Journal of Soft Computing Exploration

Homepage: https://shmpublisher.com/index.php/joscex

p-ISSN: 2746-7686
e-ISSN: 2746-0991

.

Developing a classification system for brain tumors using the ResNet152V2 CNN model architecture

Syahruu Siyammu Rhomadhon[1], Diah Rahayu Ningtias[2]
[1,2] Department of Electromedical Engineering, Sekolah Tinggi Ilmu Kesehatan Semarang, Indonesia

Article Info

Article history:

Received June 3, 2024
Revised June 14, 2024
Accepted June 20, 2024

Keywords:

MRI
Deep learning
Artificial intelligence
Diagnosis
Accuracy

ABSTRACT

According to The American Cancer Society, in 2021 there were 24,530 cases of brain and nervous system tumors. The National Cancer Institute reports that there are approximately 4.4 new cases of brain tumors per 100,000 men and women per year. Brain tumors can be detected using magnetic resonance imaging (MRI), a scanning tool that uses a magnetic field and a computer to record brain images and is able to provide clear visualization of differences in soft tissue such as white matter and gray matter. However, this cannot be done optimally because it still relies on manual analysis, so it cannot classify brain tumor types on larger datasets with the potential for error and a low level of accuracy. To accurately determine the type of brain tumor, a better classification method is needed. The aim of this study is to determine the accuracy of brain tumor calcification using the deep learning model. In this study, the classification of brain tumor types was carried out using the ResNet152V2 convolutional neural network (CNN) model which has a depth of 152 layers. The dataset used in this study was 7,023 MRI images of brain tumors consisting of 1,645 meningiomas, 1,621 gliomas, 1,757 pituitary and 2,000 normal. Research results show an accuracy value of 94.44%, so it can be concluded that the ResNet152V2 model performs well in classifying brain tumor images and can be used as a medium for physicians to more accurately diagnose brain tumor patients more accurately.

Corresponding Author:

Diah Rahayu Ningtias,
Department of Electromedical Engineering,
Sekolah Tinggi Ilmu Kesehatan Semarang,
Jln. Kolonel Warsito Sugiarto KM 2,5 Sadeng, Gunungpati, Semarang, Indonesia 50222.
Email: diahrahayuningtias@stikessemarang.ac.id
https://doi.org/10.52465/joscex.v5i2.372

1. INTRODUCTION

Brain tumor is a disease that shows the growth of brain cells unnaturally and uncontrollably in or around the brain. If a brain tumor is not treated quickly from the start, it can have a serious impact on brain function and endanger the patient's life. Brain tumors are divided into two, namely primary and secondary brain tumors. Primary brain tumors are abnormal and uncontrolled cell changes that originate in the brain cells themselves. Meanwhile, secondary brain tumors are tumors that spread to the brain from cancer in other parts of the body [1].

The American Cancer Society reported that 24.530 cases of brain and nervous system tumors were diagnosed in 2021. The estimated annual incidence rate of brain tumors is also reported to be increasing, namely 7 to 19,1 cases per 100.000 population [2]. The National Cancer Institute reports that there are around 4.4 new cases of brain tumors per 100,000 people, both men and women, per year. The estimated number of cases of brain tumors in 2022 globally is estimated at 18,250 deaths [3]. The cases in the world are increasing every year. In Indonesia, every year 300 patients diagnosed with brain tumors. Many people ignore the symptoms caused by brain tumors. Current technological developments influence the medical world because they play an active role in the detection of diseases by doctors. One disease that can be detected early is a brain tumor [4].

There are two types of brain tumor, namely glioma and non-glioma. Glioma is a type of tumor that grows from brain supporting cells (glial), and nonglial grows outside the brain supporting cells. Nonglial types are divided into slow-growing tumors (miningioma) and hormone-secreting tumors (pituitary) [5]. One method commonly used to diagnose brain tumors is magnetic resonance imaging (MRI). Magnetic resonance imaging is a scanning tool that uses a magnetic field and a computer to record images of the brain, able to provide clear visualization of the differences in soft tissue such as white matter and gray matter. However, to identify the type of brain tumor that may occur, this process is performed manually, which has the potential to cause errors and low precision when the medical team reads the MRI results [6]. Therefore, we need a technology that can help doctors classify and diagnose the type of brain tumor a patient is experiencing with minimal error and efficiency. One technology that shows significant potential in this field of classification is deep learning methods, especially convolutional neural networks (CNN) [7]. Metode deep learning lainnya dapat juga menggunakan Spiking Neural Network (SNN), metode ini masih tergolong baru sehingga tingkat akurasinya masih 87% [8].

CNN is one of the deep learning algorithms that is currently widely used in research because it can analyze visuals and has demonstrated capabilities in fields such as visual analysis and image processing. Deep learning is a branch of Machine Learning such as the development of multilayer percepton (MLP) which is designed for two-way data processing [9]. The CNN method has several architectures, in this research it only focuses on ResNet152V2, one of the Convolutional Neural Network (CNN) architectural models, which is very sophisticated and effective in image recognition. ResNet152V2 successfully overcomes problems that often occur when increasing the depth of neural networks [10].

In previous research, the classification of brain tumors and their types used a convolutional neural network carried out by with layers such as convolution layers, relu layers, merging layers, fully connected layers. The data set consists of 2,123 images from brain magnetic resonance imaging. The accuracy obtained by applying the CNN model is 92%. The classification of brain tumors using a convolutional neural network with the Efficientnet B3 architecture. The data set used consisted of 2,875 images with glioma and meningioma classes, resulting in an accuracy of 93.7% [11]. Classification of brain tumor types using MobileNetV2 architecture with a brain tumor dataset containing MRI data consisting of 3,167 brain tumor images, resulting in an accuracy value of 88.64% [12].

From several of these studies, research has been carried out on the classification of brain tumor sufferers and non-sufferers, as well as the classification of brain tumor types and grades with an accuracy of above 90%. But research on species classification is still limited. Therefore, more research is needed that can classify the types of brain tumors in sufferers using different systems and data sets. In this research, the author created a classification system to determine the type of brain tumor using the neural network convolution (CNN) method with the AlexNet architecture [13]. The system is expected to be able to classify types of brain tumors based on three types, namely glioma, meningioma, and pituitary. The results of previous studies used various approaches and designs to classify brain tumors quite accurately. However, research on the classification of brain tumor types is still limited, especially in the classification of brain tumors into three classes: glioma, meningioma, and pituitary. Therefore, further research is needed to classify the types of brain tumors in sufferers using different systems and data sets. The advantage of this research is increasing accuracy by creating a classification system to determine the type of brain tumor using the Convolution Neural Network (CNN) method with the ResNet152V2 architecture based on four classes of brain tumor disease, namely glioma, meningioma, pituitary, and normal with 7,023 images. This research aims to increase accuracy and implement this brain tumor classification system in the form of a website so that it can become a tool to assist doctors in diagnosing brain tumor patients. What differentiates this study from previous studies lies in the number of cases and the architectural model used, the study used 2,875 images which were divided into 2 classes of brain tumor disease, namely glioma and meningioma with the Efficientnet-B3 architecture and 3,167 images with the MobileNetV2 architecture [14]. This study also uses various data-augmentation techniques to increase dataset variation and reduce overfitting, which is a common problem in training deep learning models.

.

Furthermore, this research involved a more comprehensive evaluation using additional metrics such as precision, recall, and F1-Score to provide a more in-depth picture of model performance. As a further step, this study also plans to develop a mobile-based application that makes access easier for medical personnel in the field. Thus, the results of this study not only contribute to the fields of computer science and health but also have the potential to be directly applied in clinical practice, improving the speed and accuracy of brain tumor diagnosis, and ultimately providing significant benefits to patients.

2. METHOD

This study used secondary data sources of 7,023 MRI images of brain tumors in JPG format consisting of 1,621 Glioma images, 1,645 Meningioma images 1,757 Pituitary images, and 2,000 normal images divided into training images (80%), validation images (10%) and image testing (10%). ResNet152V2 is a CNN architecture type model used for image processing using Google Collaboration software. Secondary data obtained from https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset.

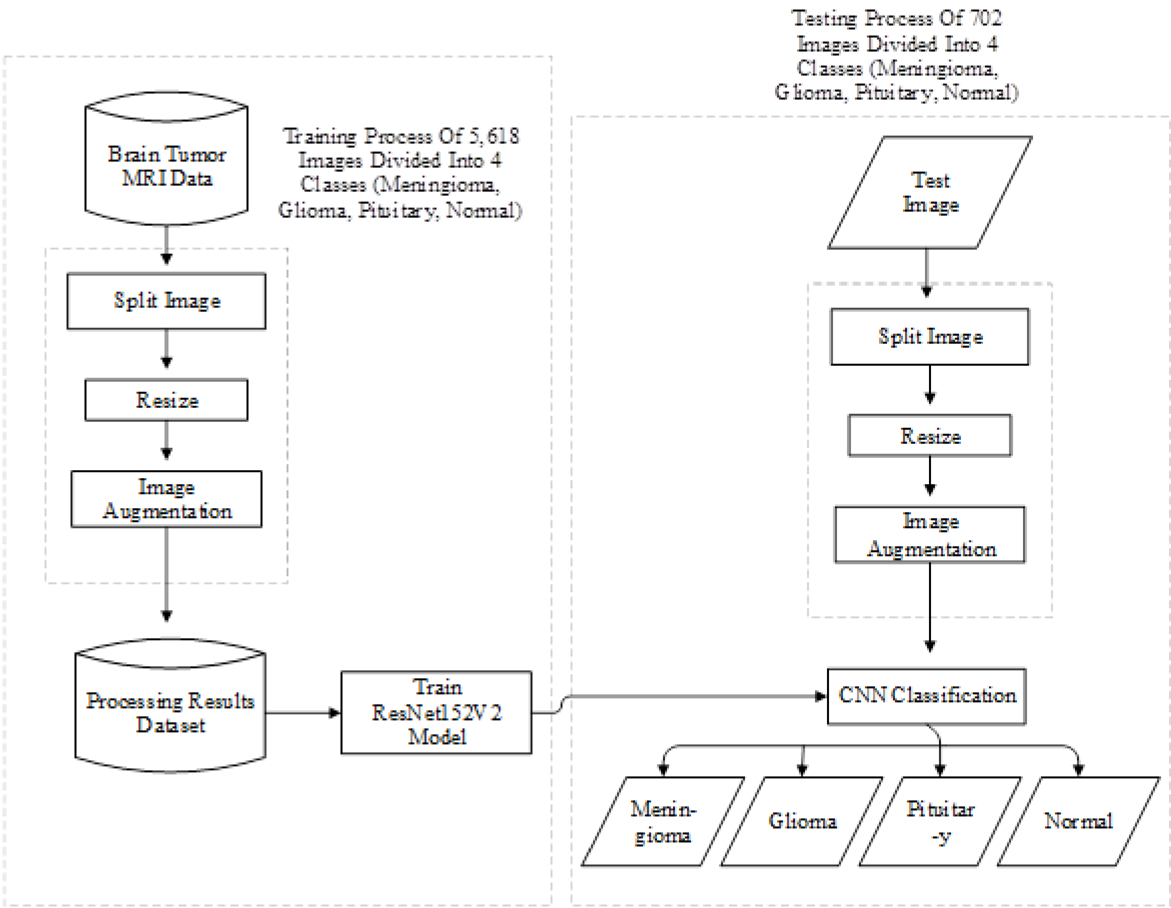


Figure 1. Flowchart of image processing

Based on the flow chart in Figure 1, this research consists of two processes, namely, the training process and the testing process. The initial stage involves selecting an MRI image of a brain tumor and then creating and developing a program to read the data. In this program there are three processes, namely starting with (1) the image split process/dividing the image into training, validation and testing images, then (2) the image resizing process to normalize it as a whole to a size of 224 × 224 pixels, then (3) perform image augmentation such as rescale 1/255, rotation range in the range of ±30 degrees, horizontal and vertical shift range in the image of 10%. The results of data processing are carried out by applying the ResNet152V2 model architecture, allowing the model to extract complex features from the data, useful for tasks such as image classification.

In the testing stage, the test images used are processed according to points (1) to (3). The results of the test images are used for the classification process, which utilizes the CNN algorithm with the ResNet152V2 model as image classification. Then testing was carried out on the CNN algorithm with a data set of 702 images used.

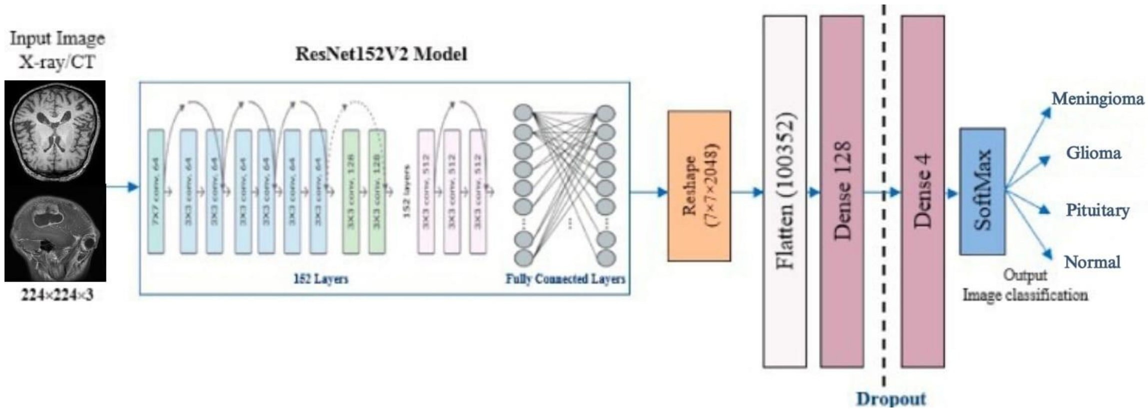


Figure 2. ResNet152V2 architecture [15]

Pre-Processing

At the pre-processing stage, the aim is to ensure that the data is entered into the model optimally and to improve the model's performance in classifying brain tumors with a more limited number of images, namely 7,023 brain tumor images, which are divided into 1,645 meningioma tumors, 1,621 glioma tumors, 1,757 tumors. pituitary and 2,000 normal. The data have been processed using various parameters, including image split, resize, and image augmentation. In Figure 2 the MRI image is input and then processed by the ResNet152V2 model to extract important features which are then flattened by the Flatten layer, processed by Dense layers to create more complex combinations and finally converted into probabilities by the Softmax layer. The final output is a probability between tumor categories (meningioma, glioma, pituitary, and normal).

Resize

Pra resizing processing in this study the image data were completely set to 224 × 224 pixels, rescaled 1/225, and random rotation. At this stage, the image file size becomes smaller, thereby speeding up the computing process. The purpose of this resizing is to ensure consistency and uniformity in the data to be used, support computational efficiency, and meet the model requirements [16].

Image split

Image split pre-processing in this research is the initial stage in processing which divides the dataset into training, validation, and testing subsets. This division is important to properly manage and evaluate the performance of the deep learning model, namely dividing it into 80% training data, 10% validation data, and 10% testing data with a ratio of 8: 1: 1 [17]. The training process uses varying parameters such as learning rates of 0.01 and 0.001 which function to control how much change in model weight is applied for each training iteration, then uses a batch size parameter of 64 in this case 64 images are processed together before the model weight change is applied, then use the Adam optimizer parameter which is one of the optimization algorithms used to optimize the weights in the model during training and adaptively regulate the learning rate efficiently and effectively in producing fast results, then use the epoch parameters 10, 15, and 25 which are the numbers times the entire dataset is used during training, in this case the training lasts for 10, 15, and 25 epochs, which means the model can see the entire dataset 10, 15, and 25 times.

Image augmentation

Image augmentation pre-processing is carried out by changing the pixel value scale to a smaller range using the Softmax activation function which is useful during model training, rotating the image within a range of ±30 degrees, shifting the width and height of the image by 10%, enlarging 20% and reversing horizontally [18]. In Figure 2 there is a Flatten layer which functions to change the output from the previous layer which has several dimensions (such as 7x7x2048) into one dimension (such as 100,352 elements). This layer is very important so that data can be passed to the next layer, which is the dense (Fully Connected) layer. Then, there is the dense layer, which is a layer that is fully connected to every neuron in the previous layer. Its main function is to perform a linear combination of the received input with the learned boboy and apply an activation function. In Dense there are 2 Dense, namely, Dense 128 which has 128 neurons and functions to process input from the Flatten layer into a more complex form. Meanwhile, Dense 4 has 4 neurons, each of which represents one class

.

to be predicted. This layer produces a value called logits which is then passed to the Softmax layer. Then the Softmax layer functions to convert the output from the last Dense layer into probability. Softmax ensures that the sum of all outputs is 1 which means that the model is very confident that the image is in that category.

Model Training

In this research, deep learning was applied with various model architectures, such as ResNet50, InceptionV3, ResNet152V2 to measure the performance of each model. From several of these models, we can determine model performance using metrics such as accuracy, precision, recall, and F1 score. The Resnet50 architecture has an accuracy value of 70.51%, InceptionV3 87.75%, and ResNet152V2 94.44%. At this stage, determine which model will be used in this research. Across various architectures, the ResNet152V2 model produces high metric evaluation performance. The algorithm for the ResNet152V2 model is shown in Figure 3.

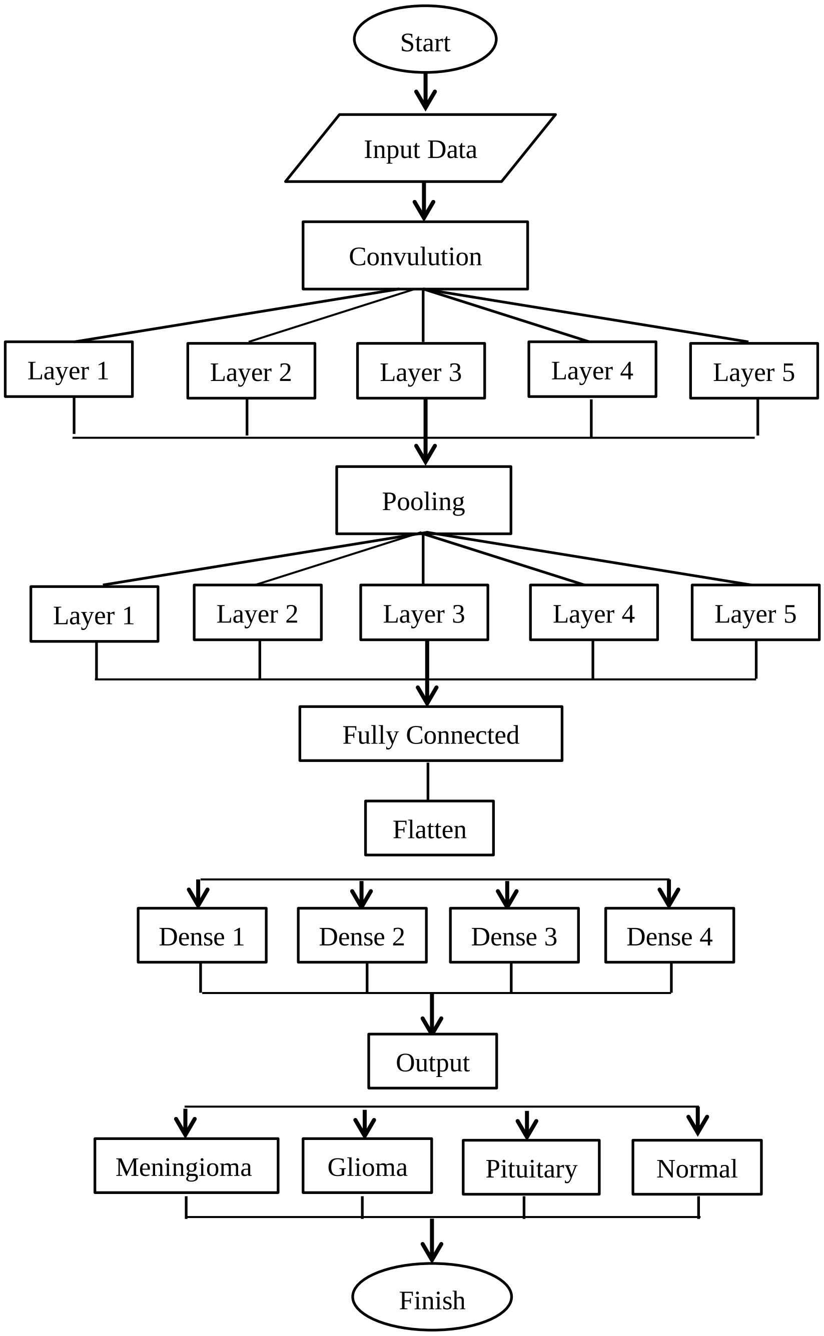


Figure 3. ResNet152V2 model algorithm

In Figure 3 there is an initial starting stage; then data input is an image of a brain tumor as input which is divided into 4 classes, namely meningioma, glioma, pituitary, and normal. In the convulsion stage, it is used to extract features from images using filters or kernels. In this research, 5 layers of convulutional layers were used. Then, at the pooling stage, this layer is used to reduce the image size by taking the maximum or average value of an area. In this study, 5 layers of maximum pooling were used. In the fully connected stage, this layer is used to connect every node from the previous layer to every node in this layer. In this study, 1 flatten layer and 4 dense layers were used. Then in the output layer is the classification result between 4 classes of brain tumors, namely meningioma, glioma, pituitary, and normal based on the input MRI image.

Implementation Phase

The classification results of the ResNet152V2 model were evaluated using accuracy, recall, precision and F1-Score metrics [19]. The evaluation process involved using a testing dataset and analyzing the model's ability to classify between four types of brain tumors, namely meningioma, glioma, pituitary, and normal. Evaluation is carried out using a confusion matrix which plays a role in helping understand the performance of the model. After that, the model for the class being tested makes predictions with the testing dataset, so that it can display images along with the prediction results obtained.

In this research, the prediction results are shown based on the prediction model function that appears in Google Collaboration. However, before that, there are testing results that show accuracy values to show the extent to which the model can perform classification correctly. The higher the accuracy value, the better the performance in classifying [20]. The results obtained show that the ResNet152V2 model is suitable for classifying brain tumor images.

3. RESULTS AND DISCUSSIONS

In this study, classification was carried out on four image classes, namely meningioma, glioma, pituitary, and normal, using deep learning Convolutional Neural Network (CNN) on the ResNet152V2 architecture. The data set used comes from a secondary source, namely the Kaggle.com website. Data set processing was carried out using the ResNet152V2 architecture with the Python programming language at Google Colaboratory. The main process of processing data with the ResNet152V2 model begins with the data training stage, which aims to train and develop a model to classify one of the four types of brain tumor. After that, the model's level of success is measured through accuracy values. The model accuracy value can be determined by testing the data using data testing. A total of 7,023 Kaggle datasets were downloaded and divided into training data of 5,618 (80%), validation data of 702 (10%) and testing data of 702 (10%), as shown in Table 1.

Table 1. Dataset

Dataset	Amount
Meningioma	1.645
Glioma	1.621
Pituitary	1.757
Normal	2.000
Total Image	7.023

Based on the results of research that has been carried out, the findings of the implementation of the ResNet152V2 model are as follows:

Training

Training results with input data produce train precision, val accuracy, train loss and val loss values [21]. This process uses a number of epochs of 25 and a learning rate of 0.001. The results of the ResNet152V2 model training process show that the model shows an increase in performance as the number of epochs increases. The training process in this research uses the ResNet152V2 model and can be seen in Figures 4 and 5, there are two graphs with the values obtained, namely training accuracy and validation accuracy. Figure 4 shows a graph of the relationship between the number of epochs and the increase in accuracy of the ResNet152V2 model. This study uses 25 epochs, the results of which are based on Figure 4 showing the accuracy value of the ResNet152V2 model. Training accuracy and validation accuracy increase with increasing epochs. At the start of training, the accuracy may still be low, but as the training continues, the model learns better from the data and its accuracy improves. At the 25th epoch, the ResNet152V2 model achieved its highest accuracy of 0.9360 or 93.60%. This figure shows that the model has a good ability to classify data correctly. This increase in accuracy indicates that the model learned well from the training data and successfully generalized its knowledge to the validation data.

Meanwhile, Figure 5 represents the loss graph of the ResNet152V2 model. Training loss and validation loss decrease as the epoch increases. At epoch 25, the lowest loss value was 0.17. A model can be said to be good if during the training process the accuracy graph is close to 1 and the loss graph is close to 0.

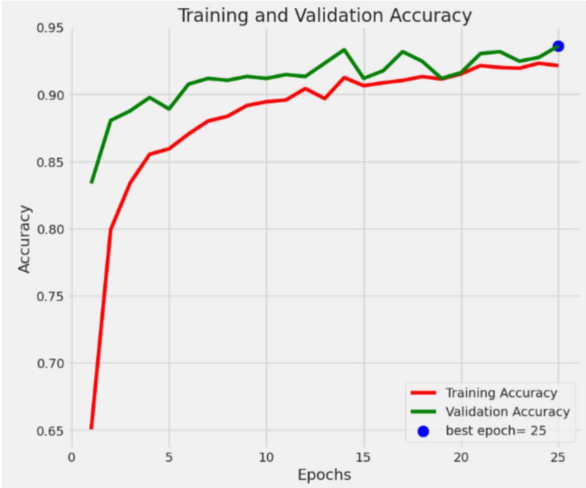


Figure 4. Accuracy graph in the ResNet152V2 model

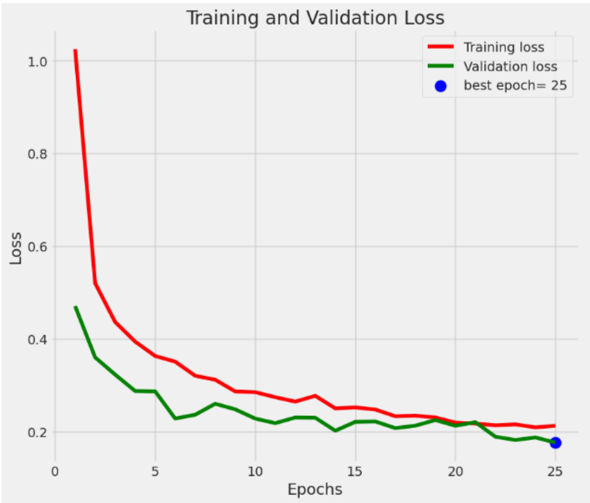
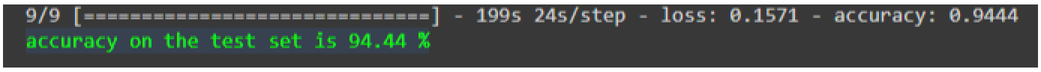


Figure 5. Loss graph on ResNet152V2

Figure 4 shows the accuracy graph of the ResNet152V2 model, namely the relationship between the number of epochs used and the model accuracy value. On the basis of this model, the results obtained are that the greater the number of epochs used, the higher the accuracy value. In this study, 25 epochs were used, producing an accuracy value close to 95%. Meanwhile, Figure 5 is a graph of the relationship between the number of epochs and the loss of the model. Where the number of epochs increases, the model loss also decreases. The more epochs used in the training data process, the more accuracy the model can increase because it has more time to adjust the weighting to suit the training data [22]. Figure 5 is a graph that shows the loss of the ResNet152V2 model during the training process. Train loss and train validation decrease as the epoch increases. At the beginning of training, the loss values tend to be high because the model is still learning to adjust its parameters. However, as the epoch increases, the model gets better at predicting correctly, so the loss value decreases. At the 25th epoch, the lowest loss value achieved was 0.17. This low loss value shows that the model makes fewer errors in its predictions. A model can be said to be good if during the training process the accuracy graph is close to 1 and the loss graph is close to 0. This means that the model is able to not only predict accurately but is also stable and consistent in its performance. Evaluation of model performance through accuracy and loss graphs is very important to ensure that the resulting model is not only accurate, but also reliable under various conditions [23].

Testing

The testing results show the accuracy value of the ResNet152V2 model, which shows the degree to which the model can perform classification well. The higher the accuracy value, the better the performance in classifying as shown in Figure 6. In this study, the accuracy value based on the calculations was 94.44%.



```
9/9 [==============================] - 199s 24s/step - loss: 0.1571 - accuracy: 0.9444
accuracy on the test set is 94.44 %
```

Figure 6. Testing result in ResNet152V2

Confusion Matrix

The performance of the Resnet152V2 model is obtained from the confusion matrix. The confusion matrix table is used to obtain metric evaluations such as accuracy, recall, precision, F1-Score. The confusion matrix results of the ResNet152V2 model are shown in Figure 7.

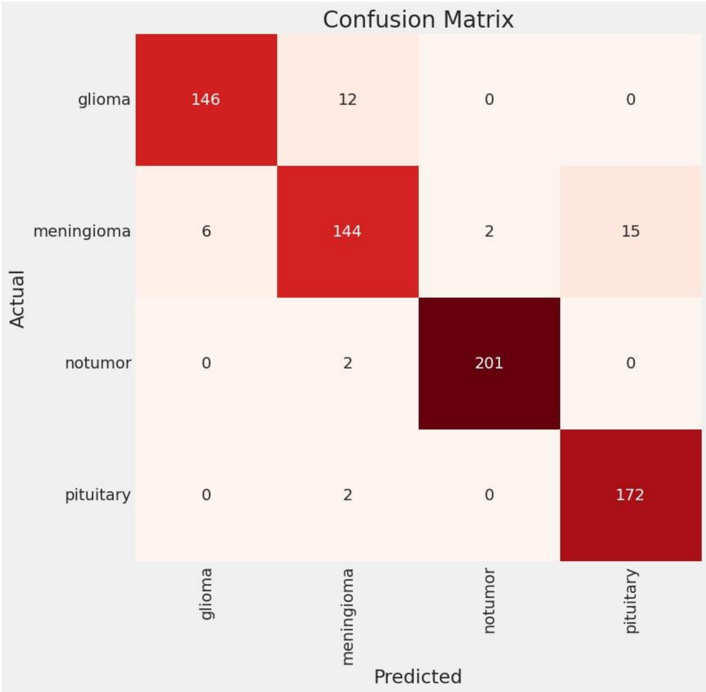


Figure 7. Confusion matrix of ResNet152V2

In this study, a confusion matrix was found as shown in Figure 7. Based on the results of the confusion matrix above, a score of 146 true positive (TP) for the Glioma class and true negative (TN) for the Meningioma, No Tumor, and pituitary classes. The value is 12 False Negative (FN) in the Glioma class, True Negative (TN) in the No Tumor and Pituitary class, and False Positive (FP) in the Meningioma class. Score 6 is false negative (FN) in the Meningioma class, false negative (TN) in the No Tumor and Pituitary class, and false positive (FP) in the Glioma class. Score 144 True Positive (TP) for Meningioma class and True Negative (TN) for Glioma, No Tumor, and Pituitary classes. Value 2: False Negative (FN) for the class of meningioma, no tumor and pituitary, True Negative (TN) for Glioma, No Tumor, and Pituitary class, and False Positive (FP) for the class of meningioma and no tumor. The score is 15 False Negative (FN) in the Meningioma class, True Negative (TN) in the Glioma and No Tumor class, and False Positive (FP) in the Pituitary class. The value is 201 True Positive (TP) in the No Tumor class and True Negative (TN) in the Glioma, Meningioma and Pituitary class. Score 172 True Positive (TP) for Pituitary class and True Negative (TN) for Glioma, Meningioma and No Tumor classes. Based on the values in the confusion matrix, accuracy, precision, sensitivity, specificity, and F1-Score are then calculated using equations (1), (2), (3), (4), and (5). This shows that the ResNet152V2 model has good performance in classifying brain tumor types in MRI images.

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{Amount\ of\ Data} \tag{1}$$

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$\text{Sensitivity} = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$\text{Specificity} = \frac{True\ Negative}{True\ Negative + False\ Positive} \tag{4}$$

$$\text{F1-}Score = 2 \times \frac{precision \times recall}{precision + recall} \tag{5}$$

Using this equation, a sensitivity of 86.22%, specificity of 97%, precision of 90%, F1-Score of 88%, and accuracy of 94.44% were obtained. Therefore, it shows that the ResNet152V2 model performs well in classifying brain tumor types on MRI images.

Performace Analysis

Table 2. Comparison of model performance result

No	Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
1	ResNet50	79,62%	57,5%	55,08%	87,28%	56,26%
2	InceptionV3	87,75%	79,72%	70,65%	94,39	74,9%
3	ResNet152V2	94,44%	90%	86,22%	97%	88%

From Table 2, performance analysis was carried out by comparing the accuracy, precision, sensitivity, specificity, and F1-Score values of the ResNet152V2 model with other models, namely ResNet50 and InceptionV3. Based on the results of the calculations carried out, the highest accuracy value for the model is ResNet152V2 to detect brain tumors in MRI images. The accuracy value of the ResNet152V2 model was 94.44%, while the InceptionV3 model obtained an accuracy value of 87.75% and the smallest accuracy was obtained using the ResNet50 model, namely only 79.62%.

4. CONCLUSION

Based on the results and discussions, this research uses a deep learning Convolutional Neural Network (CNN) in ResNet152V2 architecture to develop a classification system to determine the type of brain tumor, which is divided into four image classes: meningioma, glioma, pituitary and normal. This increases accuracy. Whenever this relates to detecting tumors in the brain from MRI information, the ResNet152V2 model works excellently. This model can be used to speed up medical personnel in the removal of brain tumors so that they are more efficient. It is also possible that it could be developed for other health cases.

REFERENCES

[1] A. Digdoyo, T. Surawan, A. S. B. Karno, D. R. Irawati, and Y. Effendi, “Deteksi Tumor Otak Dengan CNN Resnet-152,” *J. Teknol.*, vol. 9, no. 2, pp. 23–31, May 2022, doi: 10.31479/jtek.v9i2.128.

[2] F. M. Onyije *et al.*, “Risk factors for childhood brain tumours: A systematic review and meta-analysis of observational studies from 1976 to 2022,” *Cancer Epidemiol.*, vol. 88, p. 102510, Feb. 2024, doi: 10.1016/j.canep.2023.102510.

[3] M. A. Talukder *et al.*, “An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning,” *Expert Syst. Appl.*, vol. 230, p. 120534, Nov. 2023, doi: 10.1016/j.eswa.2023.120534.

[4] K. N. Deeksha, D. M, A. V Girish, A. S. Bhat, and L. H, “Classification of Brain Tumor and its types using Convolutional Neural Network,” in *2020 IEEE International Conference for Innovation in Technology (INOCON)*, IEEE, Nov. 2020, pp. 1–6. doi: 10.1109/INOCON50539.2020.9298306.

[5] T. Saputra and M. E. Al-Rivan, “Analisis Performa ResNet-152 dan AlexNet dalam Klasifikasi Jenis Kanker Kulit,” *STRING (Satuan Tulisan Ris. dan Inov. Teknol.*, vol. 8, no. 1, p. 75, Aug. 2023, doi: 10.30998/string.v8i1.16464.

[6] I. A. Kandhro *et al.*, “Performance evaluation of E-VGG19 model: Enhancing real-time skin cancer detection and classification,” *Heliyon*, vol. 10, no. 10, p. e31488, May 2024, doi: 10.1016/j.heliyon.2024.e31488.

[7] A. Ridhovan and A. Suharso, “PENERAPAN METODE RESIDUAL NETWORK (RESNET) DALAM KLASIFIKASI PENYAKIT PADA DAUN GANDUM,” *JIPI (Jurnal Ilm. Penelit. dan Pembelajaran Inform.*, vol. 7, no. 1, pp. 58–65, Feb. 2022, doi: 10.29100/jipi.v7i1.2410.

[8] D. R. Ningtias, M. Rofi’i, and B. A. Pramudita, “Utilization of Spiking Neural Network (SNN) in X-Ray Image for Lung Disease Detection,” *J. INFORMATICS Telecommun. Eng.*, vol. 7, no. 2, pp. 523–533, Jan. 2024, doi: 10.31289/jite.v7i2.10671.

[9] A. Dardzińska-Głębocka and M. Zdrodowska, “Analysis children with disabilities self-care problems based on selected data mining techniques,” *Procedia Comput. Sci.*, vol. 192, pp. 2854–2862, 2021, doi: 10.1016/j.procs.2021.09.056.

[10] M. N. Winnarto, M. Mailasari, and A. Purnamawati, “KLASIFIKASI JENIS TUMOR OTAK MENGGUNAKAN ARSITEKTURE MOBILENET V2,” *J. SIMETRIS*, vol. 13, no. 2, pp. 1–12, 2022.

[11] M. N. M. Hakim, A. B. Nugroho, and A. E. Minarno, “Prediksi Tumor Otak Menggunakan Metode Convolutional Neural

Network," *Inform. Mulawarman J. Ilm. Ilmu Komput.*, vol. 17, no. 1, p. 48, Jul. 2023, doi: 10.30872/jim.v17i1.5246.

[12] K. Amalia, R. Magdalena, and S. Saidah, "Klasifikasi Penyakit Tumor Otak Pada Citra Mri Menggunakan Metode CNN Dengan Arsitektur Alexnet," *e-Proceeding Eng.*, vol. 8, no. 6, pp. 3247–3254, 2022.

[13] B. Li, "Hearing loss classification via AlexNet and extreme learning machine," *Int. J. Cogn. Comput. Eng.*, vol. 2, pp. 144–153, Jun. 2021, doi: 10.1016/j.ijcce.2021.09.002.

[14] Tri Suhartono and Diah Rahayu Ningtias, "Classification of Pneumonia Disease Based on Web Application Using Convolutional Neural Networks (CNNs)," *Int. J. Technol. Educ. Res.*, vol. 1, no. 01 SE-Articles, pp. 129–140, Mar. 2023, [Online]. Available: https://e-journal.citakonsultindo.or.id/index.php/IJETER/article/view/267

[15] M. Neshat, M. Ahmed, H. Askari, M. Thilakaratne, and S. Mirjalili, "Hybrid Inception Architecture with Residual Connection: Fine-tuned Inception-ResNet Deep Learning Model for Lung Inflammation Diagnosis from Chest Radiographs," *Procedia Comput. Sci.*, vol. 235, pp. 1841–1850, 2024, doi: 10.1016/j.procs.2024.04.175.

[16] B. O. Olorunfemi, N. I. Nwulu, O. A. Adebo, and K. A. Kavadias, "Advancements in machine visions for fruit sorting and grading: A bibliometric analysis, systematic review, and future research directions," *J. Agric. Food Res.*, vol. 16, p. 101154, Jun. 2024, doi: 10.1016/j.jafr.2024.101154.

[17] Q. Xu, Z. Ma, N. HE, and W. Duan, "DCSAU-Net: A deeper and more compact split-attention U-Net for medical image segmentation," *Comput. Biol. Med.*, vol. 154, p. 106626, Mar. 2023, doi: 10.1016/j.compbiomed.2023.106626.

[18] T. Islam, M. S. Hafiz, J. R. Jim, M. M. Kabir, and M. F. Mridha, "A systematic review of deep learning data augmentation in medical imaging: Recent advances and future research directions," *Healthc. Anal.*, vol. 5, p. 100340, Jun. 2024, doi: 10.1016/j.health.2024.100340.

[19] N. T. Le *et al.*, "Deep Learning Approach for Age-related Macular Degeneration Detection Using Retinal Images: Efficacy Evaluation of Different Deep Learning Models," *Egypt. Informatics J.*, vol. 24, no. 4, p. 100402, Dec. 2023, doi: 10.1016/j.eij.2023.100402.

[20] K. Mani and H. Rajaguru, "A framework for performance enhancement of classifiers in detection of prostate cancer from microarray gene," *Heliyon*, vol. 10, no. 9, p. e29630, May 2024, doi: 10.1016/j.heliyon.2024.e29630.

[21] A. H. Uddin, Y.-L. Chen, M. R. Akter, C. S. Ku, J. Yang, and L. Y. Por, "Colon and lung cancer classification from multi-modal images using resilient and efficient neural network architectures," *Heliyon*, vol. 10, no. 9, p. e30625, May 2024, doi: 10.1016/j.heliyon.2024.e30625.

[22] O. G. Ajayi and J. Ashi, "Effect of varying training epochs of a Faster Region-Based Convolutional Neural Network on the Accuracy of an Automatic Weed Classification Scheme," *Smart Agric. Technol.*, vol. 3, p. 100128, 2023.

[23] F. Feng, Y.-B. Li, Z.-H. Chen, W.-T. Wu, J.-Z. Peng, and M. Mei, "Graph convolution network-based surrogate model for natural convection in annuli," *Case Stud. Therm. Eng.*, vol. 57, p. 104330, May 2024, doi: 10.1016/j.csite.2024.104330.

.