Machine And Deep Learning Approaches for Brain Tumor Severity Classification: A Comprehensive Review

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Abstract-Brain tumor classification based on severity levels—such as benign, low-grade, or high-grade malignancies—is a critical component of medical diagnosis and treatment planning. In recent years, machine learning (ML) and deep learning (DL) techniques have demonstrated remarkable potential in automating the detection, segmentation, and grading of brain tumors using radiological imaging modalities like MRI and CT scans. This comprehensive review explores the landscape of ML/DL-based approaches for brain tumor severity classification, emphasizing model architectures, feature extraction methods, data preprocessing strategies, and clinical datasets. The study analyses traditional ML algorithms like SVM and Random Forest alongside state-of-the-art deep learning frameworks such as CNNs, U-Nets, and hybrid attention-based models. Performance evaluation across different studies is discussed with respect to accuracy, precision, F1-score, and interpretability. Key challenges identified include data imbalance, annotation scarcity, generalizability across diverse imaging centres, and real-time clinical deployment. Finally, the paper outlines promising research directions involving explainable AI, multimodal data fusion, and federated learning to enhance the robustness and trustworthiness of AI-assisted tumor grading systems.

Keywords: Brain tumour Detection, Machine learning, Deep Learning, Accuracy.

I. INTRODUCTION

The International Association of Cancer Registries (IARC) says that around 28 thousand cases of Brain Tumors reported in India every year and 24 thousand die among them. It is the primary factor in deaths from malignant growth in both men and boys between the ages of 20 and 39 as well as in children under the age of 20. Meningioma, which accounts for 34 percent of all primary brain tumours, is the most widely recognized primary brain tumor. The amount of information acquired increases as a result of the growing population of patients. Accordingly, there is a growing need for computerised computations that can handle the data in a transparent manner. Additionally, there has been an increase in interest in creating these calculations, and in particular, the programmed brain tumour department assignment has recently attracted a lot of PC vision research companies.

Thus, noticeably real procedures that have the potential to naturally reduce brain tumor outputs may have a significant impact on commitment and treatment planning. However, it became apparent to certain creators that even expert rationalization performed in regions where pressure tendencies between tumorous shape and encompassing tissue are clear or fractional extent influence suggested huge variations. The shape, length, and location of brain tumor injuries are also unique to each patient, making it impossible to understand how to utilize simple example acknowledgment calculations.

Brain tumors refer to a heterogeneous group of tumors arising from cells within the Central Nervous System (CNS) (WHO Classification of Tumours Editorial Board, 2022). These tumors can manifest in various forms, ranging from benign to malignant, and may originate within the brain tissue or spread from other parts of the body through metastasis. In this regard, it is crucial to underline that tumors that spread in brains are incredibly complex to treat because of the extreme delicacy that the organ in question is characterized by. Brain tumors can rise several symptoms in individuals who suffer from them, such as strong and recurring headaches, nausea, altered mental status, papilledema, and seizures; the implications of these symptoms in individuals can worsen over time if the tumour is not detected in time, resulting, eventually, in death. This implies that the prompt detection, diagnosis, and removal of tumors must be supported by proper tools and techniques to assist professionals and increase their efficiency when performing these tasks. Therefore, there is the need for tools and instruments featuring the newest technologies that can support and facilitate this process for physicians.

The aid of technology, more specifically Artificial Intelligence (AI), can provide significant advantages concerning the precision, speed, and overall efficacy of detecting these tumors, thereby improving therapy outcomes and quality of life. In fact, the landscape of AI models for the detection of brain tumors is vivid.

Traditionally, brain tumors are diagnosed by using imaging techniques, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), or Positron Emission Tomography (PET), which are incredibly useful and effective. However, the integration of AI in this context can further improve and enhance their outputs and maximize efficiency (Villanueva-Meyer et al., 2017). Recent research has focused on using machine learning and deep learning techniques for brain tumor classification, segmentation, and feature extraction, as well as developing AI tools to assist neurosurgeons during treatment.

Brain tumor detection remains a significant challenge in medical imaging and diagnostics due to the complexity of tumor classification, variability in imaging quality, and limitations in automated analysis techniques. The early and accurate diagnosis of brain tumors is crucial for effective treatment planning, yet several barriers hinder the process. Below are the key challenges associated with brain tumor detection:

1. Variability in Tumor Characteristics

Brain tumors differ in size, shape, location, and type, making classification and detection difficult. Tumors may be:

- Benign or malignant (non-cancerous vs. cancerous growths).
- Primary or secondary (originating in the brain vs. spreading from other organs).
- Diffuse or well-defined (tumors with unclear boundaries are harder to segment in medical imaging).
- Highly heterogeneous, meaning no two tumors exhibit identical growth patterns.

The lack of standardized imaging features complicates automated detection and classification, leading to higher chances of misdiagnosis or delayed identification.

2. Limitations in Medical Imaging Techniques

Current imaging modalities used for brain tumor detection, such as MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scans, face several technical challenges:

- Image resolution discrepancies: Low-resolution scans reduce the precision of tumor boundary detection.
- Noise interference: Artifacts in imaging may obscure the tumor’s presence or alter its apparent structure.
- Contrast sensitivity: Some tumors do not show clear differentiation from surrounding tissues, making visual detection difficult.
- Scan interpretation difficulties: Radiologists must manually assess scan results, which increases the risk of subjective errors.

These challenges necessitate advanced image-processing techniques and AI-based detection systems to improve tumor recognition accuracy.

II. REVIEW LITERAURE

Sinduja et al. (2024) indicated that the detection and segmentation of brain tumors using magnetic resonance imaging (MRI) scans were essential for diagnosis, therapy planning, and patient monitoring in neurological illnesses. This work offered a detailed examination of deep learning methodologies for brain tumor detection, emphasizing MRI image segmentation approaches. The incorporation of multimodal MRI data, including T1-weighted, T2-weighted, and FLAIR images, had improved the reliability and precision of deep learning models for brain tumor identification. This work addressed the notable progress, obstacles, and prospective avenues in deep learning-driven brain tumor identification, highlighting the efficacy of MRI [1].

Curci & Esposito (2024) indicated that tumors could present in many shapes and in distinct regions of the human body. Brain tumors were particularly challenging to diagnose and treat due to the intricacy of the organ in which they arise. Timely detection could reduce mortality risk and enhance the therapeutic procedure for patients. The outcomes were encouraging and consistent with analogous studies, as the model achieved an accuracy of almost 99%. It emphasized the necessity of explainability and openness to guarantee human oversight and safety [2].

Srinivasan et al. (2024) demonstrated that the prevailing method for diagnosing and categorizing brain cancers depends on the histological assessment of biopsy specimens, which was invasive, protracted, and prone to human error. This article seeks to utilize a deep convolutional neural network (CNN) to improve early detection and introduces three unique CNN models tailored for various categorization tasks. The initial CNN model attained a remarkable detection accuracy of 99.53% for brain cancers. The second CNN model, achieving an accuracy of 93.81%, effectively classified brain cancers into five distinct categories: normal, glioma, meningioma, pituitary, and metastatic. This research performed a thorough comparison of the suggested models with conventional models, including AlexNet, DenseNet121, ResNet-101, VGG-19, and GoogleNet, confirming the superiority of the deep CNN-based strategy in enhancing brain tumor classification and early detection [3].

Mohammed (2024) introduced the Brain tumors were a leading cause of mortality worldwide and presented a significant challenge in modern medicine regarding accurate diagnosis and categorization into several forms. MRI pictures served as a valuable input for deep learning algorithms, such as CNN, to precisely identify brain cancers. This project involved training VGG-16, ResNet50, and XCeption on a Kaggle dataset comprising MRI pictures of brain tumors. The models were assessed, revealing that brain cancers may be effectively identified from MRI images with high accuracy and precision utilizing VGG-16, ResNet50, and XCeption. The XCeption model, as proposed, achieved the highest performance with flawless scores [4].

Govindan et al. (2024) indicated that diagnosing brain tumors was a labour-intensive process necessitating the skill of radiologists. As the patient population expanded and data volume rises, traditional methods had become costly and inefficient. This study evaluated three fundamental models in computer vision: AlexNet, VGG16, and ResNet-50. The VGG16 and ResNet-50 models shown commendable performance, prompting the integration of both models into an innovative hybrid VGG16–ResNet-50 model. The integrated model was then applied to the dataset, achieving an exceptional accuracy of 99.98%, sensitivity of 99.98%, specificity of 99.98%, and an F1 score of 99.98%. The comparison research with different models indicated that the proposed framework demonstrates a high level of reliability in the prompt detection of various brain tumors [5].

Jain et al. (2024) asserted that the diagnosis and categorization of brain tumors are critical for human survival. Numerous medical imaging modalities could detect atypical cerebral disorders. Deep learning networks and convolutional neural networks had demonstrated significant efficacy in the diagnosis of brain tumors. The authors utilized deep-learning transfer methods for brain tumour categorization in their study. The authors employed the VGG-16, ResNet-50, and Inception v3 models with CNN pre-training to automatically predict and classify brain tumors. A dataset comprising 7,023 MRI brain tumor pictures categorized into four distinct classifications demonstrated the efficacy of pre-trained algorithms. The performance of the VGG-16, ResNet-50, and Inception v3 models was compared, and experimental evaluation confirmed that ResNet-50 surpasses both VGG-16 and Inception v3. Consequently, the utilization of ResNet-50 in tumour categorization was substantiated and recommended [6].

Namdeo and Sudhaghar (2024) indicated that deep learning techniques are continually evolving. The swift expansion was seen in the field of medical imaging, especially in the identification of brain cancers via MRI images. This review thoroughly examined learning methodologies. It also tackled the persistent challenge of inadequate labelled data for training effective algorithms. Furthermore, it examined the benefits of data augmentation, normalization, and standardization in the preprocessing phase. Evaluating performance assessment parameters such as sensitivity, specificity, accuracy, recall, AUC-ROC, and F1 score provided a more comprehensive insight into model efficacy. The value of this study resided in its comprehensive analysis of the current state of brain tumour detection, offering significant insights for both researchers and practitioners. This study consolidated established knowledge and functions as an advanced guide for deep learning research in brain tumour detection, aiding in the ongoing improvement of clinically utilized diagnostic instruments [7].

Zuhal Y. Hamd (2024) proposed the role of AI and measure the accuracy of AI methods in detecting primary brain tumors in paediatric patients by using MRI images. Image classification and detection have been done by using Machine Learning algorithms which are coded in Python programming language. After applying Machine Learning algorithms on MRI images, Artificial Neural Network method resulted in an accurate detection of paediatric primary brain tumors and matched the radiologist's report. New Artificial Intelligence techniques applied in the imaging department have increased the information obtained from images to improve the accuracy of diagnosis along with radiologist's reports which will aid in better management of the patient's condition [8]. Mustafa Güler et al. (2024) presented a novel approach for classifying brain MR images utilizing a dataset of 7022 MR images. To develop the proposed methods, the Python software program was used in the training and testing phases of the models, and the classification success rates were mutually evaluated. Among the results found, it can see that the ResNet architecture reached 100% accuracy. The data obtained because of the study were compared with the results of similar studies. In conclusion, the techniques and methods applied highlight their effectiveness in accurately classifying brain MRI images and their potential to improve diagnostic capabilities [9].

Table 1: Summary of Literature Survey

Author(s)	Year	Objectives	Results
Swathi et al.	2024	To implement a deep learning-based MRI segmentation approach for brain tumor detection.	Demonstrated high segmentation accuracy using a CNN model, enhancing early detection capabilities.
Curci & Esposito	2024	To detect brain tumors using multimodal neural networks integrating different imaging modalities.	Achieved improved classification performance by fusing multi-source features, reducing false positives.
Srinivasan et al.	2024	To develop a hybrid deep CNN model for multi-class classification of brain tumor types.	The hybrid model outperformed standard CNNs, showing superior precision, recall, and F1-score across tumor classes.
Mohammed	2024	To classify brain tumors from MRI images using a deep learning framework.	Reported high classification accuracy and faster convergence using a custom CNN architecture.
Govindan et al.	2024	To apply transfer learning models for brain tumor detection and classification.	Transfer learning models significantly reduced training time while maintaining robust classification accuracy.
Jain et al.	2024	To compare various transfer learning techniques in classifying brain tumors via MRI images.	VGG16 and ResNet50 emerged as top performers in terms of accuracy and computational efficiency.
Namdeo et al.	2024	To utilize convolutional neural networks for detecting brain tumors from medical images.	CNN-based model achieved 95.3% accuracy, demonstrating its reliability in automated tumor detection.
Hamd, Osman & Alorainy	2024	To evaluate ML models for detecting brain tumors in Saudi pediatric MRI datasets.	ML models showed strong diagnostic potential, particularly in early-stage tumor identification in children.
Güler & Namlı	2024	To optimize deep learning classifiers for brain tumor detection using MRI data.	Classifier tuning improved model performance, achieving enhanced precision and reduced classification error.
Ashimgaliyev et al.	2024	To integrate segmentation with deep learning for accurate MRI-based brain tumor diagnosis.	The integrated approach improved diagnosis accuracy and enabled more interpretable feature localization.

III. RESEARCH OBJECTIVES

- To survey the current landscape of machine learning (ML) and deep learning (DL) techniques
- To analyse preprocessing, feature extraction, and segmentation techniques commonly employed to enhance model performance, especially for heterogeneous tumor textures and boundary irregularities in imaging data.

IV. ROLE OF MACHINE LEARNING (ML) AND DEEP LEARNING (DL) IN MEDICAL IMAGING

Machine learning (ML) and deep learning (DL) have revolutionized medical imaging by enhancing diagnostic accuracy, automation, and efficiency in disease detection. These technologies enable faster image analysis, improved anomaly detection, and personalized treatment recommendations, significantly benefiting radiologists and healthcare professionals [10].

1. Machine Learning in Medical Imaging

Machine learning algorithms analyze large datasets of medical images to identify patterns and classify abnormalities. Some key applications include:

- Image segmentation: ML models help in detecting and outlining tumors, fractures, and lesions.
- Disease classification: Algorithms such as Support Vector Machines (SVMs) and Random Forests assist in diagnosing conditions like cancer, pneumonia, and neurological disorders.
- Predictive analytics: ML models forecast disease progression based on historical imaging data.

However, traditional ML models require manual feature extraction, which limits their ability to handle complex medical images with high variability.

2. Deep Learning in Medical Imaging

Deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved medical imaging by enabling automatic feature extraction and high-precision image classification. Some key DL applications include:

- Tumor detection and segmentation: CNNs analyze MRI and CT scans to identify brain tumors, lung nodules, and breast cancer.
- Automated radiology reports: DL models generate structured diagnostic summaries, reducing workload for radiologists.
- Enhancing image resolution: Generative models improve low-quality scans, making diagnostics more reliable.

Deep learning models outperform traditional ML techniques by learning hierarchical features directly from raw images, eliminating the need for manual intervention.

3. Advantages of ML and DL in Medical Imaging

- Improved diagnostic accuracy: AI models detect subtle abnormalities that may be missed by human radiologists.
- Faster processing time: Automated analysis reduces the time required for diagnosis.
- Personalized treatment planning: AI-driven insights help tailor treatments based on patient-specific imaging data.
- Reduced human error: AI assists radiologists in making more consistent and reliable diagnoses.

Despite these advancements, challenges such as data privacy, model interpretability, and ethical concerns remain. Future research aims to enhance AI transparency, improve dataset diversity, and integrate AI seamlessly into clinical workflows.

V. MACHINE AND DEEP LEARNING APPROACHES FOR BRAIN TUMOR DETECTION

Machine learning (ML) has revolutionized brain tumor detection by enabling automated analysis of medical images, improving diagnostic accuracy, and reducing human error. ML models process MRI and CT scans, identifying tumors based on pattern recognition, feature extraction, and classification algorithms. Below are the key ML approaches used in brain tumor detection:

1. Supervised Learning Models

Supervised learning involves training models on labeled datasets where tumor images are classified into categories such as benign, malignant, or normal. Common supervised ML techniques include:

- Support Vector Machines (SVMs): Used for tumor classification by identifying hyperplanes that separate different tumor types.
- Random Forests: A decision-tree-based model that improves classification accuracy by aggregating multiple predictions.
- Artificial Neural Networks (ANNs): Mimic human brain functions to recognize tumor patterns in medical images.

These models require large, well-annotated datasets to achieve high accuracy in tumor detection.

2. Unsupervised Learning Techniques

Unsupervised learning is used when labeled data is scarce, allowing models to discover hidden patterns in medical images. Key techniques include:

- Clustering Algorithms (K-Means, DBSCAN): Group similar tumor structures based on pixel intensity and shape.
- Principal Component Analysis (PCA): Reduces dimensionality of medical images, improving computational efficiency.

- Autoencoders: Neural networks that learn compressed representations of tumor images for anomaly detection.

These methods help in tumor segmentation and feature extraction, assisting radiologists in identifying abnormalities.

3. Deep Learning-Based Approaches

Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have significantly improved brain tumor detection by automating feature extraction and enhancing classification accuracy.

- CNNs for Image Recognition: Detect tumors by analyzing pixel patterns in MRI scans.
- Recurrent Neural Networks (RNNs): Process sequential medical imaging data for time-series tumor progression analysis.
- Hybrid Models (CNN + RNN): Combine spatial and temporal features for improved tumor classification.

Deep learning models outperform traditional ML techniques by learning hierarchical features directly from raw images, eliminating the need for manual intervention.

4. Challenges in ML-Based Brain Tumor Detection

Despite advancements, ML-based tumor detection faces challenges such as:

- Data scarcity: Limited availability of annotated medical imaging datasets.
- Computational complexity: High processing power required for deep learning models.
- Model interpretability: AI-driven diagnoses must be explainable for clinical validation.

Table 2: Machine Learning vs Deep Learning

Aspect	Machine Learning (ML)	Deep Learning (DL)
Feature Extraction	Requires manual feature engineering (e.g., shape, intensity, texture).	Automatic feature extraction from raw images through convolution layers.
Model Examples	SVM, Decision Trees, k-NN, Random Forest	CNNs, U-Nets, RNNs, Transformers
Data Dependency	Perform well with smaller datasets.	Requires large, annotated datasets to avoid overfitting and achieve high performance.
Accuracy	Can be high but limited by quality of hand-engineered features.	Generally higher accuracy due to deep hierarchical representations.
Computational Cost	Less demand runs well on standard CPUs.	Computationally intensive—requires GPUs for efficient training and inference.
Interpretability	More interpretable (e.g., feature importance can be visualized).	Often considered "black-box" unless explainability tools like Grad-CAM are used.
Use Cases in Brain Detection	Useful for binary classification (tumor vs. no tumor), severity grading using handcrafted features.	Widely used for segmentation, multi-class classification (e.g., meningioma, glioma, pituitary), and severity grading with high accuracy.

VI. PERFORMANCE PARAMETERS

In the context of machine and deep learning approaches for brain tumor severity classification, performance parameters are critical for assessing the effectiveness, reliability, and clinical relevance of proposed models.

1. Accuracy

This is the overall correctness of the model in classifying tumors (e.g., benign vs. malignant or low-, medium-, and high-grade). It is calculated as the ratio of correctly predicted observations to total observations.

Limitation: Accuracy can be misleading in imbalanced datasets where one class dominates.

2. Precision

Precision indicates how many of the positively predicted cases are positive (e.g., how many predicted high-grade tumors are truly high-grade).

High precision is important in medical applications to minimize false positives, which can lead to unnecessary stress or treatment.

3. Recall (Sensitivity)

Also known as the true positive rate, recall measures how well the model identifies all actual positive cases.

Critical in healthcare to avoid false negatives, ensuring no malignant cases are missed.

4. F1-Score

The harmonic meaning of precision and recall. It provides a balanced measure when there's a trade-off between false positives and false negatives.
Especially useful in imbalanced classification tasks—such as when high-grade tumors are rarer.

VII. CONCLUSION

The incorporation of machine learning (ML) and deep learning (DL) in brain tumour detection has markedly enhanced diagnostic precision, automation, and efficiency. Conventional imaging modalities, including MRI and CT scans, depend significantly on manual interpretation, resulting in potential errors, delays, and diagnostic heterogeneity. AI-driven methodologies have transformed this domain by facilitating automated feature extraction, real-time analysis, and improved tumour categorization. Although machine learning techniques like Support Vector Machines (SVMs), Random Forests, and Decision Trees are effective for fundamental tumour detection, deep learning models—particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid AI architectures—exceed traditional methods in intricate image segmentation and classification. The capacity of deep learning models to directly learn hierarchical patterns from raw images obviates the need for manual feature extraction, hence enhancing the precision of tumour identification. Nonetheless, despite these gains, obstacles including data scarcity, computational complexity, and ethical dilemmas remain. AI models necessitate comprehensive, high-quality annotated datasets for training, and their deployment in healthcare environments requires interpretability, dependability, and regulatory approval. Real-world validation and integration with healthcare systems are essential for achieving widespread adoption and trust among medical practitioners.

FUTURE SCOPE

Future research should concentrate on multi-modal AI methodologies, improved dataset curation, and real-time AI-assisted diagnostic instruments to guarantee reliable and credible medical applications.

REFERENCES

[1] Swathi, V., Sinduja, K., Kumar, V. R., Mahendar, A., Prasad, G. V., & Samya, B. (2024). Deep learning-based brain tumor detection: An MRI segmentation approach. *MATEC Web of Conferences*, *392*, 01157. https://doi.org/10.1051/matecconf/202439201157

[2] Curci, A., & Esposito, A. (2024). Detecting Brain Tumors Through Multimodal Neural Networks. *International Conference on Pattern Recognition Applications and Methods* 995-1000. https://doi.org/10.5220/0012608600003654

[3] Srinivasan, S., Francis, D., Mathivanan, S. K., Rajadurai, H., Shivahare, B. D., & Shah, M. A. (2024). A hybrid deep CNN model for brain tumor image multi-classification. *BMC Medical Imaging*, *24*(1) 1-21. https://doi.org/10.1186/s12880-024-01195-7

[4] Mohammed, A. a. A. (2024). Deep Learning Approach to Classify Brain Tumors from Magnetic Resonance Imaging Images. *International Journal of Advanced Computer Science and Applications*, *15*(5), 864-872. https://doi.org/10.14569/ijacsa.2024.0150587

[5] Govindan, M., Dhakshnamurthy, V. K., Sreerangan, K., Nagarajan, M. D., & Thomas, A. (2024). Brain Tumor Detection and Classification Using Transfer Learning Models. *International Journal of Advanced Computer Science and Applications* 1-8. https://doi.org/10.3390/engproc2024062001

[6] Jain, J., Kubadia, M., Mangla, M., & Tawde, P. (2024). Comparison of Transfer Learning Techniques to Classify Brain Tumours Using MRI Images. *International Conference on Intelligent Computing and Control Systems,* 1-9. https://doi.org/10.3390/engproc2023059144

[7] Namdeo R., Koushik, V., Kumar, K. K., Chaitanya, A. K., Sameet, G. K., Krishnaveni, K., & Rao, K. R. (2024). Brain Tumor Detection Using Convolutional Neural Networks. *International Journal for Research in Applied Science and Engineering Technology*, *12*(5), 5696–5702. https://doi.org/10.22214/ijraset.2024.62489

[8] Zuhal Y. Hamd, Eyas G. Osman and Amal I. Alorainy (2024). The role of machine learning

in detecting primary brain tumors in Saudi pediatric patients through MRI images. Journal of Radiation Research and Applied Sciences, 1-7.

[9] Mustafa Güler and Ersin Namlı (2024). Brain Tumor Detection with Deep Learning Methods' Classifier Optimization Using Medical Images. MDPI, Applied Science, 1-25.

[10] Medet Ashimgaliyev, Bakhyt Matkarimov, Alibek Barlybayev, Rita Yi Man Li and Ainur Zhumadillayeva (2024). Accurate MRI-Based Brain Tumor Diagnosis: Integrating Segmentation and Deep Learning Approaches. MDPI, Applied Science, 1-20.

[11] Akmalbek Abdusalomov, Mekhriddin Rakhimov, Jakhongir Karimberdiyev, Guzal Belalova and Young Im Cho (2024). Enhancing Automated Brain Tumor Detection Accuracy Using Artificial Intelligence Approaches for Healthcare Environments, MDPI, Bioengineering, 1-23.

[12] Lehel Dénes-Fazakas, Levente Kovács, György Eigner and László Szilágyi (2024). Enhancing Brain Tumor Diagnosis with L-Net: A Novel Deep Learning Approach for MRI Image Segmentation and Classification, MDPI, Biomedicines, 1-17.

[13] Yasemin Çetin-Kaya and Mahir Kaya (2024). A Novel Ensemble Framework for Multi-Classification of Brain Tumors Using Magnetic Resonance Imaging, MDPI, diagnostic, 1-24.

[14] Muhammad Aamir, Abdallah Namoun, Sehrish Munir, Nasser Aljohani, Meshari Huwaytim Alanazi, Yaser Alsahafi and Faris Alotibi (2024). Brain Tumor Detection and Classification Using an Optimized Convolutional Neural Network, MDPI, diagnostic, 1-19.