Grenze International Journal of Engineering and Technology, January Issue

A Comprehensive Survey on Traditional and Advanced Techniques in Brain Tumor Detection

M. Kiran Kumar[1] and S. Kiran[2]
[1]Research Scholar, Department of Computer Science and Engineering, YSR Engineering College of Yogi Vemana University, Proddatur-YSR District-AP, India
Email: kirann.intell@gmail.com
[2]Associate Professor, Department of Computer Science and Engineering, YSR Engineering College of Yogi Vemana University, Proddatur-YSR District-AP, India

***Abstract*— One of the biggest problems facing modern medicine is the presence of brain tumors, which pose a serious threat to patients' health. The efficacy of treatment largely depends on early and precise diagnosis. This review provides a comprehensive compilation from various research projects, thereby elucidating the specificity and advancements of diagnostic approaches in brain cancer. While conventional radiological techniques set the foundation for detection, deep learning significantly improves identification and classification accuracy while enhancing efficiency. This work investigates the applications of CNNs, transfer learning, and other advanced deep learning architectures. These have been quite successful in automatically spotting cancers from MRI/CT scans with high accuracy. Hybrid models, which combine deep learning with traditional imaging techniques, are being considered to improve detection while simultaneously lowering false positive rates. This collection is highly educational for all interested in investigating deep learning's transforming potential in neuro-oncology diagnostics, as well as a complete guide for business professionals.**

***Index Terms*— Brain Tumor, Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, Tumor Classification, Hybrid Detection Models, Brain Tumor Segmentation.**

I. INTRODUCTION

Brain tumors arise from the abnormal and often uncontrollable proliferation of cells within the brain. These can be of various origins and multiply at variable rates, giving a wide range of tumors with a range of resulting clinical effects. Even a small tumor may upset normal brain function and can give rise to variable neurological symptoms, given the complexity of the brain and its microenvironment. Symptoms-from headaches and seizures to more serious cognitive or physical incapacitations-depending upon the size, location, and aggressiveness of the tumour. Malignant and benign are the two main types of brain tumours; malignant is cancerous, while the latter is non-cancerous. Though the latter is non-cancerous, they may cause serious medical problems. Generally, they remain confined to a specific region and grow very slowly, not extending into the surrounding tissues. But size being small, it decreases space inside the brain; hence, these masses can press the surrounding tissues, generating visible symptoms. In contrast, the treatment of malignant brain tumours is challenging since their aggressive nature may lead them to invade the surrounding tissues. Whereas secondary or metastatic tumours spread from other body parts to the brain, primary malignant tumours originate in the brain.

Grenze ID: 01.GIJET.11.1.306

Whichever their type may be, the effective treatment and better patient prognosis of a brain tumour depend mainly on early detection and proper diagnosis.

A. The Need of Early Detection

The diagnosis of brain tumours at an early stage increases a patient's survival chances and improvement in quality of life. A growing brain tumour might squeeze or destroy the nearby tissue of the brain, thus causing neurological symptoms. Also, early detection means a cancer is more likely to be smaller and to cause fewer symptoms. By the time symptoms appear, cancers have generally grown and spread, reducing treatment options and complicating procedures. Moreover, in case a cancer is benign, it can be more easily removed by surgical intervention, hence perhaps resulting in complete eradication and an occasional cure.

B. Precision in Assessment

While the early detection of brain tumours is of utmost importance, the exact diagnosis of the disease is even more critical. A misdiagnosis of cancer type or grade may lead to less-than-optimal treatment decisions that might be not only ineffective but also subject the patient to unwarranted risks. For example, benign tumors may be mislabeled as malignant tumors, resulting in the unnecessary aggressive treatment of cancers that do not require it. On the other hand, a malignant tumor that may have been missed would be given less aggressive treatment and might metastasize. Therefore, a complete diagnosis can help the medical personnel tailor the treatment for maximum opportunity for success and reduced possible side effects.

C. Classical Radiological Techniques: Foundation for Detection

X-rays, computed tomography scans, and magnetic resonance imaging are the main radiological imaging modalities that have been applied for many years in the diagnosis and identification of brain tumours. Computed tomography scans and MRI have become indispensable tools for neurosurgeons and neurologists. Especially helpful to visualize tumors in the brain, MRI provides dramatically clear pictures of the soft tissues of the brain by using powerful magnetic fields and radio waves. By comparison, CT scans make use of X-rays in order to generate cross-sectional images of the brain. These are particularly useful for revealing structural defects, haemorrhage, and tumors.

D. Conventions and Restraints of Conventional Approaches

These conventional methods yield a special set of problems, although they have been found to be somewhat useful. Very often the pictures received are reviewed, which results in accidental variations in diagnosis. The expertise and knowledge of the radiology expert determines lots about the accuracy and precision of the diagnosis. Still at times benign or incipient tumours can remain unnoticed, specially during normal routine scans when their main objective is not its detection. Even though these treatments were considered sophisticated at the time, they may find it difficult to accurately detect benign from malignant tumors or differentiate cancers from other neurological diseases with similar symptoms.

E. Deep learning's birth in medical diagnostics

Artificial intelligence has grown phenomenally over the last decade; deep learning, in particular, is a disruptive topic. A branch of machine learning, deep learning analyses many types of data, such as images through multi-layer artificial neural networks. Deep learning models have shown huge potential for medical imaging, especially for convolutional neural networks. These models are quite useful in tasks of image classification, segmentation, and detection since they are designed to acquire knowledge about the spatial hierarchies of information coming from the images independently and flexibly.

II. LITERATURE REVIEW

A fine perception of the subject area is thus obligatory in such a milieu of rapid technological enhancements and pragmatic difficulties. In this backdrop, the paper brings in a necessary critical survey that assesses developments and challenges in brain tumour detection methods with a view to fill up information vacuum. The survey presents a comprehensive study of the development towards brain tumour diagnosis by comparing conventional techniques with modern deep learning technology. It should be a matter of great respect for challenges alongside the celebration of successes.

This study endeavors to clarify these features so academics, doctors, and stakeholders may have direction and knowledge based on it. The most chief aim and objective are to further cooperation and creative ideas that will advance the field and raise better the standard of treatment given to consumers.

Saleh, R. Sukaik et al., in betterment and early detection/classification accuracy of the brain tumor by keeping in mind, have incorporated MRI scanners with advanced artificial intelligence techniques using CNN and deep learning. Five generally accepted pre-trained models, namely Xception, ResNet50, InceptionV3, VGG16, and MobileNet, were used in the paper. These are trained on a large dataset. The goal is to categorize brain tumors into four separate groups: no tumor, glioma, meningioma, and pituitary tumor. All the models achieved great results with F1-scores between 97.25% and 98.75%, with the Xception model at 98.75%. These findings demonstrate the enormous potential benefit of integrating artificial intelligence into MRI technology for fast and efficient classifying and identifying brain tumors, thus minimizing adverse outcomes in patients[1].

S.: Grampurohit et al. identified the capability of artificial intelligence in deep learning to analyze MRI data for diagnosis related to brain tumors. In this work, a modified VGG-16 architecture and Convolutional Neural Network were proposed for identifying tumors from MRIs. The sample size was 253 patients, out of which 155 scans showed cancers and 98 scans were tumor-free. According to findings from the study, both the CNN and VGG-16 models emerged with promising results for the identification of cancer. Although this meant more processing needs, the VGG-16 model outperformed the CNN model regarding accuracy. The work underpins deep learning in improving medical diagnosis and its potentials in handling the volume of data generated in the medical industry. P. Malik et al. emphasized the importance of early tumour detection by classifying brain malignancies into two important classes: benign and malignant[2].

The paper works on the classification of brain tumours in MRI images through some simple image processing techniques in combination with deep learning algorithms, including edge detection, segmentation using morphological operations, pre-processing, and picture enhancement. A comparison of the approach with modern deep learning models was performed to show that while simple image processing may yield acceptable results, deep learning outperforms them in accuracy and efficiency, being able to increase cancer classification capabilities. The study underlines how well deep learning finds brain cancers from MRI scans and explores its possible use for a number of imaging modalities, hence increasing its adaptability and raising the diagnostic efficiency. The accelerated patient diagnostics will have great benefits in the scientific and medical spheres[3].

Belhe et al. indicate that deep learning has a great influence on healthcare, especially regarding MRI-based brain tumor diagnosis. This work presents the development of a Convolutional Neural Network that performs classification with an accuracy as high as 96.5% on test cases with the help of advanced deep learning libraries such as Keras and TensorFlow. The work provides insight into how good deep learning can have quick diagnosis of brain tumours by scanning MRI and hence making timely patient care possible. In addition, the paper provides an opportunity to enhance the functionality of the model by adding advanced optimization layers and other approaches, such as transfer learning [4].

In order to improve the efficiency and accuracy of identifying brain cancer, Raiyan et al. applied CNNs to X-ray image analysis. Advanced approaches such as deep feature extraction with pre-trained models showed very promising results in this work, where the F1-score of classification can reach 98.5% and the test accuracy was as high as 98.4%. This deep learning method can be promising in the future with respect to rapid diagnostics of tumors at an early stage and can be easily done using the available X-rays and MRI machines, which are also much cheaper. In all this, it would be very useful to those territories where healthcare resources are very poor. Future works will pursue bigger datasets and a wider range of pre-trained models in improving model capabilities.

Geethanjali N et al. pointed out the necessity of early and correct classification of brain tumors, which could be done by MRI imaging. They underlined the fact that such speed is so highly important; in fact, it highly determines all the treatment outcomes and could be related to preventing death. For enhancement, the study was based on the dataset comprising MRI images of brains with and without tumors, and a number of image processing operations were performed, like blurring, filtering, and cropping. Then, data augmentation was performed in order to provide more variability in the dataset. With the augmented dataset, a CNN was trained capable of identifying multiple types of cancers, namely pituitary, meningioma, and glioma, at high accuracy. This approach highlights how the use of MRI imaging combined with deep learning improves the accuracy of brain tumor detection [9].

Ankiti G. admits that among all the grave types of cancer worldwide, brain tumours constitute one. Et al. looked at the vital need for quick identification and exact classification of these situations. Their work was focused on the extraction of some features from MRI scans-first, a generative model for first identification and secondly, a convolutional neural network for exact cancer classification. This work tested two networks, ResNet50 and the Xception model, using three datasets. They correspondingly achieved accuracy rates of 98.02% and 98.32%, respectively[10].

TABLE I. REVIEW OF BRAIN TUMOR DETECTION

TECHNIQUE USED with its reference	**PUBLICATION DETAILS**	**YEAR OF PUBLICATION**	**Mechanism Carried out**	**Observations including Accuracy (%) achieved if any**	**GAPS**
deep generative regularization prior [11]	Biomed. Signal Process. Control., 75, 103598.	2022	Deep learning based advanced method which does not necessitate any sort of training	It takes approximately 10 minutes for Computation	The computation Time is more
Otsu's thresholding [12]	Multimedia tools and applications. 2022 May 30:1–3.	2022	thresholding and morphology based model for brain tumor segmentation	Achieved an accuracy of 90%	Less Accurate
Machine Learning [13]	Complex Intelligent Systems, 2021. doi: 10.1007/s40747-021-00563-y.	2021	a model for automatic brain tumour detection using VGG-16	the model attained 84% accuracy	Accuracy is very low as per the current Scenarios.
Deep Learning [14]	International Conference on Intelligent Technologies (CONIT), 2021, pp. 1–6, doi: 10.1109/CONIT51480.2021.9498384	2021	Automatic mechanism	attained 85.95 percent accuracy for YOLO and 95.78 percent accuracy for FastAi.	Less accuracy and Computational Complexity
Support vector Machine [15]	2021 International electronics symposium (IES) 2021 Sep 29 (pp. 257-262). IEEE	2021	filtering, contouring and thresholding	95.83	Less Accuracy attained
Complex Networks with CNN [16]	*IEEE Access* 2020, *8*, 89281–89290.	2020	MRI categorization using a modified activation function	95.49	Computational Complexity and also Less Accurate
Multi-input Capsule Network [17]	*Neural Information Processing*; pp. 524–534	2019	Convolutional Capsule Network (ConvCaps) architecture	93.5	Less Accurate
CNN [18]	*International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, Tamil Nadu, India, 4–6 April 2019.*	2019	Convolutional Neural Network for classifying brain image datasets using feature maps pre-processed in the Curvelet domain	accuracy rate of 96%.	The primary limitation of the work was a lack of comparative analysis, which resulted in an accuracy rate of 96%.
Multi input Capsule Network [19]	*In Neural Information Processing; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 524–534*	2019	Classifying the tumors in an optimal manner	accuracy achieved is 93.5%.	It may be prone to overfitting and more simulation time due to complexity
CNN [20]	*Proceedings of IFMBE* , Publisher : Springer: pp. 183–189	2018	Detection of types of tumors	84.19	Less accuracy with imbalanced dataset

TABLE II. ACCURACY FOR DIFFERENT MODELS IDENTIFIED IN SURVEY

Ref. No.	**Methodology**	**Accuracy (%)**
[1]	Deep Learning Based Brain Tumor Classifier is proposed using CNN	between (97.25 and 98.75)
[2]	Deep Learning • .Convolutional Neural Network [CNN]. • VGG-16Architecture.	93.36, 97.16

[3]	• Straightforward Image Processing Techniques • Deep Learning Techniques	
[4]	Deep Learning using CNN	96.5
[5]	Brain Tumor Detection using Smart Deep Learning using CNN	98.4
[6]	Comparison of Deep Learning Models • VGG19 • DenseNet169 • AlexNet • InceptionV3 • ResNet101	97.2 92.8 89.5 94.3 98.6
[7]	Deep Convolutional Neural Networks (DCNN) with Transfer Learning (TL) • Proposed DCNN Model with TL • Comparison with Pre-Trained Models ▪ AlexNet ▪ ResNet101 ▪ VGG16	98.38 95.92 92.16 92.37
[8]	Deep Learning Based Brain Tumor Detection and Classification • FastAi Classification Model • YOLOv5 Object Detection Model	95.78 85.95
[9]	Deep Learning using CCN Models • ResNet50 • DenseNet • EfficientNetB1	91 90.24 99.31
[10]	Detection and Classification Using Deep Learning (CNN) • ResNet50 Architecture • Xception Architecture	98.02 98.32
[11]	Deep generative regularization prior in an unsupervised reconstruction method for low-dose CT DGR Method in suppressing the noise and keeping the edges sharper trade-off out performs FBP, SART, and SART + TV by generating higher PSNR and SSIM values.	92.98%
[12]	Otsu's thresholding technique for MRI image brain tumor segmentation. MRI	68.7955%, 95.5593%
[13]	Brain tumour detection and classification using machine learning: a comprehensive survey. PET, CT, DWI and MRI for brain tumors are widely used to analyze the brain structure. VGG-16, ResNet, Xception and Mobilenetv2 LBP and GWF for segmented of images	99.0%, 98.0%
[14]	Deep Learning Based Brain Tumour Detection and Classification The FastAi, YOLOv5	89.88%, 95.78%.
[15]	Classification of brain tumor on magnetic resonance imaging using support vector machine • Gray Level Co-occurrence Matrix (GLCM) • Support Vector Machines (SVM) for classification of meningioma, glioma, and pituitary tumors respectively.	95,83%, 94,08%, 93,33%, 96,87%
[16]	Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification with the Modified Activation Function SVM on CNNBCN	95.49%,
[17]	3D-MRI brain tumor detection model using modified version of level set segmentation based on dragonfly algorithm. • Genetic algorithm-, k-means-, and fuzzy c-means-based MRI image segmentation based on the ABC algorithm	98.10%, 85.67%
[18]	Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification • FDCT and GLCM (multi-scale and multi-resolution) SVM, PNN. • the feature extraction in Curvelet domain. Image segmentation using K-Means	98.10%
[19]	Multi-input Capsule Network for Brain Tumor Classification. In Neural Information Processing • DasNet , ResNeXt-50. ResNet for multi-task learning	90.0%

[20]	Brain Tumor Classification Using Convolutional Neural Network. • CNN, CNN Architecture Hyper-parameters Optimization	98.51%, best 84.19%
[21]	Brain Tumor Detection using Machine Learning and Deep Learning. • CNN, RELU • Xception, ResNet50, InceptionV3, VGG16, and MobileNet.	98.75%, 98.50%, 98.00%, 97.50%, 97.25%

The proposal by Nada Ahmed Alhamdi et al. was done to better the efficacy and accuracy of detection of brain tumors using machine learning and deep learning algorithms with MRI data. This was a comparative study since it explained the enhanced diagnostic capabilities of both technologies in the comparison between ML and DL approaches. Specifically, ML utilized a GLCM feature extraction technique and used SVM for classification, while DL made use of transfer learning, specifically the ResNet 50 model, to detect brain tumours in MRI images. Even though this definitely requires longer training, it emerged from these results that, in fact, deep learning algorithms outperformed those of machine learning and reached a slightly higher accuracy rate of 90.41% compared to the 73.97% for the methods of ML. This performance improvement might be due to better feature extraction capability by DL. This paper identifies how integration of AI in medical image processing contributes towards diagnosis capability improvement. It also suggests that further accuracy gain is possible by increasing the dataset size and maybe making the model extensive enough to predict tumor grades from different MRI scans or diagnose other diseases[21].

III. Advances in Brain Tumour Detection

A. Techniques of Deep Learning

Specifically, in the field of medical image analysis for diagnosis and grading of brain tumours, CNNs have shown their efficiency. In image processing tasks, convolutional neural networks are quite useful as they allow automatic dynamic gathering of knowledge about the spatial structure of the input images with the help of convolutional layers.

CNNs have been widely applied in the area of brain tumor identification to segment and classify images. Therefore, training them to differentiate the brain tumour from surrounding tissues might help in defining the outline of the tumor more precisely and classify the particular type of brain tumour, hence providing important information for diagnosis and treatment planning. Successful architectures widely used include ResNet, Inception, and U-Net. Of these, U-Net has been widely applied in the segmentation of biological images because of its ability to compile contextual information on both the local and global levels.

B. Mixed Strategies

Coupling deep learning with traditional image processing methods yields hybrid techniques in the effort to combine advantages and improve performance in identifying brain cancer. Initial preparatory stages before the images are fed into a deep learning model are usually standard image processing steps, which include noise reduction and contrast enhancement methods applied to optimize the quality of the images. The idea of feature fusion henceforth includes the combination of hand-crafted features with the deep learning component in particular for classification.

The key advantages of this approach include factoring in strengths of deep learning models in representing higher-order features with domain-specific information encapsulated in manually crafted features. Several case studies and demos using such hybrid approaches demonstrated their efficacy, for instance, CNN coupled with morphological features improved the accuracy in tumour boundary detection.

C. Applications of Data Augmentation and Transfer Learning

Various techniques of data augmentation and transfer learning have offset the problem of limited medical imaging data for training powerful deep learning models. Data augmentation typically artificially inflates the training dataset by various modifications, such as rotation, flipping, and scaling. This enhances diversity and strengthens the model's generalizability to new data. On the other hand, transfer learning leverages pre-trained models developed on large and diverse datasets and fine-tunes them using the specific medical imaging data available for the diagnosis of brain tumours. This leads to higher efficiency, especially in situations where the sample is limited or homogeneous, thereby speeding up the process of training. Further techniques can be used in order to avoid overfitting and ensure optimal performance of the models produced for fresh and unseen data. These methods call for the usage of cross-validation, ensemble, and dropout with L2 regularisation.

D. Review of Three-Dimensional Images

Processing 3D MRI and CT scans represents a big step forward in medical imaging, as it enables one to create a three-dimensional picture of the brain and provides thorough data for the detection and analysis of tumours. There are, however, several other drawbacks: most of these relate to an increase in the processing load but there is also the need for 3D convolutional filters to evaluate volumetric input. All these methods have shown promising results in classifying and segmenting brain tumors, therefore confirming that 3D image analysis has the potential to enhance accuracy and efficiency in diagnosing brain cancers.

Gaps Identified

The assessment of methods for brain tumour detection revealed the following areas of research that demand attention:

- Before Deep Generative Regularisation's introduction
  - Especially, the computation time is rather long.
- Otsu's constraint is
  - The accuracy of the method lags behind that of other cutting-edge techniques.
- VGG-16 model based machine learning
  - The present accuracy of the given instances is much below the intended levels.
- Deep learning employing FastAi and YoLO
  - Particularly using the YOLO model, the approach shows lower precision and increased computing cost.
- Supporting Vector Computer
  - Even although its precision is really good, it is nevertheless regarded as less exact than certain more sophisticated technologies.
- Multi-input Capsule Network
  - It is said to be insufficient even with its remarkable accuracy.
- Convolutional neural networks (CNN), sometimes known as curvelet feature maps
  - The main restriction is the absence of a comparison study, which fuels uncertainty on the reliability of the specified accuracy level.
- Second instance: Multi-input Capsule Network
  - This method needs longer simulation times and is more prone to overfitting due to its complex character.
- Tumour Type Identification, CNN
  - Particularly in cases of an imbalanced dataset, the reduced precision indicates the need of better data processing techniques.
- Synopsis of the found research shortcomings
  - Several techniques show either expensive computational costs or extended computation times, which emphasises the need of more efficient methods.

IV. CONCLUSIONS

This review outlines a wide spectrum of methodologies on brain tumor detection with a special focus on the application of CNNs and transfer learning techniques, from classical to state-of-the-art deep learning methods. Examination of the development in detection techniques, integration of modern deep learning approaches with conventional image processing methods to generate robust hybrid models, presents relevant development in the field within the research.

In cases where data restrictions impose serious limitations, the need for transfer learning, as well as data augmentation, will enable improved model performance and applicability. Despite the computing challenges, research into 3D image processing represents significant progress in cancer assessment. This review, with its novel development within the diagnosis of brain tumors, thus stipulates that future refinement of techniques with integration of clinical context may someday alter the landscape in neuro-oncology regarding both early detection and patient outcomes.

REFERENCES

[1] A. Saleh, R. Sukaik and S. S. Abu-Naser, "Brain Tumor Classification Using Deep Learning," 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech), Gaza, Palestine, 2020, pp. 131-136, doi: 10.1109/iCareTech49914.2020.00032.

[2] S. Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari and S. Jolad, "Brain Tumor Detection Using Deep Learning Models," 2020 IEEE India Council International Subsections Conference (INDISCON), Visakhapatnam, India, 2020, pp. 129-134, doi: 10.1109/INDISCON50162.2020.00037.
[3] M. Malik, M. A. Jaffar and M. R. Naqvi, "Comparison of Brain Tumor Detection in MRI Images Using Straightforward Image Processing Techniques and Deep Learning Techniques," 2021 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Ankara, Turkey, 2021, pp. 1-6, doi: 10.1109/HORA52670.2021.9461328.
[4] A. S. Belhe, J. A. Pagariya, V. V. Ganthade, M. Rashid and P. S. Uravane, "An Efficient Deep Learning based Approach for the Detection of Brain Tumors," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 417-421, doi: 10.1109/IC3I56241.2022.10073209.
[5] T. Raiyan, H. H. Anonna, S. K. Mondal and M. M. Khan, "Brain Tumor Detection using Smart Deep Learning," 2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 2022, pp. 0186-0190, doi: 10.1109/IEMCON56893.2022.9946602.
[6] N. Çınar, B. Kaya and M. Kaya, "Comparison of deep learning models for brain tumor classification using MRI images," 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 2022, pp. 1382-1385, doi: 10.1109/DASA54658.2022.9765250.
[7] J. Mathew and N. Srinivasan, "Deep Convolutional Neural Network with Transfer Learning for Automatic Brain Tumor Detection from MRI," 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS), Kochi, India, 2022, pp. 1-6, doi: 10.1109/IC3SIS54991.2022.9885586.
[8] N. M. Dipu, S. A. Shohan and K. M. A. Salam, "Deep Learning Based Brain Tumor Detection and Classification," 2021 International Conference on Intelligent Technologies (CONIT), Hubli, India, 2021, pp. 1-6, doi: 10.1109/CONIT51480.2021.9498384.
[9] G. N, V. Pushpalatha, R. C, S. L and S. S, "Brain Tumor Detection and Classification Using Deep Learning," 2023 Winter Summit on Smart Computing and Networks (WiSSCoN), Chennai, India, 2023, pp. 1-6, doi: 10.1109/WiSSCoN56857.2023.10133851.
[10] A. G, H. T. J, A. J, A. Bhanu and N. Ig, "Brain Tumor Detection and Classification Using Deep Learning Approaches," 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 2023, pp. 1-6, doi: 10.1109/INCET57972.2023.10169933.
[11] Unal, M.O., Ertas, M., & Yildirim, I. (2020). An unsupervised reconstruction method for low-dose CT using deep generative regularization prior. Biomed. Signal Process. Control., 75, 103598.
[12] Nyo MT, Mebarek-Oudina F, Hlaing SS, Khan NA. Otsu's thresholding technique for MRI image brain tumor segmentation. Multimedia tools and applications. 2022 May 30:1–3.
[13] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumour detection and classification using machine learning: a comprehensive survey," Complex Intelligent Systems, 2021. doi: 10.1007/s40747-021-00563-y.
[14] N. M. Dipu, S. A. Shohan, and K. M. A. Salam, "Deep Learning Based Brain Tumour Detection and Classification," 2021 International Conference on Intelligent Technologies (CONIT), 2021, pp. 1–6, doi: 10.1109/CONIT51480.2021.9498384.
[15] Hasanah U, Sigit R, Harsono T. Classification of brain tumor on magnetic resonance imaging using support vector machine. In 2021 International electronics symposium (IES) 2021 Sep 29 (pp. 257-262). IEEE.
[16] Huang, Z.; Du, X.; Chen, L.; Li, Y.; Liu, M.; Chou, Y.; Jin, L. Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification With a Modified Activation Function. IEEE Access 2020, 8, 89281–89290.
[17] Khalil, H.A.; Darwish, S.; Ibrahim, Y.M.; Hassan, O.F. 3D-MRI brain tumor detection model using modified version of level set segmentation based on dragonfly algorithm. Symmetry 2020, 12, 1256.
[18] Krishnammal, P.M.; Raja, S.S. Convolutional neural network based image classification and detection of abnormalities in M.R.I. brain images. In Proceedings of the 2019 International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, Tamil Nadu, India, 4–6 April 2019.
[19] Cheng, Y.; Qin, G.; Zhao, R.; Liang, Y.; Sun, M. ConvCaps: Multi-input Capsule Network for Brain Tumor Classification. In Neural Information Processing; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 524–534
[20] Abiwinanda, N.; Hanif, M.; Hesaputra, S.T.; Handayani, A.; Mengko, T.R. Brain Tumor Classification Using Convolutional Neural Network. In IFMBE Proceedings; Springer: Singapore, 2018; pp. 183–189
[21] N. A. Alhamdi and A. Mohamed Alshanta, "Brain Tumor Detection using Machine Learning and Deep Learning," 2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), Benghazi, Libya, 2023, pp. 89-92, doi: 10.1109/MI-STA57575.2023.10169200.