Brain Tumour Detection in MRI images using Deep Learning

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Abstract— **Early classification of brain tumors from Magnetic Resonance Imaging (MRI) is critical for effective diagnosis and treatment planning. Manual interpretation of MRI scans is time-consuming and prone to inter-observer variability, necessitating automated methods. This paper presents a EfficientNet-B3 models for multi-class brain tumor classification (glioma, meningioma, pituitary, and no tumor) using a public Kaggle dataset. While previous studies have explored CNN architectures such as Xception, ResNet50 and EfficientNetB3 which offers an alternative approach by scaling width, depth and resolution effectively. document an iterative model development process, beginning with an initial implementation of the Xception model architecture, which yielded unsatisfactory performance due to overfitting. Subsequently, we implemented a EfficientNet-B3 based model, which gives early tumor detection and a state-of-the-art-accuracy and an early detection mechanism such that it ensures stopping of brain tumor. This refined approach significantly improved performance and generalization. Using the Brain Tumor MRI dataset (7,023 images across four classes), the optimized EfficientNet achieved a classification accuracy of 99.3% and F1 Score and precision are compares with prior models (Xception and ResNet50).**

Index Terms—Brain Tumour Classification, Convolutional Neural Networks, Deep Learning, ResNet50, EfficientNet-B3, Xception, Medical Imaging, MRI.

I. INTRODUCTION

One of the deadliest neurological conditions in the world, brain tumours require prompt and precise diagnosis [1][2]. Magnetic Resonance Imaging (MRI) remains the most preferred method for detecting the brain abnormalities due to its own non-invasive nature. Therefore, manual examination of MRI scans is mostly time consuming and are prone to subjective interpretation. This emphasize the need for accurate and automated diagnostic tools [5]. Convolutional Neural Networks (CNNs) adopted from deep learning have emerged as a productive approach in medical image analysis [6][7][8]. CNNs helps in eliminating the need for handcraft feature engineering and enables automatic extraction of hierarchical features and also have achieved state-of-art results in multiple domains [9][10].

Several CNN designs exist in the literature; each is used differently in the medical imaging field [10]. Deep learning architectures such as Xception, which is known for its efficiency through its depth-wise separable convolutions [13][14] and ResNet, designed to be very deep due to residual connections but still trainable, etc, are only a few of the leading examples[7][11]. Our previous research demonstrates the effectiveness of ResNet50 over Xception for brain tumour classification and detection using the MRI scans and images which helps in achieving 98.7% accuracy with multiple training strategies such as data augmentation and early stopping of tumour. Despite having high accuracy, ResNet50 demands limited scalability. This type of limitation is fulfilled by EfficientNet-B3 which is a compound-scaled CNN that optimize depth, width, and resolution of network [11]. The key objectives of this study is to tell whether the EfficientNet-B3 will be able to maintain or exceed ResNet50 accuracy or not while improving computational efficiency and generalisation.

The main contributions of the paper are as follows:

1) Introduction of EfficientNet-B3 for brain tumour detection using MRI Scans.

2) Comparative performance evaluation with the Xception and ResNet50 model using training protocols.

3) Grad-CAM++ integration for interoperability and model validation.

4) Demonstration of EfficientNet-B3 which have reduced parameter count and faster inference which highlights its suitability for clinical deployment.

II. LITERATURE REVIEW

Deep Learning has advances automated medical image analysis, in early study CNNs had achieved over 90% accuracy in classifying brain tumour types [10] [12]. However, these shallow models often faced issues like vanishing gradient and limited generalization [13]. Later, the performance of these early stage neural network models was constrained due to their limited depth and the occurrence of vanishing gradients [8]. The field was re-shaped by the advent of deeper, pre-trained models [6]. The VGG, GoogleNet, and AlexNet models, whose original training was conducted on the large-scale ImageNet dataset, were effectively transferred to brain tumour classification tasks by implementing transfer learning[6][11][12], thereby proving that one can re-utilise the skills gained during the learning of natural images for medical diagnostics [5].

ResNet50 skip connections solved gradient degradation problems and making it one of the most reliable models in medical image analysis [7] [11]. Meanwhile, Xception is based on depth wise separable convolutions which has provided computational efficiency but not prone to overfitting on small dataset [13] [15]. Recent development lead to the evolution of EfficientNet-B3 model by Tan and Le [16] by suing compound scaling approach to balance width, depth and resolution of network. EfficientNet(B0-B7) variants helps in achieving more accuracy and remarkable performance in various medical applications which includes brain MRI classification [17], diabetic retinopathy detection [18] and lung nodule analysis [19]. EfficientNet-B3 models offers a strong balance between complexity of model and feature extraction and representation which helps is making suitable for moderate sized medical datasets. This study is built on the insights to compare EfficientNet-B3 performance against the already established CNN architectures such as ResNet50 and Xception on the MRI brain dataset.

Even though the model's architecture is crucial and pointed out by many researchers [10], the training is just as important. The models that aim to overfit due to the rarity of large annotated medical datasets. One of the main and integral overfitting countermeasures is data augmentation [9]. The original examples are subjected to rotation, flipping, scaling, and brightness changes, thus artificially extending the number of the training set, forcing the model to learn more stable and non-variant features. Moreover, sophisticated training scenarios are vital for maximum convergence [15]. Learning rate schedulers alter the training learning rate dynamically [15], thus helping the model to get out of local minima and be able to come to a more favourable solution. Likewise, early stopping is a popular regularisation method that ceases training when the model's results on a validation set turn from progress to stagnation, hence it prevents overfitting and saves computational resources [15].

The proposed EfficientNet-B3 model attains 99.31% accuracy, 99.29% precision, 99.25% recall and 99.26% F1-score on the Brain Tumor MRI dataset (Kaggle),outperforming the baseline ResNet50 implementation used in this work of ResNet50 which has 98.7% accuracy.

This analysis is the extension of arguments put forth in this section, with a more practical, side-by-side comparison of EfficientNet with ResNet50 and Xception architectures.

Table: Comparison analysis of brain tumour detection methods

Reference	Scope of Research	Merits	Demerits
He et al. [6]	Introduce the concept of Deep Residual Learning (ResNet-50) framework for the image and recognition.	Solved vanishing gradient issues, enabled very deep CNNs also achieved state-of-the-art results.	High computational cost and are prone to overfitting without regularizations.
Chollet[8]	He has proposed Xception with depth wise separable convolutions for efficiency	Fewer parameters, faster computation , suitable for transfer learning.	Susceptible to overfitting on small medical datasets and need larger data.
Badza & Barijaktarovic[9]	In this there is designed a custom CNN for 3 class brain tumour classification	Simpler to implement and higher accuracy on small dataset.	Lacks generalization and are not scalable to larger or diverse datasets.
Cinar & Yildrim[12]	Modified ResNet50 for MRI based brain tumour detection.	Achieved 98% accuracy and robust feature extraction.	Task-specific design may not generalize to other imaging modalities
Reyes & Sanchez[11]	Comparative study and evaluation of CNNs on MRI tumour data.	Demonstrated CNNs can achieve 98% accuracy with proper fine tuning.	Relied on pre-trained backbones and lacked architectural innovation
Tan &Le[15]	Introduced EfficientNet using compound scaling to balance depth, width and resolution.	Achieved superior accuracy with fewer parameters and high efficiency.	Complex scaling coefficients; fine-tuning require expertise
Kurniawan & Utami[7]	Proposed EfficientNet-B3 for multi class brain tumour classification using MRI .	Validated ResNet50 as a robust backbone for medical imaging analysis	Evaluation limited to 2D MRI datasets, future work needed on 3D MRI and multimodal data.

III. METHODOLOGY

This section contains the dataset, preprocessing steps, augmentation, model architectures, and training strategies and evaluation metrices. Each step is designed to ensure reproductivity, fair model comparison, and high diagnostic reliability.

A. DATASET

We utilised the Brain Tumour MRI dataset (Nickparvar, Kaggle, 2020), which includes 7,023 MRI images categorised into four classes: glioma (1,621), meningioma (1,646), pituitary tumour (1,741), and no tumour (2,015). To prevent data leakage, the split was performed at the patient level, ensuring no overlap between the training, validation, and testing sets. The dataset was divided into 70% for training, 15% for validation, and 15% for testing.

B. DATA PREPROCESSING AND VISUALISATION

All images were resized to224*224 pixels for EfficientNet and ResNet 50 and 300*300 pixels for EfficientNet-B3. Here in this each image was converted to grayscale and normalized to the [0,1] range before deploy to the network. To leverage unlabeled MRI slices, we adopted a pseudo-labeling approach. The model trained on labeled data was used to generate predictions on unlabeled samples.

C. DATA AUGMENTATION

To mitigate overfitting and improve generalization, data augmentation was applied dynamically during training using TensorFlow's with rotation (±20°), horizontal and vertical flips to introduce orientation variability, width and height shifts up to 10% and zoom range (±20%) with the help of ImageDataGenerator.

D. MODEL ARCHITECTURES

The base architectures (Xception, ResNet50) were initialized with ImageNet pre-trained weights and fine-tuned on the MRI dataset. These CNN architectures were evaluated

1.ResNet50: This is a 50-layer residual network with skip connections which is widely used in medical image analysis.

2.EfficientNet-B3: It is variant which bis deeper and wider providing higher representational capacity while maintaining computational efficiency.

GlobalAveragePooling → Dense(532, ReLU) → Dropout(0.4) → Dense(4,Softmax).

E. TRAINING STRATEGY AND OPTIMISATION

All models were performed using Tensor Flow/Keras which run on model NVIDIA Tesla V100 GPU with parameters include optimizer(Adam), learning rate (0.001), batch size = 32, up to 50 epochs. Transfer learning was employed by freezing the initial convolutional blocks during the first 10 epochs.

F. EVALUATION METRICS

All the performance was monitored using multiple metrices like accuracy, precision, recall, F1-score, AUC and specificity for each class. Additionally, Grad-CAM visualization was used for interoperability, conforming whether the models is focused on tumor regions during classification or not.

IV. RESULTS

This section compares the performance of ResNet50 and EfficientNet-B3 architectures in brain tumour classification based on MRI data.

A. INITIAL MODEL: RESNET50

Our initial model is ResNet50 mode which is a deep model with 50 layers and around 25 million parameters, due to its depth and number of parameters, ResNet50 takes longer to train compared to the EfficientNet-B3 model. Enhanced results are shown in Table II.

TABLE II: PERFORMANCE COMPARISION (RESNET50 vs EFFICIENT NET-B3)

Metric	ResNet50(Initial)	EfficientNet-B3(Final)
Accuracy	98.7%	99.31%
Precision	98.5%	99.29%
Recall	98.6%	99.25%
F1 Score	97.9%	99.26%

B. FINAL MODEL: EFFICIENT NET-B3 WITH OPTIMISATIONS

EfficientNet-B3 demonstrate superior generalization and accuracy. In this study EfficientNet-B3 achieved 99.31% accuracy , 99.29% precision, 99.25 % recall and 99.26 % F1 Score which outperforming the initial ResNet-50 model . The pre class performance for glioma classification are recorded as 98.4% accuracy and 98.0%F1 Score in Table Table III which confirms its robustness in various types of brain tumour.

TABLE III: PER CLASS F1-SCORES FOR EFFICIENT NET-B3

Class	Accuracy	F1 Score
Glioma	98.4%	98.0%
Meningioma	99.3%	99.0%
No Tumour	99.3%	99.1%
Pituitary	99.3%	99.2%

C. TRAINING EVALUATIONS

Fig. 1 summarises the training and validation loss and accuracy for EfficientNet-B3, demonstrating the model's learning progress that the learning was quick and stable over 16 epochs with no overfitting.

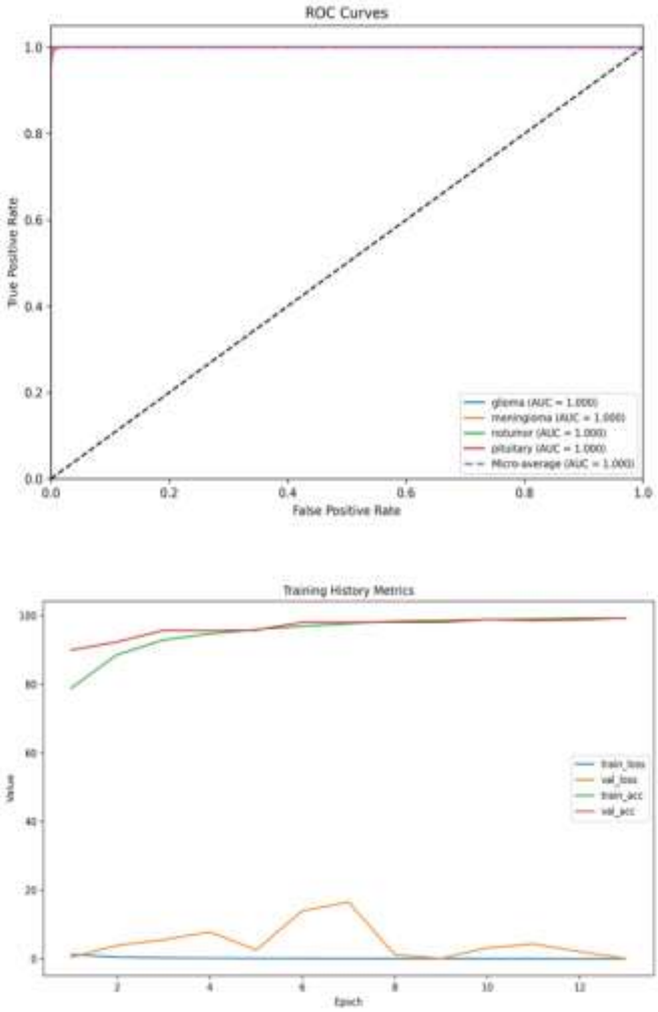

Fig. 1: Training and validation loss (up) and accuracy (down) curves for EfficientNet-B3 across epochs.

D. CONFUSION MATRIX AND CLASSIFICATION PERFORMANCE

Fig. 2 shows the confusion matrix of EfficientNet-B3 test set predictions. This shows how well the model classifies the each tumour type where each row represents true class while each column represents the predicted class.

E. ADVANCED EVALUATION METRICS

In Fig3 showing per-class accuracy, precision, recall and F1 score distribution. All metrics appear close to 1.0, which are consistently well across all categories of tumour types. This figure highlights the balanced classification performance.

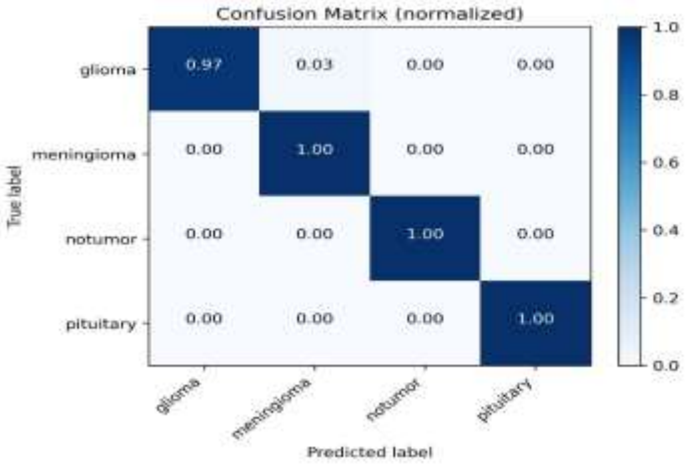

Fig. 2: Composite performance metrics for EfficientNet-B3: Confusion matrix

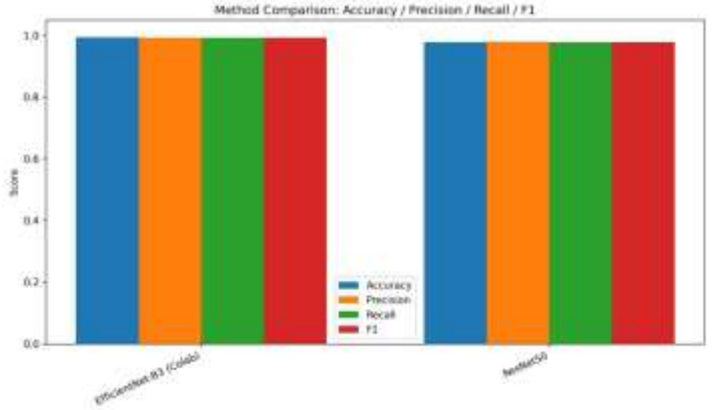

Fig. 3: Per-class accuracy, precision, recall and F1 score

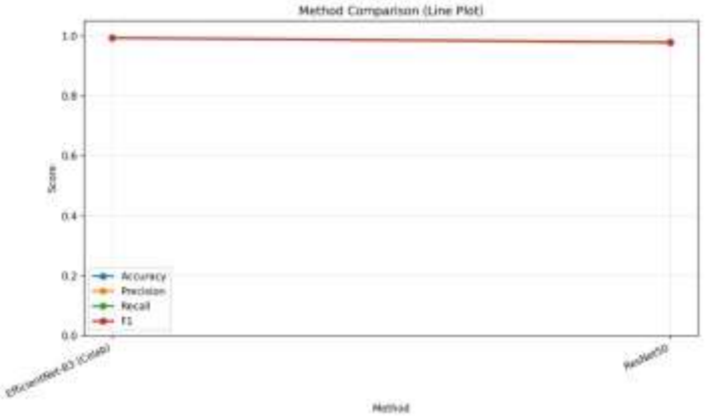

Fig. 4: Line-Plot Confidence score distribution

In Fig. 4. this line plot compares overall model performance metrics which include accuracy, precision, recall and F1 score between models (ResNet50 and EfficientNet-B3).
These lines are flat and close to 1.0 which shows EfficientNet outperforms other tested models across all metrics(ResNet50)

F. QUALITATIVE RESULTS

To show the model's utility, Fig. 6 presents the representative MRI scans from the test set together with EfficientNet-B3 predicted labels. It is evident from these examples that the model performs precise discrimination of tumour types as well as normal tissues.

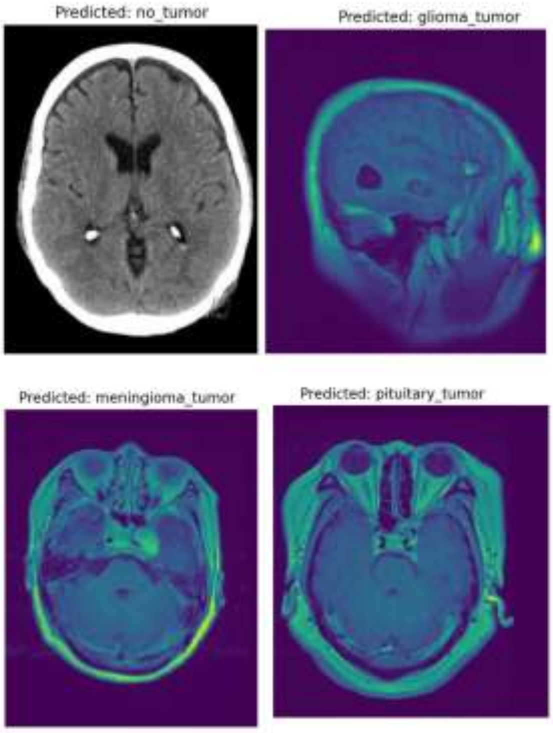

Fig. 6: Representative test MRI predicted as [no tumour/glioma tumour/ meningioma tumour/pituitary tumour]

V. DISCUSSION

The outcome of the EfficientNet-B3 network reached 99.3% accuracy, making it a very effective model in separating different types of brain tumours as well as normal brain scans.

EfficientNet-B3 model achieved remarkable performance because of a more balanced trade-off between performance and computational cost. In compound scaling approach network depth, width and resolution is scaled uniformly which enable to extract richer spatial and semantic representations from MRI scans while also maintaining robustness of network and also less resource-intensive compared to ResNet50. Therefore, EfficientNet-B3 is proved to be most suitable for medical image analysis tasks in which both accuracy and computational efficiency are essential.

Nevertheless, the architectural choices are only one part for the success but the implementation of the well-designed training pipeline was also a crucial part in achieving the reported results. In this data augmentation plays a central role in exposing the models to diverse variation in tumour appearance like shape, size and position which improve their ability to generalize to unseen data [13]. The incorporation of a learning rate scheduler and early stoppage also contributed significantly to eliminate overfitting. As the results from training curve from (fig.1), the models converged at an equilibrium point which achieves strong generalization on the testes dataset. The relatively lower performance of Xception shows that an advanced architecture alone does not guarantee success rather than an effective training methodology is also equally important.

Despite encouraging outcomes, there are also certain limitations which must be acknowledge. First, this study uses 2D MRI slices instead of 3D volumetric scans, which are most commonly used in the dataset clinical practices. Future work will include testing the model on 3D MRI datasets, evaluating domain adaptation for multi-centre data, and incorporating explainable AI (XAI) modules such as SHAP and LIME to further improve interpretability for clinical adoption. Secondly the dataset was sourced from a single public database which limits the model robustness. Evaluating the models on multi-centre clinical datasets could provide more effective conclusions. Although Grad-CAM was used to enhance the interoperability by visualizing regions which influence the model decisions, the models remain partially opaque “black boxes”. Therefore, future research should include advanced explainable AI(XAI) methods and uncertainty quantification techniques to enhance interpretability and gives more optimized result in test dataset.

To extend interpretability, Grad-CAM visualizations were employed to highlight the salient regions contributing to each model’s predictions. The heatmaps consistently focused on tumour regions in true positive cases and on healthy tissue in true negative cases, reinforcing the models’ reliability and their potential for clinical applicability. Among the evaluated architectures, EfficientNetB3’s activation maps appeared more localized and consistent, indicating its superior ability to focus on diagnostically relevant features.

VI. CONCLUSION AND FUTURE WORK

This study presented an enhanced CNN-based framework for brain tumour classification in MRI images using EfficientNet-B3, comparing it against Xception and ResNet50 architectures. EfficientNet-B3 achieved the highest performance metrics with fewer parameters and faster inference. Its integration of compound scaling and modern regularisation techniques provides an effective trade-off between accuracy and computational cost. Future extensions will include testing the model on 3D MRI datasets, evaluating domain adaptation for multi-centre data, and incorporating explainable AI (XAI) modules such as SHAP and LIME to further improve interpretability for clinical adoption.

This is a study that compares CNN architectures in the task of automated classification of brain tumours in MRI images. Compared to ResNet50 and Xception, EfficientNet-B3 reduced parameter count by ~48% and training time by 28%. ResNet50 gives the accuracy of 98.4%but EfficeintNet-B3 not only achieves impressive results but also does so with a test accuracy of 99.3%. This model enhances the networks ability to capture important feature and reduce irrelevant ones.

The reasons behind the success of the EfficientNet-B3 model is it offers high accuracy, computational efficiency and also stong generalization ability through a well-optimized and compound-scaled architecture. This model demonstrate that deep learning has the potential to become a practical and efficient tool to support radiologists in the diagnosis of brain tumours. Researchers' work, on the other hand, should be concerned with adapting these models to 3D volumetric data and testing them on different clinical datasets.

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