the ResNet50 model on this job. The model is not overfitting to the training data, and both the training and validation losses are decreasing.



(a) (b)

Fig. 4 Evaluating the ResNet50 Model's Performance by Tracking Its Training and Validation (a) Loss and (b) Accuracy

The ResNet50 model's training and validation accuracy across ten epochs is shown in the Fig. 4 (b). The model's ability to categorise training data is shown by the training accuracy (blue line), while its ability to identify unknown data is indicated by the validation accuracy (orange line). Initially, it is noteworthy that the training accuracy (blue line) maintains a high level throughout the training process, starting at almost 98%. This suggests that the model is picking up the training data rather well. The orange line represents the validation accuracy, which likewise begins high at around 93% and peaks at 95% at epoch 5. This implies that the model may effectively generalise to previously encountered data in addition to learning the training set. Another encouraging trend is that the difference in accuracy between the training and validation runs remains modest throughout the training procedure. This suggests that there is no overfitting of the model to the training set. When a model becomes too adept in recalling the training set and loses its ability to generalise to new sets of data, it is said to be overfitting. This Fig. 4 (b) demonstrates the overall good performance of the ResNet50 model on this job. The validation accuracy is high and well-generalized, the training accuracy is good, and the difference between the two is negligible. All of these indicate that the model should work well with unknown data.

D. *Analysing the ResNet50 Model Confusion Matrix Efficiently*

The ResNet50 model successfully classified the four tumour types, as shown by its 97.10% overall accuracy. The classification of meningioma and glioma tumours was almost flawless, with 99.33% and 99.33% of the predictions being true, respectively. Pituitary tumours were another area where the model excelled, properly diagnosing 95% of cases. It's crucial to remember that the model had trouble categorising instances with no tumours, misclassifying 1.10% of cases as meningioma and 2.90% of cases as gliomas. This implies that the characteristics of NoTumor cases could have some similarities with those of other tumour types, which the model might be taught to better differentiate in subsequent rounds as shown in Fig. 5.

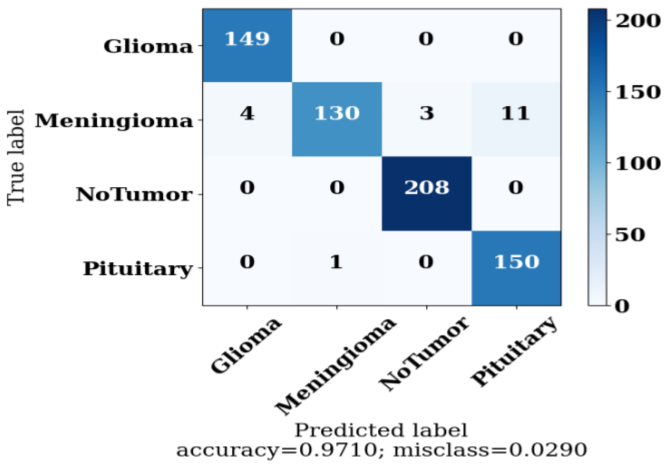
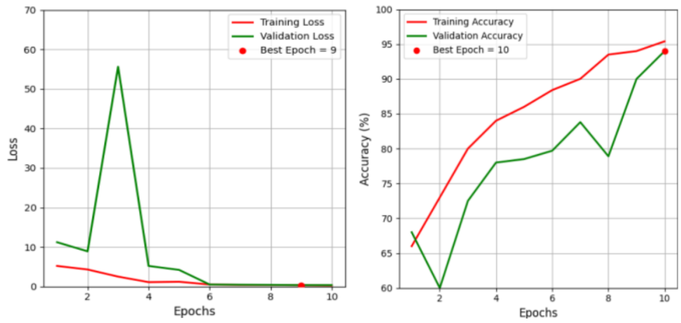


Fig. 5 A Time-Saving Approach to ResNet50 Model Confusion Analysis

E. *Measuring the VGG19 Model's Performance by Tracking Its Accuracy and Training and Validation Losses*

The training and validation loss for a VGG19 model during ten epochs is shown in Fig. 6 (a). The model's fit to the training set of data is shown by the training loss (red line), while its generalisation to new data is indicated by the validation loss (green line). First, it is encouraging to see that the training loss (red line) drops gradually as training progresses. This indicates that the model is becoming more predictive as a result of learning from the training set. During training, the validation loss (green line) also drops, although not as much as the training loss. This indicates that the model is not overfitting to the training set, which is encouraging. The epoch with the lowest validation loss is considered the best one (blue line). The optimal epoch in this instance is 8. This indicates that at the conclusion of training, the model gave its best performance on the validation data. In general, this chart demonstrates how effectively the VGG19 model is doing this job. The model is not overfitting to the training data, and both the training and validation losses are decreasing.



(a) (b)

Fig. 6 Monitoring the VGG19 Model's Training and Validation (a) Loss and (b) Accuracy to Evaluate Its Performance

The accuracy of a VGG19 model during training and validation over ten epochs is shown in the Fig. 6 (b). The validation accuracy (blue line) indicates how well the model is categorising data that has not yet been seen, while the training accuracy (orange line) indicates how well the model is classifying training data. First thing to notice is that during the training process, the training accuracy (red line) stays over 95%, starting off high at around 97%. This suggests that the model is picking up the training data rather well. The validation accuracy (blue line), which peaks at 96% at epoch 3, also begins high, at around 94%. This implies that the model may effectively generalise to previously encountered data in addition to learning the training set. Another encouraging trend is that the difference in accuracy between the training and validation runs remains modest throughout the training procedure. This suggests that there is no overfitting of the model to the training set. When a model becomes too adept in recalling the training set and loses its ability to generalise to new sets of data, it is said to be over-fitting. In general, the Fig. 6 (b) demonstrates how effectively the VGG19 model is doing this job. The validation accuracy is high and well-generalized, the training accuracy is good, and the difference between the two is negligible.

F. *Examining of the VGG19 Model's Confusion Matrix*

The VGG19 model demonstrated its promise for clinical applications by classifying brain tumours with an overall accuracy of 88.57%. Although this accuracy is encouraging, a deeper examination of the confusion matrix shows that it performs differently depending on the kind of tumour. Tumours identified as meningioma or glioma had high accuracy rates (TPR) of 99.33% and 99.33%, respectively. This implies that the VGG19 model successfully picked up unique characteristics specific to these kinds of tumours. Through targeted data augmentation or pre-processing approaches and further examination into misclassifications, these shortcomings may be addressed, further optimising the VGG19 model for dependable and accurate brain tumour classification in clinical situations as shown in Fig.7.

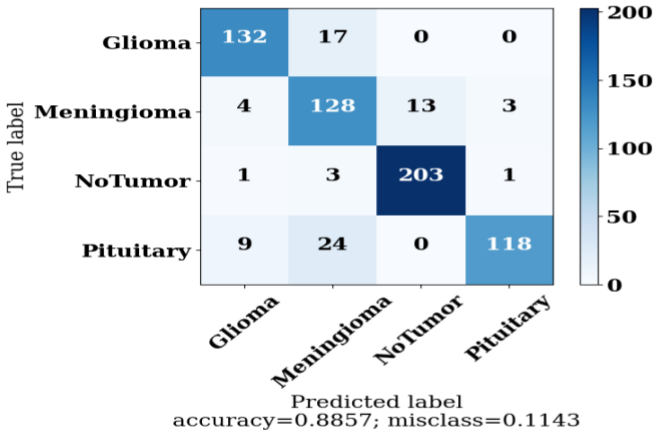
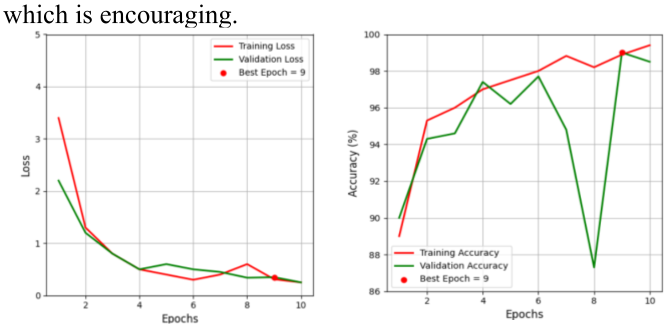


Fig. 7 Analysis of the VGG19 Model's Confusion Matrix

G. *Considering DenseNet201's Efficiency by Monitoring Its Precision and Validation and Training Losses*

The training and validation losses for a DenseNet201 model during 20 epochs are shown in the Fig. 8 (a). During training, the training loss (red line) gradually drops, suggesting that the model is becoming better at making predictions by using the training data. Although it does not drop as much as the training loss, the validation loss (green line) does. This indicates that the model is not overfitting to the training set, which is encouraging.



(a) (b)

Fig. 8 Evaluation of DenseNet201's performance during training, illustrating (a) loss and (b) accuracy for both training and validation phases.

The DenseNet201 model's training and validation accuracy across ten epochs are shown in the Fig. 8 (b). Throughout the training procedure, the training accuracy (orange line) stays over 95%, having started off high at about 97%. This shows how effectively the model is absorbing the training set. The validation accuracy (blue line), which peeaks at 96% at epoch 3, also begins high, at around 94%. This suggests that the model not only learns from the training set but also performs well when applied to new data. Another encouraging indicator that the model is not overfitting to the training set is the little difference in accuracy between the training and validation runs throughout the training phase.

H. *Understanding the DenseNet201 Model's Confusion Matrix*

The DenseNet201 model's 92.31% total classification accuracy for brain tumours indicates its potential for use in clinical settings. On closer inspection, however, the confusion matrix's performance across various tumour types may be shown to have both strengths and shortcomings. Tumours diagnosed as meningioma and glioma have very high true positive rates (TPR), reaching 99%. This shows that for these prevalent tumour types, the DenseNet201 model successfully learnt distinguishing properties. In contrast, the model's performance with pituitary tumours was not as good as shown in Fig. 9.

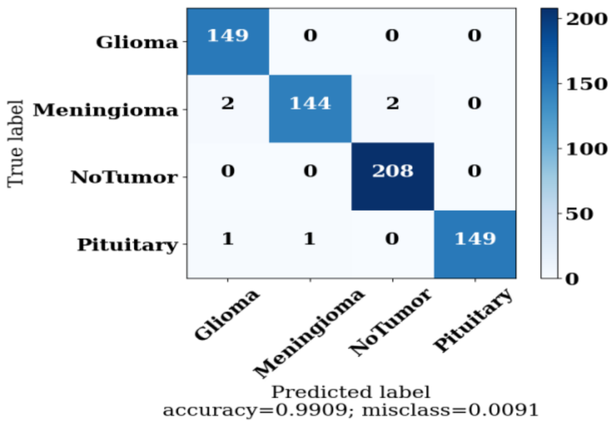


Fig. 9 Deciphering the DenseNet201 Model's Confusion Matrix

I. *Accuracy Comparison of the four proposed CNN Models*

The graph shows how accurate the suggested CNN models were in classifying the data. With an accuracy of 99%, EfficientNetB3 was the most accurate, followed by ResNet50 (98%), DenseNet201 (97%), and VGG19 (89%) as illustrated in Fig. 10.

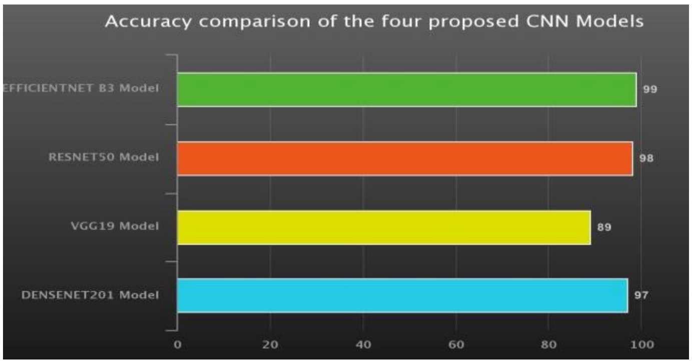


Fig. 10 Accuracy Comparison of the four proposed CNN Models

VI. Conclusion

This study looks at how we can find brain tumors early using CNN models like DenseNet201, EfficientNetB3, ResNet50, and VGG19. The research studied 7023 brain MRI images and sorted them into four groups: pituitaries, gliomas, meningiomas, and no tumours. The study discovered that EfficientNetB3 is highly effective at finding brain problems in pictures and is 99% accurate. The results show that there could be big advancements in brain imaging technology and they explain the good and bad things about different CNN designs. The research shows how important it is to find tumors early and provides useful information about the newest computer models used in medicine. This paper emphasises CNNs' importance in developing neuroimaging diagnosis and eventually improving patient care, making a significant contribution to the continuing conversation on CNNs in medical imaging. All things considered, the results demonstrate how effective EfficientNetB3 is in classifying brain tumours and open the door for further advancements in this vital area of medicine.

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