JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 10. NO. 1 AUGUST 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i1.5223

BRAIN TUMOR CLASSIFICATION USING INCEPTIONRESNET-V2 AND TRANSFER LEARNING APPROACH

Vallent Austin Theasar Kurniawan[1]; Elan Cahya Niswary[2]; Christian Sri Kusuma Aditya [3*]; Didih Rizki Chandranegara[4]

Department of Informatics[1,2,3,4]
Universitas Muhammadiyah Malang, Indonesia[1,2,3,4]
umm.ac.id[1,2,3,4]
vallentaustin@webmail.umm.ac.id[1], elancahya@webmail.umm.ac.id[2], christianskaditya@umm.ac.id[3*], didihrizki@umm.ac.id[4]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract—*Brain, a highly intricate organ within the central nervous system, plays a fundamental role in information processing, cognition, motor control, and consciousness. Brain tumors pose severe threats to brain function and overall human well-being. Timely detection of these tumors is imperative for life-saving interventions. A dataset comprising four categories: no tumors, meningioma tumors, glioma tumors, and pituitary tumors was regarded in this research. The employed of the InceptionResNet-V2 architecture combined with Transfer Learning and data augmentation proposed to obtain optimal results on brain tumor classification types. Transfer learning act as fine tuning, enabling the model to acquire fundamental low-level image features from a comprehensive dataset. It then leverages higher-level features to become more tailored to the specific training data. This method is employed to improve the model's adaptability to the training data. The InceptionResNet-V2 architecture utilized in the evaluation using test data, in Scenario 1, achieved 94.18% accuracy. Scenario 2, which combined augmentation with InceptionResNetV2, showed an improvement in accuracy to 95.10%. Furthermore, in Scenario 3, the combination of InceptionResNetV2 with Transfer Learning and augmentation resulted in an impressive accuracy of 96.63%, demonstrating its effectiveness in brain tumor classification. Transfer learning aligns the model by acquiring low-level image features and utilizing higher-level features to improve adaptability to the training data.*

Keywords: *brain tumor, classification, inceptionresnet-v2, transfer learning.*

Intisari— *Otak, organ yang sangat rumit di dalam sistem saraf pusat, berperan penting dalam pemrosesan informasi, kognisi, kontrol motorik, dan kesadaran. Tumor otak merupakan ancaman besar terhadap fungsi otak dan kesehatan manusia secara keseluruhan. Deteksi dini tumor ini sangat penting untuk tindakan penyelamatan nyawa. Dalam penelitian ini, dataset terdiri dari empat jenis tumor: tidak ada tumor, tumor meningioma, tumor glioma, dan tumor pituitary. Penggunaan arsitektur InceptionResNet-V2 yang dikombinasikan dengan Transfer Learning dan augmentasi data digunakan untuk mencapai hasil yang optimal dalam mengklasifikasikan jenis-jenis tumor otak. Transfer learning berperan sebagai fine tuning, yang memungkinkan model untuk memperoleh fitur gambar tingkat rendah yang mendasar dari kumpulan data yang komprehensif. Kemudian memanfaatkan fitur tingkat yang lebih tinggi untuk menjadi lebih disesuaikan dengan data pelatihan yang spesifik. Pendekatan ini diimplementasikan untuk meningkatkan kemampuan adaptasi model terhadap data pelatihan. . Arsitektur InceptionResNet-V2 yang digunakan pada evaluasi menggunakan data test, dalam Skenario 1 akurasi model sebesar 94,18%. Skenario 2, yang menggabungkan augmentasi dengan InceptionResNetV2, menunjukkan peningkatan akurasi menjadi 95,10%. Selanjutnya, pada Skenario 3, kombinasi InceptionResNetV2 dengan Transfer Learning dan augmentasi menghasilkan akurasi yang mengesankan yaitu 96,63%, yang menunjukkan keefektifannya dalam klasifikasi tumor otak. Transfer learning menyelaraskan model dengan memperoleh fitur gambar* *tingkat rendah dan memanfaatkan fitur tingkat yang lebih tinggi untuk meningkatkan kemampuan beradaptasi dengan data pelatihan.*

Kata Kunci: *tumor otak, klasifikasi, inceptionresnet-v2, transfer learning.*

INTRODUCTION

The human body depends heavily on the vital functions performed by the brain [1]. Serving as the central command for the entire nervous system, it controls various bodily functions and organs [2]. The brain outer layer called the cerebral cortex, processes sensory information, generating motor activities, and facilitating complex cognitive functions like language [3]. It is essential to prioritize brain health as it directly impacts overall well-being and longevity [4].

Brain abnormalities, especially tumors, pose a serious risk to human health [5]. Brain tumor is a situation marked by abnormal growth of brain cells, disrupting the functioning of the nervous system. There are two main types of brain tumors: benign and malignant [6]. These tumors are categorized into four grades, with grades 1 and 2 being benign and grades 3 and 4 considered malignant [7]. Benign tumors, classified as low-grade, are non-cancerous and do not spread to other parts of the brain. In contrast, malignant tumors, identified as high-grade, are cancerous and have the potential to spread rapidly other parts of the body, leading to swift and severe consequences, including fatal outcomes [8].

Brain tumors can affect not only adults but also children at a young age [9]. Several factors, including increasing age, radiation exposure, and family history, can heighten the risk of developing brain tumors. It is crucial to note, however, that having these risk factors does not guarantee the onset of a brain tumor [10]. Early detection plays a pivotal role in saving lives [11]. Delays in treatment significantly contribute to the mortality rate, often because medical intervention occurs at advanced stages [12]. Diagnosis is essential to assess the tumor's spread and determine the most suitable treatment for the patient [13]. Timely diagnosis and intervention are key to improving outcomes and ensuring the well-being of those affected by brain tumors.

Multiple methods are employed to detect brain tumors early, with digital technology playing a significant role in health imaging approaches. Common methods for health imaging are CT scans, X-rays, and MRI. Among these, MRI stands out as the most effective and widely utilized technique for diagnosing brain tumors [14]. MRI utilize a radio waves and powerful magnetic field to generate detailed images of. internal organs, offering comprehensive insights into the body's internal structures. This method not only provides in-depth information about internal organs but also excels in producing highly detailed images crucial for the detection and treatment of tumors [15].

Numerous research has explored the intricacies of MRI image analysis, particularly in brain MRI image classification and segmentation. Researchers have explored a multitude of algorithms to identify brain tumors through MRI images. Notably, Agus Eko and colleagues (2021) conducted significant research in this domain, introducing a Convolutional Neural Network (CNN) approach to detect brain tumor. Their research incorporated Hyperparameter Tuning, optimizing the CNN method to achieve remarkable accuracy in classifying brain tumor types, with the third model scenario yielding a notable 96% accuracy [16]. Another noteworthy research by Chetana Srinivas and team (2022) employed transfer learning techniques, utilizing pre-trained CNN models such as ResNet-50, VGG-16 and Inception-V3. Their research demonstrated the effectiveness of VGG-16 with an accuracy of 96%, Inception-v3 with 78%, and ResNet-50 with 95% accuracy [17].

Several significant studies have contributed refor classification of brain tumor images in recent years. M. Milica and colleagues (2020) employed a Convolutional Neural Network (CNN) using a blend of two 10-fold cross-validation approaches and two databases, achieving an impressive accuracy of 96.56% [18]. In another study, Monikka Nur Winnarto and her team (2022) utilized the CNN MobileNetV2 architecture, attaining accuracy results of 88.64% and a loss value of 0.3424 in their classification of tumor types [19]. Furthermore, Soheila Saeedi and colleagues (2023) explored deep learnig methods, including 2D Convolutional Neural Network (CNN) and convolutional auto-encoder networks, along with various machine learning approaches for brain tumor classification. Their results demonstrated a training accuracy of 96.47% for the proposed 2D CNN and 95.63% for the auto-encoder network [20].

InceptionResNet-V2 represents a specialized category of Convolutional Neural Networks (CNNs) designed to generate features essential for classification tasks. It is the outcome of merging the Inception structure with Residual Network connections (ResNet). The architecture of

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 10. NO. 1 AUGUST 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i1.5223

InceptionResNet-V2 revolves around three key components: convolution layers, activation layers, and pooling layers [21]. This model innovatively combines inception modules and residual network connections, resulting in a deep and highly efficient architecture tailored for extracting intricate features from images.

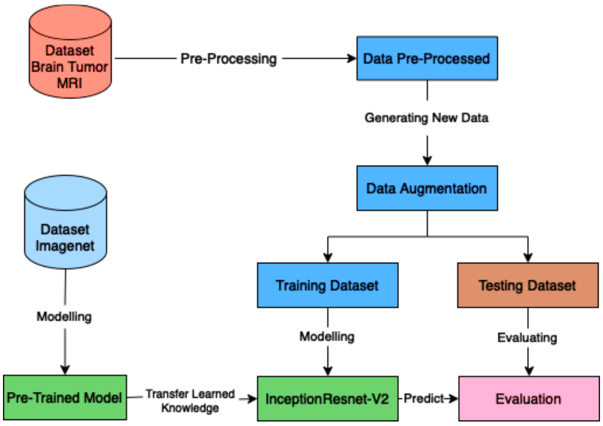
In recent times, a specialized form of deep learning called deep transfer learning has surfaced as a prominent approach in research concerning image classification challenges, visual categorization and object recognition [22]. CNN models are involved in this technique, which was originally designed for related applications. The metrics accuracy achieved through transfer learning based algorithms outperformed those obtained through manual engineering methods [23].

In this study we implemented the InceptionResNetV2 model, that was adopted based on insights from previous research results which proved effective in extracting image features of varying scale and complexity [24], and also integrated with a transfer learning approach. In the transfer learning method, models pre-trained on large datasets can transfer their knowledge to new tasks, such as brain tumor classification. By combining these two methods and by parameter selection, it is expected to achieve higher accuracy results that can perform more accurate classification than previous methods.

The rest of the paper follows the structure outlined. Section 2 introduce the concept of transfer learning, outlines the dataset utilized, and describes the proposed classification algorithm's structure. Section 3 delves into the specifics of the experiments conducted, shares the evaluation outcomes, and offers a discussion on these results. Finally, Section 4 offers the concluding remarks for this paper.

MATERIALS AND METHODS

The research methodology in this research started with acquiring a dataset from the Kaggle website. Subsequently, the data was subjected to a data splitting stage, where it was separated and organized. Following the data splitting process, various data augmentation were applied to enhance datasets. The subsequent step involved the creation and training of the research model, which was built on the InceptionResNet-V2 architecture. Finally, the research concluded with the evaluation of the model's performance, Figure 1 illustrated the detailed research flow.

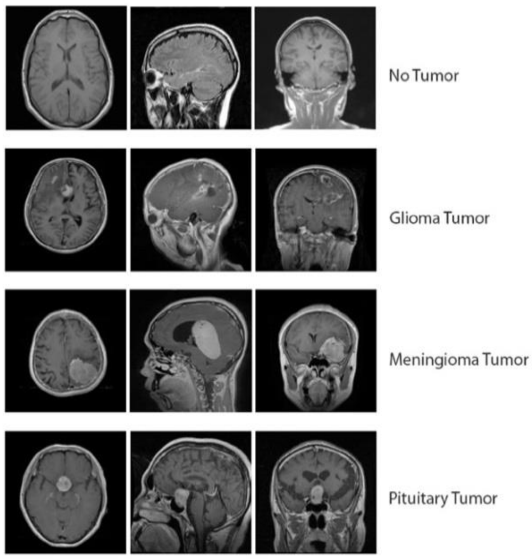


Source: Research Results, 2024

Figure 1. Research Flowchart Diagram

A. Dataset

This research used a dataset named "Brain Tumor Classification MRI (Magnetic Resonance Imaging)," obtained from the Kaggle website. This dataset comprised 4 classes: 500 images no tumor, 926 images glioma tumors, 937 images meningioma tumors, and 901 images pituitary tumors with total 3264 images [25]. As detailed in the introduction, brain tumors are categorized into four grades, with grade 1 and grade 2 termed as benign tumors and grade 3 and grade 4 referred to as malignant tumors. Among primary brain tumors, glioma, meningioma, and pituitary tumors are the most prevalent forms. Glioma originates from internal brain cells known as glial cells, that have a vital role in maintaining the normal function of neurons. The example of images presented in Figure 2



Source: Brain Tumor Classification [25], 2020

Figure 2. Image samples for every brain label

Meningioma tumors originate from the brain lining around the brain and spinal cord inside the skull. Pituitary tumors develop abnormally in the region of the pituitary gland, situated within the skull, among the brain and nasal passages [26]. Meningioma and pituitary tumors are considered benign, signifying that they do not extend to other cells, tissues, or body parts. In contrast, glioma is malignant and has the potential to spread to different organs in the body.

B. Data Preprocessed

In the data pre-processing stage, image resizing was performed. This step aimed to reduce the dimensions of image data without compromising essential features. The primary objective of image resizing was to enhance computational efficiency during the training of the data. Specifically, the image size was adjusted from 512 x 512 pixels to 150 x 150 pixels. Smaller images will train significantly faster, and possibly even converge quicker [27]. Using smaller images can also help the network generalise better, too, as there is less data to overfit.

C. Data Augmentation

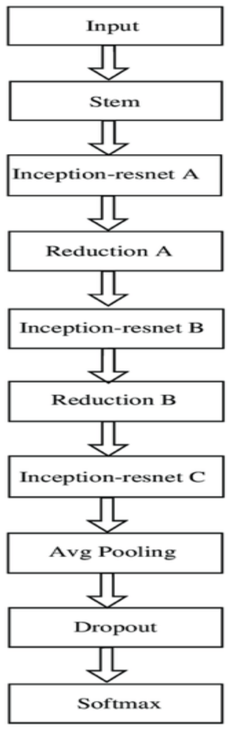
The objective of data augmentation process was to expand the dataset by transforming the original images into different variations. Augmentation introduces diverse data variations, thereby enhancing the performance of classification results [13]. In this study, the augmentation technique applied involved rotation by 30 degrees, width shift by 0.01, height shift by 0.01, zoom range of 0.2, and horizontal flipping was enabled (horizontal_flip = true).

D. Data Splitting

During this stage, the dataset was split into three subsets: training data, validation data, and test data. Training and validation data were utilized for model training, whereas test data served as the dataset for predictions after the model had been trained. The Brain Tumor Classification MRI dataset was split into portions, with 80% assigned for training data, 10% for validation data, and another 10% for test data. Employing the validation set to assess various models to identify the top-performing one. Once we determine the most effective model, we utilize the test set to measure its performance.

E. InceptionResNet-V2 and Transfer Learning Approach

InceptionResNet-V2 was utilized model as the core architecture in this study. InceptionResNet-V2 represents a fusion of two prominent network designs: residual connection and Inception architecture. This hybrid model incorporates residual connections, ensuring highly efficient performance[28]. The architecture of InceptionResNet-V2 comprises modules such as Inception-Resnet-A, Inception-Resnet-B, and Inception-Resnet-C blocks [29]. Figure 3 illustrates the detailed architecture of the InceptionResNetV2 model utilized in this research.



Source: Chandranegara [24], 2023
Figure 3. InceptionResNet-V2 Model Architecture

In this research, a CNN model architecture was employed for the purpose of classifying brain tumors within MRI images. The model in this research encompassed the following components: an input layer set at 150 x 150, GlobalAveragePooling2D, Dropout (0.5), and a Dense layer (1024). The GlobalAveragePooling2D layer served to mitigate overfitting by reducing the number of model parameters[30]. GlobalAveragePooling2D also helps to reduce the complexity of the model and retain critical information needed for classification tasks. The Dense layer contributed to a deeper and more intricate learning process, facilitating enhanced feature extraction from pre-processed image data that had undergone GlobalAveragePooling2D. To prevent overfitting, the Dropout layer was employed as a regularization technique. The architectural design specifics of the model are presented in Table 1.

VOL. 10. NO. 1 AUGUST 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i1.5223

Table 1. Model Architecture

Layer	Filter	Activation
Input (150, 150)	-	-
GlobalAveragePooling2D	-	-
Droput	0.5	-
Dense	1024	relu
Dropout	0.5	-
Dense	128	relu
Dense	4	softmax

Source: Research Results, 2024

Transfer learning was utilized ini this research. Transfer learning was a method in Machine Learning where a model has been trained and developed for a task can be reused for another related task [31]. The approach of transfer learning is referred to as "inductive transfer learning" when both the source and target domains have labeled data available for a classification task. [32]. Applying transfer learning to a pre-trained CNN (Convolutional Neural Network) representation is made easier with Tensor Flow [33]. Transfer Learning is typically employed in scenarios where a new dataset is of smaller scale compared to original dataset used for initial model training. The concept behind applying transfer learning in the context of fine-tuning is to enable the model to grasp fundamental, low-level image features from a comprehensive dataset, while utilizing higher-level features to cater specifically to the nuances of the training data. This process is carried out with the goal of enhancing the model's adaptability to the specific characteristics of the training data.

RESULTS AND DISCUSSION

The initial step involved data collection from the specified sources as outlined in the aforementioned methodology. The dataset was categorized into four classes: no tumor, glioma tumor, meningioma tumor, and pituitary tumor for classification purposes. Following the division outlined above, the dataset was split with 80% assigned for training, 10% for validation, and 10% for testing. Subsequently, data augmentation was performed using rotation, width shift, height shift, zoom, and horizontal flip techniques. The experiment employed callback techniques including ModelCheckPoint and ReduceLROnPlateau on Keras library. The data was then trained on a model created utilizing the M1 GPU. In this study conducted experiments with 3 different scenarios. Experimental results can provide an assessment of the effects of using transfer learning. The table below presents the test scenarios and descriptions of the scenario, as presented in Table 2.

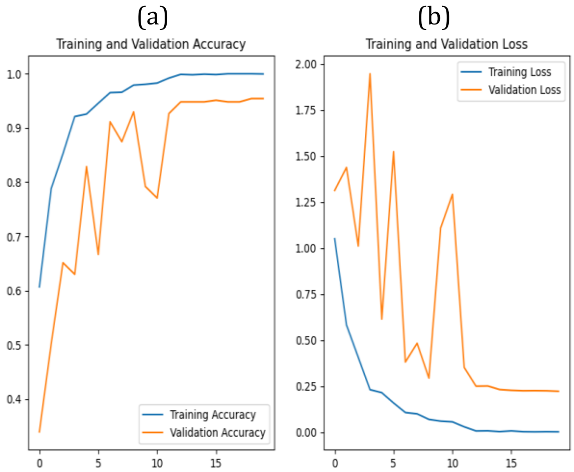
Table 2. Description of Scenario

Scenario	Description
Scenario 1	InceptionResNet-V2
Scenario 2	InceptionResNet-V2 + Data Augmentation
Scenario 3	InceptionResNet-V2 + Data Augmentation and Transfer Learning

Source: Research Results, 2024

A. Scenario 1

In scenario 1, training was executed using the Adamax optimizer for 20 epochs and categorical_crossentropy classification. The model was trained without transfer learning, and data augmentation were not utilized. Figure 4 illustrates the accuracy and loss results in the scenario model.



Source: Research Results, 2024

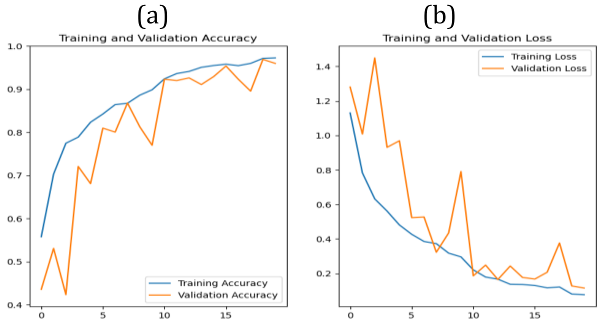
Figure 4. (a) accuracy and (b) loss graph training model InceptionResnet-V2 scenario 1

Figure 4 shows the accuracy and loss plot results of scenario 1, where the model trained using the training data shows signs of overfitting and instability in the graphical results. Both the validation accuracy and loss show significant differences in value when compared to the training accuracy and loss. The training accuracy result obtained from the InceptionResNet-V2 model of scenario 1 is 99.96%, and the training loss is 0.17. The validation accuracy result based on the graph above is 95.41%, and the validation loss is 0.22. Moreover, the accuracy obtained for evaluating the model using test data is 94.18%.

B. Scenario 2

In scenario 2, training has been carried out using the same parameters as scenario 1, the model was trained utilizing data augmentation techniques. Figure 5 illustrates the accuracy and loss results of this scenario model.

(a) (b)



Source: Research Results, 2024

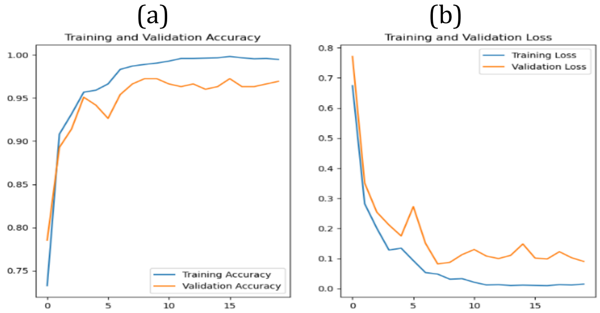
Figure 5. (a) accuracy and (b) loss graph training model InceptionResnet-V2 scenario 2

Figure 5 shows the accuracy and loss plot results of scenario 2, where the model trained using the training data gets unstable results. The use of augmentation techniques, which is performed by increasing the training dataset through the creation of modified copies using existing data, can prevent overfitting of the model, as shown by the difference in graph lines between training and validation. The result of the training accuracy of scenario 2 is 97.28%, with a training loss of 0.07. The validation accuracy result based on the graph above is 96.01%, with a validation loss of 0.11. In addition, the accuracy result obtained for model evaluation using test data is 95.10%.

C. Scenario 3

In scenario 3, training using the same parameter as previous scenarios. The model was trained using transfer learning with ImageNet weights and employs data augmentation techniques. The following is a plot of accuracy and loss results for scenario model in Figure 6.

(a) (b)



Source: Research Results, 2024

Figure 6. (a) accuracy and (b) loss graph training model InceptionResnet-V2 scenario 3

Figure 6 shows the accuracy and loss plot results of scenario 3, where the model trained using the training data produced more stable graphical results. The usage of transfer learning and utilizing data augmentation techniques to this model shows good results and there is no overfitting. The results of the training accuracy are 99.46% and training loss 0.01. The validation accuracy results obtained 96.93% and validation loss 0.09. The pre-training model used proved sufficient in achieving reasonable classification accuracy, given the limited size of the training set, as it was originally trained on a dataset consisting of millions of images (ImageNet). Moreover, the accuracy obtained while conducting the model evaluation using the test data is 96.63%.

D. Model Evaluation

The evaluation results of this study were conducted using test data. In this study, we evaluated the model comprehensively by comparing the results with those from previous research, as seen in Table 3.

Table 3. Comparison with Previous Research

Author	Model	Accuracy (%)
Minarno et al [16]	CNN with Hyperparameter Tuning	96.00
Scenario 1	InceptionResNet-V2	94.18
Scenario 2	InceptionResNetV2 + Augmentation	95.10
Scenario 3	InceptionResNetV2 + Transfer Learning + Augmentation	96.63

Source: Research Results, 2024

The evaluation results of this study were conducted using test data. The InceptionResNet-V2 model, which combines features from the Inception and ResNet architectures, proved to be beneficial. The results of this study demonstrate the effectiveness of using the InceptionResNetV2 model, particularly when combined with transfer learning and data augmentation techniques. The improvements observed across the three scenarios suggest that these methods can significantly enhance model performance and stability. The accuracy achieved in Scenario 3 (96.63%) aligns closely with other recent studies. For instance, Agus Eko et al. (2021) achieved an accuracy of 96% using a CNN approach with hyperparameter tuning. Similarly, Chetana Srinivas and team (2022) demonstrated that using VGG-16 and ResNet-50 could achieve accuracies of 96% and 95%, respectively. The findings of this study corroborate these previous results and further highlight the potential of combining advanced neural network architectures with data augmentation and transfer learning for effective brain tumor classification. The use of transfer learning, in particular, leverages pre-trained models on large datasets, thus enabling better feature extraction and improved classification accuracy even with limited training data.

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 10. NO. 1 AUGUST 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i1.5223

CONCLUSION

The results show that using the InceptionResNet-V2 architecture model, which integrates transfer learning and applies augmentation techniques, significantly contributes to improving model accuracy. The highest accuracy of the three model scenarios performed was obtained in the third scenario, with an accuracy rate of 96.63%. This was achieved through the application of the transfer learning method, where the knowledge possessed by the pre-trained model on a large dataset can be transferred to a new task, namely the identification and separation of brain tumor types. Furthermore, the use of augmentation techniques also positively influenced the results, allowing the model to learn better the variation and complexity of the data. Therefore, the combination of transfer learning and augmentation techniques enabled the model to achieve high accuracy in the task, while the reliability of the model was verified using test data. It is recommended for future research, involving further exploration of new model parameters and developing brain tumor classification methods. By highlighting these findings, this study provides a foundation for further research to achieve better performance and results, especially in incorporating residual network connections and inception structures in combined architecture models.

ACKNOWLEDGEMENT

This manuscript is based on research supported by the Informatics Study Program, Muhammadiyah University of Malang. The author also would like to thank for UMM Informatics Laboratory for supporting the implementation of this research.

REFERENCE

[1] K. N. Qodri, I. Soesanti, and H. A. Nugroho, Krisna Nuresa Qodri "Image analysis for MRI-based brain tumor classification using deep learning", IJITEE (International Journal of Information Technology and Electrical Engineering), vol. 5, no.1, pp. 21-28, 2021, doi: 10.22146/ijitee.62663.

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

[3] K. Pattabiraman, S. K. Muchnik, and N. Sestan, "The evolution of the human brain and disease susceptibility," Curr Opin Genet Dev, vol. 65, pp. 91–97, 2020, doi: 10.1016/j.gde.2020.05.004.

[4] F. J. Díaz-Pernas, M. Martínez-Zarzuela, D. González-Ortega, and M. Antón-Rodríguez, "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network," *Healthcare (Switzerland)*, vol. 9, no. 2, Feb. 2021, doi: 10.3390/healthcare9020153.

[5] J. Kang, Z. Ullah, and J. Gwak, "Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers," Sensors, vol. 21, no. 6, pp. 1–21, 2021, doi: 10.3390/s21062222.

[6] Senan, E. M., Jadhav, M. E., Rassem, T. H., Aljaloud, A. S., & Mohammed, B. A. (2022). "Early diagnosis of brain tumour MRI images using hybrid techniques between deep and machine learning". *Computational and Mathematical Methods in Medicine, 2022*, Article ID 8330833, 17 pages. https://doi.org/10.1155/2022/8330833

[7] A. Raza *et al.*, "A Hybrid Deep Learning-Based Approach for Brain Tumor Classification," *Electronics (Switzerland)*, vol. 11, no. 7, Apr. 2022, doi: 10.3390/electronics11071146.

[8] H. Dave, N. Kant, N. Dave, and D. Ghorui, "Brain Tumor Classification Using Deep Learning," pp. 155-175, 2021. [Online]. Available: http://www.ijeast.com

[9] R. Andre, B. Wahyu, and R. Purbaningtyas, "Klasifikasi Tumor Otak Menggunakan Convolutional Neural Network Dengan Arsitektur Efficientnet-B3," *JUST IT: Jurnal Sistem Informasi, Teknologi Informasi dan Komputer*, vol. 12, no.3, 2021, doi: 10.24853/justit.12.3.55-59.

[10] R. Rakhman Wahid, F. Tri Anggraeni, and B. Nugroho, "Implementasi Metode Extreme Learning Machine untuk Klasifikasi Tumor Otak pada Citra Magnetic Resonance Imaging," *Prosiding Seminar Nasional Informatika Bela Negara*, vol. 1, pp. 16-20, 2020.

[11] 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, Jan. 2022, doi: 10.3390/axioms11010034.

[12] W. Hastomo and S. dan Sudjiran, "Convolution Neural Network Arsitektur Mobilenet-V2 Untuk Mendeteksi Tumor Otak," Seminar Nasional Teknologi

Informasi dan Komunikasi STI&K (SeNTIK), vol. 5, no. 1, 2021, [online]. Available: https://ejournal.jak-stik.ac.id/index.php/sentik/article/view/3355.

[13] Magadza, T.; Viriri, S. "Deep Learning for Brain Tumor Segmentation: A Survey of State-of-the-Art" Journal of Imaging, vol. 7, no. 2, 2021, doi: https://doi.org/10.3390/jimaging7020019.

[14] Khan, F., Ayoub, S., Gulzar, Y., Majid, M., Reegu, F. A., Mir, M. S., Soomro, A. B., & Elwasila, O. (2023). MRI-based effective ensemble frameworks for predicting human brain tumor", Journal of Imaging, vol. 9, no. 8, p. 163, 2023, https://doi.org/10.3390/jimaging9080163

[15] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, "Brain tumor classification in MRI image using convolutional neural network," Mathematical Biosciences and Engineering, vol. 17, no. 5, pp. 6203–6216, 2020, doi: 10.3934/MBE.2020328.

[16] A. E. Minarno, M. Hazmi Cokro Mandiri, Y. Munarko, and H. Hariyady, "Convolutional Neural Network with Hyperparameter Tuning for Brain Tumor Classification," Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control, vol. 4, 2021, doi: 10.22219/kinetik.v6i2.1219.

[17] C. Srinivas et al., "Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images," J Healthc Eng, vol. 2022, 2022, doi: 10.1155/2022/3264367.

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

[19] M. N. Winnarto, M. Mailasari, and A. Purnamawati, "Klasifikasi Jenis Tumor Otak Menggunakan Arsitekture Mobilenet V2," Jurnal SIMETRIS, vol. 13, no. 2, 2022, doi: 10.24176/simet.v13i2.8821.

[20] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," BMC Med Inform Decis Mak, vol. 23, no. 1, Dec. 2023, doi: 10.1186/s12911-023-02114-6.

[21] A. Thomas, P. M. Harikrishnan, P. Palanisamy, and V. P. Gopi, "Moving Vehicle Candidate Recognition and Classification Using Inception-ResNet-v2," in Proceedings - 2020 IEEE 44th Annual Computers, Software, and Applications Conference, COMPSAC 2020, Institute of Electrical and Electronics Engineers Inc., Jul. 2020, pp. 467–472. doi: 10.1109/COMPSAC48688.2020.0-207.

[22] Plested, J., & Gedeon, T. (2022). "Deep transfer learning for image classification: a survey". *a survey. arXiv preprint arXiv:2205.09904.]*, 2022, [online]. Available: https://doi.org/10.1234/example.

[23] Hilal, A. M., Al-Wesabi, F. N., Alzahrani, K. J., Al Duhayyim, M., Hamza, M. A., Rizwanullah, M., & García Díaz, V. (2022). Deep Transfer Learning based Fusion Model for Environmental Remote Sensing Image Classification Model. *European Journal of Remote Sensing*, 55(sup1), 12-23. https://doi.org/10.1080/22797254.2021.2017799

[24] Didih Rizki Chandranegara, Jafar Shodiq Djawas, Faiq Azmi Nurfaizi, and Zamah Sari, "Malware Image Classification Using Deep Learning InceptionResNet-V2 and VGG-16 Method," Jurnal Online Informatika, vol. 8, no. 1, pp. 61–71, Jun. 2023, doi: 10.15575/join.v8i1.1051.

[25] S. Bhuvaji, A. Kadam, P. Bhumkar, and S. Dedge, "Brain Tumor Classification (MRI)," Kaggle, 2020.

[26] Tandel, G. S., Balestrieri, A., Jujaray, T., Khanna, N. N., Saba, L., & Suri, J. S. "Multiclass magnetic resonance imaging brain tumor classification using artificial intelligence paradigm" *Computers in Biology and Medicine*, 122, p. 103804, 2020, doi: 10.1016/j.compbiomed.2020.103804

[27] Habib, G., & Qureshi, S.. Optimization and acceleration of convolutional neural networks: A survey. *Journal of King Saud University - Computer and Information Sciences, 34*, 2022, 4244-4268. doi:10.1016/j.jksuci.2020.10.004.

[28] T. S. Azzahra, J. J. Cerelia, F. Azhar, L. Nugraha, and A. A. Pravitasari. "Enthusiastic International Journal Of Applied Statistics And Data Science MRI-Based Brain Tumor Classification Using Inception Resnet V2", 2023, [Online].Available:https://journal.uii.ac.id/ENTHUSIASTIC

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 10. NO. 1 AUGUST 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i1.5223

[29] J. Wang, X. He, S. Faming, G. Lu, H. Cong, and Q. Jiang, “A Real-Time Bridge Crack Detection Method Based on an Improved Inception-Resnet-v2 Structure,” *IEEE Access*, vol. 9, pp. 93209–93223, 2021, doi: 10.1109/ACCESS.2021.3093210.

[30] P. Chhikara, P. Singh, P. Gupta, and T. Bhatia, “Deep convolutional neural network with transfer learning for detecting pneumonia on chest x-rays,” in Advances in Intelligent Systems and Computing, Springer, 2020, pp. 155–168. doi: 10.1007/978-981-15-0339-9_13.

[31] Abou Baker, N., Zengeler, N., & Handmann, U. (2022). A Transfer Learning Evaluation of Deep Neural Networks for Image Classification. *Machine Learning and Knowledge Extraction,* vol. *4, no.* 1, 22-41. doi:10.3390/make4010002.

[32] Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. "A comprehensive survey on transfer learning." *Proceedings of the IEEE*, vol. 109, no. 1, pp. 43-76, 2020, doi: 10.1109/JPROC.2020.3004555

[33] Kandel, I., & Castelli, M. (2020). "Transfer learning with convolutional neural networks for diabetic retinopathy image classification. A review." *Applied Sciences* vol. 10, no. 6, 2021, doi: 10.3390/app10062021.