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Advancements in Multiclass Brain Tumor Detection and Classification: A Comprehensive Review

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Abstract*: The detection and classification of brain tumors play a crucial role in medical imaging analysis, facilitating early diagnosis, treatment planning, and patient monitoring. With recent advancements in automated methods, particularly in the multiclass scenario, this comprehensive review aims to provide a detailed analysis of state-of-the-art techniques and methodologies in multiclass brain tumor detection and classification. The review covers various aspects, including dataset characteristics, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics. Additionally, it discusses the challenges associated with this field and proposes future research directions to enhance the advancements in brain tumor analysis further. This review is a valuable resource for researchers and practitioners working towards improving brain tumor detection and classification accuracy and efficacy*.

Keywords: Brain tumor classification, CNN, InceptionV3, Exception, Transfer learning.

I. INTRODUCTION

Brain tumours are one of the most complex medical disorders to treat, and they impact the lives of millions of people worldwide. The diagnosis of brain tumours at an early stage and their correct categorization are both necessary for developing successful treatment plans and improving patient outcomes. In recent years, significant progress has been made in developing automated brain tumor detection and classification methods, particularly in the multiclass scenario.Multiclass brain tumor detection refers to accurately identifying and distinguishing between different types of brain tumors, including gliomas, meningiomas, pituitary adenomas, and others. This classification is crucial as different tumor types require specific treatment approaches and have varying prognoses.

The advent of advanced medical imaging technologies, such as magnetic resonance imaging (MRI), has revolutionized the field of brain tumor analysis. These imaging modalities generate high-resolution and detailed images that can be leveraged for accurate detection and classification. However, analyzing brain tumor images poses significant challenges due to the complexity of tumor characteristics, tumour appearance variability, and various anatomical structures.This exhaustive study seeks to give an in-depth examination of the current state-of-the-art techniques and methodology used in detecting and classifying multiclass brain tumours by providing an overview of such techniques and processes. It covers various aspects, including dataset characteristics, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics.

Understanding the characteristics of available datasets is crucial for training and evaluating models. Additionally, preprocessing techniques, such as image denoising, normalization, and segmentation, play a vital role in enhancing the quality of brain tumor images and extracting relevant information. Feature extraction methods, including traditional handcrafted features and deep learning-based approaches, extract discriminative features from the images to aid in accurate classification.Classification algorithms, ranging from traditional machine learning techniques to deep learning architectures, are utilized to classify brain tumors. These algorithms utilize the extracted features to differentiate between different tumor types. Evaluation metrics play a critical role in assessing the performance of brain tumor detection and classification systems. Metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) are commonly used to evaluate the effectiveness of these systems.

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Despite the advancements, multiclass brain tumor detection and classification still face several challenges. These include the scarcity and imbalance of labeled datasets, the interpretability of models, the integration of multimodal data, and the need for real-time analysis. Addressing these challenges will drive further advancements in this field and improve the accuracy and efficiency of brain tumor analysis.

This comprehensive review aims to provide researchers and practitioners with a comprehensive understanding of the current state of multiclass brain tumor detection and classification. By examining the datasets, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics, this review will facilitate the development of innovative methodologies and solutions to enhance brain tumour analysis's accuracy and clinical applicability.

II. LITERATURE SURVEY

Modern medical practices often use MR imaging for the diagnosis of brain cancer. This part closely examines how well brain tumours are known to be detected and categorized.

Review on Brain Tumor Detection

Sakshi Ahuja et al. [1] employed transfer learning and the superpixel approach for identifying brain tumours and segmenting the brain. This model was trained using the VGG 19 transfer learning model, and the dataset that was utilized was from the BRATS 2019 brain tumour segmentation competition. The tumour was segmented into LGG and HGG pictures using the superpixel approach. Consequently, an average dice index of 0.934 was generated in contrast to the data obtained from the ground truth.

U-Net was utilized by Hajar Cherguif et al.[2] for the semantic segmentation of medical pictures. The U-Net design was utilized to develop a decent convoluted 2D segmentation network. The model that was proposed was tested and evaluated with the help of the BRATS 2017 dataset. The suggested design for the U-Net network consisted of 27 convolutional layers, 4 deconvolutional layers, and a Dice coef of 0.81.

Deep learning techniques, which involve deep neural networks, were utilized by ChirodipLodh Choudhury and colleagues [3] in order to acquire reliable data from MRI scans. These approaches were combined with a Convolutional Neural Network model to achieve this goal. An architecture for a CNN with three layers was suggested, and this design was then coupled to a fully connected neural network. It was possible to get an F-score of 97.33 and an accuracy of 96.05 percent.

Images obtained from an MRI with a T1 weighting were evaluated by Ahmad Habbie et al.[4], who used a semi-automatic segmentation technique to determine whether or not a brain tumour was present. They used an active contour model. Analyses were conducted on the effectiveness of morphological active contour without edge, snake active contour, and morphological geodesic active contour. The findings reveal that MGAC had the best performance out of the three organizations.

In this research, Neelum et al. [5] employed a concatenation strategy for the deep learning model, and they examined the chance of the patient having a brain tumour. In order to identify and categorize brain cancers, pre-trained deep learning models, which include Inception v3 and DenseNet201, were utilized. The Inception v3 model was pre-trained to extract the features, which were then concatenated to classify the tumours. After that, a softmax classifier was used to complete the classification process.

Hybrid Classifiers were utilized in Ms Swati Jayade et al. [6] .'s study. Malignant and benign tumours were the two categories that were used for classifying tumours. The Gray level Cooccurrence Matrix (GLCM) feature extraction approach produced the feature dataset. One strategy that combines KNN and SVM classifiers has been suggested to improve the classification process's effectiveness.

Zheshu Jia et al. [7] produced a fully automated heterogeneous segmentation using SVM (Support Vector Machine). The author of this study is Zheshu Jia. A classification system known as a probabilistic neural network classification system has been employed to train and test the accuracy of tumour identification in MRI images. The multi-spectral brain dataset is employed, and the automated segmentation of meningiomas is the primary emphasis of this model.

To locate the edges in the CT and MRI scans, Dr AkeySungheetha and Dr Rajesh Sharma R.[8] utilized the Gabor transform in conjunction with the soft and hard clustering. MRI scans comprised a total of 4500, whereas CT images comprised 3000 of the specimens examined. K-means clustering was utilized in order to categorize related

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characteristics into distinct sub-groups. The author used fuzzy c methods to express the photos in the form of the attributes of a histogram.

A Bayesian technique was employed by Parnian Afshar et al.[9] in order to classify brain tumours by using capsule networks. Because CNN is prone to losing essential spatial information, capsule networks were utilized instead of CNN to get more successful tumour identification findings. The BayesCap framework was the team's suggestion. In order to validate the suggested model, they employed a standard dataset consisting of cases of brain tumours.

Review of Brain Tumor Classification

Togacar et al. [10] created a BrainMRNet network using the modulo and hypercolumn technique. The original photos were first subjected to preprocessing and then sent to the attention module. The convolutional layer receives the picture and processes it based on the attention module, which controls the focal regions of the image. The BrainMRNet model's convolutional layers make extensive use of the hypercolumn strategy. Using this technique, we increasedaccuracy to 96.05% since the characteristics collected from each successive layer were saved in the array tree of the final layer.

Kibriya et al. [11] established an approach based on the fusion of many features to classify brain tumours. We first apply the minimum-maximum normalization approach to the original photos and then use enormous data extension to the preprocessed images to solve the data issue. The final output and accuracy of 97.7% result from a combination of a support vector machine (SVM) and a k-nearest neighbour (KNN) classifier trained on data from the GoogLeNet and ResNet18 deep CNN models.

Brain tumours may be detected and classified using a CNN developed by Sajjad et al. [12]. The authors achieved a 94.58% accuracy rate by using a Cascade CNN algorithm for segmenting the tumours in the brain and a fine-tuned version of VGG19 for classifying them.

Shanthakumar [13] employed watershed segmentation on brain MRI scans to localize tumours. The accuracy of tumour segmentation was improved to 94.52% using this segmentation approach, which uses a preset labelling scheme to achieve this result. Separating tumour regions in MR images of the brain is possible by Prastawa et al. [30]. Although this approach has an 88.17% success rate, it can only identify the outside abnormal boundaries of the tumour area and not the interior boundary.

Gumaei et al. [14] suggested a hybrid feature extraction technique based on a regularised extreme learning machine (RELM) to classify brain tumours. Preprocessing is performed using the min-max normalization contrast enhancement approach; feature extraction is performed using a hybrid PCA-NGIST method, and brain tumour classification is performed using the RELM method. The overall precision of this job was 94.23%.

When used to contrast-enhanced magnetic resonance imaging (CE-MRI), a fine-tuned pre-trained VGG19 model improved outcomesand reported an average accuracy of 94.82%. After addressing the issue of overfitting using the ResNet50 CNN model and global average pooling, Kumar et al. [15] suggested a brain tumour technique with an average accuracy of 97.48%. These game-changing advances have garnered widespread attention in medical image analysis. Brain picture categorization by machine learning and an understanding of brain architecture was proposed by Veeramuthuet al. [16].

Shen et al. [17] revealed the results of a deep learning-specific study of medical picture analysis. While they cover much ground, specific crucial points have been overlooked. Medical image segmentation is essential for prompt treatment planning, categorizing, and identifying brain tumours from MR images. Methods for MRI Classification There are many brain tumours. Imaging the brain with MRI (Magnetic Resonance Imaging) is the standard diagnostic procedure for evaluating tumours in the head. Traditional machine learning methods often assign a classification to a brain tumour based on an arbitrary attribute or the discretion of a radiologist. In this study, we use ensemble modelling using the SVM & CNN classifier on MRI scans of the brain to distinguish between benign and malignant tumours. In addition, threshold-based segmentation management causes blurred edges and limits when recognizing brain tumours. Using Resnet-50 and TL, a deep learning model was created for detecting and diagnosing brain tumours. The accuracy rate of their experiments is 95%. Researchers used block-wise-based transfer learning to accomplish fivefold cross-validation. 95 percent accuracy. Their technology (CEMRI) was tested using a benchmark dataset constructed from T1-weighted MR images. They are classifying MRI scans of the brain using Google's neural network architecture. A classification accuracy of 98% was achieved.

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As a classifier, a support vector machine-based method is utilized [18]. Classification and feature extraction are two applications of CNN. Two convolutional layers and two fully linked layers are used in this structure. In a study using nine deep learning models, they employed Transfer Learning to identify brain tumours with a TL accuracy of 97.39%. In order to delve into MR data, they switched to deep learning mode. Classification of MRI scans was successful to the tune of 98.71 percent using the suggested approach. Despite the small size of the research, the findings were striking. CNN's blueprints were spot-on in every respect. VGG also achieved 96 percent accuracy, ResNet50 achieved 89 percent, and InceptionV3 achieved 89 percent.

Accuracy of 75% [19] As reported by CNN, modern buildings are designed to work at lightning speeds while maintaining a 98.24 percent accuracy rate. Multi-scale analysis of MRI scans of brain tumours using CNN is highly recommended. They tested the suggested model on the MRI image dataset and found that it had a 97.3 percent accuracy in classifying the images [20]. In order to classify brain tumours, the CNN model uses two convolutional layers and two fully connected layers to gather relevant data for feature extraction. Classifying brain tumours, they had a 97% success rate [21].

Khairandish et al. [22] explained how brain tumors behave, and with the aid of many methodologies and the analysis of research studies using various criteria, it offers a clear image of this stage. The examination is conducted with the dataset, proposed model, proposed model performance, and type of method used in each paper. Between 79 and 97.7% of the publications under study had accurate results. They employed Convolutional Neural Network, K-Nearest Neighbour, K-Means, and Random Forest algorithms, in that sequence (highest frequency of use to lowest). Here Convolutional Neural Network gave the highest accuracy of around 79-97.7%

Someswararao et al. [23] developed a new novel method for detecting tumors in MR images using machine learning techniques, particularly the CNN model, in this study. This study combined a CNN model classification challenge for determining whether or not a subject has a brain tumor with a computer vision problem to crop the brain from MRI scans automatically. Other techniques used were Convolutional Neural Network, K-Means Clustering and the highest Accuracy is given by Convolutional Neural Network, which is around 90%.

Choudhury et al. [24] proposed a new CNN-based system that can distinguish between different brain MRI images and label them as tumorous or not. The model's accuracy was 96.08%, and its f-score was 97.3. The model uses a CNN with three layers and only a few preprocessing steps to yield results in 35 epochs. This study emphasizes the significance of predictive therapy and diagnostic machine-learning applications. Other techniques used were Support Vector Machine, Convolutional Neural Network, k-Nearest Neighbour, Boosted trees, Random forest and Decision trees. The suggested approaches are certain to be very efficient and accurate in detecting, categorizing, and segmenting brain tumours. Automatic or semi-automatic precision

In [16],this study identifies the MRI images with the help of a Recurrent Neural Network (RNN). The BP NN activation function was first used to scale up and down the network's nodes. The number of nodes in the hidden layer was set to 270 and then brought back down to 230 using the log sigmoid function. Finally, we have reached the optimal performance for RNN thanks to a bump in the node count to 300. For optimalefficiency, we use an Elman network. When the number of nodes increases, so does the amount of performance mistakes. When used in the recognition process, Elman networks were shown to be both quick and accurate compared to other ANN systems. When compared to Elman's 88.14%, our ratio was 76.47%.

III. DISCUSSION

The paper thoroughly analyses the state-of-the-art techniques and methodologies in multiclass brain tumor detection and classification. The review covers various aspects, including dataset characteristics, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics. Here, we will discuss the essential findings and implications of the review.

The review highlights the importance of accurate and efficient multiclass brain tumor detection and classification for early diagnosis, treatment planning, and monitoring. It emphasizes the advancements in automated methods, particularly with medical imaging technologies like MRI. These advancements have significantly improved the accuracy and efficacy of brain tumor analysis.

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The discussion reveals that the choice and characteristics of datasets play a critical role in developing and evaluating brain tumor detection systems. The availability of publicly accessible datasets and proper annotation and ground truth information is crucial for training and validating models. The review also highlights the challenges posed by dataset imbalance and heterogeneity, as different brain tumor types may have varying prevalence in the dataset.

Classification algorithms, ranging from traditional machine learning techniques to deep learning architectures, are compared in terms of their performance in multiclass brain tumor detection and classification. The review highlights the strengths and limitations of different algorithms and emphasizes the exceptional performance of deep learning models in this domain.

The evaluation metrics discussed in the review, including accuracy, sensitivity, specificity, and area under the curve (AUC), provide insights into the performance of brain tumor detection systems. The choice of appropriate evaluation metrics depends on the specific goals of the system and the importance of different classification errors in the clinical context.

The review also identifies several challenges in multiclass brain tumor detection and classification. These challenges include data scarcity and imbalance, interpretability and explainability of models, integration of multimodal data, and the need for real-time analysis. Addressing these challenges will pave the way for further advancements in this field and improve the accuracy and efficiency of brain tumor detection and classification systems.

The comprehensive review ofmulticlass brain tumor detection and classification advancements provides valuable insights into the field's current state. By examining datasets, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics, the review contributes to understanding the strengths, limitations, and future directions in multiclass brain tumor analysis. The review's findings can guide researchers and practitioners in developing innovative methodologies to enhance brain tumor detection and classification accuracy and clinical applicability.

IV. CONCLUSION

The comprehensive review on multiclass brain tumor detection and classification has shed light on the advancements, challenges, and future directions in this critical field. The review has provided a comprehensive understanding of the current state-of-the-art methodologies by analyzing dataset characteristics, preprocessing techniques, feature extraction methods, classification algorithms, and evaluation metrics.

The review emphasizes the importance of accurate and efficient multiclass brain tumor detection and classification in facilitating early diagnosis, treatment planning, and patient monitoring. The advancements in medical imaging technologies, particularly MRI, have significantly improved the quality and availability of brain tumor images, enabling more sophisticated analysis approaches.

Various preprocessing techniques, including denoising, normalization, and segmentation, have been explored to enhance the quality of brain tumor images and extract relevant information. These techniques play a crucial role in ensuring reliable and accurate analysis.

Feature extraction methods have been investigated, ranging from traditional handcrafted features to deep learning-based approaches. The review highlights the potential of deep learning models, such as convolutional neural networks (CNNs), in automatically learning discriminative features from brain tumor images. However, the challenge of interpretability and the need for large labeled datasets remain essential considerations.

Classification algorithms, including traditional machine learning techniques and deep learning architectures, have been compared regarding their performance in multiclass brain tumor detection and classification. The review showcases the strengths and limitations of different algorithms and highlights the exceptional performance of deep learning models.

While significant progress has been made, the review identifies challenges in multiclass brain tumor detection and classification. These challenges include data scarcity and imbalance, interpretability of models, integration of multimodal data, and the need for real-time analysis. Overcoming these challenges will drive further advancements in the field and improve the accuracy and efficiency of brain tumor analysis.

The comprehensive review provides a valuable resource for researchers and practitioners in multiclass brain tumor detection and classification. By synthesizing the current state-of-the-art methodologies and highlighting areas for future

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research, the review contributes to developing innovative approaches to enhance the accuracy, clinical applicability, and patient outcomes in brain tumor detection and classification.

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