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Early brain tumor classification and segmentation through the use of deep reinforcement learning and deep learning techniques

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***Abstract*—Recent research publications from 2020 to 2023 have primarily focused on the before time identification and categorization of brain tumors, a critical concern for both adults and children due to their high level of danger. The predominant approach involves a amalgamation of transfer learning, DL, and supervised ML algorithms. Notably, deep reinforcement learning, semi-supervised learning, and generative adversarial networks have not been featured in these studies. Researchers have widely employed data augmentation techniques to enhance the volume of available data. The studies have relied on FLAIR, BraTS, and custom datasets. Segmentation techniques have encompassed K-means, CNN, HAAR Discrete Wavelet Transformer (DWT), and Otsu's watershed algorithms to refine the identification process.**

***Index Terms*— brain tumors, adults and children, Reinforcement Learning, Semi-supervised learning, generative AI.**

I. INTRODUCTION

Brain tumors, both in children and adults, remain a leading cause of mortality. MRI serves as a crucial tool for pinpointing these tumors. However, manual identification by clinicians is time-consuming and may not catch tumors in their early stages. This underscores the need for artificial intelligence (AI) technology to develop a system adept at recognizing and classifying brain cancer in its incipient phases. The genesis of a brain tumor arises from irregular cell growth within the body. These tumors can manifest as primary or secondary in nature, with each case varying in size, location, and growth rate. Leveraging the untapped potential of less active brain regions for early detection is a promising avenue. Should a tumor emerge in a less active section, symptoms might not surface immediately, allowing the tumor to grow substantially before detection.

Primary brain tumors initiate within the brain itself, and they are classified as either glial or non-glial. They can range from non-cancerous to malignant. Secondary brain tumors, also termed metastatic tumors, arise from primary tumors originating in other body regions. Those with primary brain tumors may exhibit symptoms like headaches, seizures, altered mental function, visual disturbances, nausea, and challenges with balance or coordination. Essentially, brain tumors fall into categories of benign or malignant, constituting different forms of brain cancer.

Physicians invest substantial time in manually identifying early brain tumors. Recent technological advancements have revolutionized people's lives, providing solutions to a wide array of challenging everyday situations. Central to this transformation is Artificial Intelligence (AI), encompassing subfields like ML, DL, semi-supervised learning, and RL. Any of these AI techniques can be harnessed to develop an automated system for detecting and categorizing brain tumors. Generally, supervised learning techniques are employed for precise classification and detection.

II. LITEARURE REVIEW

According to the research survey [1], they mainly focused on four significant characteristics in order to identify and classify brain tumors in both adults and children. The key components are the prediction techniques, the variety of applications, and the datasets used. It has been investigated how accurate machine learning and deep learning techniques are at predicting tumors. The research articles come from more than 40 distinct academic publications.

Finding out which techniques result in the most accurate tumor predictions for adults and children is the main objective of this survey. The article's coverage span was from 2015 until 2021.a comparison analysis of machine learning, deep learning, and ensemble learning. One of these technologies that is doing a great job at its job is deep learning. Studies reveal that semi-supervised learning, reinforcement learning, and clustering algorithms have not gained much traction. Harvard, Kaggle, Figshare, Flair, and BraTS have all been utilized by them.

They have created a revolutionary deep learning method for classifying the various kinds of brain tumors in this article [2]. The transfer learning algorithm had to be reconfigured for the produced model. Pre-processing the data allowed for the proposed model to be optimized. Algorithms for transfer learning like Xception, ResNet50V2, InceptionResNetV2, and DenseNet201 have been used by them. They made use of a dataset that included 3064 photos divided into three classes: pituitary tumors, gliomas, and meningiomas. The data files were available in MATLAB format. The prediction scores attained by the algorithms were 99.40%, 99.68%, 99.36%, and 98.72%, in that order. To produce a large dataset from a small one, they have used data augmentation.

For accurate tumor segmentation, a model based on multimodal information was developed in this work [3]. This study used a combination of edge information from MRI and deep semantics to classify the different kinds of cancers. Three modules make up the suggested approach: a semantic decomposition module, a boundary detection module, and a feature integration model. They have employed datasets from BraTS. In particular, BraTS2018,2019, and 2020, in that order. Swim Transformer is used into the semantic decomposition module to draw out semantic attributes from the tumor images. To enhance the feature representation, the edge detection module integrated CNN with Edge Spatial Attention Block. To manipulate the data, they have used data augmentation. They have used the Hausdorff and Dice scores to assess the model's performance.

In fact, one of the hectic issues in salutary image analysis is brain tumor decomposition [4]. Accurately identifying and localizing brain tumors in brain cancer cases is the main goal. Notably, some methods based on DL have shown promising outcomes in this field. This paper provides a panoramic analysis of newly developed DL-based brain tumor decomposition algorithms while accounting for notable technological advancements. Using information from more than 150 academic publications, this survey covers a wide range of technical topics, such as multi-modal processing, network architecture design, and segmentation in unbalanced situations.

The research report [5] suggests a method for cancer early diagnosis. They have diagnosed three various tumor forms, involving gliomas, meningiomas, and pituitary gland tumors, using a combination of machine learning algorithms and two deep learning algorithms. A dataset including 3264 MRI pictures was used. Pre-processing, data augmentation, enhancement, and hyperparameter tuning were applied to the MRI images. They have created Convolutional Auto Encoder Networks and 2D-CNNs. 94% and 95% accuracy have been attained by this architecture, respectively.

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They presented a method in this paper to address the computational complexity and accuracy in detecting edge features in brain tumors [6]. A Harris Hawks Optimized Convolution Network (HHOCNN) was created by them. This model's primary goal is to lessen erroneous tumor detection and noisy pixelation in MRI images. In order to limit the loss of concealed edge characteristics and locate the malignant region that segments border regions, they have implemented the candidate region approach. After that, CNN will be used to classify these segmented characteristics. To assess the model's performance, these metrics include raster accuracy, inaccuracy rate, accuracy, preciseness, and reactiveness. The suggested approach has reduced misclassification errors to attain 98% accuracy in tumor detection.

Presented a CNN architecture in this study [7] for precise brain tumor identification. The suggested model is contrasted with many transfer learning methods, including Inception V3, ResNet-50, and VGG-16. They have classified four types of cancers, including meningioma, gliomas, pituitary, and no tumor, using an MRI dataset consisting of 3263 images. In order to evaluate the model, they take into account the AUC, accuracy, recall, and loss. The suggested approach works better than transfer learning techniques. The suggested model has a loss of 0.25, 93.3% accuracy, 98.43% AUC, and 91.19% recall. Conversely, the ResNet-50 transfer learning model demonstrated an accuracy of 81.10%, an AUC of 94.20%, 81.04%, and a loss of 0.85%. The VGG-16 model has attained 71.60% accuracy, 89.60% AUC, 70.03% recall, and 1.18% loss and the Inception V3 have attained 80.0% accuracy, 89.14% AUC, 79.81% recall, and 3.67% loss.

The most prevalent and deadly kind of brain tumor, gliomas, is the subject of this article [8]. A method to differentiate between high-grade and low-grade gliomas has been proposed. The T1W, T2W, and FLAIR images made up the dataset. The aim of the proposed model is to identify gliomas with the highest possible accuracy. CNN, comprising of AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50, has been taken into consideration in this study. The training and testing procedure was conducted using the fivefold cross- validation, or K5-CV, approach. For FLAIR, T2W, and T1W-MRI data, the recommended ensembled classifier yielded maximum test accuracies of 98.88±0.63%, 97.98±0.86%, and 94.75±0.61%, respectively [8]. This indicates how well the ensemble method works to improve classification results.

This experimentation presents a narrative method for identifying intracranial neoplasm using the integration of data mining and machine learning approaches [9]. The model has been implemented using the BraTS 2014 and BTD20 datasets. The preprocessing, augmentation, and background noise removal applied to MRI images make up the dataset. A method called Social Spider Optimization (SSO) has been developed by them. The integrated approach seeks to optimize brain tumor identification efficacy and accuracy. The distinctive characteristics of MRI pictures are extracted using the SVD technique. An algorithm is applied to these collected features in order to identify and classify cancers. The Naïve Bayes, SVM, and KNN algorithms are merged with the SSO method. The outcomes show how successful the suggested approach is at locating brain tumors. In particular, the technique attained a mean accuracy of 98.61%, with a reactivity of 95.79% and a preciseness of 99.71% on the BRATS 2014 dataset. The suggested approach performed significantly better when used on the BTD20 database, averaging 99.13% accuracy, 99% reactivity, and 99.26% preciseness.

They surveyed different image segmentation methods for the identification and classification of brain tumors in this study [10]. The BraTS dataset-2018 was used by the researchers, who used MATLAB to perform each strategy. For the purpose of segmenting the tumors, they have taken into account Otsu's, watershed, level set, K-means, HAAR Discrete Wavelet Transform (DWT), and Convolutional Neural Network (CNN). Accuracy, precision, F-measures, recall, and response time were employed in conjunction with response time to analyse the efficacy of the models. According to the study, the accuracy rates of the Otsu, watershed, level set, K-means, DWT, and CNN approaches were 71.42%, 78.26%, 80.45%, 84.34%, 86.95%, and 91.39%, respectively, while the CNN methodology showed a response time of 2.519 seconds.

Seven CNN models have been proposed in this article [11] in order to identify and categorize the different types of brain tumors. Along with a basic CNN, the paper has taken into consideration 6 pre-trained models. They used the Msoud dataset, which included 7023 photos from SARTAJ, Br35H, and Figshare, in that order. There are four classes in the dataset: gliomas, meningiomas, pituitary, and no tumor. To classify the tumors, the images undergo preprocessing and data augmentation, after which key features are retrieved. Xception, MobileNetV2, InceptionV3, InceptionResNetV2, EfficientNetB0, and a Generic CNN were among the CNN models that were examined in the study. Out of all the models evaluated, which included 6 early-trained models and a common CNN, InceptionV3 turned out to be the best CNN model. It attained a remarkable 97.12% average accuracy.

The study presented in this article [12] attempts to categorize RMB images into six different groups. The MBINet and Self-ONN with eight layers of classifier, has been proposed by the researchers. The sensor-based microwave brain imaging technology is used in the trials to create a dataset from RMB pictures. There are 1320 photos in the database. After training on the original RMB pictures, the MBINet model produced remarkable performance metrics. It showed, in particular, 96.97% accuracy, 96.93% precision, 96.85% recall, 96.83% F1-score, and 97.95% specificity. Subsequent classification tests revealed that the MBINet model achieved an accuracy of about 98%, outperforming 4 Self-ONNs, two basic CNNs, ResNet50, ResNet101, and DenseNet201 models. This shows that, when compared to the other models examined, the MBINet model has a higher classification capability.

Advanced techniques including machine learning, deep learning, and adversarial networks are being used in recent studies for the identification and categorization of intracranial neoplasm [13]. Even yet, a few crucial actions are still needed to confirm the outcomes because of the maximum execution duration and possible errors. This paper presents a novel method that combines the SSO algorithm integrated into the RBNN with an integrated salience-K-mean segmentation strategy. Based on this combination, the Saliency-K-mean- SSO-RBNN model is created. In order to precisely segment the tumor locations, a integrated Saliency Map is created using a K-means cluster-based segmentation technique. The goal of this novel strategy is to improve the accuracy and efficacy of brain cancer classification. The Saliency-K-mean- SSO-RBNN model showed 96%, 92%, and 94% classification accuracies. In comparison to current techniques, these results support the proposed approach's efficacy and promise for accurately identifying brain cancer.

This study presents a number of statistical image enhancement and computational intelligence methods for the detection of cancer and intracranial neoplasm. Furthermore, the research offers an assessment framework utilizing specified methodology and dataset kinds for a particular system [14]. The report provides a thorough overview of topics like component extraction, augmentation approaches, the anatomy of brain tumors, accessible datasets, and identification using DL, TL, and ML models. In the end, the paper compiles all the data needed to recognize and understand tumors, including their advantages, disadvantages, developments, and future directions.

A comparison of the developmental characteristics of brain tumors in adults and children is explored in this article. The concept, as delineated in [15], suggests that epigenetic pathways could function in the origin of progenitor cells for cancer in both adult and paediatric populations. However, it is observed that the development of adult brain tumors requires more mutations than does the case of childhood cancers. This shows that the underlying mechanisms causing tumor formation in these various age groups differ. Understanding the pathways and mechanisms behind these events is made possible by the Hallmarks of Cancer Theory. According to our theory, the earliest phases of carcinogenesis are indicated by the appearance of tumor initiating cells. We also highlight the important function that epigenetics plays in the development of these cancer initiating cells.

As per the recent global cancer data published by the WHO in 2020, encephalon cancers account for 2.5% of all tumor- related deaths and 1.6% of tumor incidence worldwide. Notably, China has the highest rates of both brain tumor morbidity and mortality, with rates reaching 32% and 26%, respectively [16]. There has been a notable increase in the incidence rate each year, particularly among younger individuals. Among brain tumor cases, gliomas constitute approximately 30% and represent the most prevalent and invasive type. They are characterized by significant invasion, a high recurrence rate, and a generally unfavourable prognosis. While surgery remains the primary treatment for brain tumors, complete removal can be challenging due to the aggressive nature of the cancer and its ill-defined borders.

Furthermore, it's worth noting that approximately 90% of surgical cases lead to tumor recurrences. As a result, radiation therapy and chemotherapy are currently considered standard treatments for brain tumors following surgical removal [17]. One prominent chemotherapeutic agent utilized in brain tumor treatment is temozolomide (TMZ). This medication exerts its effects by attaching a methyl category to the purine bases within DNA, ultimately leading to cell destruction. While TMZ serves as a first-line chemotherapeutic option for brain tumors, its short half-life necessitates higher dosage levels for effectiveness. These challenges motivated us to develop an advanced framework that combines deep learning and evolutionary algorithms. This innovative approach enabled us to automatically construct the ResNet architecture, achieving remarkably high accuracy in classifying 3 distinct types of encephalon tumors using a large dataset of MRI scans. By incorporating these two concepts into the construction of deep learning-based ResNet architectures, we were able to enhance optimization performance, mitigate the risk of getting stuck in local optima, and strike a valuable balance between convergence speed and solution diversity. The study's results, showcasing an impressive average accuracy of 0.98694 for our framework, demonstrate how effectively our IACO-ResNet algorithm facilitates the automatic classification of brain tumors.

A refined transfer learning method known as Efficient Nets was presented in this paper [18]. The family of Efficient Nets, which includes EfficientNetB0 through EfficientNetB4, is used. The Figshare-Brain tumor dataset, a CE-MRI dataset, is utilized to differentiate between three different tumor forms, including gliomas, pituitary, and meningiomas. The first step in the suggested fine-tuning procedure for pre- trained Efficient Nets is the incorporation of many top layers—among them a fully connected layer intended for the categorization of various kinds of encephalon tumors—into the Efficient Net model. This approach improves the model's ability to classify brain cancers with accuracy. Impressive results were obtained, with an overall test accuracy of 98.86%, precision of 98.65%, recall/sensitivity of 98.77%, and F1 score of 98.71%.

This article [19] develops an attention mechanism and an autonomous 3D segmentation methodology for a brain tumor division technique. Enhancing the correctness and precision of brain tumor division in 3D medical imaging is the aim of including an attention mechanism. Using the proposed network system on the BraTS 2019 test set produced the following outcomes: Using 0.30 million features and 25.81 billion operations, the proposed ADHDC-Net achieved Dice coefficients of 77.91% for augmenting tumor, 89.94% for the entire tumor, and 83.89% for tumor core segmentation [19]. This implies that a high degree of precision may be used to distinguish between the different tumor locations.

In this work, a unique novel deep fully convolutional neural network is used. RSPA, ASPP, RSPA, and the categorization module make up the four primary modules of the suggested network. These components work together to provide a foundation for a trustworthy and precise diagnosis of brain tumors. The results show that the suggested method performs better than the most advanced techniques already in use. More precisely, when compared to the most modern methods, the method in [20] produced the best accuracy on all datasets. Using the recommended method, the Cheng, Brats-small2C, and Brats-sm datasets in particular showed remarkable accuracy rates of 99.78%, 99.33%, and 96.33%.

VII. CONCLUSION

In this article, we undertook a comprehensive literature review to gain insight into and analyse automated systems designed for the identification and categorization of brain tumors, employing state-of-the-art tools and technologies. Our findings indicate that current systems predominantly leverage machine learning, deep learning, and transfer learning algorithms for these tasks. Notably, there are no papers that have explored the application of deep reinforcement learning, generative adversarial networks, or semi-supervised learning in this context. Additionally, a common approach in these systems involves the utilization of data augmentation techniques to augment the quantity of MRI images for enhanced detection and classification performance.

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