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A LITERATURE SURVEY ON BRAIN TUMOR CLASSIFICATION USING HYBRID MACHINE LEARNING TECHNIQUES

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ABSTRACT: Brain tumor occurs owing to uncontrolled and rapid growth of cells. If not treated at an initial phase, it may lead to death. Despite many significant efforts and promising outcomes in this domain, accurate segmentation and classification remain a challenging task. A major challenge for brain tumor detection arises from the variations in tumor location, shape, and size. There is abundance of hidden information in stored in the Health care sector. With appropriate use of accurate data mining classification techniques, early prediction of any disease can be effectively performed. In the medical field, the techniques of ML (machine learning) and Data mining holds a significant stand. Majority of which is adopted effectively. The research examines list of risk factors that are being traced out in brain tumor surveillance systems. Also the machine learning assures to be highly efficient and precise for brain tumor detection, classification and segmentation. To achieve this precise automatic or semiautomatic methods are needed. Relations and patterns from the data can be extracted. The techniques of Machine Learning (ML) and Data mining are being effectively employed for brain tumor detection and prevention at an early stage.

Keywords: Machine Learning (ML), brain tumor, Data mining

I. Introduction

Brain tumors are one of the most dangerous types of brain diseases that can develop due to abnormal cell growth inside the skull. Brain tumors can be categorized into two types: primary tumors and secondary tumors. Primary brain tumors account for 70% of all tumors and spread only in the brain, whereas secondary brain tumors form in other organs such as the breast, kidney, and lung before migrating to the brain. According to a study by NBTF, in US alone, around 29,000 cases of primary brain tumor are diagnosed each year, resulting in the death of 13,000 people [5].

Similarly, in the United Kingdom, about 42,000 people with primary brain tumors die each year. Glioma, Meningioma, and Pituitary tumors are the most prevalent brain tumors. Glioma tumor is caused by unusual growth in Glial cells that constitute 80% of the brain. Among all primary tumors, it has the highest fatality rate. Meningioma tumors develop in the brain's protective membrane, the meninges spinal cord. In contrast, the pituitary tumor develops in the pituitary gland. This is gland produces various necessary hormones [2].

Tumor basically symbolizes abnormal and uncontrollable growth of cells within the body. Brain tumor signifies a malformed mass of tissue wherein the cells multiply abruptly and ceaselessly within the brain tissues (l).Brain tumor segmentation involves separating distinct tumor cells (effective tumor, solid, edema, and necrosis) from the normal brain cells (GM - grey matter, WM - white matter, and CSF - cerebrospinal fluid). Concerning brain tumor research, the unnatural cells tend to be explored any time. The procedure of MRI doesn't involve any pain or radiation and is a non-invasive brain. image process. Early diagnosis and immediate treatment of brain tumor definitely increases the survival chances of an individual [10].

Brain tumors can lead to death if left untreated [11]. The complexity of brain tumors poses challenges for healthcare providers in diagnosing and caring for affected patients. Early detection of brain tumors and initiation of treatment play vital roles in the survival rate of these patients. Brain tumor biopsy is not as easy as biopsy of other parts of the body, as it

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must be performed with surgery. Therefore, the need for another method for accurate diagnosis without surgery is crucial. It is essential to promote early diagnosis of brain tumors because they are the most common cause of cancer-related deaths in children and people up to 40 years of age. Therefore, it is necessary to devise strategies to accelerate early diagnosis of brain tumors. An early diagnosis of brain tumor implies faster response in treatment, thereby increasing the surviving rates of patients. A process designed to automatically detect, locate and classify brain tumors is desirable. AI and ML have gained prominence in almost every field of decision-making and can be successfully implemented for the detection and classification of brain tumors. Magnetic Resonance Imaging (MRI) is the best and most commonly used option for diagnosing brain tumors.

Although the pituitary tumor is benign, it can cause hormonal deficiencies and irreparable damage to vision. Hence, an early and accurate diagnosis of brain tumors is necessary to protect patients from damaging effects. Depending on their objective, brain tumors can be diagnosed using various medical imaging technologies. Ultrasonography (US), magnetic resonance imaging (MRI), and computed tomography (CT) are three of the widely used techniques [3].

The most prevalent noninvasive imaging technology is magnetic resonance imaging (MRI), which does not emit any harmful ionizing radiation during the examination like X-rays. Furthermore, it generates clear images of soft tissues and can acquire modalities like FLAIR, T1, and T2, using a variety of parameters. Proper identification of tumor type is a difficult task as the tumors usually vary in shape, intensity, size, and location. Usually, the medical professionals visually inspect the images and meticulously mark out the tumor regions in the images. Because of the surrounding healthy tissues, tumor borders are frequently blurred. As a result, the manual identification process via optical inspection is time-consuming and can cause misinterpretation of the tumor.

Furthermore, manual tumor detection relies heavily on the radiologist's experience. It should also be mentioned that the human eye cannot distinguish between distinct shades of grey shown in MRI scans. Other prominent reasons for tumor misinterpretation include fatigued radiologists or noisy MRIs caused by variations in imaging devices. Thus, automated systems are appropriate when radiologists want to visually evaluate the depth of the tumor or identify the type of tumor to reduce the likelihood of biopsy [4].

Various researchers have proposed CAD-based brain tumor detection methods. However, the limitation of traditional ML-based algorithms is that they use a hand-crafted feature extraction strategy. The features are extracted from training images before classification. Brain tumor classification techniques can be divided into Machine Learning (ML) based methods and Deep Learning (DL) based methods. The ML-based systems employ handcrafted feature extraction and manual segmentation before classification that is time-consuming and errorprone. These methods typically require the assistance of an expert with extensive experience to discover optimal feature extraction and segmentation algorithms for proper tumor identification.

II. Literature Survey

C.Hemasundara Rao, Dr. P.V. Naganjaneyulu, Dr.K.Satya Prasad et.al[30] explains an automated method for detecting and segmenting affected the brain tumor areas. There are three stages in the proposed method: 1. initial segmentation 2. Modeling of energy functions and 3. Optimizing the energy

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function. To achieve reliable segmentation, the information present in T1 and FLAIR MRI images are being utilized. CRF (Conditional random field) based framework is employed to merge the information existing in T1 and FLAIR in probabilistic region.

Atiq Islam et.al [36] described about using the new MultiFD (multi-fractal) feature extraction and enhanced AdaBoost classification schemes for brain tumor detection and segmentation. By making use of MultiFD feature extraction strategy, the brain tumor tissue-texture is extracted. The enhanced AdaBoost classification methods are adopted to detect if the brain tissue is tumor affected or not. The scheme exhibits high complexity.

Shamsul Huda et.al [31] presents hybrid feature selection using ensemble classification for per forming brain tumor diagnosis. For acquiring of decision rules, decision Tree, GANNIGMAC, Bagging C based wrapper approach are adopted and the decision rules are simplified by making use of hybrid feature selection that merges (Decision Tree + MRMR C + GANNIGMAC + Bagging C).

Sergio Pereira et.al [33] presents automated methods for brain tumors identifying and type cataloging by utilizing MRI images of brain right from the initial time when one could attempt to scan and freight medical images in the computer system. On the contrary, NN (Neural Networks) and SVM (Support Vector Machine) being the commonly adopted methods lately as they offer better performance.

J. Seetha and S. Selvakumar Raja et.al, [25] described the usage of MRI images for brain tumor diagnosis. The MRI scan usually produces data in abundance which makes the manual classification process of tumor vs non-tumor very time consuming. Though it offers precise quantitative metrics for restricted no: of images. Therefore there arises a need for automated and trustworthy classification approaches to reduce the human death ratio. The automated brain tumor classification tends to be very complex in large spatial and structural inconsistency of nearby areas of brain tumor. Herein, proposed an automatic brain tumor detection approach by adopting the CNN classification.

Varuna Shree N, Kumar TNR et.al, [26] explained the targets on noise removal technique, extraction of GLCM(gray-level co-occurrence matrix) features, brain tumor region growing segmentation (DWTbased) for minimizing the complexity and enhancing the performance. Subsequently, the morphological filtering is employed that aids in noise removal which may get build up after segmentation. The probabilistic neural network classifier is being utilized for training and testing the accuracy performance for detecting tumor location concerning the MRI images of brain.

Garima Singh, Dr. M.A. Ansari et.al,[34] presents a technique to classify and analyze the image de-noising filters like the Adaptive filter, Median filter, Un-sharp masking filter, Averaging filter and Gaussian filter that are employed to eliminate additive noises prevailing within the MRI images which includes: speckle noise, Gaussian, Salt & pepper noise. PSNR and MSE are utilized for comparing the de-noising performance of all the strategies taken into account. For successful brain tumor identification, a novel idea is being recommended by making use of normalized histogram and segmentation via K-means clustering algorithm. Naïve Bayes Classifier and SVM are adopted for classifying the MRIs effectively, thereby offering precise prediction and classification.

H. Mzoughi, I. Njeh, A. Wali et al., [12] demonstrated 3D CNN architecture for

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glioma brain tumor classification into Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) utilizing the entire volumetric T1-Gado MRI sequence from Brats 2018 dataset. Using small kernels, the architecture combined local and global contextual information with lower weights, based on a 3D convolutional layer and a deep network. The system achieved 96.49% accuracy.

S. Maqsood, R. Damasevicius, and F. M. Shah et al. [6] suggested a brain tumor detection method employing edge detection and U-NET model. The tumor segmentation framework enhances image contrast and performs edge detection fuzzy logic. The features are extracted from decaying subband images and then classified using the U-NET architecture, which detects the presence of meningioma in brain images.

M To˘gaçar, B Ergen, and Z C¨omert et al. [13] developed BrainMRNet using attention modules and the hypercolumn method. Initially, the images were preprocessed before being sent to the attention modules. Attention modules determine the key regions of an image and send the image to convolutional layers. Hypercolumn is one of the important techniques used by the BrainMRNet model in the convolutional layers. The features extracted from each layer are maintained by the array structure in the final layer using this technique. The system achieved an accuracy of 96.05%.

S. Khawaldeh, U. Pervaiz, A. Rafiq, and R. S. Alkhawaldeh et al. [27] suggested a CNN model to detect brain tumors and Glioma tumors by improving pretrained architecture and achieving 91% overall accuracy. Despite the tremendous amount of work in this field, developing a good and practical technique for classifying brain MR images still requires additional research. They only perform binary classification of brain tumors and disregard multiclass classification, requiring additional analysis to determine the kind of tumor.

A. H. Khan et al. [1] proposed a Hierarchical Deep Learning-Based Brain Tumor classification method. The study was conducted on MRI images from Kaggle dataset and achieved 92.13% classification accuracy. However, the system needs to be tested before deploying for clinical setup for brain tumor classification due to low overall accuracy.

A. K. Anaraki, M. Ayati, and F. Kazemi et al. [20] employed the Genetic Algorithms (GA) to find an optimal CNN architecture with lesser computation cost for the classification of brain tumors. They obtained 94.2% accuracy to classify Glioma, Meningioma, and Pituitary tumors from MRI images. However, GA could not find optimal CNN architecture, thus resulting in poor overall accuracy.

P. M. Siva Raja and A. V. rani, et.al [14] employed Bayesian fuzzy clustering (BFC) technique for image segmentation, nonlocal mean filter for image denoising and scattering transform, information-theoretic measurements, and wavelet packet Tsallis entropy for feature extraction and a hybrid DAE strategy for brain tumor classification. However, this technique takes a long time to compute and is computationally inefficient.

Gumaei A, Hassan MM, Hassan MR, Alelaiwi A, Fortino G. et al. [21] introduced an automated approach to assist radiologists and physicians in identifying different types of brain tumors. The study was conducted in three steps: brain image preprocessing, brain feature extraction, and brain tumor classification. In the preprocessing step, brain images were converted into intensity brain images in the range of [0, 1], using a min–max normalization rule. In the next step, the PCA-NGIST method (a combination of

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normalized GIST descriptor with PCA) was adopted to extract features from MRI images. In the final step, Regularized Extreme Learning Machine (RELM) classification was applied to identify and classify the tumor types. The results reported 94.23% accuracy.

Pashaei A, Sajedi H, Jazayeri N. et al. [28] developed different methods to identify meningioma, glioma, and pituitary tumors. In their model, a CNN was used to extract hidden features from images and select features. The proposed model consisted of four convolutional layers, four pooling layers, one fully connected layer, and four batch normalization layers. The authors used ten epochs, 16 iterations per epoch, and the learning rate in this model was 0.01. The performance of the proposed model was evaluated using a tenfold crossvalidation method, and 70% and 30% of the data was applied for training and system testing, respectively. The study compared the proposed method with MLP, Stacking, XGBoost, SVM, and RBF, and the results showed the high accuracy of the proposed method (93.68%).

Mittal M, Goyal LM, Kaur S, Kaur I, Verma A, Jude HD et al. [22] used the combination of Stationary Wavelet Transform (SWT) and a new Growing CNN (GCNN) to automate the segmentation process. In fact, they utilized these effective methods to identify brain tumors by MRI images. The evaluation results showed that the technique proposed in the study had the highest accuracy compared to the genetic algorithm; K-NN, SVM, and CNN.

Paul JS, Plassard AJ, Landman BA, Fabbri D et al. [32] used deep learning methods to classify brain images related to meningioma, glioma, and pituitary tumors. In this research, the same dataset, i.e., 3064 T1-weighted contrast-enhanced MRI brain images of 233 patients, was applied; two types of neural networks, i.e., fully connected and CNNs, were designed. Moreover, a fivefold cross-validation technique showed that the general methods, with an accuracy of 91.43%, worked better than the specific methods, which required image dilation.

Abiwinanda N, Hanif M, Hesaputra ST, Handayani A, Mengko TR, et.al [23] described CNN diagnose the three most common types of brain tumors. In the learning process, the “adam” optimizer was used, which is a method for stochastic optimization using the stochastic gradient descent principle. In the study, the CNN was trained by 3064 T-1 weighted CE-MRI from brain tumor images provided by Cheng. The dataset included 1426 images of meningiomas, 708 images of gliomas, and 930 images of pituitary tumors. Of all the available images, 700 images from each class were applied, of which 500 were used for the training phase, and another 200 images were considered for the validation phase. In this model, all convolutional layers in the architectures used 32 filters, ReLu was used as an activation function, the maxpool kernel size was 2×2, and all the fully connected layers used 64 neurons. There were three neurons in the output layer, and the softmax activation function was employed at the output layer. The best reported accuracy rates for training and validation were 98.51% and 84.19%, respectively.

Khan MA, Arshad H, Nisar W, Javed MY, Sharif M, et.al [7] described An MRI scan is used to completely analyze different body parts, and it also helps to detect abnormalities in the brain at earlier stages than other imaging modalities. Hence, complex brain structures make tumor segmentation a challenging task. This review discusses preprocessing approaches, segmentation techniques, feature extraction and reduction methods, classification methods, and deep learning approaches. Finally, benchmark datasets and performance measures are presented.

Neelum Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran and Muhammad Shoaib *et al.* [15] proposed the use of two pre-trained deep learning models i.e. Inception-v3 and DensNet201 for developing a multi-level feature extraction and concatenation method for the early detection of brain tumors and their classification. At first, they have extracted the features from different Inception modules from the pre-trained Inception-v3 model. Then they have passed those features to the softmax classifier to perform the classification of the brain tumors. Secondly, they have used a pre-trained DensNet201 to extract features from various DensNet blocks. Then they have concatenated those features and passed them to the softmax classifier to classify the brain tumors. The dataset that they have used comprised of three classes of brain tumors and it is available publicly. Their proposed methodology has produced exceptional results and outperformed all the existing state-of-the-art ML and Deep Learning (DL) models for brain tumor detection and classification.

Janki Naik and Sagar Patel, et.al [35] used the decision tree classification algorithm for the detection and classification of brain tumor from MRI images. In the pre-processing step they have used the median filtering process and texture feature extraction technique has been used to extract the features. Their proposed model has exhibited improved efficiency in comparison to the traditional image mining methods. The results that they have obtained have been compared with the Naïve Bayesian classification algorithm. The decision tree classification algorithm has achieved a precision of 100%, Sensitivity of 93%, Specificity of 100% and Accuracy of 96%.

Gopal S. Tandel, Antonella Balestrieri, Tanay Jujaray, Narender N. Khanna, Luca Saba and Jasjit S. Suri *et al.* [16] have proposed a transfer-learning-based AI paradigm using a Convolutional Neural Network (CNN) for brain tumor classification using MRI data. The transfer-learning-based CNN model has been benchmarked against six different ML classification algorithms, namely Decision Tree, Linear Discrimination, Naive Bayes, Support Vector Machine, K-nearest neighbour and Ensemble. Their proposed model has proven to be very useful in multiclass brain tumour grading and has yielded better results in comparison to the other ML models.

Ahmad M. Sarhan, et.al [17] has presented a computer-aided detection (CAD) technique for the classification of brain tumors in MRI images. The features from the brain MRI images have been extracted by utilizing the Discrete Wavelet Transform (DWT). The extracted features have then been applied to a CNN to classify the input MRI image. His proposed approach has produced an overall accuracy of 98.5%.

Heba Mohsen, El-Sayed A. El-Dahshan, El-Sayed M. El-Horbaty and Abdel-Badeeh M. Salem *et al.* [29] proposed the development of a Deep Neural Network (DNN) classifier for the classification of brain tumors on a dataset comprising of 66 brain MRI images of 4 types of brain tumors, namely, normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors. They have combined the classifier with DWT for feature extraction and principal components analysis (PCA). The DNN classifier yielded extremely good results with an average classification rate of 96.97%, average recall of 0.97, average precision of 0.97, average F-Measure of 0.97 and average area under the ROC curve (AUC) of 0.984 of all the four classes (normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors).

Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, Faiza Akram and Muhammad Imran, *et al.* [18] have conducted three studies using three architectures of convolutional neural networks (AlexNet, GoogLeNet, and VGGNet) to perform the classification of brain tumors such as meningioma, glioma, and pituitary. Then they have explored the transfer learning techniques, i.e., finetune and freeze using MRI slices of brain tumor dataset. They have applied data augmentation techniques to The MRI images to generalize the results, increase the dataset samples and reduce the chance of over-fitting. The proposed fine-tune VGG16 architecture has attained the highest accuracy up to 98.69% in terms of classification and detection.

Arı, O. F. Alcin, and D. Hanbay et al. [19] fused deep features obtained from AlexNet and VGG16.)e fused feature vector was then classified via Extreme Learning Machine (ELM). The study was conducted on MRI images from publicly available Figshare, Rider, and REMBRANDT datasets. The system achieved 96.6% accuracy.

N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, and M. O. Alassafi et al. [8] extracted deep features using VGG16, VGG19, and AlexNet and classified the features via ensemble classifiers. The system achieved the highest accuracy of 94.3%.

Z. N. K. Swati, Q. Zhao, M. Kabir et al., [24] classified brain tumor MRI images using fine-tuned AlexNet and VGG with an accuracy of 94.8%. P. Saxena, A. Maheshwari, and S. Maheshwari et al. [9] employed ResNet, Inception-V3, and VGG-16 and achieved the highest accuracy of 95% via ResNet. However, the techniques obtained a low overall performance and need to be tested before real-time deployment.

III. Conclusion

The accurate brain tumor detection is still very demanding because of tumor appearance, variable size, shape, and structure. Although tumor segmentation methods have shown high potential in analyzing and detecting the tumor in MR images, still many improvements are required to accurately segment and classify the tumor region. Existing work has limitations and challenges for identifying substructures of tumor region and classification of healthy and unhealthy images. The machine learning methods have contributed significantly but still require a generic technique. These methods provided better results when training and testing are performed on similar acquisition characteristics (intensity range and resolution); however, a slight variation in the training and testing images directly affects the robustness of the methods. In future work, research can be conducted to detect brain tumors more accurately, using real patient data from any medium (different image acquisition (scanners). Handcrafted and deep features can be fused to improve the classification results. Hence, the machine learning achieved to be highly efficient and precise for brain tumor detection, classification and segmentation.

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