SETSCI Conference Proceedings
SETSCI Conference Proceedings 22, 39-42, 2025

International Symposium on AI-Driven Engineering Systems
June 19-20, 2025, Tokat, Türkiye

https://doi.org/10.36287/setsci.22.10.001
2687-5527/ © 2015 The Authors. Published by SETSCI

Brain Tumor Classification Using Fine-Tuned Transfer Learning

Mustafa Suban Dut[1], Meriç Çetin[1*]

[1]Department of Computer Engineering, Pamukkale University, 20160, Pamukkale, Denizli, Türkiye

[*](mcetin@pau.edu.tr)

Abstract – Brain tumor is a progressive disease that significantly affects human life. These diseases can reduce the quality of life by causing losses in motor and cognitive functions. Since the chance of treatment decreases when not diagnosed early, advanced technologies are needed for diagnosis and prognosis. In this study, the applicability of transfer learning-based approaches for the classification of brain tumors was investigated. For this purpose, the classification performance of a proposed convolutional neural network model was compared with the performances of pre-trained transfer learning models such as VGG16, ResNet50 and InceptionV3. The designed models were trained on two different brain tumor datasets with two and four classes. The obtained results were analyzed by comparing the performance parameters of each model on different datasets. As a result, pre-trained transfer learning models supported by fine-tuning applications showed high performance in both two-class and four-class brain tumor classification tasks.

Keywords – Brain tumor classification, deep learning, transfer learning, fine tuning

I. Introduction

The brain, the most complex organ in the human body, controls and coordinates many functions. In general, brain cells are formed through the process of neurogenesis, and it takes about six months for a new brain cell to fully mature. However, if the DNA of the brain cell is damaged or some genes are dysfunctional, it leads to the uncontrolled growth of dysfunctional cells, which causes brain abnormalities [1]. The growth and accumulation of abnormal cells during the renewal process of brain cells is called a brain tumor [2]. As Rasa et al. have stated, more than 308,102 diagnoses are made worldwide each year, and 251,329 people lose their lives due to primary brain tumors [1]. Early diagnosis and classification of brain tumors, which are a progressive disease, provide faster access to appropriate treatment. In this way, the progression of the disease can be slowed down. More sensitive and accurate diagnostic methods can reduce long-term adverse effects by allowing brain tumors to be brought under control at an early stage. Diagnosis of a brain tumor is made based on the results of disease history, neurological examination, high-throughput clinical imaging devices and pathological examinations. Imaging tests such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) are usually used in the diagnosis of brain tumors, and a biopsy may be performed to determine the type of tumor [3].

In recent years, developments in the field of artificial intelligence have allowed doctors to diagnose diseases earlier and more accurately in the health field [4, 5]. Machine Learning (ML) and Deep Learning (DL) algorithms have made significant progress in medical imaging analysis and have played a critical role in the classification of many types of cancer. Transfer Learning (TL) allows pre-trained models to transfer knowledge in a shorter time and with higher performance in cases where large and labeled data sets are not available. TL is also used to improve the performance of deep learning models. Instead of training a new model from scratch, TL uses the knowledge and features acquired by the pre-trained model. There are many models used in transfer learning; these include models such as VGG (Visual Geometry Group), ResNet (Residual Network), Inception, MobileNet, DenseNet.

In particular, biomedical data used in the diagnosis of neurological diseases create difficulties in the analysis process due to their limited amount and labeling difficulties. This study has shown that TL methods can be used effectively for the early diagnosis of brain tumors. In this context, some transfer learning-based DL models widely used in the literature were designed to classify two different brain tumor data sets. Simulation studies were carried out with VGG16, ResNet50, InceptionV3 models and a Convolutional Neural Network (CNN) model proposed in this study. In the simulation studies, the effects of data pre-processing techniques such as data augmentation, data normalization and class balancing for model training on model performances were investigated. In order for deep learning models to produce more general and accurate results, hyper-parameter optimization was used to fine-tune the parameter sets and the effect of this optimization was compared. It is thought that the findings of the study will encourage the use of deep learning methods in the early diagnosis processes of critical diseases such as brain tumors, thus increasing the accuracy and speed of health services. Thus, patients can receive faster and more accurate diagnoses, treatment processes can be improved, and the quality of overall healthcare services can be increased.

II. Related Works

Brain tumors occur as a result of abnormal cell growth in the brain or spinal cord. Tumors can be benign or malignant and can cause neurological symptoms with localized effects. Treatment options include surgery, radiotherapy, and chemotherapy. ML techniques are increasingly used to classify and prognosticate brain tumors. DL algorithms can determine tumor types and stages with high accuracy, especially by analyzing neurological diseases obtained from MRI and CT scans [6].

There are many studies in the literature using deep learning architectures on brain tumor classification. In one of these studies, Saxena et al. [7] achieved 95% accuracy in the ResNet50 model by using the transfer learning method to classify brain tumor data. In [8], 93.94% accuracy was achieved with the model designed by using discrete wavelet transform to classify brain tumor data. In a different study [9], GoogleNet-based transfer learning was applied to classify brain MRI images and 97.1% accuracy was achieved. Rehman et al. [10] used three different pre-trained CNN models (VGG16, AlexNet and GoogleNet) together with a transfer learning approach to classify 3 specific brain tumors as meningioma, glioma and pituitary with 98.67% accuracy. In [11], 92.9% accuracy was achieved by using Naive Bayes and k-nearest neighbor techniques to estimate tumor grades. In [12], 2D CNN and convolutional auto-encoder-based DL methods were developed to classify brain tumors (glioma, meningioma, pituitary gland tumors) from MRI images with high accuracy. The proposed 2D CNN model showed the best performance with 96.47% training accuracy and 95% recall rate. In a study where the validity and reliability of the results were analyzed using explainable artificial intelligence and ViT models, the performance of various DL architectures (VGG16, InceptionV3, VGG19, ResNet50, InceptionResNetV2, and Xception) was evaluated with the performance of the IVX16 model combining TL models. The proposed IVX16 model showed the best performance by reaching 96.94% accuracy rate [13]. In [14], tumor diagnosis in normal, low-grade glioma and high-grade glioma categories was performed using the VGG19 transfer learning model. In [15], it is stated that it is important to adjust the hyper-parameters and learning parameters of the model in order to use a pre-trained deep CNN based on transfer learning in medical imaging. In [16], brain MRI scan images were classified as cancerous and non-cancerous using the CNN method. With the transfer learning method, the CNN models developed from scratch were compared with the pre-trained VGG16, ResNet50 and InceptionV3 models and 96% accuracy rate was achieved with the VGG16 model. Paul et al. [17] worked with a four-layer CNN model consisting of two convolutional and two fully connected layers and achieved 91.43% accuracy rate for brain tumor classification.

III. Materials and Method

Deep learning methods are a sub-branch of machine learning and exhibit superior performance in data analysis using multi-layered artificial neural networks. In particular, deep learning methods are effective tools for identifying complex patterns and structures on large data sets. The use of deep learning methods in the diagnosis and early detection of brain tumors has provided significant advances in the fields of medical imaging and signal processing [18].

A. Convolutional Neural Networks

Convolutional neural networks are deep learning models used to achieve successful results especially on image data. These models learn data features using convolutional and pooling operations organized in layers. Deep CNN models obtain more effective results on complex data structures by learning the connections between neurons in many layers. In this study, a CNN model specially designed for the early diagnosis of brain tumors was used. This model passes the input image through various convolutional and pooling layers. The first convolutional layer starts with 32 filters and a 3×3 kernel size and uses the ReLU activation function. The subsequent pooling layer reduces the feature maps by performing the max_pooling operation. The second and third convolutional layers use 32 and 64 filters with he_uniform kernel initialization to extract deeper features. The flattening layer of the model converts the feature maps from the convolutional layers into a single vector. This is followed by a fully connected layer (dense) with 64 neurons and a ReLU activation function. To prevent over-learning, the damping layer randomly disables neurons by 30%. Finally, the output layer of the model contains neurons equal to the number of classes and performs classification using the softmax activation function. The model was compiled with the categorical cross-entropy loss function and the Adam optimization algorithm and evaluated with the accuracy metric. The layer structure of the proposed CNN model is given in Table 1.

Table 1. The layer structure of the proposed CNN model

Layer	Output Type	Parameters
Conv2d	None, 62, 62, 32	896
activation	None, 62, 62, 32	0
max_pooling2d	None, 31, 31, 32	0
Conv2d_1	None, 29, 29, 32	9,248
Activation_1	None, 29, 29, 32	0
max_pooling2d_1	None, 14, 14, 32	0
Conv2d_2	None, 12, 12, 64	18,496
activation_2	None, 12, 12, 64	0
Max_pooling2d_2	None, 6, 6, 64	0
flatten	None, 2304	0
dense	None, 64	147,520
Activation_3	None, 64	0
dropout	None, 64	0
Dense_1	None, num_classes	(64+1) x numClasses
Activation_4	None, num_classes	0

B. Pre-Trained Convolutional Neural Networks

Transfer learning is used to achieve high accuracy on smaller datasets by using the knowledge of models trained on large datasets. Transfer learning has methods such as feature extraction, fine-tuning and transfer of model weights. With feature extraction, image features are extracted using the convolutional layers of the pre-trained model, but it retrains the fully connected layers. By using fine-tuning, some upper layers of the pre-trained model are re-trained, but the lower layers are generally kept constant. With the transfer of model weights, the weights of the pre-trained model are taken as the starting point and the entire network is trained with new data.

Thanks to TL methods, training time is shortened, good results are obtained with less data, the model adapts better to the new dataset, the previous knowledge of the model is preserved and it adapts faster to new data.

Some pre-trained deep learning models commonly used for transfer learning, ResNet50, InceptionV3 and VGG16, were preferred in this study to be compared with a CNN model proposed for brain tumor classification. ResNet50 uses skip connections to solve the gradient vanishing problem encountered during the training of deep neural networks. InceptionV3 is a CNN architecture developed by Google and provides more effective feature extraction by using different sized filters together in the same layer. VGG16 is a CNN architecture popular among deep learning models and consists of 16 layers. This model increases the depth by using small 3x3 filters and achieves high accuracy rates.

IV. Results

When working with complex and high-dimensional data such as medical images, the use of various pre-processing techniques increases the accuracy and generalization capacity of the model. For example, data augmentation increases the size and diversity of the available dataset, preventing the model from overfitting and improving its overall performance. Data normalization ensures that each feature is within a certain range, allowing the model to learn faster and more consistently. Separation of training and validation data is important to objectively evaluate the performance of the model. Typically, 70-80% of the dataset is reserved for training and 20-30% for validation. This separation prevents the model from overfitting and provides a more reliable method for estimating its performance in the real world. Class balancing is used to correct for unbalanced distribution of classes in the dataset. Imbalanced classes can make it difficult for the model to learn some classes and can reduce overall performance. The metrics used to evaluate performance in simulation studies measure how well the model performs its intended task. In a binary classification task, data samples are usually predicted to be either positive or negative. Each predicted binary label has four possible states: true positive (TP) is a correctly predicted positive result, true negative (TN) is a correctly predicted negative result, false positive (FP) is a positive predicted negative example, and false negative (FN) is a negative predicted positive example. The equations for the most commonly used evaluation metrics for binary classification, accuracy, sensitivity (or recall), specificity, and precision, respectively, are given below.

$$\begin{gathered}
Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \in [0,1], \\
Precision = \frac{TP}{TP + FP} \in [0,1], \\
Sensitivity = \frac{TP}{TP + FN} \in [0,1], \\
F1 - Score = \frac{2 * Precision * Sensitivity}{Precision + Sensitivity} \in [0,1]
\end{gathered} \tag{1}$$

In this study, two datasets obtained from the Kaggle platform belonging to brain tumor disease were used as an example of TL-based analysis of neurological disorders, one containing two different classes and the other containing four different classes. Two-class Br35h dataset was used in the brain tumor classification task. Br35h contains MRI brain scans collected from various sources and divided into two main classes: tumors are indicated as "Yes" and tumors are indicated as "No". The dataset consists of MRI images obtained from different hospitals and clinics using standard MRI devices. The dataset consists of a total of 3000 images. 1500 of these images were obtained from patients and the other 1500 were obtained from healthy individuals [19]. In the other tumor dataset used in this study, there are a total of 3264 images. In this 4-class dataset, the distribution of the dataset is quite close for the classes other than the healthy individuals class [20].

In the fine-tuning phase applied to the transfer learning models used in this study, all weights or some layers of the model were updated according to the datasets and the overall performance of the model was increased. This increased the learning capacity of the models. The classification results of fine-tuned TL-based models designed for two different datasets related to brain tumor disease are presented in Table 2 and Table 3. The classification performances of the validation data are given with accuracy, precision, sensitivity and F1-Score.

Table 2. The classification results of fine-tuned transfer learning models for two-class Br35h dataset

Model	Accuracy	Precision	Sensivity	F1-Score
VGG16	0.99	0.99	1	0.99
ResNet50	1	1	1	0.99
InceptionV3	1	0.99	0.99	0.99
CNN	0.97	0.97	0.98	0.97

Table 3. The classification results of fine-tuned transfer learning models for four-class brain tumor dataset

Model	Accuracy	Precision	Sensivity	F1-Score
VGG16	0.96	0.96	0.96	0.95
ResNet50	0.93	0.93	0.93	0.93
InceptionV3	0.97	0.97	0.97	0.97
CNN	0.87	0.88	0.87	0.87

V. CONCLUSION

In this study, the applicability of some transfer learning-based models for the purpose of brain tumor classification was tested and the use of these methods was optimized. In this context, the performances of transfer learning models VGG16, ResNet50, InceptionV3 models and a proposed convolutional neural network trained on two brain tumor datasets consisting of different classes were compared via classification metrics. Various data pre-processing processes were used to improve the performance of the models. Pre-trained deep learning models were re-trained with the fine-tuning method. At this stage, all weights or some layers of the models were updated and their learning capacities were increased. The results obtained on the two-class Br35h dataset show that the models reached high accuracy levels. ResNet50 and InceptionV3 models provided 100% accuracy, VGG16 achieved 99%, and the specially trained CNN model achieved 97% accuracy. For the four-class brain tumor dataset, the InceptionV3 model gave the best result with 97% accuracy. The VGG16 model showed 96% accuracy, and the ResNet50 model showed 93% accuracy. The CNN model, on the other hand, exhibited lower performance compared to the other models with 87% accuracy. This shows that the specially designed CNN model is less generalizable and that transfer learning-based models provide more successful results in more complex classification tasks. As a result, the transfer learning approach stands out as a very effective method, especially in areas with limited data such as medical image analysis. Pre-trained models supported by fine-tuning applications showed high performance in both two-class and four-class brain tumor classification tasks.

REFERENCES

[1] S. M. Rasa, M. M. Islam, M. A. Talukder, M. A. Uddin, M. Khalid, M. Kazi and M. Z. Kazi, "Brain tumor classification using fine-tuned transfer learning models on magnetic resonance imaging (MRI) images," *Digital Health*, 10, 20552076241286140, 2024.

[2] J. Amin, M. Sharif, M. Raza, T. Saba, R. Sial and S.A. Shad, "Brain tumor detection: A long short-term memory (lstm)-based learning model," *Neural Computing and Applications*, 32(20), pp: 15965-15973, 2020.

[3] A. Saleh, R. Sukaik and S. S. Abu-Naser, "Brain tumor classification using deep learning," *International Conference on Assistive and Rehabilitation Technologies,* pp: 131-136, 2020.

[4] H.A. Khan, W. Jue, M. Mushtaq and M. U. Mushtaq, "Brain tumor classification in mri image using convolutional neural network," *Math. Biosci. Eng,* 17, pp: 6203, 2020.

[5] F. D. E. Baran and M. Cetin, "Evrişimli sinir ağları kullanarak beyin tümörü sınıflandırması," *Researcher*, 4(02), 76-83, 2024.

[6] Y. Sun, S. Zhu, K. Ma, W. Liu, Y. Yue, G. Hu, H. Lu and W. Chen, "Identification of 12 cancer types through genome deep learning," *Scientific Reports*, 9(1), 17256, 2019.

[7] P. Saxena, A. Maheshwari and S. Maheshwari, "Predictive modeling of brain tumor: A deep learning approach," *Innovations in Computational Intelligence and Computer Vision,* Springer, pp: 275-285, 2021.

[8] H. Mohsen, E. S. A. El-Dahshan, E. S. M. El-Horbaty and A. B. M. Salem, "Classification using deep learning neural networks for brain tumors*," Future Computing and Informatics Journal*, 3(1), pp: 68-71, 2018.

[9] S. Deepak and P. Ameer, "Brain tumor classification using deep cnn features via transfer learning," *Computers in Biology and Medicine*, 111, pp: 103345, 2019.

[10] A. Rehman, S. Naz, M. I. Razzak, F. Akram and M. Imran, "A deep learning-based framework for automatic brain tumors classification using transfer learning," *Circuits, Systems, and Signal Processing*, 39(2), pp: 757-775, 2020.

[11] V. Romeo, R. Cuocolo, C. Ricciardi, L. Ugga, S. Cocozza, F. Verde, A. Stanzione, V. Napolitano, D. Russo, G. Improta et al. "Prediction of tumor grade and nodal status in oropharyngeal and oral cavity squamous-cell carcinoma using a radiomic approach," *Anticancer Research*, 40(1), pp: 271-280, 2020.

[12] S. Saeedi, S. Rezayi, H. Keshavarz, and S. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," *BMC Medical Informatics and Decision Making*, 23(1), 16, 2023.

[13] S. Hossain, A. Chakrabarty, T. R. Gadekallu, M. Alazab and M. J. Piran, "Vision transformers, ensemble model, and transfer learning leveraging explainable AI for brain tumor detection and classification," *IEEE Journal of Biomedical and Health Informatics*, 28(3), 1261-1272, 2023.

[14] Z. N. K. Swati, Q. Zhao, M. Kabir, F. Ali, Z. Ali, S. Ahmed and J. Lu, "Content-based brain tumor retrieval for MR images using transfer learning," *IEEE Access*, 7, 17809-17822, 2019.

[15] R. Chelghoum, A. Ikhlef, A. Hameurlaine and S. Jacquir, "Transfer learning using convolutional neural network architectures for brain tumor classification from MRI images," In IFIP International Conference on Artificial Intelligence Applications and Innovations (pp. 189-200). *Cham: Springer International Publishing,* 2020.

[16] 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*, 2021.

[17] J. S. Paul, A. J. Plassard, B. A. Landman and D. Fabbri, "Deep learning for brain tumor classification," *In Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging* (Vol. 10137, pp. 253-268), 2017.

[18] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, and C. I. Sánchez, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, 42, 60-88, 2017.

[19] (2024) A. Hamada. Br35H: Brain Tumor Detection 2020. [Online]. Available: https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection

[20] S. Bhuvaji, Brain tumor classification (mri). [Online]. Available: https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri