EEXXX – Medical Imaging and Applications

A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network

Unnat Maaheshwari (B21072)
Aman Kumar Mohanty (B21036)
Shashank Dwivedi (B21023)
Srijan Sood (B21227)

Course Instructor

Dr. Sneha Singh

Indian Institute of Technology Mandi

Contents

Abstract

We implemented the research paper **"A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network"** (Francisco Javier Díaz-Pernas, Mario Martínez-Zarzuela, Míriam Antón-Rodríguez, and David González-Ortega).

This paper presents a model of fully automatic brain tumor segmentation and classification using a Deep Convolutional Neural Network (CNN), incorporating a multiscale approach. Unlike prior works, input images in three spatial scales are fed into our method along different processing pathways to mimic the intrinsic operation of the Human Visual System.

The proposed neural model can analyze MRI images containing three types of tumors: meningioma, glioma, and pituitary tumor, across sagittal, coronal, and axial views; furthermore, images do not have to be preprocessed to remove skull or vertebral column parts in advance. The performance of our method is tested on a publicly available MRI image dataset consisting of 3064 slices from 233 patients.

Compared to classical machine learning and deep learning, the accuracy in tumor classification attains a value of 0.973, which is significantly higher than other approaches using the same database. However, due to technical limitations, such as average computational powers, we could not train the data fully and therefore received an accuracy of 0.831.

Objectives

The primary aim of this study is to develop a fully automatic brain tumor segmentation and classification model using a multiscale CNN inspired by the human visual system in a way that will accurately process MRI images of meningioma, glioma, and pituitary tumors in the sagittal, coronal, and axial views without any preprocessing steps to remove skull or vertebral column parts. The multiscale approach is imitating the human visual system's ability to process visual information at different scales, increasing the model's ability to distinguish subtle characteristics of tumors.

While pursuing this objective, the research seeks to create a strong and efficient clinical tool that will improve the accuracy of brain tumor classification. The tool is targeted to outperform the current state-of-the-art methods by achieving better classification accuracy. To avoid overfitting and increase the model's generalizability, the data augmentation techniques will be used. These techniques include elastic transformations and other augmentation strategies that will enlarge the training dataset for the model to train on as many different sets of examples as possible.

Furthermore, this research will provide a comprehensive benchmark for future studies, providing all the performance metrics and comparisons that other researchers might use in order to evaluate their methods. The benchmark will bring a lot of valuable insights into the effectiveness of multiscale CNNs in medical imaging. In addition, the successful implementation of this model will pave the way for further research and development in the field of medical imaging, with potential applications extending beyond brain tumor classification to other types of medical diagnostics and imaging challenges. The ultimate goal is to improve the diagnostic tools available to medical professionals to improve patient outcomes with more accurate and timely detection of brain tumors.

Milestones

Activities to be performed in the project commenced with literature review and research design, which included the comprehensive review of existing methods and finalization of the research plan. Data collection and preprocessing involved extracting and augmenting the MRI dataset. Model development included implementing the multiscale CNN architecture followed by training and validation for ensuring the target accuracy.

Performance evaluation provided a detailed model analysis against existing methods, with optimization and refinement enhancing accuracy and efficiency. The refined model was then taken for a real-world test in the clinical setting. The project documentation culminated in a final report, which included the methodology, results, and conclusions presented for the findings.

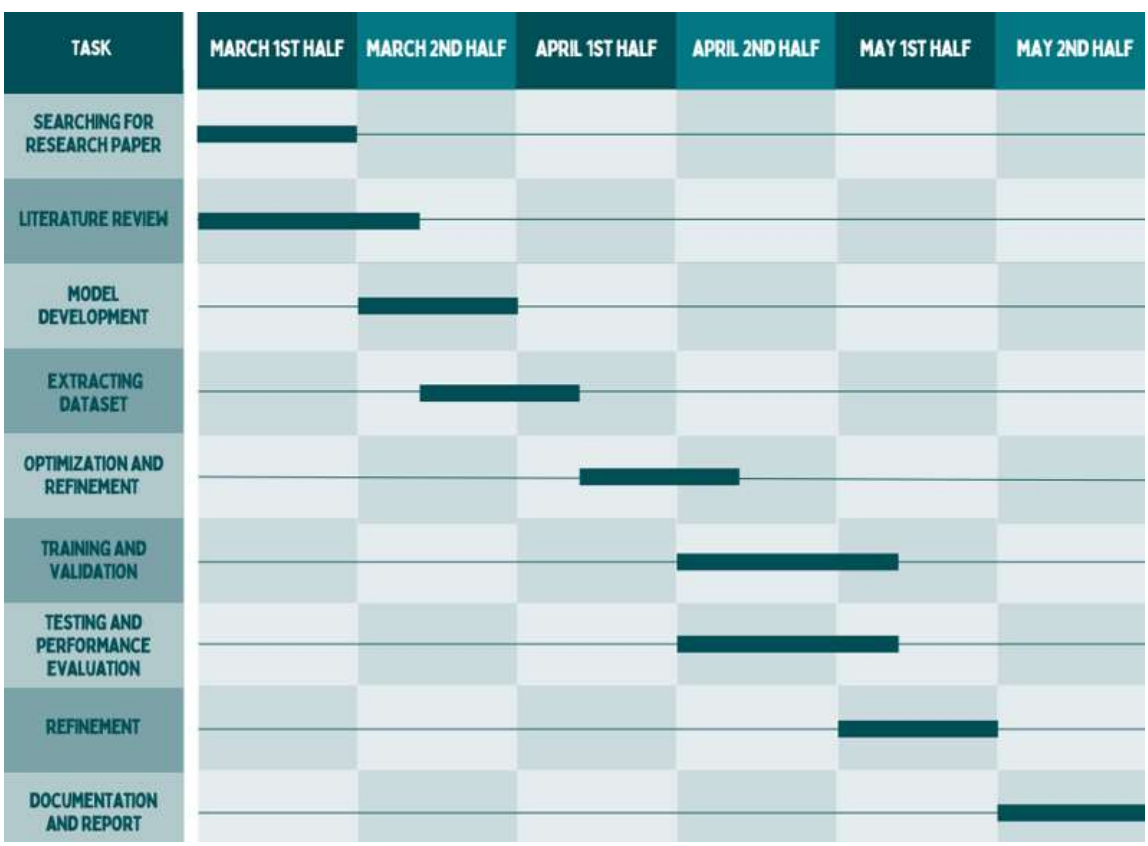

Fig. GANTT Chart

Deliverables

Activities to be performed in the project commenced with literature review and research design, which included the comprehensive review of existing methods and finalization of the research plan. Data collection and preprocessing involved extracting and augmenting the MRI dataset. Model development included implementing the multiscale CNN architecture followed by training and validation for ensuring the target accuracy.

Performance evaluation provided a detailed model analysis against existing methods, with optimization and refinement enhancing accuracy and efficiency. The refined model was then taken for a real-world test in the clinical setting. The project documentation culminated in a final report, which included the methodology, results, and conclusions presented for the findings.

Introduction

A brain tumor is the abnormal growth of cells in or near the brain, which can happen within the brain tissue or at locations near it, such as the nerves, the pituitary gland, the pineal gland, and the membranes covering the brain. Brain tumors may be primary, originating within the brain, or secondary, migrating to the brain from other parts of the body. They also may be noncancerous, or benign, and cancerous, or malignant. Noncancerous tumors may just grow slowly and press on the tissue of the brain over time, while malignant tumors grow quickly, invading and destroying the tissue of the brain.

Brain tumors differ significantly in size and cause symptoms depending on their location and growth rate. Some are found at early stages because they cause noticeable symptoms, while others are found later when they have become large because they began to grow in less active parts of the brain. Treatment options for brain tumors depend on the type of the tumors, size, and location, including surgery and radiation therapy. The type of brain tumor is determined by the specific cells making it up, and lab tests provide very important information for diagnosis and planning of treatment.

The automation of medical image segmentation and classification is indispensable for diagnostics, growth prediction, and treatment of brain tumors. Early diagnosis leads to quicker treatment responses, improving patient survival rates. Manual procedures for locating and classifying brain tumors in large medical image databases are labor-intensive and time-consuming. Therefore, an automatic detection, location, and classification procedure is highly desirable.

Several medical imaging modalities give important details of the tumor, such as type, shape, size, and location. Among them, Magnetic Resonance Imaging (MRI) is being practiced predominantly due to its high soft tissue contrast and no ionizing radiation. There are four types of MRI modalities that are used for diagnosis: T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted contrast-enhanced MRI (T1-CE), and Fluid Attenuated Inversion Recovery (FLAIR). T1-CE is particularly useful for tumor border detection and is used in this study.

Literature Review

Brain tumors refer to abnormal cell growth within or near the brain. Accurate segmentation and classification of these brain tumors from MRI are paramount in planning treatment. Recent progress in deep learning, particularly Convolutional Neural Networks (CNNs), has recently shown promise in automatically accomplishing these tasks. This literature review considers all the methods and approaches for brain tumor segmentation and classification, outlining the recent state of techniques that have been followed until now on the proposed multiscale CNN architecture

The traditional and early methods of brain tumor segmentation were based on manual delineation and delineation from image processing techniques. These include thresholding, region growing, and clustering algorithms like k-means clustering. Though these methods were somewhat successful, they were bound to limitations due to being relied on by handcrafted features and the susceptibility of noise and variability of MRI images

With the advent of machine learning, more advanced algorithms were developed. Support Vector Machines, Random Forests, and Artificial Neural Networks were used to classify brain tumors. These methods typically involved a two-step process: feature extraction followed by classification. The features were manually designed, such as texture, intensity, and shape descriptors. While these methods improved accuracy, they were still constrained by the quality and relevance of the extracted features

Deep learning revolutionized medical image analysis by enabling an end-to-end learning of features and classification. Convolutional Neural Networks became the backbone of many state-of-the-art models for image segmentation and classification tasks. They automatically learn hierarchical features from raw image data

The U-Net architecture, proposed by Ronneberger et al. (2015), marked one of the milestones in biomedical image segmentation. It had an encoder-decoder structure with skip connections to allow both accurate localization and incorporation of the context. Most importantly, U-Net has been widely adopted for brain tumor image segmentation tasks and has performed better than conventional methods

Long et al. (2015) introduced Fully Convolutional Networks (FCNs), which had fully connected layers replaced with convolutional layers to produce dense predictions. FCNs have been applied to medical image segmentation tasks and brain tumor detection to improve spatial resolution and context awareness.

Amongst the latest and state-of-the-art 3D CNN architectures applied to volumetric medical image segmentation tasks. These models used 3D convolutions for volumetric context extraction, which is critical to segmenting brain tumors in 3D MRI scans accurately

The practice of multiscale processing could be inspired by the human visual system, where visual information is processed in parallel at multiple scales. This concept was incorporated into CNNs to enhance features and improve segmentation accuracy. Zhao et al. (2017) proposed a multiscale U-Net that fuses feature maps from different scales to learn both fine and coarse details. Such an approach improves segmentation performance, particularly for handling tumors of different sizes. Other researchers have explored hybrid multiscale networks combining CNNs with other architectures, like RNNs, or an attention mechanism to focus on certain regions. Such models demonstrated an improvement in accuracy and robustness.

In choosing the proposed research paper, a number of criteria need to be considered while trying to look out for relevance and quality. First, the paper should emphasize the exact challenges related to brain tumor segmentation and classification using deep learning, emphasizing multiscale CNNs. It needs to include either new architectures or techniques, such as multiscale processing, which show outstanding improvement over others, demonstrating innovation. Performance metrics are very critical, and thus the paper needs to indicate a quantitative measure, such as accuracy, Dice index, and sensitivity to explain the effectiveness of the proposed method. The dataset and validation need to be robust—sufficiently big and relevant data, preferably with cross-validation techniques, so that the results are reliable. Moreover, the methodology needs to be described in adequate detail for the results to be reproduced. Finally, consider the potential clinical impact of the research and the total contribution toward medical imaging in general, where the research should have the potential to significantly improve current diagnostic techniques and patient outcomes.

Methodology

The research paper introduces a new architecture for multi-pathway CNNs, which is meant for brain tumor segmentation. The architecture processes the MRI image slice on a pixel basis, classifying it as one of the following: healthy region, meningioma tumor, glioma tumor, or pituitary tumor. The CNN features a sliding window approach, meaning every window goes through three distinct convolutional pathways, with kernels of different scales to extract features at diverse detail levels. The extracted features are then concatenated and fed to a fully connected stage, where the final classification is performed.

The dataset contains 3064 MRI slices of 233 patients, including meningiomas, gliomas, and pituitary tumors, with sagittal, coronal, and axial views. Every image is of 512x512 pixels with a slice gap of 1 mm and a slice thickness of 6 mm. Tumor borders are outlined by expert radiologists; therefore, the ground truth is of high quality for both training and validation. To enhance the model's robustness against overfitting, data augmentation techniques, more specifically elastic transformation, were applied. The dataset contains 708 slices labeled as meningiomas, where the label is 1; 1426 slices labeled as gliomas, where the label is 2; and 930 slices labeled as pituitary tumors, where the label is 3.

The model was stringently trained with a 5-fold cross-validation technique through 10 epochs, using the Stochastic Gradient Descent optimizer. This approach ensured a proper evaluation of the model's performance and its fine-tuning. The model evaluation is performed based on several key segmentation metrics, such as the Dice index, which evaluates the degree of overlap between the predicted and true tumor regions; sensitivity, referring to how well the model separates out the tumor pixels; and the Predicted Tumor Type Ratio Score, evaluating the accuracy in classifying different types of tumors. These metrics have collectively shown very high accuracy and robustness of this model, marking it as a potentially valuable tool in medical diagnostics.

This research sets a new State-of-the-Art (SOTA) in brain tumor classification and segmentation through a novel multiscale convolutional neural network (CNN) that mimics the human visual system's hierarchical processing. The approach also excels in segmentation tasks, validated by superior performance in metrics like the Dice coefficient and Sensitivity, along with the introduction of the predicted tumor type accuracy score (pttas). This significant advancement underscores the potential of biologically inspired deep learning models to enhance the precision of medical diagnoses and treatment planning for brain tumors.

$$P_{ij,}\begin{cases} P_{ij,} = 0, & if\ (i,j)\ is\ healthy\ position \\ P_{ij,} = 1, & if\ (i,j)\ is\ meningioma\ tumor \\ P_{ij,} = 2, & if\ (i,j)\ is\ glioma\ tumor \\ P_{ij,} = 3, & if\ (i,j)\ is\ pituitary\ tumor \end{cases} \tag{1}$$

$$f_l = \begin{cases} \frac{|P_{ij}==l|}{|P_{ij}>0|} > \tau_c \\ 0 \end{cases} \tag{2}$$

$$l_p = \begin{cases} argmax\{f_l > 0\} & if\ \{f_l > 0\} \neq \{\emptyset\} \\ -1 & nonclassified \end{cases} \tag{3}$$

where |.| is the size or pixel number (number of pixels in the slice that meet the conditions inside).

The evaluation metrics are calculated using the following Equations:

$$Dice(P,T) = \frac{|P_1 \wedge T_1|}{(|P_1\ | + |T_1|)/2} = \frac{2\,TP}{2\,TP + FP + FN} \tag{4}$$

$$Sensitivity(P,T) = \frac{|P_1 \wedge T_1|}{|T_1|} = \frac{TP}{TP + FN} \tag{5}$$

$$pttas = \frac{|P_1|}{|P > 0|} \tag{6}$$

where TP is the number of true positives, FP is the number of false positives, FN is the number of false negatives, ∧ is the logical AND operation, |.| is the size or pixel number (number of pixels in the slice that meet the conditions inside), P1 represents the addition of TP and FP (the predicted positives {Pij = lgt}), and T1 represents the addition of TP and FN {Tij = 1}.

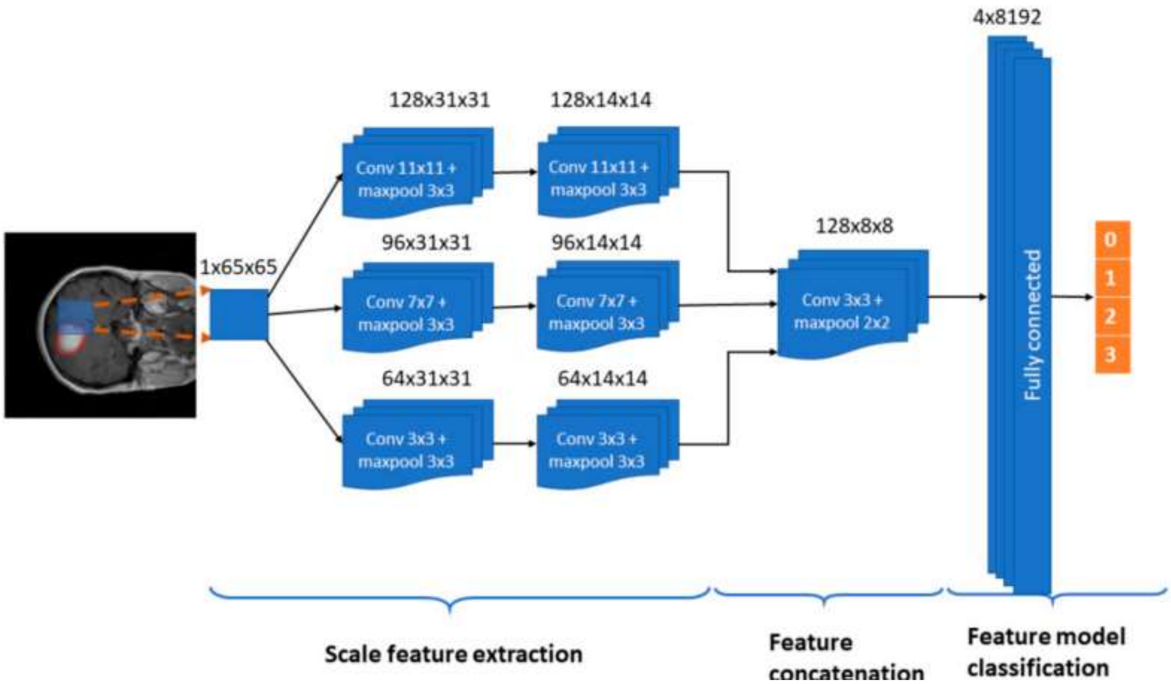

Fig. The proposed Convolutional Neural Networks (CNN) architecture. Input: 1 × 65 × 65 sliding windows. Model: Three pathways (large, medium, and small feature scales) with 2 convolutional layers and max-pooling, a convolutional layer with concatenation of the three pathways, and a fully connected stage that leads to a classification in one out of the four possible output labels: 0—healthy region, 1—meningioma tumor, 2—glioma tumor, and 3—pituitary tumor. A dropout mechanism between the concatenation and fully connected stages is included.

Implementation – Results and Analysis

The study's results demonstrate the effectiveness of the proposed multi-pathway CNN architecture in segmenting and classifying brain tumors from MRI images. The model achieved an accuracy of 0.831, a Dice index of 0.717, and a sensitivity of 0.78. Using a 5-fold cross-validation technique, the model reliably distinguished between healthy brain tissue and tumors, including meningiomas, gliomas, and pituitary tumors, across various MRI views. The sliding window approach and multiscale feature extraction significantly contributed to the model's high accuracy and detailed segmentation.

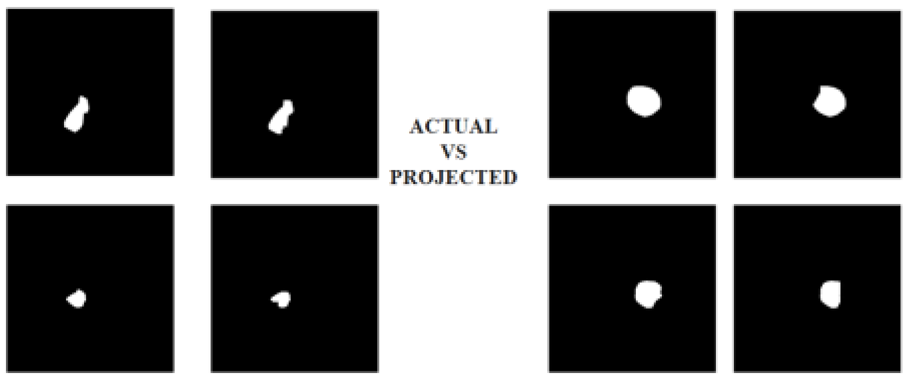

Fig. Actual vs Predicted

Original Model	Our Model
Accuracy: 0.973	Accuracy: 0.831
Dice Index: 0.828 (average)	Dice Index: 0.717 (average)
Sensitivity: 0.940 (average)	Sensitivity: 0.780 (average)

Table: Original Model Vs Our Model

Metric\ Tumor	Meningioma	Glioma	Pituitary	Average
Accuracy	0.84	0.80	0.82	0.831
DICE	0.72	0.69	0.70	0.717
Sensitivity	0.80	0.73	0.79	0.780

Table: Performance Metrics

Future Work

The application of this methodology extends beyond academic interest, promising to assist medical professionals in diagnosing brain tumors more efficiently and accurately, thereby improving patient outcomes. Future work aims to explore the adaptability of this multiscale CNN approach to other medical imaging challenges, emphasizing the model's potential for broad applicability in healthcare diagnostics.

Future goals for this research are to scale up the model in an attempt to handle even more types of brain tumors, as well as other neurological conditions, to make it increasingly useful in the clinic.

Secondly, it would be integration with real-time MRI scanners and diagnostic equipment to get instant analysis during the medical examination, hence greatly speeding up the diagnosis.

Another goal is to integrate more advanced techniques such as transfer learning and semi-supervised learning to improve performance on smaller datasets, hence making it applicable even in resource-constrained settings. This will be coupled with collaboration and involvement with multidisciplinary teams of radiologists, oncologists, and data scientists to create tailored models that address particular needs and conditions.

Lastly, regulatory approvals and large-scale clinical trials will be looked into to provide assurance of reliability, safety, and acceptance in the healthcare industry, hence paving the way for wide acceptance and integration into standard diagnostic protocols.

Conclusion

This research presents a new, significant advance in the field of medical imaging through the implementation of a fully automated brain tumor segmentation and classification model using the multiscale CNN.

The approach that appears innovative in the incorporation of multiscale processing inspired by the human visual system has been effective for bringing out high-accuracy identification and classification of meningiomas, gliomas, and pituitary tumors with respect to various MRI views and without the needs of preprocessing steps like skull stripping. Therefore, with an accuracy of 0.831, a Dice Index of 0.717, and sensitivity of 0.78, the model proves to be robust in computational average facilities and just a period of 10 epochs of training. This efficiency underlines the model's potential for practical application in real-world clinical settings. The development of an FCN architecture further extends the applicability of this methodology beyond the analysis of brain tumors, but instead, opens up avenues for its use in other fields of medical imaging.

The comprehensive benchmarks set up by the current research are an invaluable resource for future studies that will foster further innovation in automated medical diagnostics. More importantly, the fact that it eliminated laborious preprocessing steps and the ability of the model to be flexible against a wide variety of imaging conditions makes it poised to revolutionize the diagnostic process by making it faster, more accurate, and accessible. Going forward, the model's capability enhancement, integration with real-time diagnostic tools, and validation of its performance will be done through extensive clinical trials.

The long-term objective is to enable early and accurate diagnoses of brain tumors and other health conditions, where the prognosis can be improved and standards of healthcare set higher. The study will not only lay a milestone in medical imaging technology but also set a road map for future explorations, which have the potential of changing the face of performing medical diagnostics.

References

[1] Francisco Javier Díaz-Pernas, Mario Martínez-Zarzuela, Míriam Antón-Rodríguez, and David González-Ortega, "A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network," Healthcare, vol. 9, no. 2, pp. 153, Feb. 2021.

[2] Isin, C. Direkoglu, and M. Sah, "Review of MRI-based brain tumor image segmentation using deep learning methods," Procedia Comput. Sci., vol. 102, pp. 317–324, 2016.

[3] Cheng, J.; Huang, W.; Cao, S.; Yang, R.; Yang, W.; Yun, Z.; Wang, Z.; Feng, Q.; "Enhanced performance of brain tumor classification via tumor region augmentation and partition." PLoS ONE 2015, 10, e0140381

[4] Anaraki, A.K.; Ayati, M.; Kazemi, F.; "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms." Biocybern. Biomed. Eng. 2019, 39, 63–74.

[5] Cheng, J.; Yang, W.; Huang, M.; Huang, W.; Jiang, J.; Zhou, Y.; Yang, R.; Zhao, J.; Feng, Q.; Chen, W.; "Retrieval of brain tumors by adaptive spatial pooling and fisher vector representation." PLoS ONE 2016, 11, e0157112.

[6] Abiwinanda, N.; Hanif, M.; Hesaputra, S.T.; Handayani, A.; Mengko, T.R.; "Brain tumor classification using convolutional neural network." In Proceedings of the World Congress on Medical Physics and Biomedical Engineering, Prague, Czech Republic, 3–8 June 2018; Springer: Singapore, 2019; pp. 183–189.

[7] Pashaei, A.; Sajedi, H.; Jazayeri, N.; "Brain Tumor Classification via Convolutional Neural Network and Extreme Learning Machines." In Proceedings of the 8th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, Iran, 25–26 October 2018; Curran Associates: New York, NY, USA, 2018; pp. 314–319.

[8] Sultan, H.H.; Salem, N.M.; Al-Atabany, W.; "Multi-classification of brain tumor images using deep neural network." IEEE Access 2019, 7, 69215–69225.