Brain Tumor Diagnosis and Grading Using Multi-Task Convolutional Networks on MRI Images

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*Abstract :-* Brain tumors are important medical issues and must be detected quickly and accurately to give the right treatment. Checking the MRI scans manually can be slow process and can have many human errors, so to make it easy and error-free, we use automated solutions, which are very important in the medical field. In our research, we found that there are many models that help us to find the brain tumors and the type of brain tumors. We reviewed the mostly used model known as Convolutional Neural Networks (CNN), which uses the BRATS dataset to create a better system for classifying and segmenting brain tumors. The aim is to improve both segmentation precision and classification accuracy, solving the problems while detecting the types and levels of brain tumor detection. The research used several deep learning methods. Techniques like Res-Net and VGG-Net, along with hybrid models such as Caps-Net and VGG-Net were applied. While these have helped find tumors better, gaps still exist in the research. A major issue is that there are not enough brain tumors classified thoroughly. Many models struggle to tell apart different tumors, and older methods often made mistakes in outlining the tumor areas on MRI scans. The approach of using deep learning boosts pixel-wise segmentation and enables accurate classification into different tumor types. It helps in clearly defining the tumor borders. This results in both tumor classification and segmentation, which can achieve high accuracy across various tumor types and levels.

*Keywords: Brain Tumor Detection, Segmentation, Convolutional Neural Networks(CNN), Tumor Classification, BRATS Dataset, Deep Learning, Tumor Grade Prediction, Pixel-Wise Segmentation, Medical Image Analysis, Data Augmentation, Tumor Boundary Detection.*

# Introduction

Brain tumors are a serious challenge in medical diagnosis because of the need for early detection to ensure the best possible treatment. MRI (Magnetic Resonance Image) is the method for detecting brain tumors, as it gives us clear images of the brain and the tumor present in the brain. When doing the analysis, these scans manually are taking more time and can give the errors.

The difficulties in this field come from the wide range of variation and similarities in brain tumor characteristics, like size and shape of the tumors, even within the same tumor type, which can lead to other diseases. Misdiagnosing a brain tumor can have the worst consequences for a patient’s chance of survival, which makes for an increased interest in automated image processing technologies as a solution to the limitations of manual diagnosis. We reviewed various algorithms for detection and classification of brain tumors, with many studies focused on achieving high performance results and achieving low error rates. Deep learning algorithms, and specifically convolutional neural networks (CNN), are becoming more popular for the development of automated systems for accurate classification and segmentation of brain tumors, as in manual processes it is more time-consuming.

In many of the research papers, we found that many researchers have successfully used CNNs to classify brain tumors. Models like Res-Net, VGG-Net, and hybrid models such as Caps-Net, VGG-Net have shown improved accuracy in identifying tumors from MRI scans. These deep learning models are used for learning complex features on their own, providing better results than traditional methods, which were based on manually selecting features. Still, there are gaps, particularly in classifying specific types of tumors like gliomas, meningiomas, and pituitary tumor and the Levels in which The brain tumor lies. Many of the models only distinguish about the detection of brain tumors or give low precision, while segmentation (outlining the tumor's boundaries) is important.

## OBJECTIVE

The main aim is to build an automated system that detects, classifies, and segments brain tumors using deep learning techniques. It would be very resourceful to detect early and accurate brain tumors since it eliminates the errors that are made during manual processes and also enhances the accuracy with which tumors are classified, and the boundaries of tumors are segmented from MRI scans. Methods such as data augmentation, regularization, and the application of datasets like BRATS would make it clear that the model is performing efficiently in medical use, which makes the health professionals achieve further decision-making abilities for much better treatments of patients.

# Literature Survey

1. Neelum Noreen et al proposed a multi-level feature extraction method based on use of Inception-v3 and DenseNet201 models. Features in different layers were extracted and passed through a softmax classifier. The model was experimented on a publicly available dataset with three-class brain tumors. Inception-v3 achieved 99.34% and DenseNet201 99.51% accuracy. The result outperform all state of the art deep learning techniques for the classification task.
2. Hasnain Ali Shah et al proposed Brain Tumor Detection Approach Using MRI Images by Using Effcetivnet B0. Improved images and data augmentation improved the quality and size of the dataset. The model had obtained high classi cation accuracy compared to VGG16 and InceptionV3. Automatic deep model is quite efficient for the diagnosis process. Improved accuracy in diagnosis was achieved comparing with conventional CNNs.
3. Wenxin Wang et al demonstrated the techniques of VE-JP and CycleGAN for cancerous portion of brain tumour segmentation and detection. CycleGAN generates abnormal ones from normal images, where as VE-JP reconstructs normal images but takes into consideration only pathologic region. The hybrid has enabled precise segmentation for tumor. The focus was on joint probability for conditional generation. The model shows that great improvement has been made over existing methods.
4. Ayesha Younis et al was able to classify with better accuracy in using ResNet50 with transfer learning and data augmentation. The classification for brain tumor, such as meningioma, glioma, and pituitary gland tumors, is done. It can reach up to 99% accuracy for a dataset of 5712 images. The model uses regularization techniques to prevent overfitting. This model gave much better performance compared with other models.
5. Maram Fahaad Almufareh et al has compared YOLOv5 and YOLOv7 about the detection of three types of brain tumors meningiomas, gliomas, and pituitary tumors detected from MRI images. The YOLO models were compared with the RCNN and Mask RCNN. According to the study, YOLO reported higher accuracy in detections. This study emphasized the progress in real-time tumor detection.
6. Surendran Rajendran et al exploited the U-Net architecture to attain brain tumor segmentation from MRI images. Here, an architecture was developed with skip connections as well as a fully convolutional design. It basically just extracted the fine details of the tumor from the MRI images. U-Net worked very well for precise detail-based segmentation. It is one of the most powerful architectures in the area of medical image applications.
7. Muhammad Rizwan et al implemented a classification of brain tumors using high-resolution MRI images by categorizing them as pituitary, glioma, and meningioma. Additionally, the sub-classification of gliomas into Grade-2, Grade-3, and Grade-4 also performed. This always used to grade the tumor and diagnosed it with more accuracy. GCNN would provide reliable performance for use in the clinical environment.
8. Karrar Neamah et al reviewed deep learning models for the classification & detection of brain tumors from 2019 to 2022. The crucial models studied are CNNs, transfer learning, and hybrid techniques. Data augmentation, attention mechanisms, and diffusion models were discussed. After discussing various approaches, their strengths and limitations, the strengths and limitations together produced valuable insights for future research.
9. Ayesha Jabbar et al introduced a hybrid model called Caps-VGG-Net model for the detection and classification of tumours. It is a strong combination of CapsNet and VGGNet, which can be effectively trained on very large datasets. It was trained on high-quality images from BraTS-2020 and BraTS-2019 datasets. Amazing classification scores were achieved with this model. This approach helps in the automatic tumor classification by radiologists.
10. Zheshu Jia et al presented a segmentation model based on structural, morphological, and relaxometry information. The algorithm was able to successfully overcome a few drawbacks that had been noted in the manual tumor detection process carried out by radiologists. FAHS-SVM integrated ELM training to maximize tumor and surrounding tissue segmentation accuracy. Uniformity was realized in tumor and surroundings segmentation. The model improved clinical practice settings with sensitivity and efficiency.
11. Sunita Roy et al designed two new CNN models named S-Net and SA-Net for the brain tumor segmentation model. With a basic architecture of U-Net, Merge Blocks applied global and local context, while Attention Blocks did the trick in giving importance to areas of interest for better segmentation. Annotated samples were optimized along with data augmentation to ensure a proper use of models during training. It highlighted efficient performance in brain tumor segmentation using the above models.
12. Wenqing Li et al proposed a correction diffusion model that corrects the systematic error in MRI segmentation. In this model, the Vector Quantized Variational Auto-encoder is used for compressing and stabilizing data. Again, the MultiFusion Attention Mechanism is introduced to improve the performance of the model. The experiments are conducted on datasets including BraTS2019 and BraTS2020. It upgrades the accuracy of the model significantly in terms of segmentation.
13. Involutional Neural Networks (Inv-Nets) was proposed by et al Abdullah A. Asiri for brain tumor classification. Inv-Nets lowered the computational complexity compared to traditional CNNs. It was used for a four-class classification problem. The technique proved effective in resource-limited scenarios. This is one of the methods used for medical image analysis.
14. Ji-Hyeon Lee et al used the Gaussian filters. To enhance generalizability, the technique applied GridMask. For partially occluded tumors, the proposed improvement is the use of a Patterned GridMask. Four deep learning models: ViT-B/16, EfficientNetV2-M, were applied to the evaluation. The system has the potential for early detection and diagnosis of an advanced form.
15. Sohaib Asif et al utilized AI and deep learning architectures for the early classification of brain tumors. Models utilized for the process are Xception, Dense-Net121, and InceptionResNetV2 to extract features from MRI images. The models are tested on benchmark datasets performances using the ADAM optimization algorithm. Their model obtained high-performance accuracy in classification. Effective work for supporting automated medical imaging diagnosis.
16. Xiaoyi Lin et al improved the classification of brain tumour using EfficientNet-B0 on MRI images. Techniques in image enhancement and data augmentation are applied to enhance the approach. Deep learning models show improvement over traditional models VGG16 and InceptionV3 with high diagnostic accuracy as well as class-wise robust classification. This presents an interphase of fine-tuned architectures from deep learning.
17. Saif Ahmad et al applied transfer learning techniques with 2D MR images for the purpose of classifying brain tumors. Models used included VGG-16, ResNet50, and DenseNet201. Transfer learning significantly improved the early diagnosis of brain tumors and helped in proper treatment. In the study, a labeled dataset comprising both normal and abnormal images of brain was used. The method enhanced the diagnosis accuracy compared to traditional methods.
18. Abdullah A. Asiri et al The candidate used MRI diagnosis with diagnosis based on adaptive Wiener filtering and ICA. This removed noise and removed contrast variability in MRI images. SVM did a very good classification and segmentation of the tumors. The enhanced image gave automatic accuracy. The overall system improved the accuracy percentage in the diagnosis of brain-related cancerous diseases.
19. Sedat Metlek et al proposed a hybrid convolutional model for brain tumor segmentation. The model was strictly on a region of interest rather than processing the whole images. With reduced computational costs and better performance on segmentation, the approach was evaluated on datasets acquired from BraTS 2018, 2019, and 2020. The results obtained were highly efficient in the detection of tumors and their segmentation.
20. Ruqsar Zaitoon et al has designed a model for the diagnosis of Brain Tumours using RU-Net2+ and DBT-CNN. The designed model performs tumor detection, segmentation, classification, and survival prediction. BraTS dataset is used for the training and test set of the proposed algorithm. The results proved to be very promising wherein it has rightly categorized the patients based on their survival rates with the DBT-CNN classifier. This has sorted the improvement in the care of a patient with the application of such an automatic system.
21. Javaria Amin et al presented a fractional-chicken swarm optimization approach for tumor classification. After proper optimization, the algorithm was applied to train a deep recurrent neural network (RNN). The proposed model classified the brain tumor with accurate severity level. Feature extraction along with noise reduction was included in some preprocessing techniques. The proposed system enhanced the precision in classification.
22. Xiaoman Zhang et al proposed a self-supervised segmentation approach using a two-stage Sim2Real training regimen. For the pre-training phase, models were trained on simulated tumors and fine-tuned with real datasets such as BraTS2018 and LiTS2017. Features of interest were mapped directly to segmentation tasks by using the layer decomposition method, which had improved segmentation accuracy. Results were better compared to traditional methods.
23. Dr. R. Cristin et al in his work utilized MRI based brain tumor classification with the help of a fractional-chicken swarm optimization algorithm. The best result was achieved with the derivative factor combined with the behavior pattern of the chicken swarm and was trained as a deep RNN by optimizing the algorithm with excellent classification accuracy. The proposed approach efficiently classified the levels of severity of the tumor.
24. Mohammad Shahjahan Majib et al proposed a computer-assisted approach for tumor segmentation and classification. The paper presents numerous experiments with hybrid models and 16 transfer learning models. The best performance was achieved by VGG-SCNet. The automatic system diagnosed more accurately than the manual ones. It is an early sensitive tumor detector with better clinical outcome.
25. Mohammad Ashraf Ottom et al used encoder-decoder architectures with skip connections for 2D brain tumour segmentation task. Tehniques of data augmentation were utilised to reinforce the training. The proposed model showed impressive performance by achieving a high value of the dice similarity coefficient. The approach demonstrated good applicability for automatic tumour segmentation. Such a system has potential for clinical deployment.

##### Methodology

[20, 19] The BraTS dataset is widely used for brain tumor classification and segmentation due to its comprehensive collection of MRI images. [25,11] Data augmentation techniques such as rotation, scaling, and flipping are applied to enhance model generalization by expanding the dataset. [18] MRI images are preprocessed using normalization for uniform contrast and brightness, followed by adaptive Wiener filtering for noise reduction.

[25] Texture features are extracted using the Gray Level Cooccurrence Matrix (GLCM) to improve feature representation for accurate tumor segmentation.

[2] The EfficientNet-B0 model will be used as the backbone for brain tumor classification due to its efficient parameter count and high accuracy in classification tasks. [7] The Gaussian Convolutional Neural Network (GCNN) will classify segmented tumors into specific categories, such as pituitary, glioma, and meningioma, enhancing classification precision. [9] A hybrid approach that combines VGGNet for feature extraction with CapsNet for classification will be applied, which is particularly effective for classifying complex tumor structures.

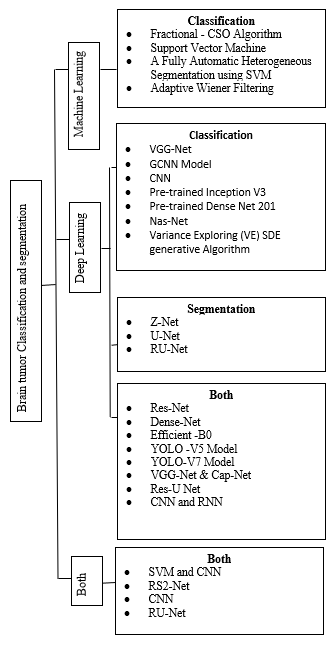


FIGURE 1. **Models Used in Cited Papers.**

[25] Brain tumor segmentation will be performed using the U-Net architecture, which is renowned for its skip connections and fully convolutional design, allowing it to capture intricate details in MRI images. [20] Additionally, RU-Net2+ will be used to enhance segmentation by combining U-Net with recurrent units, making it more effective for processing sequential data. [11] Attention blocks will also be added to U-Net to improve accuracy by helping the model focus on the most relevant regions in the MRI images.[22] The U-Net and RU-Net2+ models will be trained on the BraTS dataset, using the dice similarity coefficient as the performance metric for precise brain tumor segmentation. Self-supervised learning will be applied to enhance model robustness by pre-training the models on large synthetic datasets with simulated tumors. After pre-training, the models will be fine-tuned on real datasets like BraTS 2018, 2019, and 2020, combining the advantages of both simulated and real-world data.

EfficientNet-B0 and GCNN models will be trained on the segmented MRI images for tumor classification, focusing on traditional tumor classes such as glioma, meningioma, and pituitary, as well as glioma sub-classes (Grade-II, III, IV). [15, 2] Transfer learning techniques will be employed by pre-training Efficient-Net on larger, general-purpose datasets before fine-tuning it on brain MRI images, enhancing performance and reducing training time.

1. A Recurrent Neural Network (RNN) will be trained on features extracted from segmented tumor images to accurately predict survival rates using temporal patient data.

[15] Apply learning rate schedulers and L2 regularization to prevent overfitting, using the Adam optimizer with an optimized learning rate for faster convergence.

[14] Fine-tune the model using Grid Mask to improve generalization.

[25] For segmentation, evaluate the model using the (DSC) Dice Similarity Coefficient and Intersection over Union (IoU) to measure the overlap between predicted and actual tumor regions.

[7] For classification, assess performance using accuracy, precision, recall, and F1-score to distinguish tumor types.

[20] For survival prediction, use Mean Squared Error (MSE) and C-index to evaluate the accuracy of predicted survival rates.

| ***Paper Reference*** | Model | Result(s) in % |
| --- | --- | --- |
| [1] | PRE-TRAINED INCEPTION-V3, PRE-TRAINED DENSNET201 | 99.34 |
| [2] | CNN EfficientNet-B0 model | 98.87 |
| [3] | Variance Exploding (VE) generative models (SGMs) | 96 |
| [4] | Res-U Net | 98 |
| [5] | YOLO V5 MODEL  YOLO V7 MODEL | 93 |
| [6] | U-Net  Three-Dimensional CNN | 96 |
| [7] | GCNN model | 99 |
| [8] | CNN and RNN | 99 |
| [9] | VGGNet and CapsNet models | 98 |
| [10] | Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS-SVM) | 92 |
| [11] | S-Net and SA-Net  U-Net | 99.63 |
| [12] | First Stage: U-Net Segmentation, Second Stage: Corrective Diffusion Model, Vector Quantized Variational Autoencoder,Multi-Fusion Attention Mechanism. | 98 |
| [13] | CNNs and InvNets | 99 |
| [14] | ViT-B/16, Max ViT-B, Tres-Net-M, and EfficientNetV2-M | 99 |
| [15] | Xception, NasNet Large, DenseNet121 and InceptionResNetV2 | 82 |
| [16] | RS2-net architecture | 97 |
| [17] | VGG-16, VGG-19,  ResNet50, InceptionResNetV2, InceptionV3, Xception, and DenseNet201. | 99.36 |
| [18] | (SVM) & adaptive Wiener filtering, neural networks | 95 |
| [19] | ResUNet+ architecture | 93 |
| [20] | RU-Net2+ for tumor segmentation and the DBT CNN for classification | 92 |
| [21] | First Stage: U-Net Segmentation, Second Stage: Corrective Diffusion Model, Vector Quantized Variational-Auto  encoder, Multi-Fusion Attention Mechanism. | 92 |
| [22] | Different Models are used | 94 |
| [23] | Fractional-chicken swarm optimization (CSO) algorithm | 92 |
| [24] | VGG-SCNet’s | 81 |
| [25] | Znet (U-Net or other CNN-based architectures tailored) | 97.95 |

TABLE 1. **Result Summery of Studied Models.**

##### Conclusion

We concluded that the most efficient approach for our project is to use a (CNN) after reading numerous research papers on the segmentation and classification of brain tumors. CNNs are more efficient at recognizing pictures and medical image analysis, which makes them more appropriate for brain tumor identification and segmentation. The BRATS dataset offers annotated MRI scans that reflect different grades and types of brain tumors; we also selected it for further study.

The BRATS dataset, that provides more precise and useful data required to train a model, is extensively used in brain tumor research. Our project's main goal is to create a CNN-based system which can precisely segment the tumor regions in MRI images to determine brain tumor levels in categories like high grade, low grade, and mid grade.

By eliminating manual analysis and helping physicians make better, quicker decisions about how to treat patients, this technology has the potential to increase the speed and accuracy of brain tumor identification. Our study addresses the urgent demand for trustworthy, automated tools in medical diagnostics by focusing on both the classification and segmentation parts.

##### References

1. N Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, and Muhammad Shoaib, “A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor,” IEEE March 2020.
2. Hasnain Ali Shah, Faisal Saeed, Sangseok Yun, Jun-Hyun Park, Anand Paul, and Jae-Mo Kang, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet," IEEE March 18, 2022.
3. Wenxin Wang, Zhuo-Xu Cui, Guanxun Cheng, Chentao Cao, Xi Xu, Ziwei Liu, Haifeng Wang, Yulong Qi, Dong Liang, and Yanjie Zhu, "A Two-Stage Generative Model with CycleGAN and Joint Diffusion for MRI-based Brain Tumor Detection" IEEE Journal of Biomedical and Health Informatics June 2024.
4. Younis, Q. Li, Z. Afzal, M. J. Adamu, H. B. Kawuwa, F. Hussain, and H. Hussain, "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," IEEE June 2024.
5. M. F. Almufareh, M. Imran, A. Khan, M. Humayun, and M. Asim, "Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning," IEEE Feb 2024.
6. S. Rajendran, S. K. Rajagopal, T. Thanarajan, K. Shankar, S. Kumar, N. M. Alsubaie, M. K. Ishak, and S. M. Mostafa, "Automated Segmentation of Brain Tumor MRI Images Using Deep Learning" IEEE July 2023.
7. M. Rizwan, A. Shabbir, A. R. Javed, M. Shabbir, T. Baker, and D. Al-Jumeily OBE, "Brain Tumor and Glioma Grade Classification Using Gaussian Convolutional Neural Network" IEEE Mar. 2022.
8. K. Neamah, F. Mohamed, M. M. Adnan, T. Saba, S. A. Bahaj, K. A. Kadhim, and A. R. Khan, "Brain Tumor Classification and Detection Based DL Models: A Systematic Review" IEEE Jan. 2024.
9. Jabbar, S. Naseem, T. Mahmood, T. Saba, F. S. Alamri, and A. Rehman, "Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model" IEEE July 2023.
10. Z.Jia and D.Chen, “Brain Tumor Identification and Classification of MRI Images Using Deep Learning Techniques” published in IEEE 2020
11. Sunita Roy, Rikan Saha, Suvarthi Sarkar, Ranjan Mehera, Rajat Kumar Pal, (Member, IEEE), and Samir Kumar Bandyopadhyay, (Senior Member, IEEE), "Brain Tumor Segmentation Using S-Net and SA-Net" IEEE March 2023.
12. Wenqing Li, Wenhui Huang, and Yuanjie Zheng, "CorrDiff: Corrective Diffusion Model for Accurate MRI Brain Tumor Segmentation" IEEE Journal of Biomedical and Health Informatics March 2024.
13. Abdullah A. Asiri, Ahmad Shaf, Tariq Ali, Maryam Zafar, Muhammad Ahmad Pasha, Muhammad Irfan, Saeed Alqahtani, Ahmad Joman Alghamdi, Ali H. Alghamdi, Abdullah Fahad A. Alshamrani, Maqbool Aleylyani, and Sultan Alamri, "Enhancing Brain Tumor Diagnosis: Transitioning from Convolutional Neural Network to Involutional Neural Network" IEEE October 2023.
14. Ji-Hyeon Lee, Jung-Woo Chae, and Hyun-Chong Cho, "Improved Classification of Different Brain Tumors in MRI Scans Using Patterned-GridMask" IEEE March 2024.
15. Sohaib Asif, Wenhui Yi, Qurrat Ul Ain, Jin Hou, Tao Yi, and Jinhai Si, "Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors from MR Images" IEEE February 2022.
16. Xiaoyi Lin, Mingyu Wang, Fei Li, Ziyue Xu, Senior Member, IEEE, Jia Chen, Xin Chen, Member, IEEE, Chenglang Yuan, Songxiong Wu, Yanji Luo, Jingxian Shen, Shi-Ting Feng, and Bingsheng Huang, "Improving Tumor Classification by Reusing Self-Predicted Segmentation of Medical Images as Guiding Knowledge" IEEE March 2024.
17. Saif Ahmad and Pallab K. Choudhury, "On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images" May 2022.
18. Abdullah A. Asiri, Toufique Ahmed Soomro, (Senior Member, IEEE), Ahmed Ali Shah, (Senior Member, IEEE), Ganna Pogrebna, Muhammad Irfan, and Saeed Alqahtani, "Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification," IEEE March 2024.
19. Sedat Metlek and Halit Çetiner, "ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation," IEEE July 2023.
20. Ruqsar Zaitoon and Hussain Syed, "RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction" IEEE October 2023.
21. Javaria Amin, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin, and Ramesh Sundar Nayak, "Brain Tumor Detection and Classification Using Machine Learning: A Comprehensive Survey" Complex & Intelligent Systems,November 2022.
22. Xiaoman Zhang, Weidi Xie, Chaoqin Huang, Ya Zhang, Xin Chen, Qi Tian, and Yanfeng Wang, "Self-Supervised Tumor Segmentation with Sim2Real Adaptation" IEEE Journal of Biomedical and Health Informatics September 2023.
23. Dr. R. Cristin, Dr. K. Suresh Kumar, and Dr. P. Anbhazhagan, "Severity Level Classification of Brain Tumor Based on MRI Images Using Fractional-Chicken Swarm Optimization Algorithm" The Computer Journal October 2021.
24. Mohammad Shahjahan Majib, Md. Mahbubur Rahman, (Member, IEEE), T. M. Shahriar Sazzad, Nafiz Imtiaz Khan, and Samrat Kumar Dey, "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images" IEEE Access August 2021.
25. Mohammad Ashraf Ottom, Hanif Abdul Rahman, and Ivo D. Dinov, "Znet: Deep Learning Approach for 2D MRI Brain Tumor Segmentation" IEEE Journal of Translational Engineering in Health and Medicine May 2022.