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A design of a brain tumor classifier of magnetic resonance imaging images using ResNet101V2 with hyperparameter tuning

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ABSTRACT

Brain tumors are a disease that is quite dangerous and requires severe treatment. One thing that is quite important is the process of diagnosing the brain tumor. This diagnosis process requires intense attention, and differences in interpretation may arise. Machine learning has been used in several fields, including disease diagnosis. This paper proposes an intelligent diagnostic tool for brain tumors using ResNet101v2. ResNet101V2 is used to classify meningioma, glioma, pituitary, and normal from magnetic resonance imaging (MRI) images. This research includes data collection, data preprocessing, ResNet101v2 design and evaluation. We investigate three models of ResNet101v2 for brain tumor classification. The best model achieves an accuracy of 96.2%.

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1. INTRODUCTION

The brain is a vital organ and acts as the center of intelligence, interpreter of the senses, control of body movements, and behavior controller. This organ has hundreds of billions of interconnected cells through trillions of connections. Brain tumor is deadly because of its aggressive nature, heterogeneous characteristics, and low survival rate. Therefore, this brain tumor needs to be identified as early as possible. This identification can then be followed up with therapy appropriate to the type of brain tumor. This encourages the need to develop methods for classifying brain tumors. Classification of brain tumors is conducted by considering their location, texture, shape, and aggressiveness [1]–[5].

Brain cancer treatment depends on how accurate the diagnosis of the tumor is. A definitive diagnosis of a brain tumor can be made by histopathological examination via biopsy. Another supporting examination is a computed tomography (CT) scan or magnetic resonance imaging (MRI) of the head Lateralization of interictal temporal lobe hypoperfusion in lesional and non-lesional temporal lobe epilepsy using arterial spin [6]–[9]. Manual human diagnosis requires years of special training and good stamina and concentration. Therefore, an intelligent brain tumor classification system is needed [10]–[12]. Machine learning or artificial intelligence has been applied to several applications [13]–[17]. Brain tumor MRI image classification has been carried out using convolutional neural networks (CNN) [18]–[22]. This study proposes a classification system of brain tumors using ResNet101V2 from MRI images [23]–[25].

This paper is then written in the following structure. First, section 2 describes the research method in detail. Then, the results and discussion are described in section 3, including the performance of the ResNet101V2 model. Section 4 concludes the paper.

2. RESEARCH METHOD

Figure 1 shows a system of the brain tumor classifier of MRI images using ResNet101V2. The system consists of data collection and processing, and the ResNet101V2 model is used as the classifier. Data preparation includes data labeling and cleaning.

Figure 1. Brain tumor classifier of MRI images using ResNet101V2

2.1. Data collection and processing

The data used in this research is MRI images with a resolution of 512×512. The data distribution of the dataset is listed in Table 1. The data used in this research is from Sardjito General Hospital, Figshare, SARTAJ, and Br35H datasets [26], [27]. Data from Sardjito General Hospital was collected from ten patients diagnosed with various types of brain tumors. The data from Sardjito General Hospital consists of 18 meningiomas from three patients, six pituitaries from one patient, and 28 gliomas from five patients [28], [29]. Figshare, SARTAJ, and Br35H datasets comprise 1645 meningioma, 1621 glioma, 1757 pituitary, and 2000 normal.

Table 1. Data collection

Class	Training data	Validation data	Test data
Meningioma	1765	207	105
Pituitary	1615	190	96
Normal	1700	200	100
Glioma	1949	229	115
Total	7029	826	416

2.2. ResNet101V2

This research used Python programming with several libraries such as Pandas, NumPy, and TensorFlow [30]–[32]. We present three ResNet101V2 models in this paper. Table 2 lists the hyperparameter of the Resnet101v2 models.

Table 2. The hyperparameter of Resnet101v2 models

No	Name	Rotation range	Width shift range	Shear range	Zoom range	Learning rate	Trainable layer
1	Model#1	40	0.20	0.20	0.20	0.001	0
2	Model#2	30	0.15	0.15	0.15	Piecewise constant scheduling	0
3	Model#3	30	0.15	0.15	0.15	Piecewise constant scheduling	10

3. RESULTS AND DISCUSSION

3.1. Model#1

Figure 2 shows the accuracy of model#1 on training and validation data. Model#1 has a training accuracy of 92.2%, validation accuracy of 92.4%, and test accuracy of 91.1%. Figures 3 and 4 show the receiver operating characteristic (ROC) and the confusion matrix of model#1 [33]–[35]. The meningioma class has the lowest accuracy, with an accuracy of 83.8%.

3.2. Model#2

Figure 5 shows the training and validation accuracy of model#2. Model#2 has a training accuracy of 94.8%, validation accuracy of 93.2%, and test accuracy of 91.4%. Figures 6 and 7 show the ROC and the confusion matrix of model#2. The meningioma class has the lowest accuracy, with an accuracy of 81.9%, and has the smallest area under the curve based on the precision-recall (PR) curve. Fluctuations decrease where the loss and accuracy values slope and will move towards a concurrent condition. The difference in loss values between training data and validation data increases, but the difference between validation and test data decreases. Model#2 has unsatisfactory results because it is still below the research threshold of 95.0% but has resolved the problems in model#1.

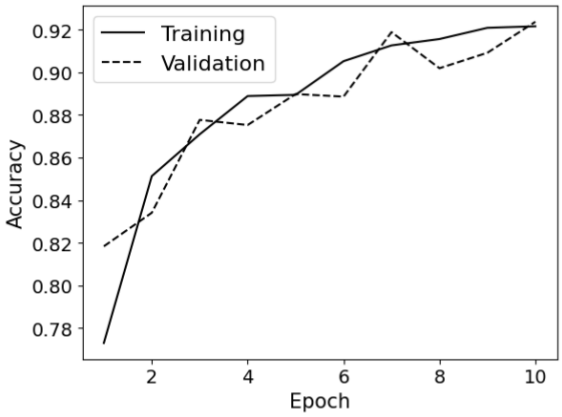

Figure 2. Accuracy of model#1 [37]

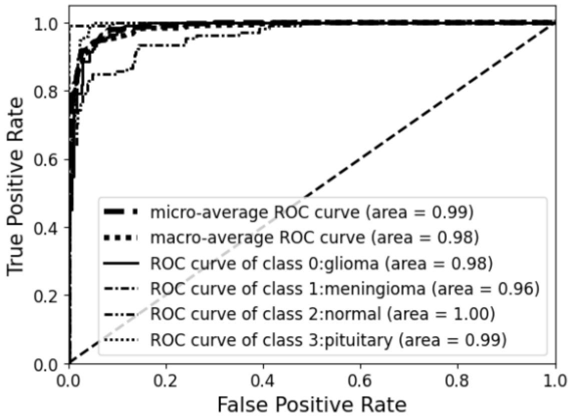

Figure 3. ROC of model#1

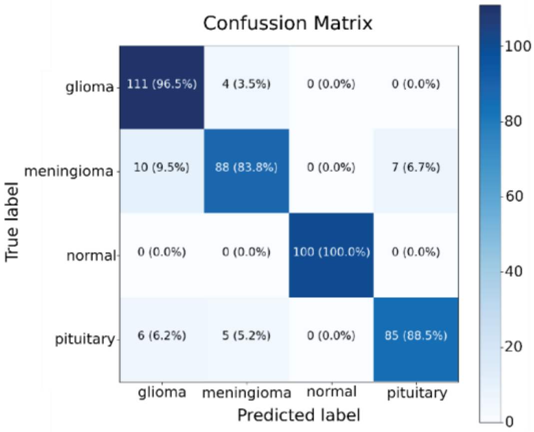

Figure 4. Confusion matrix of model#1

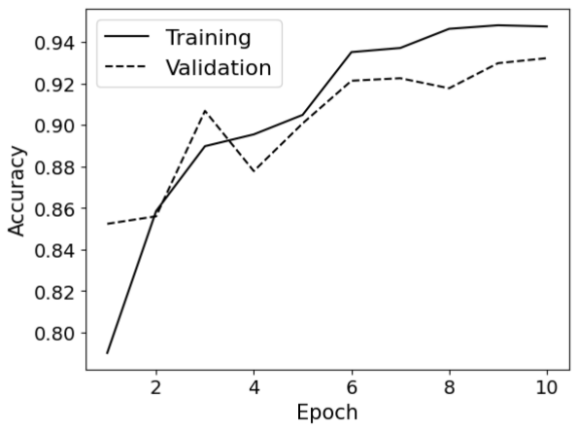

Figure 5. Accuracy of model#2

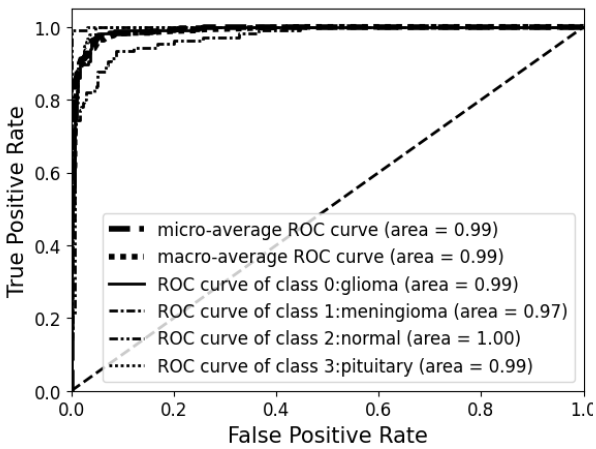

Figure 6. ROC of model#2

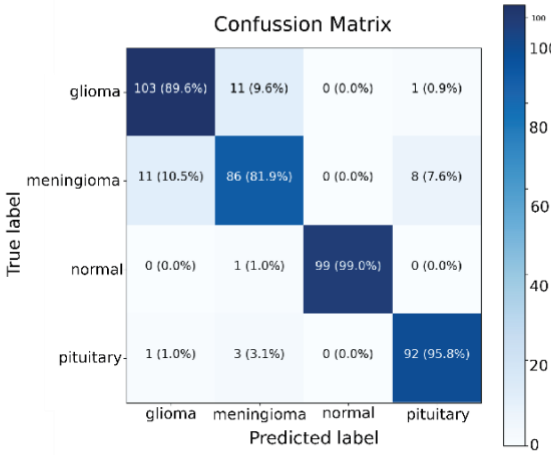

Figure 7. Confusion matrix of model#2

3.3. Model#3

Figure 8 shows the training and validation accuracy of model#3. Model#3 has a training accuracy of 98.4%, validation accuracy of 96.9%, and test accuracy of 96.2. Figures 9 and 10 show the ROC and the confusion matrix of model#3. Table 3 compares the performance of the three models of ResNet101v2.

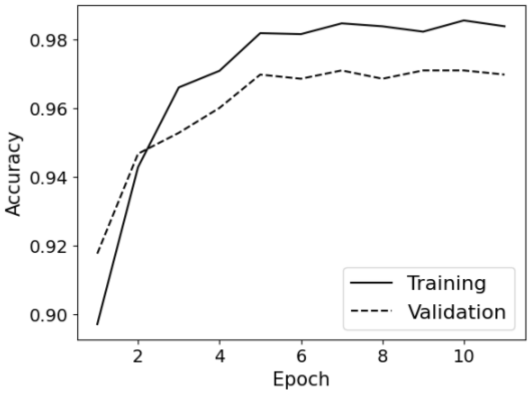

Figure 8. Accuracy of model#3

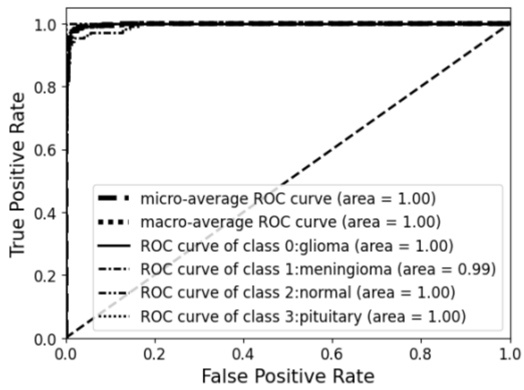

Figure 9. ROC of model#3

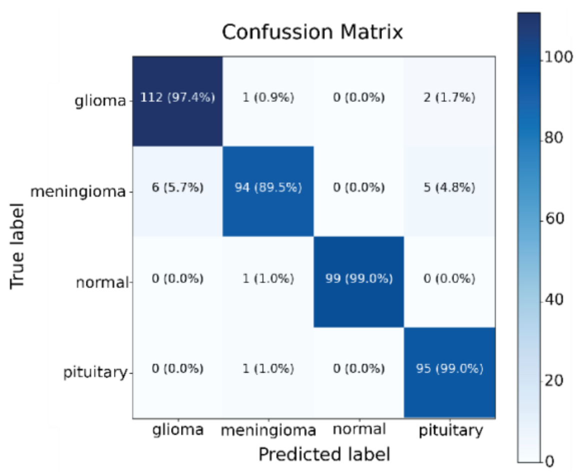

Figure 10. Confusion matrix of model#3

Table 3. Performance of ResNet101V2 models

Model type	Training time (s)	Accuracy (%)		
		Train	Validation	Test
Model#1	4086	92.2	92.4	92.3
Model#2	4045	94.8	93.2	91.4
Model#3	4687	98.4	96.9	96.2

4. CONCLUSION

This paper presented our proposed brain tumor classification system from MRI images using ResNet101v2. Our work includes data collection, processing, model training, and evaluation. ResNet101V2 has been successfully applied as a tool for classifying brain tumors based on the results of MRI images. The experimental results show that our best model achieved a training accuracy of 98.4%, validation accuracy of 96.9%, and test accuracy of 96.2%.

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REFERENCES

[1] G. S. Tandel, A. Tiwari, and O. G. Kakde, "Performance enhancement of MRI-based brain tumor classification using suitable segmentation method and deep learning-based ensemble algorithm," *Biomedical Signal Processing and Control*, vol. 78, 2022, doi: 10.1016/j.bspc.2022.104018.

[2] M. Yaqub *et al.*, "DeepLabV3, IBCO-based ALCResNet: a fully automated classification, and grading system for brain tumor," *Alexandria Engineering Journal*, vol. 76, pp. 609–627, 2023, doi: 10.1016/j.aej.2023.06.062.

[3] L. Li, M. Wang, X. Jiang, and Y. Lin, "Universal multi-factor feature selection method for radiomics-based brain tumor classification," *Computers in Biology and Medicine*, vol. 164, 2023, doi: 10.1016/j.compbiomed.2023.107122.

[4] P. Kanchanamala, K. G. Revathi, and M. B. J. Ananth, "Optimization-enabled hybrid deep learning for brain tumor detection and classification from MRI," *Biomedical Signal Processing and Control*, vol. 84, 2023, doi: 10.1016/j.bspc.2023.104955.

[5] E. Özbay and F. A. Özbay, "Interpretable features fusion with precision MRI images deep hashing for brain tumor detection," *Computer Methods and Programs in Biomedicine*, vol. 231, 2023, doi: 10.1016/j.cmpb.2023.107387.

[6] F. Rentzeperis *et al.*, "Lateralization of interictal temporal lobe hypoperfusion in lesional and non-lesional temporal lobe epilepsy using arterial spin labeling MRI," *Epilepsy Research*, vol. 193, Jul. 2023, doi: 10.1016/j.eplepsyres.2023.107163.

[7] A. S. R. Mohamed *et al.*, "Prospective validation of diffusion-weighted MRI as a biomarker of tumor response and oncologic outcomes in head and neck cancer: results from an observational biomarker pre-qualification study," *Radiotherapy and Oncology*, vol. 183, Jun. 2023, doi: 10.1016/j.radonc.2023.109641.

[8] Y. Wang *et al.*, "Assessment of stroke risk using MRI-VPD with automatic segmentation of carotid plaques and classification of plaque properties based on deep learning," *Journal of Radiation Research and Applied Sciences*, vol. 16, no. 3, 2023, doi: 10.1016/j.jrras.2023.100630.

[9] A. B. Abdusalomov, M. Mukhiddinov, and T. K. Whangbo, "Brain tumor detection based on deep learning approaches and magnetic resonance imaging," *Cancers*, vol. 15, no. 16, Aug. 2023, doi: 10.3390/cancers15164172.

[10] E. Dandil, M. Çakiroğlu, and Z. Ekşi, "Computer-aided diagnosis of malign and benign brain tumors on MR images," *Advances in Intelligent Systems and Computing*, vol. 311. Springer International Publishing, pp. 157–166, 2015. doi: 10.1007/978-3-319-09879-1_16.

[11] O. Turk, D. Ozhan, E. Acar, T. C. Akinci, and M. Yilmaz, "Automatic detection of brain tumors with the aid of ensemble deep learning architectures and class activation map indicators by employing magnetic resonance images," *Zeitschrift fur Medizinische Physik*, 2023, doi: 10.1016/j.zemedi.2022.11.010.

[12] S. Arora and M. Sharma, "Deep learning for brain tumor classification from MRI images," *Proceedings of the IEEE International Conference Image Information Processing*, vol. 2021, IEEE, pp. 409–412, 2021. doi: 10.1109/ICIIP53038.2021.9702609.

[13] D. E. P. Lebukan, A. N. I. Wardana, and N. Effendy, "Implementation of plant-wide pi-fuzzy controller in tennessee eastman process," *Proceedings - 2019 International Seminar on Application for Technology of Information and Communication: Industry 4.0: Retrospect, Prospect, and Challenges, iSemantic 2019*. IEEE, pp. 450–454, 2019. doi: 10.1109/ISEMANTIC.2019.8884301.

[14] R. Y. Galvani, N. Effendy, and A. Kusumawanto, "Evaluating weight priority on green building using fuzzy AHP," in *2018 12th South East Asian Technical University Consortium (SEATUC)*, Mar. 2018, pp. 1–6. doi: 10.1109/SEATUC.2018.8788887.

[15] N. Effendy, N. C. Wachidah, B. Achmad, P. Jiwandono, and M. Subekti, "Power estimation of G.A. siwabessy multi-purpose reactor at start-up condition using artificial neural network with input variation," *Proceedings - 2016 2nd International Conference on Science and Technology-Computer, ICST 2016*. IEEE, pp. 133–138, 2017. doi: 10.1109/ICSTC.2016.7877362.

[16] S. Prihanto, N. Effendy, and N. Nopriadi, "Hand gesture-based automatic door security system using squeeze and excitation residual networks," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 13, no. 2, pp. 1619–1624, Jun. 2024, doi: 10.11591/ijai.v13.i2.pp1619-1624.

[17] E. D. Kurniawan, N. Effendy, A. Arif, K. Dwiantoro, and N. Muddin, "Soft sensor for the prediction of oxygen content in boiler flue gas using neural networks and extreme gradient boosting," *Neural Comput & Applic*, vol. 35, no. 1, pp. 345–352, 2023, doi: 10.1007/s00521-022-07771-8.

[18] E. Irmak, "Multi-classification of brain tumor MRI images using deep convolutional neural network with fully optimized framework," *Iranian Journal of Science and Technology - Transactions of Electrical Engineering*, vol. 45, no. 3, pp. 1015–1036, 2021, doi: 10.1007/s40998-021-00426-9.

[19] M. Aggarwal, A. K. Tiwari, M. P. Sarathi, and A. Bijalwan, "An early detection and segmentation of brain tumor using deep neural network," *BMC Medical Informatics and Decision Making*, vol. 23, no. 1, Apr. 2023, doi: 10.1186/s12911-023-02174-8.

[20] F. Taher, M. R. Shoaib, H. M. Emara, K. M. Abdelwahab, F. E. Abd El-Samie, and M. T. Haweel, "Efficient framework for brain tumor detection using different deep learning techniques," *Frontiers in Public Health*, vol. 10, Dec. 2022, doi: 10.3389/fpubh.2022.959667.

[21] M. M. Badža and M. C. Barjaktarović, "Classification of brain tumors from mri images using a convolutional neural network," *Applied Sciences*, vol. 10, no. 6, 2020, doi: 10.3390/app10061999.

[22] Z. Rasheed *et al.*, "Brain tumor classification from MRI using image enhancement and convolutional neural network techniques," *Brain Sciences*, vol. 13, no. 9, Sep. 2023, doi: 10.3390/brainsci13091320.

[23] L. Ji, Z. Wei, J. Hao, and C. Wang, "An intelligent diagnostic method of ECG signal based on Markov transition field and a ResNet," *Computer Methods and Programs in Biomedicine*, vol. 242, 2023, doi: 10.1016/j.cmpb.2023.107784.

[24] W. Xu, Y. L. Fu, and D. Zhu, "ResNet and its application to medical image processing: Research progress and challenges," *Computer Methods and Programs in Biomedicine*, vol. 240, 2023, doi: 10.1016/j.cmpb.2023.107660.

[25] S. Yu, Z. Zhang, S. Wang, X. Huang, and Q. Lei, "A performance-based hybrid deep learning model for predicting TBM advance rate using attention-ResNet-LSTM," *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 16, no. 1, pp. 65–80, 2024, doi: 10.1016/j.jrmge.2023.06.010.

[26] M. M. Islam, P. Barua, M. Rahman, T. Ahammed, L. Akter, and J. Uddin, "Transfer learning architectures with fine-tuning for brain tumor classification using magnetic resonance imaging," *Healthcare Analytics*, vol. 4, 2023, doi: 10.1016/j.health.2023.100270.

[27] M. Celik and O. Inik, "Development of hybrid models based on deep learning and optimized machine learning algorithms for brain tumor multi-classification," *Expert Systems with Applications*, vol. 238, 2024, doi: 10.1016/j.eswa.2023.122159.

[28] B. S. Alemu, S. Feisso, E. A. Mohammed, and A. O. Salau, "Magnetic resonance imaging-based brain tumor image classification performance enhancement," *Scientific African*, vol. 22, 2023, doi: 10.1016/j.sciaf.2023.e01963.

[29] K. V. Hoebel *et al.*, "Not without context—a multiple methods study on evaluation and correction of automated brain tumor segmentations by experts," *Academic Radiology*, vol. 31, no. 4, pp. 1572–1582, 2023, doi: 10.1016/j.acra.2023.10.019.

[30] J. Chen, T. Jiang, D. Yu, and H. Hu, "Pattern-based circular reference detection in Python," *Science of Computer Programming*, vol. 227, 2023, doi: 10.1016/j.scico.2023.102932.

[31] Y. El jariri *et al.*, "New tool in python for spectroscopic data analysis: application to variable stars data from the Oukaimden and OHP observatories," *Astronomy and Computing*, vol. 43, 2023, doi: 10.1016/j.ascom.2023.100708.
[32] A. Geron, *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow*. Massachusetts, USA: O'Reilly Media Inc., 2019.
[33] S. K. -Bayrakdar *et al.*, "Detection of periodontal bone loss patterns and furcation defects from panoramic radiographs using deep learning algorithm: a retrospective study," *BMC Oral Health*, vol. 24, no. 1, Jan. 2024, doi: 10.1186/s12903-024-03896-5.
[34] W. Du *et al.*, "Deep learning in computed tomography to predict endotype in chronic rhinosinusitis with nasal polyps," *BMC Medical Imaging*, vol. 24, no. 1, Jan. 2024, doi: 10.1186/s12880-024-01203-w.
[35] C. B. Gupta *et al.*, "Improving the precision of shock resuscitation by predicting fluid responsiveness with machine learning and arterial blood pressure waveform data," *Scientific Reports*, vol. 14, no. 1, Jan. 2024, doi: 10.1038/s41598-023-50120-5.

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