Institute of Research and Publication Indonesia (IRPI)
Public Research Journal of Engineering, Data Technology and Computer Science
Journal Homepage: https://journal.irpi.or.id/index.php/predatecs
Vol. 3 Iss. 1 July 2025, pp: 31-41
ISSN(P): 3024-921X | ISSN(E): 3024-8043

Implementation of Deep Learning for Brain Tumor Classification from Magnetic Resonance Imaging

Nur Alfa Husna[1*], Desvita Hendri[2] , Muhammad Farid Wajdi[3], Ella Silvana Ginting[4], Chintya Harum Pramesthi[5]

[1,2]Department of Information Systems, Faculty of Science and Technology, Universitas Islam Negeri Sultan Syarif Kasim Riau, Indonesia
[3]Master of Arts in Social Anthropology, University of Sussex, United Kingdom (UK)
[4]Department of Management, Faculty of Technology Management and Business, University Tun Hussein Onn Malaysia, Malaysia
[5]Departement of Clinical Medicine,Faculty Internasional Education College, Yangtze University,China

E-Mail: [1]12150321301@students.uin-suska.ac.id, [2]12150320281@student.uin-suska.ac.id, [3]nstnfarid@gmail.com, [4]ellaginting86@gmail.com, [5]cehapramesthy28@gmail.com

Received Jul 20th 2024; Revised Mar 25th 2025; Accepted Apr 27th 2025; Available Online Jul 05th 2025, Published Jul 31th 2025
Corresponding Author: Nur Alfa Husna

Abstract

Brain Tumors are a medical problem that causes many people to die in the world due to brain cancer. Brain Tumors are one of the dangerous types of brain cancer. MRI is well proven in the assessment of brain Tumors, although conventional imaging has limitations in evaluating the extent of the Tumor. In the field of medicine, there has been an increase in large amounts of data and traditional models cannot manage such data efficiently. So there is a need for medical image analysis that can store and analyse large medical data efficiently. This research will adopt a deep understanding transfer learning approach with four models namely VGG16, VGG19, MobileNetV2 and ResNet50 to classify 2 types of image shapes that detect whether a person has a brain Tumor or not using Magnetic Resonance Imaging (MRI) data with Convolution Neutral Network (CNN). The number of datasets used is 4600 MRI images with 2 classes namely Brain Tumor and Health. The hyperparameters used are image size 224x224 pixels, training data ratio 70%, test data 30%, using Adam optimizer, learning rate 0.0001, using batch size 64 and epoch value 50. The best results in this study were obtained by MobileNetV2 architecture with an accuracy of 88.77%.

Keyword: Brain Tumor, Convolution Neutral Network, Magnetic Resonance Imaging, MobileNetV2, ResNet50

1. INTRODUCTION

The brain is a complex human organ that has very important functions for the human body. The brain has billions of active cells, making it the centre of control and coordination for the central nervous system located inside the human skull [1]. Therefore, brain Tumor is a life-threatening condition [2]. Brain Tumor is a medical problem that causes many people to die in the world due to brain cancer. Brain Tumor is one of the dangerous types of brain cancer due to its critical nature. Based on data from the Global Cancer Observatory in 2021, brain Tumor cases in Indonesia reached 5,964 cases with the death rate being in 12th position with 5,298 cases [3]. One of the most commonly used strategies in the differential diagnosis process in identifying Tumor types is Magnetic Resonance Imaging [4].

Magnetic Resonance Imaging (MRI) is known as magnetic resonance imaging that can provide fundamental information before and after surgery. MRI-generated image segmentation plays an active role in diagnosis and treatment [5]. MRI is well proven in the assessment of brain Tumors, although conventional imaging has limitations in evaluating the extent of Tumors [6]. In the field of medicine, there has been an increase in large amounts of data and traditional models cannot manage such data efficiently. This will become a problem if it continues to be ignored, hence the need for medical image analysis that can store and analyse large medical data efficiently. This research will solve the problem by classifying Tumors from MRI image segmentation using Convolution Neutral Network (CNN) by comparing four architectures namely VGG16, VGG19, MobileNetV2 and ResNet50 [4].

CNN is an artificial neural network architecture that is often used to analyse visual data. CNNs can automatically recognise many types of visual patterns by extracting important features from images without the need for human intervention or complex pre-processing. The combination of different CNN architectures with transfer learning techniques has brought significant improvements in image classification performance [7]. This research will use the well-known trained models ResNet-50, VGG-16, and Inception V3 with ImageNet. The comparison of these CNN models is expected to achieve better computational results with a low error rate so as to provide accurate diagnoses [8].

Previous research related to this research topic is research by Prerepa Gayathri et al (2023). This research uses CNN to detect brain Tumors by exploring the VGG-16 architecture. The VGG-16 architecture.
was compared with other architectures namely EasyDL, GoogLeNet, GrayNet, ImageNet, CNN, Multivariable Regression model and Neural Network. The result of this study is that the VGG-16 architecture achieved 91% accuracy, in the initial training and then to 94% after hyperparameter optimisation. This shows that if VGG-16 is explored further, it will be an architecture that has good potential in detecting brain Tumors [9].

Furthermore, research conducted by Amena Mahmoud, et al in 2023, this study compared several CNN models namely VGG-16, VGG-19, and Inception-V3 using the AQO optimizer to detect brain Tumors. This research divided 80% training data and 20% testing data. They used 3 types of brain Tumors namely Glioma, Hyposyphilis and Meningioma. The results of this study showed that the VGG-19 model achieved the best accuracy of 98.95% [10]. Then research 2023 by Zahid Rasheed, et al related to CNN comparing VGG16, VGG19, ResNet50, MobileNetV2, and InceptionV3 models. With an image size of 224x224 pixels on VGG16, VGG19 and ResNet50 and 299x299 pixels on InceptionV3. The results show that brain Tumors can be categorised with high accuracy. This is evidenced by the high classification accuracy of 98.04% and the f1-score success rate of 98% respectively. The ResNet50 model obtained superior accuracy, precision, f1-score rate and gain compared to other models [11].

Another study by Tahia Tazin, et al (2021) discussed the comparison with three CNN models namely VGG19, InceptionV3 and MobileNetV2 and incorporated new ways to improve performance in detecting brain Tumors. This research focuses on improving accuracy on transfer learning strategies. The results of this study show that the MobileNetV2 model has higher accuracy than the VGG19 and InceptionV3 models, which is 92% [12]. Further research by Muhammad Yaqub, et al (2020) which compares 10 optimizers on CNN models namely AdaDelta, Adagrad, Adam, SGD, CLR, RMSProp, NAG, Nadam and Adamax in detecting brain Tumors. With MRI image data obtained from BraTS2015. Quantitatively and graphically, Adam optimiser has much better performance. NAG and RMSProp models have poor performance and some other optimisers such as AdaDelta and Adamax provide minimal risk and SGD optimiser performance is lower than Adam. This study found that Adam optimiser has the highest accuracy of 99.2% compared to other optimisers [13].

Based on previous research, this study will adopt a deep understanding of transfer learning approach with four models namely VGG16, VGG19, MobileNetV2 and ResNet50 using Adam optimizer to detect brain Tumor disease. This study classifies 2 types of image types that detect whether a person has a brain Tumor or not using MRI data with CNN. The hyperparameters used are image size 224x224 pixels, training data ratio 70%, test data 30%, using Adam optimizer, learning rate 0.0001, using batch size 64 and epoch value 50. The purpose of this study is to compare and evaluate the performance of CNN architecture on brain Tumor disease using MRI images to find an architecture that can produce high accuracy. So that it can be used to get accurate diagnosis results and reduce the level of subjectivity in medical procedures.

2. MATERIAL AND METHOD

The flow of the research method can be seen in Figure 1.

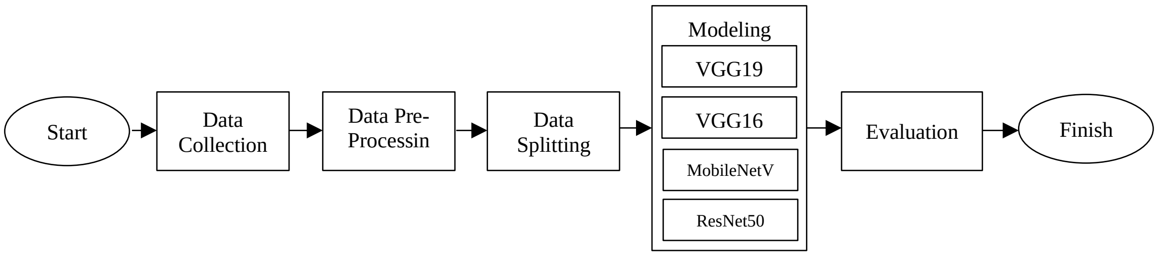

Figure 1. Research Methodology

The researchers of this study applied the VGG16, VGG19, MobilNetV2, and ResNet50 models on a large dataset of 4,600 different types of cerebral MRI images. The photos in the database included IRM photographs that were gathered from Kaggle.com. Four network designs for convolutional neural networks (CNNs) were tested in this study to see how well they performed picture categorization. Image recognition and classification have been carried out using traditional CNN models [14]. Comparing these four CNN architectures which were specifically created to categorize Tumors will help us better understand how well they function. Future technological advancements and the development of better methods may benefit from these insights. With the use of Google Colab, the model was created using 50 epoch.

2.1. Data Collection

The initial stage carried out in this research is data collection. The dataset used in this study consists of 4600 images of brain Tumor disease from the Kaggle database (https://www.kaggle.com/datasets/preetviradiya/brian-Tumor-dataset). This dataset contains 2 types of categories: brain Tumor or not. After the data collection process, further analysis will be carried out to understand the variables of the two types of data in Figure 2 by preprocessing the data. The percentage of data of both classes can be seen in Figure 2 and a random image from the dataset in Figure 3.

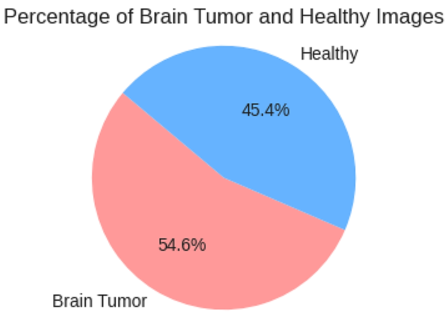

Figure 2. Percentage of Data

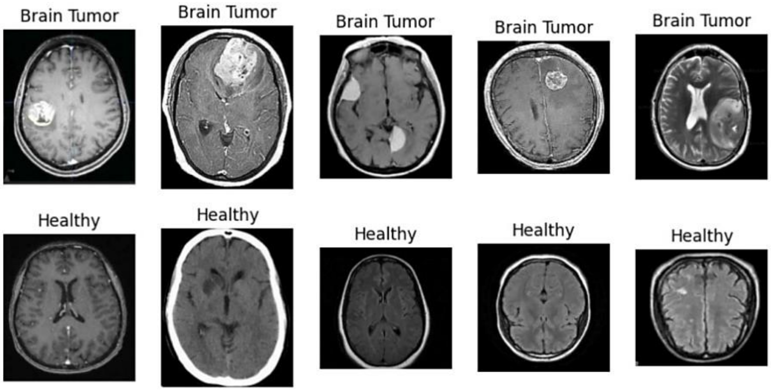

Figure 3. Dataset

2.2. Pre Processing

The objective of the pre-processing phase is to improve image quality, remove irrelevant data, and enhance the contrast of MRI images [8]. Before feeding the images into the model, image preprocessing is used to improve the image data. Rotation, resizing, normalisation, rescaling (grey scaling), and cropping are all examples of preprocessing or commonly called augmentation [15]. An explanation of normalisation and augmentation can be seen in Table 1.

Table 1. Augmentations used

Parameter	Grade	Information
Rescale	1./255	Scaling the image pixel valuesfrom [0, 225] to [0,1]. Thisprocess is done to facilitate the training process on the model.
Rotation_range 45	45	Rotate the image up to 45 degrees randomly in a clockwise or anti- clockwise direction. This process helps the model become morerobust to rotation.
Horizontal_flip	True	Randomly flip the image in a horizontal direction.
Vertical_flip	True	Randomly flip the image in a vertical direction.

2.3. Data Splitting

Based on MRI data of brain Tumor disease obtained from Kaggle with 4600 images, the data has 2 classes namely Brain Tumor and Healthy. In the concept of Deep Learning, there is a division of data, namely training data, test data and validation data. Data sharing techniques are divided into 2 types, namely Cross Validation and Hold out. In this study, the data sharing technique used is Hold out with a ratio of 70:30, namely 70% of training data and 30% of test data. The dataset division can be seen in Table 2.

Table 2. Dataset division

Hold out	Class	70:30		Data Validation
		Training Data	Test Data	
70:30	Brain Tumor	1759	754	292
	Healthy	1460	627	352

2.4. Method

2.4.1. Adam Optimizer

Adam's Optimiser is an adaptive learning rate optimisation algorithm designed to train deep neural networks, known for its effectiveness in a wide range of applications. [16] [17]. It combines the benefits of two other optimisation algorithms, namely RMSProp and AdaGrad, by maintaining separate learning rates for each parameter and adapting them based on the first and second moments of the gradient [18]. Recent studies have explored improvements to Adam's optimiser, such as an improved version that incorporates adaptive coefficients and composite gradients to address convergence speed and global optimisation challenges [19]. Moreover, studies have shown that Adam performs well on diverse architectures and outperforms stochastic gradient descent in settings where the latter struggles, demonstrating its robustness and efficiency in optimising deep learning models.

2.4.2. VGG16

The Vision Geometry Group at the University of Oxford developed the VGG16 model [20]. In 2014, he won the Imagenet competition [21]. The VGG16 design consists of a series of seamless convolution blocks followed by an integrated pooling couch. Each convolutional layer uses a filter with a kernel size of 3 x 3 and pass 1 (stride 1), with padding that uses the same value as the stride. Conversely, each pooling layer uses a 2 × 2 pool size and a 2 stride [22]. The classification layer, which consists of a fully connected layer and a softmax layer, comes after the convolutional layer [23]. There are three fully connected (FC) sofas in this. The fully connected couch arrangement in the VGG16 model is consistent across all networks, meaning that each FC couch has the same number of channels. Every cached layer in this model makes use of the non-linear rectified unit's (ReLU) activation function. The architecture described above allows VGG16 to handle and classify images with a high degree of accuracy, making it one of the most widely used models in image recognition and classification competitions like Imagenet. The VGG16 architecture can be seen in Figure 4.

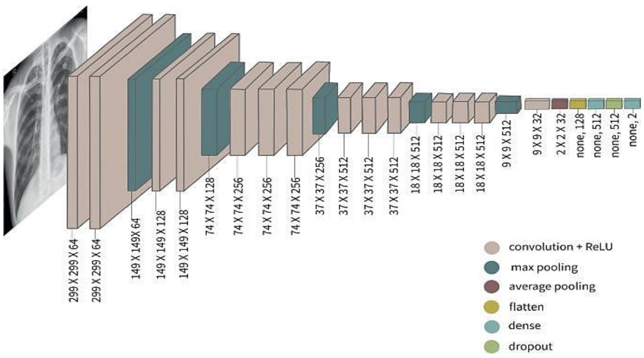

Figure 4. VGG16 Architecture

2.4.3. VGG19

VGG19 is a deep convolutional neural network architecture that has been used in various research studies for tasks such as medical image classification, bathymetry inversion, plant recognition, and COVID-19 detection. In the context of medical image classification, VGG19 has been compared to other models such as VGG16 and Resnet50, showing varying accuracy based on image type and data augmentation [24]. Moreover, in bathymetry inversion, VGG19 was used alongside SAR and multibeam data to achieve highly accurate results for shallow marine areas, showing strong correlation with measured data and improved relative error rates [25]. Furthermore, VGG19 has been used in an automatic tuberculosis detection system, achieving a high classification accuracy of 98.6190% with a Gaussian SVM-medium classifier [26]. Finally, in COVID-19 detection, the BND-VGG-19 method combining batch normalisation and dropout layers showed superior performance with an accuracy rate of 95.48% compared to existing diagnostic methods [15]. The VGG19 architecture can be seen in Figure 5.

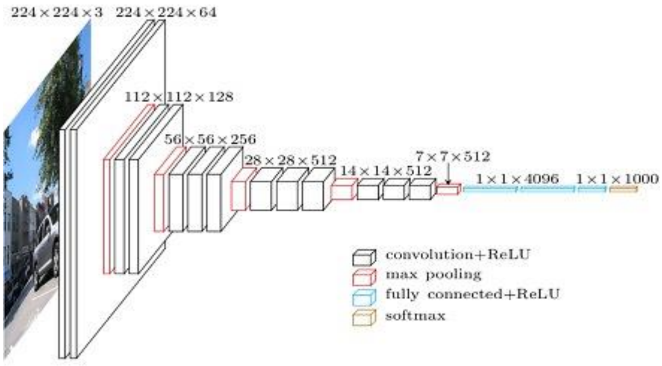

Figure 5. VGG19 Architecture

2.4.4. MobileNetV2

MobileNetV2 is a lightweight and efficient neural network architecture that has been successfully applied in various domains such as target detection in autonomous driving scenarios [27], polyp image segmentation for colonoscopy examination, RAW image processing on mobile devices for production of high quality photos [28], and even in the diagnosis of diseases such as COVID-19 through the classification of chest X-ray images [29]. The MobileNetV2 architecture has been adapted and optimised for edge hardware platforms, featuring versatility and adaptability to different computing environments [30]. With its ability to balance performance and efficiency, MobileNetV2 has proven to be a valuable tool in deep learning applications, offering high accuracy rates, fast processing speeds, and the ability to run on resource-constrained devices such as mobile phones and embedded systems. The MobileNetV2 architecture can be seen in Figure 6.

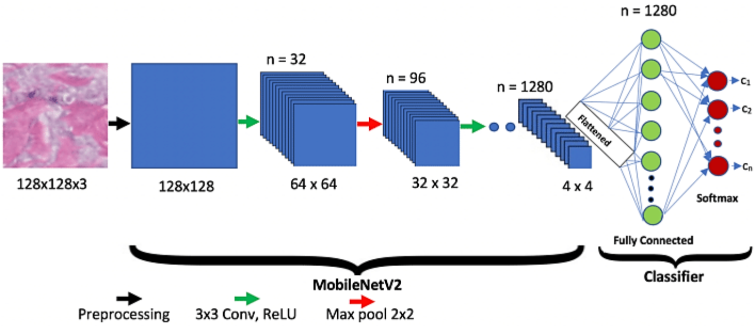

Figure 6. MobileNetV2 Architecture

2.4.5. ResNet50

ResNet50 is a CNN architecture that has been widely used in various research studies for different applications. It has been used in predicting primary Tumor sites in spinal metastases using MRI, achieving an AUC-ROC of 0.77 and a top-1 accuracy of 52.97% [31]. In addition, ResNet50 has been integrated into an End-to-End Object Detection system, showing an improvement in object detection performance in images of about 90% compared to traditional CNN models, and increasing the speed of object detection for real-time applications [32]. The ResNet50 architecture can be seen in Figure 7.

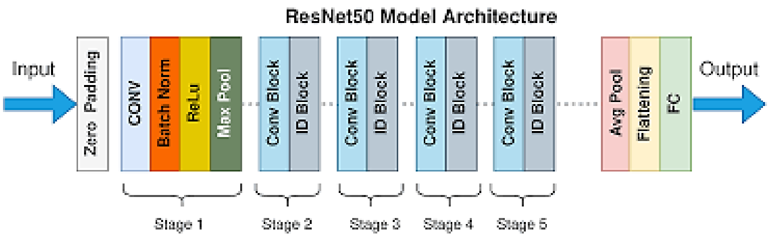

Figure 7. MobileNetV2 Architecture

ResNet50 has been evaluated in face recognition tasks, showing varying accuracy with and without mask occlusion compared to other models such as ViT and Swin transformers [33]. Furthermore, the use of ResNet50 in defect detection models, especially with transfer learning, has shown good recognition performance and interpretability [34]. This ResNet50 architecture employs multiple layers, such as the Dense, Flatten, and Dropout layers, to progressively process image data on brain disease datasets until producing the desired class prediction [35].

3. RESULTS AND ANALYSIS

3.1. VGG16 Model

In the VGG16 model with Adam optimiser, the results with an accuracy of 79% were trained with 70% training data and 30% testing data obtained from Kaggle. The VGG16 curve can be seen in Figure 8 and the confusion matrix in Figure 9.

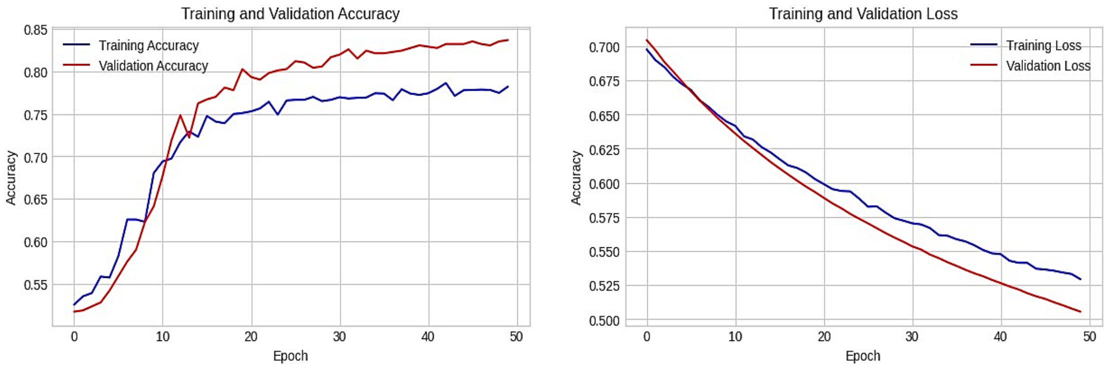

Figure 8. VGG16 Training and Validation Curves

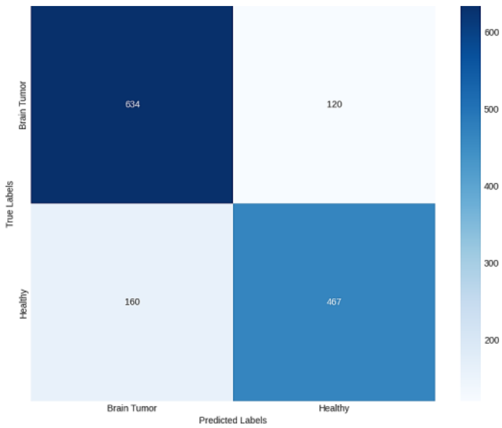

Figure 9. Confusion Matrix VGG16

3.2. VGG19 Model

In the VGG19 model with Adam optimiser, the results with an accuracy of 76% were trained with 70%training data and 30% testing data obtained from Kaggle. The VGG19 curve can be seen in the Figure 10 and the confusion matrix in the Figure 11.

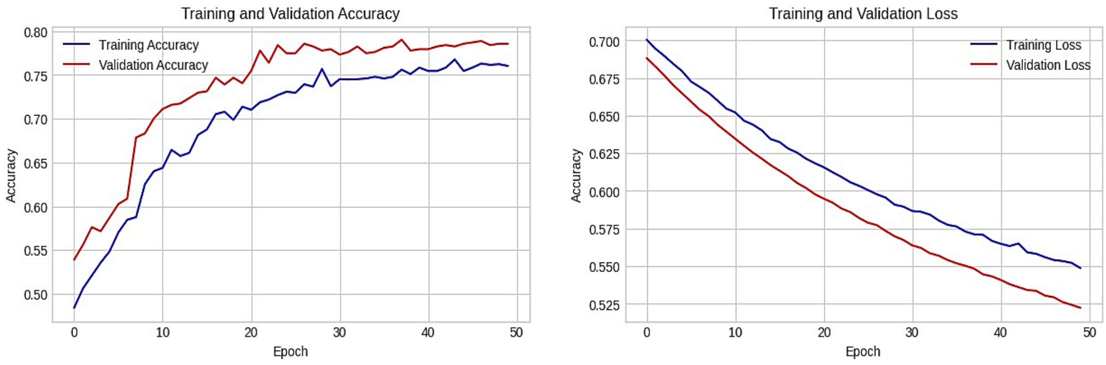

Figure 10. VGG19 Training and Validation Curves

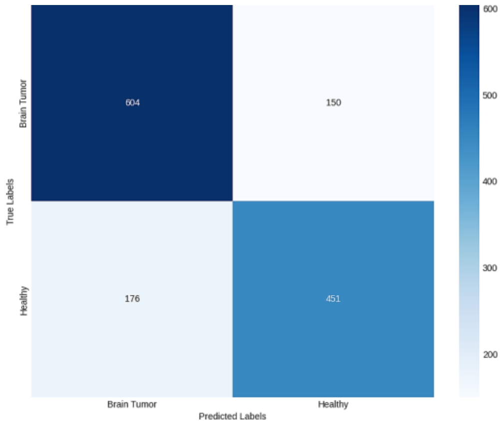

Figure 11. Confusion Matrix VGG19

3.3. MobileNetV2 Model

In the MobileNetV2 model with Adam optimiser, the results with an accuracy of 88% were trained with 70% training data and 30% testing data obtained from Kaggle. The MobileNetV2 curve can be seen in the Figure 12 and the confusion matrix in the Figure 13.

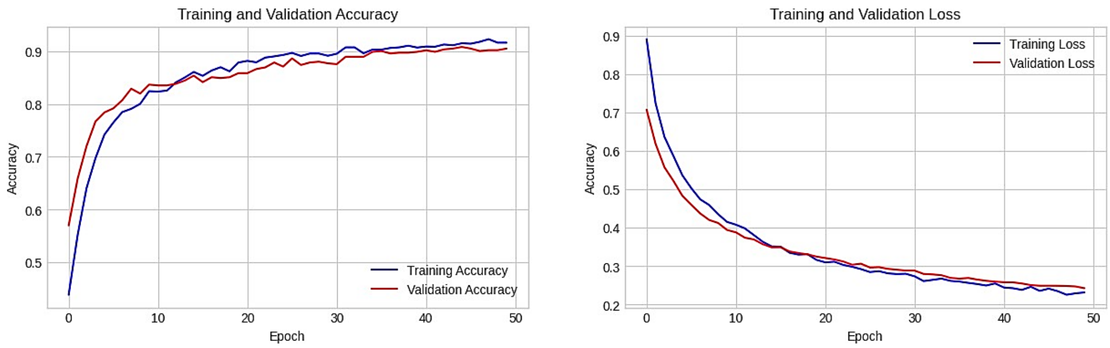

Figure 12. MobileNetV2 Training and Validation Curves

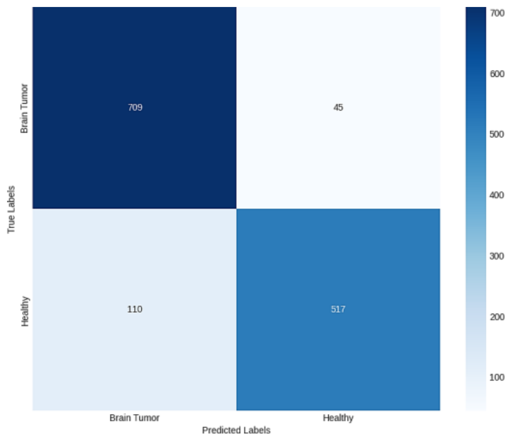

Figure 13. MobileNetV2 Confusion Matrix

3.4. ResNet50 Model

In the ResNet50 model with Adam optimiser, the results with an accuracy of 71% were trained with 70% training data and 30% testing data obtained from Kaggle. The ResNet50 curve can be seen in the Figure 14 and the confusion matrix in the Figure 15.

The following is a description of the precision, recall, f1-score and support values that have been obtained by each model, namely on VGG16, VGG19, MobileNetV2 and ResNet50 can be seen in Table 4 and classification Report comparison results can be seen in Figure 16.

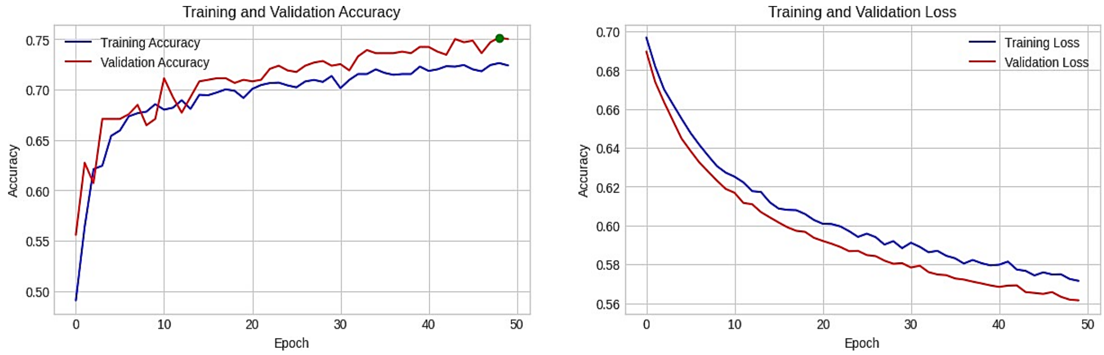

Figure 14. ResNet50 Training and Validation Curves

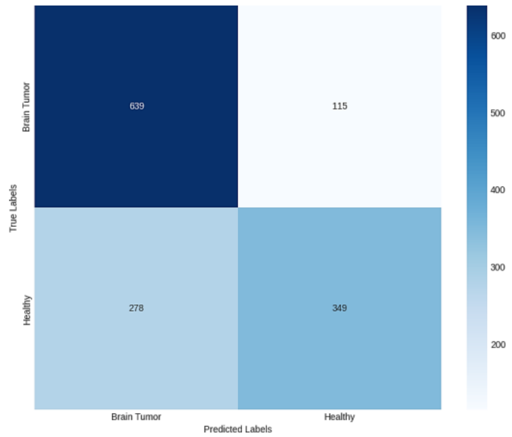

Figure 15. Confusion Matrix ResNet50

Table 4. Classification Report

Class	Architecture	Recall	Precision	F1-Score	Support
Brain Tumor		0.84085	0.79849	0.81912	754
Healthy	VGG16	0.74482	0.79557	0.76936	627
Accuracy				0.79725	1381
Brain Tumor		0.80106	0.77436	0.78748	754
Healthy	VGG19	0.71930	0.75042	0.73453	627
Accuracy				0.76394	1381
Brain Tumor		0.94032	0.86569	0.90146	754
Healthy	MobileNetV2	0.82456	0.91993	0.86964	627
Accuracy				0.88776	1381
Brain Tumor		0.84748	0.69684	0.76481	754
Brain Tumor	ResNet50	0.55662	0.75216	0.63978	627
Healthy				0.71542	1381

Based on the accuracy results obtained have been obtained from each model namely VGG16, VGG19, MobileNetV2 and ResNet50. The results of the comparison of the four architectures can be seen in Table 5 and the representation of the comparison diagram in Figure 17.

Table 5. Model Accuracy Comparison

VGG16	VGG19	MobileNetV2	ResNet50
79.72	76.39	88.77	71.54

Based on Table 5, it can be seen that of the four models that have been compared, namely VGG16, VGG19, MobileNetV2 and ResNet50. The model that has the best accuracy value is obtained from MobileNetV2 with 88% accuracy, then VGG16 with 79% accuracy, then VGG19 with 76% accuracy and finally ResNet50 with 71% accuracy.

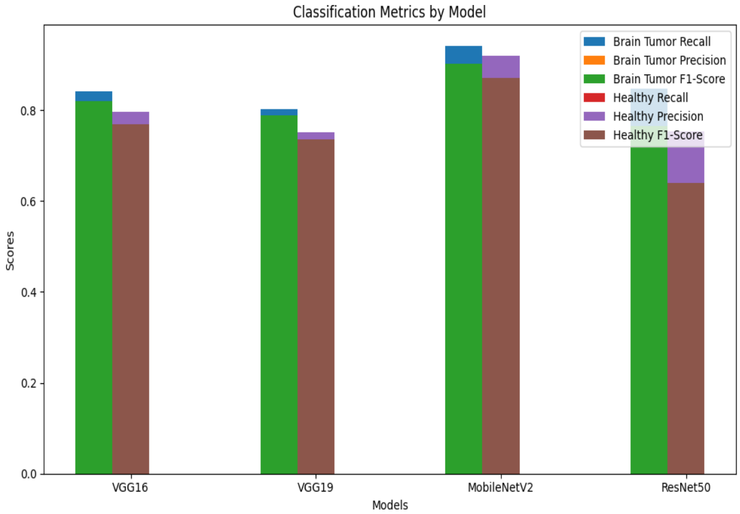

Figure 16. Classification Report Comparison

4. DISCUSSION

Based on the comparison of the four tested models, MobileNetV2 demonstrated the best performance in classifying brain Tumors from MRI images, achieving an accuracy of 88.77%. The advantage of MobileNetV2 over VGG16, VGG19, and ResNet50 lies in its lighter and more efficient architecture, allowing it to handle image data with fewer parameters. VGG16 and VGG19 also showed relatively good performance, with accuracies of 79.72% and 76.39%, respectively, while ResNet50 had the lowest accuracy at 71.54%. This indicates that model complexity does not always directly correlate with increased accuracy but rather depends on how the model is optimized for a specific task.

Furthermore, a deeper analysis of precision, recall, and f1-score reveals that MobileNetV2 achieves the best balance in detecting both Brain Tumor and Healthy classes compared to the other models. This model effectively reduces false positives and false negatives more efficiently than the others. VGG16 and VGG19 still exhibit higher false positive rates, which could potentially lead to misdiagnosis of brain Tumors. Although ResNet50 is a more complex model with residual connections, it proved to be less optimal in handling MRI data from this dataset, likely due to its inability to extract specific features effectively from the MRI images used in this study.

5. CONCLUSION

This study evaluates the performance of four deep learning architectures—VGG16, VGG19, MobileNetV2, and ResNet50—in classifying brain Tumor MRI images into two categories: Brain Tumor and Healthy. Among these models, MobileNetV2 demonstrated the highest accuracy of 88.77%, highlighting its efficiency in feature extraction and computational performance. VGG16 and VGG19 achieved competitive results with 79.72% and 76.39% accuracy, respectively, while ResNet50 had the lowest accuracy at 71.54%. These findings underscore the importance of selecting an appropriate CNN architecture based on both accuracy and computational efficiency.

A key contribution of this study is its comparative analysis of deep learning models with consistent hyperparameter settings, ensuring a fair evaluation. The results suggest that lightweight architectures like MobileNetV2 can achieve high accuracy while maintaining computational efficiency, making them suiTable for real-world medical applications, particularly in resource-constrained environments. Future research can expand on these findings by exploring additional CNN architectures, optimizing hyperparameters further, integrating attention mechanisms, or employing ensemble learning techniques to improve classification accuracy. Moreover, incorporating larger and more diverse datasets could enhance model generalization and robustness in real-world clinical scenarios.

REFERENCES

[1] D. R. Nayak, N. Padhy, P. K. Mallick, M. Zymbler, and S. Kumar, “Brain Tumor Classification Using Dense Efficient-Net,” Axioms, vol. 11, no. 1, 2022, doi: 10.3390/axioms11010034.

[2] N. Alturki et al., “Combining CNN Features with Voting Classifiers for Optimizing Performance of Brain Tumor Classification,” Cancers (Basel)., vol. 15, no. 6, pp. 1–15, 2023, doi: 10.3390/cancers15061767.

[3] “Global Cancer Observatory, ‘Global Cancer Observatory in Indonesia,’ 2021.” [Online]. Available: https://gco.iarc.fr/today/en

[4] I. A. El Kader, G. Xu, Z. Shuai, S. Saminu, I. Javaid, and I. S. Ahmad, “Differential deep

convolutional neural network model for brain Tumor classification," Brain Sci., vol. 11, no. 3, 2021, doi: 10.3390/brainsci11030352.

[5] Z. Liu et al., "Deep learning based brain Tumor segmentation: a survey," Complex Intell. Syst., vol. 9, no. 1, pp. 1001–1026, 2023, doi: 10.1007/s40747-022-00815-5.

[6] A. A. Akinyelu, F. Zaccagna, J. T. Grist, M. Castelli, and L. Rundo, "Brain Tumor Diagnosis Using Machine Learning, Convolutional Neural Networks, Capsule Neural Networks and Vision Transformers, Applied to MRI: A Survey," J. Imaging, vol. 8, no. 8, pp. 1–40, 2022, doi: 10.3390/jimaging8080205.

[7] O. Özkaraca et al., "Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images," Life, vol. 13, no. 2, 2023, doi: 10.3390/life13020349.

[8] D. Rastogi, P. Johri, and V. Tiwari, "Augmentation based detection model for brain Tumor using VGG 19," Int. J. Comput. Digit. Syst., vol. 13, no. 1, pp. 1227–1237, 2023, doi: 10.12785/ijcds/1301100.

[9] P. Gayathri, A. Dhavileswarapu, S. Ibrahim, R. Paul, and R. Gupta, "Exploring the Potential of VGG-16 Architecture for Accurate Brain Tumor Detection Using Deep Learning," J. Comput. Mech. Manag., vol. 2, no. 2, pp. 13–22, 2023, doi: 10.57159/gadl.jcmm.2.2.23056.

[10] A. Mahmoud et al., "Advanced Deep Learning Approaches for Accurate Brain Tumor Classification in Medical Imaging," Symmetry (Basel)., vol. 15, no. 3, 2023, doi: 10.3390/sym15030571.

[11] Z. Rasheed et al., "Automated Classification of Brain Tumors from Magnetic Resonance Imaging Using Deep Learning," Brain Sci., vol. 13, no. 4, 2023, doi: 10.3390/brainsci13040602.

[12] T. Tazin et al., "A Robust and Novel Approach for Brain Tumor Classification Using Convolutional Neural Network," Comput. Intell. Neurosci., vol. 2021, 2021, doi: 10.1155/2021/2392395.

[13] M. Yaqub et al., "State-of-the-art CNN optimizer for brain Tumor segmentation in magnetic resonance images," Brain Sci., vol. 10, no. 7, pp. 1–19, 2020, doi: 10.3390/brainsci10070427.

[14] P. D. Rinanda, D. N. Aini, T. A. Pertiwi, S. Suryani, and A. J. Prakash, "Implementation of Convolutional Neural Network (CNN) for Image Classification of Leaf Disease In Mango Plants Using Deep Learning Approach," Public Res. J. Eng. Data Technol. Comput. Sci., vol. 1, no. 2, pp. 56–61, 2024, doi: 10.57152/predatecs.v1i2.872.

[15] T. Siddharth, B. S. Kirar, and D. K. Agrawal, "Plant Species Classification Using Transfer Learning by Pre-trained Classifier VGG-19," IETE J. Res., vol. 68, no. 03772063, pp. 2345–3140, 2022.

[16] W. Wardianto, F. Farikhin, and D. M. Kusumo Nugraheni, "Analisis Sentimen Berbasis Aspek Ulasan Pelanggan Restoran Menggunakan LSTM Dengan Adam Optimizer," JOINTECS (Journal Inf. Technol. Comput. Sci., vol. 8, no. 2, p. 67, 2023, doi: 10.31328/jointecs.v8i2.4737.

[17] S. C. Toh, S. H. Lai, M. Mirzaei, E. Z. X. Soo, and F. Y. Teo, "Sequential Data Processing for IMERG Satellite Rainfall Comparison and Improvement Using LSTM and ADAM Optimizer," Appl. Sci., vol. 13, no. 12, 2023, doi: 10.3390/app13127237.

[18] F. Kunstner et al., "Noise Is Not the Main Factor Behind the Gap Between SGD and Adam on Transformers, but Sign Descent Might Be," J. Curr. Sci. Technol., vol. 13, no. 1, pp. 23–35, 2023, doi: 10.14456/jcst.2023.3.

[19] J. Chen, R. Zhang, and Y. Liu, "An Adam-enhanced Particle Swarm Optimizer for Latent Factor Analysis," 2023.

[20] A. Nana Hermana, D. Rosmala, and M. Gustiana Husada, "Transfer Learning for Classification of Fruit Ripeness Using VGG16," ACM Int. Conf. Proceeding Ser., pp. 139–146, 2021, doi: 10.1145/3450588.3450943.

[21] K. Kusrini, S. Suputa, A. Setyanto, I. M. A. Agastya, H. Priantoro, and S. Pariyasto, "A comparative study of mango fruit pest and disease recognition," TELKOMNIKA (Telecommunication Comput. Electron. Control., vol. 20, no. 6, p. 1264, Dec. 2022, doi: 10.12928/telkomnika.v20i6.21783.

[22] M. Bouni, B. Hssina, K. Douzi, and S. Douzi, "Impact of Pretrained Deep Neural Networks for Tomato Leaf Disease Prediction," J. Electr. Comput. Eng., vol. 2023, 2023, doi: 10.1155/2023/5051005.

[23] A. Bhola, S. Verma, and P. Kumar, "A comparative analysis of deep learning models for cucumber disease classification using transfer learning," J. Curr. Sci. Technol., vol. 13, no. 1, pp. 23–35, 2023, doi: 10.14456/jcst.2023.3.

[24] Kamal and H. Ez-zahraouy, "A comparison between the VGG16 , VGG19 and ResNet50 architecture frameworks for classi cation of normal and CLAHE processed medical images," Res. Sq., pp. 0–16, 2023.

[25] J. Cui et al., "High-Precision Inversion of Shallow Bathymetry under Complex Hydrographic Conditions Using VGG19—A Case Study of the Taiwan Banks," Remote Sens., vol. 15, no. 5, 2023, doi: 10.3390/rs15051257.

[26] R. Mohan, S. Kadry, V. Rajinikanth, A. Majumdar, and O. Thinnukool, "Automatic Detection of Tuberculosis Using VGG19 with Seagull-Algorithm," Life, vol. 12, no. 11, 2022, doi:

10.3390/life12111848.
[27] Y. Huang et al., "Mobilenetv2_CA Lightweight Object Detection Network in Autonomous Driving," Technologies, vol. 11, no. 2, pp. 9489–9510, 2023, doi: 10.3390/diagnostics13101664.
[28] A. Ignatov et al., "PyNet-V2 Mobile: Efficient On-Device Photo Processing With Neural Networks," Proc. - Int. Conf. Pattern Recognit., vol. 2022-Augus, pp. 677–684, 2022, doi: 10.1109/ICPR56361.2022.9956598.
[29] S. Narduzzi, E. Turetken, J. P. Thiran, and L. A. Dunbar, "Adaptation of MobileNetV2 for Face Detection on Ultra-Low Power Platform," Proc. - 2022 9th Swiss Conf. Data Sci. SDS 2022, pp. 1–6, 2022, doi: 10.1109/SDS54800.2022.00008.
[30] M. Ragab et al., "COVID-19 Identification System Using Transfer Learning Technique With Mobile-NetV2 and Chest X-Ray Images," Front. Public Heal., vol. 10, no. March, pp. 1–15, 2022, doi: 10.3389/fpubh.2022.819156.
[31] K. Liu et al., "Prediction of Primary Tumor Sites in Spinal Metastases Using a ResNet-50 Convolutional Neural Network Based on MRI," Cancers (Basel)., vol. 15, no. 11, 2023, doi: 10.3390/cancers15112974.
[32] E. Suherman, B. Rahman, D. Hindarto, and H. Santoso, "Implementation of ResNet-50 on End-to-End Object Detection (DETR) on Objects," SinkrOn, vol. 8, no. 2, pp. 1085–1096, 2023, doi: 10.33395/sinkron.v8i2.12378.
[33] Y. Huang, L. Lin, P. Cheng, J. Lyu, R. Tam, and X. Tang, "Identifying the Key Components in ResNet-50 for Diabetic Retinopathy Grading from Fundus Images: A Systematic Investigation," Diagnostics, vol. 13, no. 10, 2023, doi: 10.3390/diagnostics13101664.
[34] L. Zhang, Y. Bian, P. Jiang, and F. Zhang, "A Transfer Residual Neural Network Based on ResNet-50 for Detection of Steel Surface Defects," Appl. Sci., vol. 13, no. 9, 2023, doi: 10.3390/app13095260.
[35] D. Hastari, S. Winanda, and A. R. Pratama, "Application of Convolutional Neural Network ResNet-50 V2 on Image Classification of Rice Plant Disease," vol. 1, no. January, pp. 71–77, 2024.