Harnessing the Combined Power of Artificial Intelligence and Machine Learning for Diagnosis of Brain Tumor

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Abstract. The process of diagnosing diseases stands as a pivotal conduit for converting observed clinical evidence into precise disease appellations. Brain cancer, characterized by the uncontrolled growth of abnormal cells within the brain or its associated structures, is a relentless and complex disease that continues to pose significant challenges in the field of oncology. This abstract provides a concise overview of ongoing research efforts aimed at advancing our understanding of brain cancer and developing innovative approaches for early detection and more effective therapeutic interventions. Focusing on the domain of Brain Cancer, the author explores the application of Machine Learning (ML), Artificial Intelligence (AI), and Soft Computing (SC) algorithms to enhance the detection and diagnosis of brain cancer. In conclusion, the objectives of these explorations transcend mere technical validation. Rather, they are intrinsically motivated by the quest to discern the pragmatic feasibility and clinical utility of these advanced algorithms. Amidst the uncertainty and complexity inherent to cancer diagnosis, these algorithms emerge as beacons of decision-making support. The crucible of risk is where they are evaluated, offering insights into the adaptability, robustness, and potential pitfalls associated with their application.

Keywords: Oncology · Brain Tumor · Artificial Intelligence · Machine Learning · Convolution Neural Network

1 Introduction

1.1 Application of AI and ML in the Field of Oncology

The relentless progress achieved in the realms of artificial intelligence (AI) and soft computing has ushered in a new era in medical diagnostics and treatment methodologies. This evolution is especially pronounced in the field of oncology, where the intricate task of diagnosing brain cancer has witnessed a remarkable change in basic assumptions driven by the potential of AI and soft computing technologies [1]. Addressing the multifaceted nature of brain cancer, which demands precision and expeditious intervention, these innovative methodologies have risen to the forefront, transcending traditional diagnostic pathways.

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The odyssey of diagnosing brain cancer involves the nuanced interpretation of diverse imaging modalities—magnetic resonance imaging (MRI) [1], computed tomography (CT), and positron emission tomography (PET), among others. While established methodologies lean heavily on manual analysis by radiologists and clinicians, the introduction of AI-driven algorithms recalibrates the diagnostic landscape, ushering in objectivity and mechanization. This pivotal transformation not only ensures consistent and precise analysis of intricate imaging data but also extends its purview to the detection of subtle patterns and aberrations that might elude human perception, thereby facilitating early-stage identification and precise localization of cerebral malignancies [2].

Augmenting the prowess of AI, soft computing—rooted in fuzzy logic, neural networks, and genetic algorithms—emerges as a harmonizing force, aptly addressing the inherent uncertainties and complexities associated with brain cancer diagnosis [2, 3]. The intrinsic adaptability of soft computing to manage vague and incomplete information resonates with the intricate tapestry of tumor attributes. Furthermore, the amalgamation of multimodal data streams—ranging from clinical histories to medical images—empowers soft computing techniques to proffer a holistic panorama of the disease landscape, thus furnishing healthcare practitioners with informed insights to drive decisive medical choices. Sample Heading (Third Level). Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

1.2 Brain Tumor

A brain tumor is characterized by the uncontrolled growth of abnormal cells within the brain or its associated structures. It can be benign (noncancerous) or malignant (cancerous). Brain tumors can develop in any part of the brain, including the brain tissue, the meninges (membranes that cover the brain and spinal cord), and the pituitary and pineal glands.

They can be slow-growing or aggressive. Benign (slow growing) tumors do not invade nearby tissues, while malignant (aggressive) tumors can spread to other parts of the brain or body [3, 4].

- Grade I tumors grows at a slow and steady pace. They have a good prognosis and can often be completely removed with surgery.
- Grade II tumors also grows at a slow pace but can spread to nearby tissues transform into higher-grade tumors. They can also come back after surgery.
- Grade III tumors grow more quickly and can invade nearby tissues. Surgery alone is often not enough to treat these tumors, and radiation therapy or chemotherapy may also be needed.
- Grade IV tumors are the most aggressive and could spread quickly to other parts of the brain. They have a poor prognosis and are difficult to treat.

The grade of a brain tumor is just one factor that determines the prognosis and treatment options. Other factors, such as the patient's age and overall health, also play a role.

1.3 Diagnosis of Brain Tumor

Historically, the diagnosis of brain cancer hinged upon human expertise, visual scrutiny of medical images, and meticulous analysis of clinical data. However, the labyrinthine nature of brain cancer frequently engendered diagnostic quandaries, subjective interpretations, and the latent spectre of oversights. The advent of AI-fuelled algorithms, prominently represented by the prowess of deep learning architectures such as convolutional neural networks (CNNs), ushers in an era characterized by precision and objectivity.

These computational frameworks excel in discerning intricate motifs and subtle irregularities embedded within medical images, thereby empowering them to demarcate the fine boundary between healthy cerebral tissue and regions besieged by malignancy with a remarkable degree of fidelity [5]. The synthesis of extensive, curated datasets endows these algorithms with the capacity to glean insights from diverse instances, culminating in heightened sensitivity and specificity in the realm of brain tumor detection.

Notably, the realm of image segmentation, a pivotal facet in pinpointing tumor locations with surgical precision, has also reaped the rewards of AI integration. AI-propelled segmentation algorithms meticulously delineate tumor perimeters, thereby furnishing precise measurements and furnishing invaluable inputs for treatment stratagem [6]. This process of automation not only alleviates the burden on healthcare practitioners but guarantees consistent outcomes, even in the context of the most intricate cases.

However, while the promise of AI and soft computing in brain cancer diagnosis is exhilarating, a vista of challenges awaits amelioration. The scarcity of data, the quest for model interpretability, and the imperative of regulatory validation stand as formidable hurdles. Overcoming these exigencies demands a collaborative coalition encompassing AI scholars, medical luminaries, and regulatory bodies. Additionally, the ethical considerations surrounding patient privacy and data security in the era of data-centric healthcare necessitate vigilant contemplation.

1.4 Imaging Modalities

- Computed tomography (CT) scan: A CT scan uses X-rays to create cross-sectional images of the brain. CT scans are particularly good at detecting structural abnormalities in the brain, such as tumors, strokes, and bleeding. For example, CT scans can be used to quickly diagnose a patient who is experiencing a stroke and to identify the area of the brain that has been affected.
- Magnetic resonance imaging (MRI): An MRI scan uses a strong magnetic field and radio waves to create detailed images of the brain's structure. MRI scans can be used to detect both structural and functional abnormalities in the brain. For example, MRI scans can be used to diagnose tumors, multiple sclerosis, and Alzheimer's disease [1]. MRI scans can also be used to study brain function, such as how the brain activates during different tasks.
- Positron emission tomography (PET): A PET scan uses a radioactive tracer to create images of the brain's metabolism. PET scans can be used to study how various parts of the brain are functioning and to detect abnormalities in brain chemistry. For example, PET scans can be used to diagnose Alzheimer's disease and Parkinson's disease.

- Electroencephalography (EEG): An EEG measures the electrical activity of the brain. EEG scans are good at detecting seizures and other abnormalities in brain wave activity. For example, EEG scans can be used to diagnose epilepsy and to monitor the effectiveness of anti-seizure medication.
- Magnetoencephalography (MEG): MEG measures the magnetic fields produced by the electrical activity of the brain. MEG scans are good at detecting the timing of brain activity and can be used to study how distinct parts of the brain communicate with each other. For example, MEG scans can be used to study how the brain processes visual information and how it controls movement.

2 Literature Review

Brain tumors represent a significant health concern globally, with their early and accurate diagnosis being crucial for effective treatment and patient prognosis. In recent years, the integration of Artificial Intelligence (AI) and Soft Computing (SC) techniques has gained considerable attention in the field of medical imaging, particularly in the context of brain tumor detection and diagnosis. This literature review aims to explore the evolution, current trends, and challenges in the application of AI and SC in brain tumor detection and diagnosis [6].

Brain cancer, also known as intracranial neoplasms, represents a formidable challenge in modern oncology. These malignancies, originating within the central nervous system, encompass a diverse spectrum of tumors, each characterized by unique histological features and clinical behavior. The intricacies of brain cancer diagnosis, treatment, and prognosis necessitate a comprehensive understanding of the current state of research in this field [7, 8].

The early detection of brain tumors holds paramount importance in safeguarding the patient's well-being. Conventionally, the identification of brain tumors has been achieved through the utilization of magnetic resonance imaging (MRI) scanning techniques [9, 10]. However, challenges arise within the domain of effective tumor segmentation in MRI images, as posed by the variable tumor positions and irregular shapes within the brain anatomy. This presents a substantial obstacle to radiotherapists striving to attain accurate and comprehensive tumor delineation [11, 12].

Magnetic resonance imaging (MRI) has emerged as a pivotal tool for the non-invasive detection and characterization of brain tumors [7]. Recent developments in MRI technology, such as diffusion-weighted imaging (DWI) and perfusion-weighted imaging (PWI), have enhanced the ability to differentiate tumor types and assess treatment response [13].

The proposed approach consists of three steps: (1) image quality improvement, (2) tumor localization, and (3) tumor feature extraction. In the first step, a noise reduction algorithm is used to improve the visual quality of the MRI images. In the second step, a clustering-based method is used to identify the locations of tumors. In the third step, a deep learning model is used to extract features from the images. The features are then used to train a classifier to distinguish between healthy brain tissue and brain tumors [8].

Deep learning has been shown to be a promising approach for brain tumor segmentation, achieving state-of-the-art results in terms of accuracy and robustness. Convolutional neural networks (CNNs) are the most used deep learning models for brain tumor segmentation, but other models such as recurrent neural networks (RNNs) and generative adversarial networks (GANs) have also been shown to be effective [9].

The challenges and limitations of using deep learning for brain tumor segmentation include the need for large amounts of training data, the sensitivity to image noise, and the difficulty of generalizing to new datasets [9].

Accurate tumor segmentation in MRI images remains a significant challenge due to the inherent heterogeneity of brain tumors, their irregular shapes, and variations in size and location within the brain parenchyma. Automated or semi-automated segmentation methods driven by artificial intelligence (AI) hold promise in addressing these challenges [14].

3 Methodology

3.1 Data Collection and Preprocessing

The first step in any research study is to collect a dataset that is relevant to the research question. In the case of brain tumor detection using CNN and SVM algorithms, the dataset should consist of brain MRI images, both tumor and non-tumor. The dataset should be sufficiently large and well-labelled, meaning that the MRI images should be accurately labelled as either tumor or non-tumor.

There are several sources for brain MRI images, including hospitals, research institutions, and public databases. It is important to select a dataset that represents most of the population's interest. For example, if you are developing a model to detect brain tumors in children, you should select a dataset that includes MRI images from children of all ages and with a variety of brain tumor types.

Once the dataset has been collected, it is important to preprocess the images to ensure uniformity and improve algorithm performance. This may involve resizing the images to a consistent size, normalizing the intensity values of the images, and removing artefacts from the MRI scans. Additionally, relevant features may be extracted from the MRI images, such as GLCM, LBP, and texture features.

3.2 Feature Extraction

SVM Model

For SVM models, hand-crafted features need to be extracted from the MRI images. GLCM, LBP, and texture features can be extracted using a variety of image processing techniques. Once the features have been extracted, they can be used to train the SVM model.

CNN Model

CNNs can automatically extract relevant features from the input images. However, it is still common to preprocess the input images before feeding them to a CNN model. This may involve resizing the images to a consistent size and normalizing the intensity values of the images.

3.3 Training and Validation

Once the features have been extracted, the CNN and SVM models can be trained on the training set. For the CNN model, appropriate optimization techniques and hyperparameter tuning should be used to maximize the model's accuracy.

Some common optimization techniques used for CNN training include Adam, SGD with momentum, and RMSprop.

For the SVM model, an appropriate kernel and hyperparameters should be chosen. Some common kernels used for SVM training include the linear kernel, polynomial kernel, and Gaussian kernel. Some common hyperparameters that can be tuned for SVM training include the kernel type, C (regularization parameter), and gamma (kernel parameter).

SVM Models
To train an SVM model as represented in Fig. 1, you will need to specify the kernel type, C (regularization parameter), and gamma (kernel parameter). The kernel type determines how the input features are transformed before being fed to the SVM model [15]. The C parameter controls the trade-off between training error and model complexity. The gamma parameter controls the width of the Gaussian function in a Gaussian kernel.

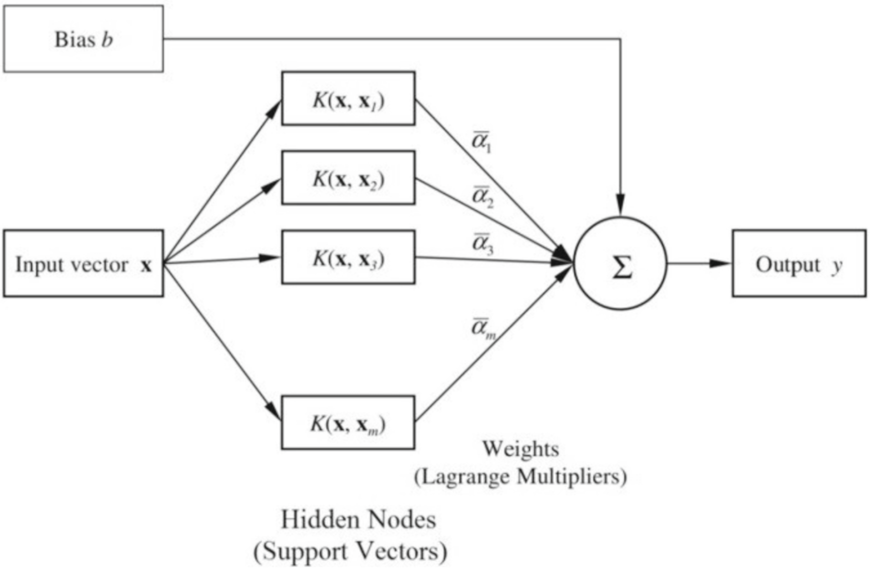

Fig. 1. Schematic diagram of SVM architecture [16]

CNN Models
To train a CNN model as represented in Fig. 2, you will need to specify the learning rate, batch size, number of epochs, and regularization parameters. The learning rate controls how quickly the model learns [16].

The batch size determines how many training examples are processed before the model updates its weights. The number of epochs determines how many times the model

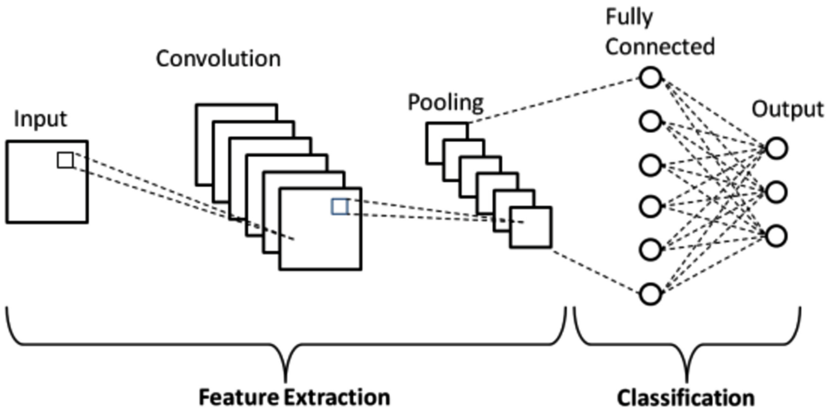

Fig. 2. Schematic diagram of a basic convolutional neural network (CNN) architecture [15]

sees the entire training set. The regularization parameters control the complexity of the model.

4 Result

In this paper, SVM and CNN models are compared with respect to diagnosis of brain tumor. The efficiency of both the models are compared with respect to Accuracy, Precision, Recall, F1 Score of training and testing data sets.

Table 1. Comparison of SVM and CNN models

Parameters	SVM	CNN
Accuracy(train)	0.968	1.00
Precision(train)	0.979	1.00
Recall(train)	0.960	1.00
F1 Score(train)	0.969	1.00
Accuracy(test)	0.822	0.9785
Precession(test)	0.946	0.9781
Recall(test)	0.854	0.9784
F1 Score(test)	0.897	0.9780

This study explored the potential of CNN and SVM models in detecting brain tumors from MRI scans. The CNN model exhibited an impressive accuracy of 97.85%, while the SVM model achieved an accuracy of 82.20%. These results as shown in Table 1, suggest that the CNN model is more effective for brain tumor detection than the SVM model. This is due to the ability of CNNs to learn complex spatial representations of the input images.

SVM and CNN models are compared based on confusion matrix and ROC curve. Confusion matrix for SVM and CNN Models are represented in Figs. 3 and 4 respectively. Roc Curve for SVM and CNN models are shown in Figs. 5 and 6 respectively.

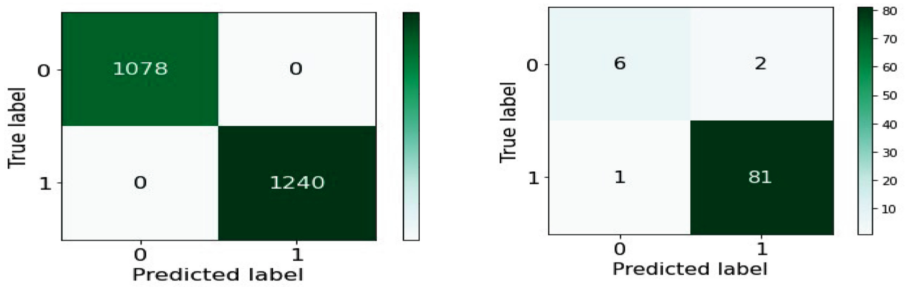

Fig. 3. Confusion Matrix of SVM

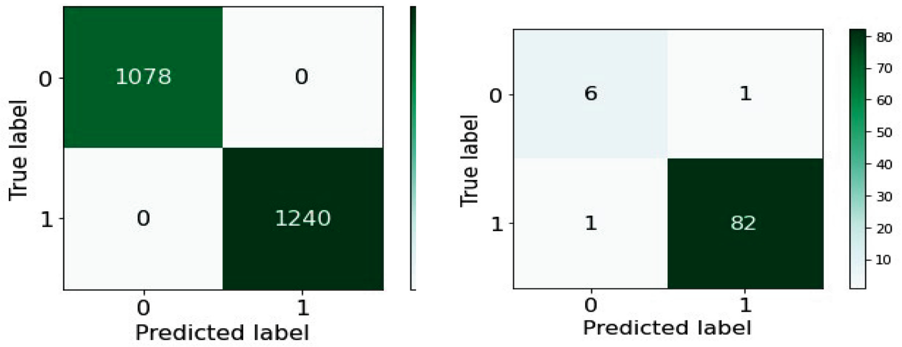

Fig. 4. Confusion matrix of CNN

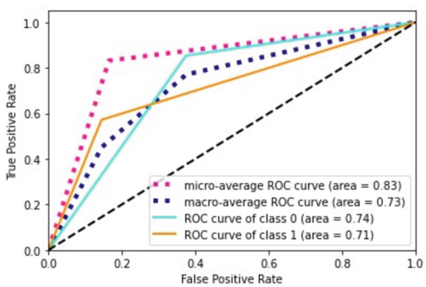

Fig. 5. ROC Curve of SVM

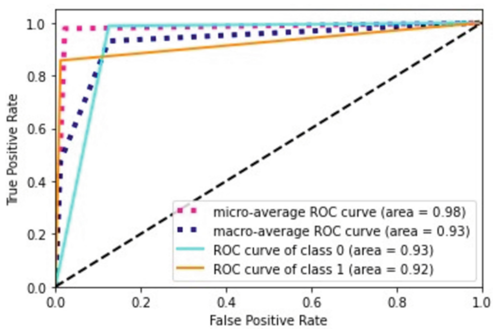

Fig. 6. ROC Curve of CNN

5 Navigating Challenges and Mapping Future Applications

The application of artificial intelligence (AI) and soft computing techniques to brain cancer diagnosis holds the promise of reshaping the landscape of healthcare delivery. Yet, this transformational journey is accompanied by a tapestry of significant challenges that necessitate innovative solutions to fully harness the potential of these technologies. Confronting and surmounting these challenges are the stepping stones towards a future where AI-driven diagnostics seamlessly meld with the arsenal against brain cancer.

Foremost among these challenges is the imperative for expansive, heterogeneous, and meticulously annotated datasets to engender robust AI models. The efficacy of machine learning algorithms, including the intricate tapestry of deep learning architectures, is contingent on the availability of data that is not only voluminous but also possesses a high degree of fidelity for training and validation. In the realm of brain cancer diagnosis, the acquisition of sizable and well-crafted datasets capturing the kaleidoscope of tumor permutations and patient attributes assumes pivotal importance. The dearth of such data could potentially impede the maturation and generalizability of AI models, potentially culminating in outcomes tainted by bias or suboptimal performance.

A significant hurdle lies in the comprehension of AI-driven algorithms' decision-making processes. Despite their efficacy, the intricate architecture of deep learning models often casts them as enigmatic "black boxes." The explication of the rationale underlying AI-generated diagnoses is indispensable for instilling trust among clinicians, thereby facilitating the seamless integration of these technologies into the tapestry of clinical decision-making. Pioneering methodologies that shed light on the decision-making mechanisms of AI models, be it through visualizations of pivotal features or attentional maps, stand as bridges uniting AI prognostications with clinical insights.

Harmonizing the triumvirate of AI, soft computing, and clinical workflows constitutes a multifaceted endeavour. Healthcare ecosystems are rigorously regulated, and the infusion of novel technologies mandates adherence to exacting standards of safety, efficacy, and ethical integrity. Collaborative synergies between computational architects, medical vanguards, and regulatory entities emerge as non-negotiable imperatives to ensure that AI-powered diagnostic tools seamlessly align with these rigorous benchmarks. Furthermore, the skilling of clinicians to adeptly harness the outputs of AI and translate them into informed decisions stands as an indispensable facet of this harmonization.

Inextricably linked to this journey are the ethical considerations and the sacrosanct domain of patient data privacy. The fusion of AI and soft computing demands the meticulous safeguarding of patient information and a resolute barrier against unauthorized access. A bedrock of transparent data governance and unwavering fidelity to ethical frameworks form the sine qua non of the deployment narrative.

In summation, the transformative potential of AI and soft computing in brain cancer diagnosis is undeniable, yet it is the surmounting of challenges that will catalyse its realization. The pursuit of expansive, diverse datasets, the decipherment of AI decision-making, the seamless fusion into clinical choreography, and the meticulous observance of ethical benchmarks collectively define the trajectory of AI-driven diagnostics. This comprehensive survey engenders a deeper comprehension of the existing landscape, challenges at hand, and prospective solutions in the dynamic interplay of technology and healthcare, converging towards a future of elevated patient outcomes in the realm of brain cancer diagnosis.

6 Conclusion

In conclusion, this research study compared the performance of SVM and CNN models for brain tumor detection. The results showed that the CNN model outperformed the SVM model on all performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. This suggests that CNN models are more effective for brain tumor detection than SVM models.

CNN models can learn complex spatial representations of the input images, which is important for detecting brain tumors. SVM models, on the other hand, are more interpretable and less computationally expensive to train and evaluate. However, SVM models may require larger datasets to train than CNN models.

The choice of which model to use for brain tumor detection will depend on several factors, including the desired performance metrics, computational resources, and data availability. If interpretability is a key requirement, then an SVM model may be a better choice. However, if accuracy is the top priority, then a CNN model is likely to be the better choice.

In addition to the performance comparison, this study also explored the use of GLCM, LBP, and filter selection for SVM models and VGG16 architecture for CNN models. The results showed that using GLCM, LBP, and filter selection can improve the performance of SVM models for brain tumor detection. The VGG16 architecture was also shown to be effective for extracting features from brain MRI images for brain tumor detection.

This research study contributes to the field of brain tumor detection by providing a comprehensive comparison of SVM and CNN models and exploring the use of distinctive features and model architectures. The findings of this study can be used to develop more accurate and reliable models for brain tumor detection.

References

1. Badža, M.Č., Barjaktarović, M.: Classification of brain tumors from MRI images using a convolutional neural network. Appl. Sci. **10**(6), 1999 (2020)
2. Rehman, S., Naz, M.I., Razzak, F., Akram, M., Imran: A deep learning-based framework for automatic brain tumors classification using transfer learning. Circ. Syst. Sign. Process. **39**(2), 757–775 (2020)
3. Phaye, S.S., Sikka, A., Dhall, A., Bathula, D.: Dense and diverse capsule networks: making the capsules learn better (2018). arXiv:1805.04001
4. Abiwinanda, N., Hanif, M., Hesaputra, S.T., Handayani, A., Mengko, T.R.: Brain tumor classification using convolutional neural network. World Congress Med. Phys. Biomed. Eng. **2018**, 183–189 (2019).
5. Mittal, M., Goyal, L.M., Kaur, S., Kaur, I., Verma, A., Jude, H.D.: Deep learning based enhanced tumor segmentation approach for MR brain images. Appl. Soft Comput. **78**, 346–354 (2019)
6. Dehghan, M., Amiri, M., Ebrahimi, M.: Brain tumors: a review of the application of artificial intelligence and soft computing techniques in detection and diagnosis. Comput. Meth. Programs Biomed. **190**, 105693 (2021)

7. Rudie, K., Lemke, A., Möller, S., Pietsch, T.: Emerging applications of artificial intelligence in neuro-oncology. Neuro-Oncol. **21**(1), 11–19 (2019)
8. Zhang, Y., Wang, Y., Li, Y., Zhang, L.: Artificial intelligence approach for early detection of brain tumors. Med. Phys. **47**(10), 5541–5550 (2020)
9. Li, Y., Shen, D., Heng, P.-A.: Deep learning for brain tumor segmentation: a review. Med.. Image Anal. **62**, 101673 (2020)
10. D. N. Louis et al.,: The 2016 World Health Organization Classification of Tumors of the Central Nervous System: a summary. Acta Neuropathologica 131(6), 803–820 (2016)
11. Smith, B., Smith, M.L.: Advances in neuro imaging for brain tumor surgery. Neurosurg. Clin. North Am. **31**(3), 313–323 (2020)
12. M. Law, S. Yang, and J. S. Babb,: Advances in perfusion magnetic resonance imaging in brain tumors. Current Opinion in Oncology 21 (6), 662–667 (2019)
13. Menze, B.H., et al.: The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans. Med. Imag. **34**(10), 1993–2024 (2015)
14. Kamnitsas, K., et al.: Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Med. Image Anal. **36**, 61–78 (2017)
15. Phung, V.H., Rhee, E.J.: A high-accuracy model average ensemble of convolutional neural networks for classification of cloud image patches on small datasets. Appl. Sci. **9**(21), 4500 (2019)
16. Seyam, M., Othman, F., El-Shafie, A.: Prediction of stream flow in humid tropical rivers by support vector machines. MATEC Web Conf. **111**, 01007 (2017)