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Classification Insights into Brain MRI Classification: Techniques, Interpretability, and Future

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Abstract: *This research paper comprehensively analyses various techniques for classifying brain MRI images. Through an extensive literature survey, the study explores and evaluates the effectiveness of different methodologies, ranging from traditional machine learning approaches to advanced deep learning models, in the context of brain tumour classification. The review critically examines feature extraction, selection methods, and classification algorithms, focusing on their performance in enhancing diagnostic accuracy. The synthesis of existing literature provides valuable insights into the current landscape of brain MRI classification techniques, shedding light on their strengths, limitations, and potential areas for future research.*

Keywords: Brain MRI, Deep Learning, CNN, SVM, KNN, ML

I. INTRODUCTION

In the intricate landscape of neurology, the emergence of brain tumors presents a formidable challenge. The human brain, with its billions of intricate cells, becomes a battleground when these cells decide to divide uncontrollably. The consequences are profound, compromising the health of the brain and its neighboring cells. This diverse array of tumors, ranging from benign to malignant, low-grade to high-grade, gliomas to meningiomas, and pituitary tumors, underscores the complexity of the challenge at hand. Early diagnosis and automatic tumor classification are the pillars of effective treatment planning for medical practitioners. The cost per patient associated with brain tumors has reached unprecedented heights, making it the highest among all cancer types. The urgency for a solution is evident, as these tumors can strike individuals of any age, disrupting the delicate balance of specific cell types and triggering rapid growth that jeopardizes typical brain function. Whether cancerous (malignant) or non-cancerous (benign), these formidable tumour cells demand attention. Primary brain tumors, originating within the brain tissue, present a treatable challenge with the potential for slowed expansion through the right drugs. On the other hand, secondary or metastatic tumors, originating elsewhere in the body necessitate proper surgery or radiation therapy for a chance at a cure.

The stakes are high, as brain tumors not only threaten the affected region but also pose a risk to neighbouring brain tissue. Monitoring their development is crucial in ensuring patient survival. In response to this pressing need, the "Mri Brain Classification" project emerges as a beacon of hope, aiming to redefine the landscape of brain tumor diagnosis and treatment. The field of medical imaging has witnessed significant advancements in recent years, with a focus on automatic classification methods. Machine Learning (ML) and Deep Learning (DL) approaches have taken center stage, each with unique advantages and challenges. ML methods, reliant on feature extraction and selection, have been foundational in classification. However, the advent of DL methods, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, including MRI analysis, offering unparalleled accuracy.

The journey has challenges; DL methods demand large training datasets, incur high time complexity, and may need help with small datasets and expensive GPUs. Nevertheless, transfer learning has emerged as a potential remedy for mitigating these challenges. The landscape of machine learning-based classifiers is diverse, featuring SVM, RF, FCM, CNN, NB, KNN, SMO, and DT. The simplicity and computational efficiency of CNN implementation have garnered significant attention, especially for applications with small datasets and ease of adoption by individuals with varying

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levels of expertise. As delve deeper into the realm of brain tumor classification, the project aims to bridge the gap between traditional ML and cutting-edge DL. It acknowledges the challenges posed by confined and imbalanced MR imaging datasets and strives to pave the way for technological improvements in feature extraction. The fusion of high- and low-level features without human intervention becomes a focal point, promising a more effective system for brain tumor classification. The complexities of tumor types, such as meningiomas, add another layer to the challenge. These tumors, invading the brain and spinal cord with three layers of membranes known as meninges, demand meticulous attention. Survival rates are intricately tied to tumor size, location, and patient age. Accurate diagnosis and effective treatment become paramount, and this is where MRI, with its varied pulse sequences, plays a crucial role.

However, manual assessment of brain MR scans is daunting for radiologists, prompting the need for computer-aided diagnosis (CADx). Traditional ML approaches, emphasizing pre-processing, feature extraction, and classification, face challenges in obtaining discriminative features. The limitations become apparent in the realm of brain tumor segmentation, especially when dealing with the structural complexity and variability of tumors. Enter deep learning, a game-changer in brain MRI categorization. By eliminating the need for manual feature extraction, DL methods offer a self-learning approach, requiring minimal pre-processing and showcasing promise in reducing the semantic gap between high- and low-level details. Convolutional Neural Networks (CNNs), tailor-made for image analysis, emerge as a powerful tool for feature extraction and bridging the semantic divide.

The journey towards a comprehensive solution involves the classification of brain tumors and the crucial aspect of segmentation. Manual recognition and tracking of brain tumor progression are time-consuming and prone to errors, necessitating an automated method to replace outdated manual systems. The significance of accurate segmentation is emphasized, especially in scenarios where tumors vary in appearance and shape. The research takes center stage on the BRATS (Brain Tumor Segmentation) dataset, a repository of images capturing the complexity of brain tumors. By training and assessing the Xception and Inception architectures on this dataset, the project aims to push the boundaries of medical image processing. The ultimate objective is to refine the understanding of brain tumors, improve diagnostic accuracy, and pave the way for more effective and personalized treatment plans. It symbolizes the fusion of technology and compassion, offering hope in the face of complexity and advancing the frontier of healthcare. Join us on this journey as strive to make a meaningful impact on the lives of those affected by the intricate challenges posed by brain tumors.

II. LITERATURE SURVEY

2.1 Brain MRI Classification

Nowadays, tumours are common and can be found anywhere. According to scientific terms, cells can lose control of their growth and develop abnormally large or abnormally shaped tissues if they do not divide correctly or in order. Any portion of bodies is susceptible to tumour formation. When compared to tumours in other parts of the body, brain tumours are the worst since they make therapy and treatment uncertain. So, to find brain tumours using image processing, a detailed survey is conducted. The various tumour kinds and their stages. Brain tumour identification using machine learning and fusion approaches was the subject of various studies. There was also a discussion of the different kinds of brain tumours and how neural networks can identify them. Researchers looked at the most important characteristics that might be utilized to extract features from brain tumours.[1]

To identify the impacted tumour location using MRI, the suggested algorithm is straightforward. It helps calculate the area of brain tumours and deals with pre-processing and segmentation of the affected region of interest and morphological operations. Initially, applying Median and Slantlet filters to remove MRI noise was helpful. Using the healthy cells as a reference, the final picture depicts the tumour cells spot on. The malignancy degree has been used to classify the pointed tumour. Based on the categorization of the experimental results, half of the brain tumour images are medium-stage, 10% are low-stage, and both may be treated. On the other hand, 40% are of high stage, suggesting that treatment is complex.[2]

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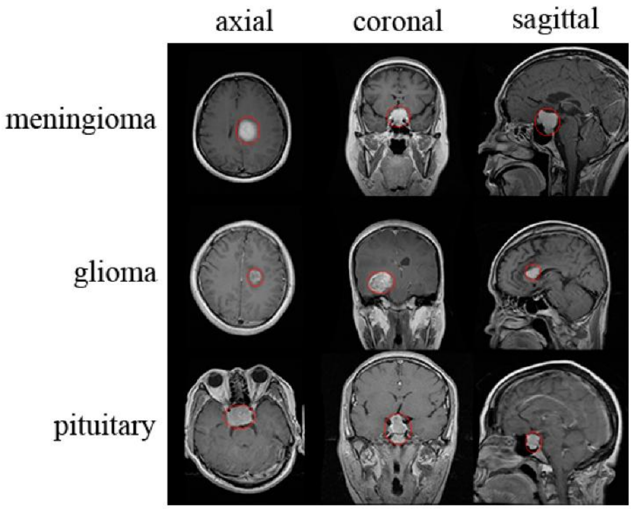

Fig.1 Brain MRI Classification

This study aims to design and test a classification system that can be applied to cerebral palsy (CP) records to categorize MRI results of children with CP. METHOD The pathologic patterns that manifest at various stages of brain development formed the basis of the classification system. Maldevelopments, predominately white matter injury, predominately grey matter injury, other, and normal results comprise the MRI categorization system (MRICS). A comprehensive handbook, including test cases, was created to describe these patterns ( ). They compared MRICS to other categorization algorithms and reviewed the relevant literature. Applicability and inter-rater reliability were tested in an exercise. Experts in the field of cerebral palsy (CP) or those involved with the CP registry were asked to participate in the exercise, and they could choose to categorize 18 MRIs or CP MRI reports of youngsters. RESULTS There was potential for harmonization and compatibility between MRICS and the classification systems used in the literature. In general, the interrater reliability was good (k=0.69; 0.54-0.82) among the 41 participants, and when employing the imaging-based categorization, it was perfect (k=0.81; 0.74-0.92). [3]

Brain tumour extraction is a crucial part of medical imaging anatomy. This aims to aid in medical diagnosis, which in turn helps treat illness. From simple threshold methods to more complex ones, such as deformable and hybrid approaches, this work aims to showcase a variety of MR brain picture segmentation techniques. This research aims to find brain tumours as soon as possible. This work addresses gliomas, the most common form of malignant brain tumours. This paper summarises several studies that used deep learning methods, such as a Convolutional Neural Network, to segment brain tumours. [4]

2.2 Deep Learning

This study discusses using deep learning and transfer learning to categorize brain cancers based on magnetic resonance imaging (MRI). Training and research can use transfer learning across various domains, functions, and distributions. A dataset that is available to the public was used in this study. There are 253 photos in the dataset; 98 show brains clear of tumours, and 155 show tumours. The methods utilized in this study include ResNet, Xception, DenseNet, NASNet, and Visual Geometry Group (VGG). The results demonstrate that the ResNet50 model and VGG16 achieve a 96% accuracy rate. The outcomes show that medical image processing is within the purview of transfer learning. [5]

This paper aims to enhance the classification of brain tumor grades (low-grade and high-grade glioma) and distinguish between brain images with and without tumors. The models demonstrate improved performance and reduced computational costs compared to a pure 3D convolutional ResNet18 model. Training from scratch and pre-training with weights from an action recognition dataset were compared. Notably, this study underscores the potential of spatiospatial models to outperform fully 3D convolutional models for specific tasks, such as brain tumor classification using the BraTS dataset. However, further comparisons across different tasks are recommended for a comprehensive evaluation. The study's limitation lies in using only T1 contrast-enhanced images for tumor classification, suggesting potential performance improvement by incorporating all available image types. [6]

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Brain cancers can be more accurately diagnosed with efficient classification methods using Magnetic Resonance Imaging (MRI). Prior research has employed algorithms like AlexNet and Support Vector Machine (SVM) to categorize brain MRIs. For a more precise and relevant categorization, augment it with gender and age as higher qualities. In addition, a DNN and a deep learning CNN-based method are suggested for efficient categorization. Other deep learning architectures, including LeNet, AlexNet, ResNet, and more conventional methods like SVM, are also employed for analysis and comparison. When analyzing brain tumours, age and gender biases are crucial because of their usefulness and involvement in classification. The suggested method generally beats both the current SVM and AlexNet. Overall, 88% accuracy was achieved with the LeNet Inspired Model and 80% with the CNN-DNN, while 82% and 64% were achieved with SVM and AlexNet, respectively, with the best accuracy being 100%, 92%, 92%, and 81%. [7]

One of the requirements of modern medicine is the use of automation in the healthcare sector. Such automation approaches are essential for radiologists and clinicians to accurately diagnose patients and organize their treatments. It is challenging to segment the tumour component from MR brain pictures automatically. Various techniques have been used to improve the automated system's segmentation efficiency. Nevertheless, medical image analysis segmentation can constantly be enhanced. This study suggests a method for segmenting images of brain tumours using deep learning. SWT and the novel Growing Convolution Neural Network are the suggested approach (GCNN) components. The primary goal of this project is to improve the standard system's accuracy. This study compares it to CNN and Support Vector Machine (SVM). Compared to SVM and CNN, the experimental findings show that the suggested method performs better across the board, including accuracy, PSNR, and MSE. [8]

This paper presents a method that effectively combines Deep Neural Networks (DNNs) and discrete wavelet transforms (DWTs) to categorize brain MRIs as usual, glioblastoma, sarcoma, or metastatic bronchogenic carcinoma. Even though it uses fewer hardware requirements and processes large-size images (256 x 256) more comfortably, the new approach architecture is similar to convolutional neural networks (CNN) architecture. Also, the DNN classifier performs very well compared to more conventional classifiers. Eventually, CNN will replicate the DWT's success and see how the two systems compare.[9]

Uncontrolled cell proliferation without outside stimuli is the hallmark of brain tumours. Brain tumours are extremely dangerous and can be deadly if detected late. Neurosurgeons and specialists use magnetic resonance imaging (MRI) scans to detect brain malignancies. Despite these limitations, several deep-learning approaches to brain tumour detection have been developed. Diagnosing a brain tumour relies heavily on the precise localization and measurement of the tumour. A hotspot for research into image processing and related methodologies, medical image processing is an intricate and challenging field. Brain tumour detection uses several sophisticated deep learning and machine learning methods. In this research, the performance of several networks—including CNN, ResNet, VGG16, and inception—to see which one achieved the highest level of accuracy in identifying brain tumours. Using these algorithms for magnetic resonance imaging (MRI) scans allows for the rapid and accurate prediction of brain tumours, which helps with patient treatment. This study analyzed four distinct methods and concluded that convolutional neural network architecture provided the best fit and accuracy. [10]

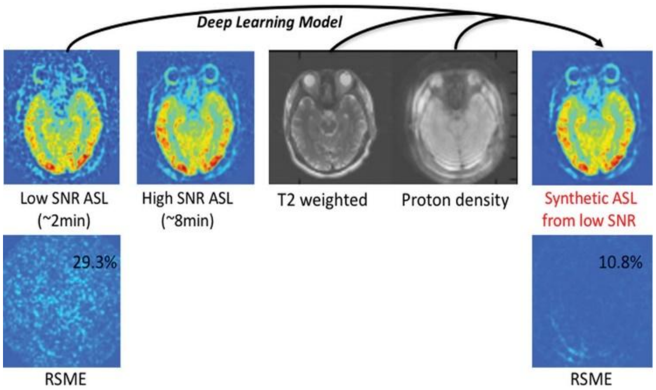

Fig.2 Brain MRI using Deep Learning

To categorize brain cancers into four types—glioma, meningioma, no tumour, and pituitary—this study presents a new and successful method for extracting and classifying features from brain MRIs. To evaluate the efficiency of the classification process, Additionally detailed the ROC, PRC, and cost curves. achieved 100% accuracy with the AlexNet CNN+RF model, 98.15% with the AlexNet CNN+SMO model, 88.55% with the AlexNet CNN+BayesNet model, and 86.25% with the AlexNet CNN+NB model. This research introduces a crucial method to categorize brain cancers from magnetic resonance imaging (MRI). One disadvantage of the current work is that the proposed model was examined using a relatively sized dataset. Therefore, future evaluations with big data size are crucial for gauging the model's performance. Another drawback is that real-world MRI data from Bangladeshi patients has yet to be used to test the suggested method.[11]

2.3 Convolutional Neural Network

Five different deep CNN models for benign and malignant brain tumour classification are detailed in this work: AlexNet, Vgg16, ResNet18, ResNet50, and GoogLeNet. With a precision of 0.937, recall of 1, and an F-measure value of 0.96774, the fine-tuned AlexNet model outperformed all other models tested on the benign and malignant brain MRI clinical dataset. Additionally, AlexNet's MRI brain classification findings are better than the current classical ML and DL approaches. Compared to traditional ML methods, it has been demonstrated by obviating the need for pre-processing, feature extraction, and feature selection. The focus will shift in the future to investigating robust DL architecture for faster, more accurate brain MRI categorization.[12]

Brain tumour segmentation using magnetic resonance imaging (MRI) is an essential medical tool for diagnostics, prognosis, growth prediction, tumour density assessment, and patient treatment planning. Brain tumours' diversity in structure, form, frequency, location, and visual characteristics (such as intensity, contrast, and visual change) makes tumour segmentation challenging. Intelligent medical picture segmentation is a promising new area for study into brain tumours, thanks to the recent developments in Deep Neural Networks (DNN) for image classification tasks. Due to the complexity and difficulty of even a little gradient diffusion, DNN training consumes a lot of time and computing power. To circumvent DNN's gradient problem, this study presents a practical approach to brain tumour segmentation using the Improved Residual Network (ResNet). Improving projection shortcuts or keeping track of all the available connection links are two ways to upgrade existing ResNet. Later stages receive these details, which increase ResNet's accuracy and allow it to learn faster. Existing ResNet's three primary components—information flow through network levels, residual building block, and projection shortcut—are all addressed by the proposed upgraded Resnet. This method streamlines the procedure while reducing computational expenses. [13]

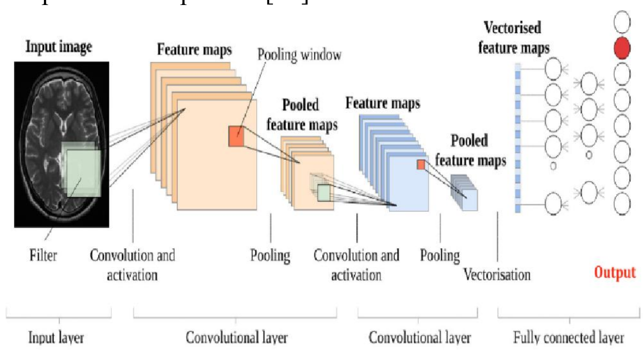

Fig.3 CNN Model for Brain MRI

Tumor categorization in magnetic resonance imaging (MR) pictures is introduced in this work using a novel deep learning approach. A generative adversarial network (GAN) uses a pre-trained deep neural network to learn the structure of magnetic resonance (MR) pictures in its convolutional layers and to extract robust features from various MR image datasets. Afterwards, the fully linked layers are swapped out, and the entire deep network is taught to differentiate between three types of tumours. The six-layer deep neural network classifier has around 1.7 million weight parameters and other methods. Each patient averages 13 images, and this procedure is applied to all of them (930 images). The entire design performance is evaluated using 5-fold cross-validation, which outperforms state-of-the-art approaches in accuracy. [14]

Meningioma, glioma, and pituitary tumours are only a few examples of brain cancers that may be classified using a pre-trained DCNN architecture VGG16 based on transfer learning. Improved classification accuracy is a byproduct of the proposed study, which uses transfer learning to circumvent the limitations of DCNN architectures' training data sample. Overfitting and vanishing gradient concerns are prevented by the suggested framework's employment of the GAP layer at the output. The state-of-the-art learning-based methods on the Figshare dataset with the suggested method achieve a classification accuracy of 98.93 percent. Medical professionals can benefit from this planned study since it will help them make better decisions about the types of brain tumours, which could decrease diagnosis errors. There is a need for improvement, even if the proposed DCNN architecture based on transfer learning has performed exceptionally well. Training can make use of a more extensive dataset down the road. Additionally, problems with feature dimensionality during parameter and weight transfers can be resolved. [15]

This article aimed to automate the process of brain cropping from MRI scans using convolutional neural network (CNN) model classification and to determine whether the subject has a brain tumour. The final accuracy is greater than 50% compared to the baseline. (random guess). However, it might be enhanced by tweaking the model's hyperparameters or using more train images.[16]

There has been much focus on medical picture classification recently, and the most popular neural network model for this type of task is the Convolutional Neural Network (CNN). CNN uses a complex architecture of several building blocks—convolution, pooling, and fully linked layers—to adaptively determine features via backpropagation. The primary goal of writing this paper was to train a convolutional neural network (CNN) model to detect brain cancers in MRI scans that had been boosted with a T1 weight. There are two significant components to the suggested system. The images should be pre-processed before employing CNN for classification using various image processing methods. Three different kinds of brain tumours are included in the dataset of thirty-one hundred sixty-four photographs used in the experiment (glioma, meningioma, pituitary). [17]

Classifying brain tumours is one of the most challenging problems in medical image processing. This research offers a hybrid approach that combines Neutrosophy with a Convolutional Neural Network (NS-CNN). The goal is to determine if the parts of brain pictures segmented from tumour regions are benign or malignant. The neutrosophic set-expert maximum fuzzy-sure entropy (NS-EMFSE) method was used to segment MRI images in the first stage. In the classification stage, CNN was used to obtain the features of the segmented brain pictures, which were then classified using SVM and KNN classifiers. On 80 cases of benign tumours and 80 cases of malignant tumours, a 5-fold cross-validation-based experimental evaluation was conducted. Using a variety of classifiers, the results showed that the CNN features performed exceptionally well in classification. While simulation results confirmed output data with an average success rate of 95.62%, experimental results show that CNN features demonstrated superior classification performance with SVM. [18]

Identifying brain tumours accurately and promptly is crucial for effective disease therapy. Not only does early diagnosis aid in the development of more effective drugs, it has the potential to save lives when the time comes. The development of biomedical informatics and computer-aided diagnosis has many advantages for neuro-oncologists. Instead of manually diagnosing a tumour, a tedious and error-prone process, machine learning algorithms have lately been utilized to process medical images and data. Computer-aided mechanisms are utilized to improve the results of conventional, traditional diagnosis methods. The standard method uses a fully connected network for classification after a convolutional neural network (CNN) extracts information. [19]

Significant problems surround detecting, segmenting, and extracting contaminated tumour regions from Magnetic Resonance Imaging (MRI) pictures. However, this is a laborious and repetitive procedure that relies on the skill of radiologists or clinical experts. Concepts in image processing can conceptualize the different anatomical structures of human organs. Using simple imaging techniques to detect aberrant structures in the human brain is complicated. In this research, a method for segmenting brain tumours using deep learning techniques is developed, called Fully Automatic Heterogeneous Segmentation, using a Support Vector Machine (FAHS-SVM). Incorporating a novel, entirely autonomous method built on structural, morphological, and relaxometry features, this study suggests isolating the entire cerebral venous system into magnetic resonance imaging (MRI). A hallmark of the segmenting function is the remarkable homogeneity of its anatomical components and their surrounding brain regions. One learning algorithm is the ELM, which uses hidden nodes in one or more layers. Regression and classification are only two of the many

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applications of these types of networks. The accuracy of tumour detection in brain MRI images has been trained and tested using a probabilistic neural network classification method. The numerical findings reveal an impressive 98.51% accuracy rate in identifying normal and pathological tissue from brain MRI scans, proving the efficacy of the proposed approach. [20]

Their study aimed to harness the capabilities of deep learning, particularly CNNs, to effectively categorize brain tumours based on information extracted from MRI scans. By contributing to the field of medical image analysis, the project sought to enhance the accuracy of brain tumor classification, with potential implications for improved diagnosis and treatment planning. The specifics of their methodology and findings were detailed in the journal's 10th volume, 6th issue, providing insights into the application of CNNs in neuroimaging. [21]

2.4 SVM, KNN Techniques

This research presents a new approach to classifying brain cancers, using segmentation, feature extraction, and multiclass classification to distinguish between four types of primary and secondary brain tumours. Although these tumours vary in size, shape, location, and severity, they may share a typical pattern of textures. The suggested approach comprises multiple model-texture features and an RBF kernel support vector machine based on fuzzy logic. The suggested system has a classification accuracy of 98.6% for meningioma-type tumours, 99.29% for metastasis, 97-8.7% for grade II gliomas, and 98.5 % for grade III gliomas. A CAD system can be created by combining the approaches for segmenting, extracting features, and classifying brain tumours. Radiologists could use this method to localize, diagnose, and interpret magnetic resonance imaging (MR) scans of brain malignancies better. [22]

By combining K-means clustering with a kernel-based support vector machine, this research presents a system for the efficient automated segmentation and classification of brain tumours (K-SVM). Classification of brain tumours is the final stage after pre-processing and segmentation, including feature extraction and selection. Skull stripping and the median filter are used to remove the ROIs. The feature extraction process uses textural features based on the Discrete Wavelet Transform (DWT), and principal component analysis is employed to choose the most significant features (PCA). Brain tumours can be classified as benign or malignant using kernel-based support vector machines (K-SVMs). Analyzing the results shows that the suggested framework is effective for identifying benign or malignant tissues in brain MRI images, with an accuracy of 98.75%, a precision of 95.43%, and a recall of 96.65%. Compared to state-of-the-art methodologies, the simulation results highlight the proposed methodology's accuracy, precision, and recall significance. We intend to integrate multiple classifiers and feature selection procedures in future work to assess the classifier's selective scheme. [23]

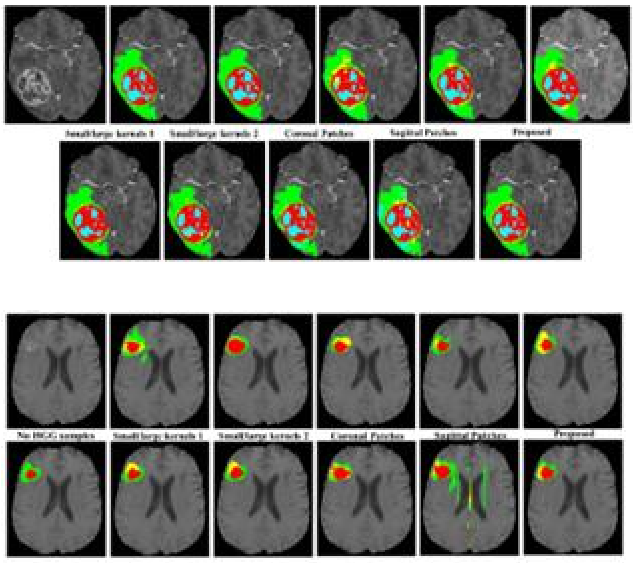

Fig.4 Brain Tumour Segmentation

Brain tumour detection is a challenging and vital area of medical image processing. Recent years have seen a proliferation of methods developed by researchers to detect and classify brain tumours. Nevertheless, most methods for training neural network models depend on MRI scans of a specified size. For this analysis, a dataset with dimensions of 128 by 128. Researchers have conducted comparison studies by comparing and evaluating various feature extraction approaches and classifiers. Researchers found that three-layer convolutional neural networks outperformed more conventional machine learning techniques for feature extraction and classification of pituitary, meningioma, and glioma. [24]

Brain MRI classification is a crucial undertaking. A method for automatically distinguishing between benign and malignant brain tumours, as well as between low-grade and high-grade gliomas, is presented in this study. This method uses the GLCM methodology to create a feature vector from an image's texture. The extracted features were categorized using the KNN and supervised SVM algorithms. Using the clinical database's 251 photos (85 of which are malignant and 166 of which are benign) and the Brats 2012 training database's 80 images (50 of which are low-grade gliomas and 30 of which are high-grade gliomas), the suggested system is tested. The suggested approach achieves an accuracy of 96.5 percent using SVM and 86.5 percent using KNN on the clinical database and 85.5 percent and 72.5 percent using SVM and KNN on the Brats database, respectively. [25]

2.5 Hybrid Approach

The suggested hybrid method was applied to brain MRI images to determine if a brain tumour was benign or malignant. By eliminating the need for human labourers and the associated risks of inaccuracy, an automated method for detecting brain tumours has emerged. This method combines the use of DWT (Discrete Wavelet Transform) for feature extraction, PCA (principal component analysis) for feature reduction, and SVM (support vector machine) for MR image classification. There is room for improvement in the future to better optimize precision and reduce the root-mean-square error rate. [26]

Brain tumours cause severe problems with the human nervous system and are currently considered the most severe illness affecting humans. A tumour is an abnormal, uncontrolled proliferation of brain cells. Its segmentation-based identification ranks high among the most challenging medical tasks. Image recognition by hand is labour-intensive and fraught with the possibility of human mistakes. One of the most valuable tools for diagnosing brain tumours is the Magnetic Resonance Imaging (MRI) technology, which provides detailed brain and skull images. The time-saving and highly effective automatic segmentation and classification method is ideal. The study recommends classifying tumours as benign or malignant based on MRI imaging. This work proposes a hybrid classifier strategy combining SVM and KNN classifiers to enhance efficiency.[27]

For brain tumour classification, a hybrid VGG16 NADE model has been suggested. With its 16 layers, the VGG16 pre-trained CNN can extract fine-grained features from MRI scans. The architecture's softmax function and Adam optimizer handle learning and classification. After removing unnecessary brain pictures and smoothing out the tumour border, a neural autoregressive density estimator (NADE) is used. The NADE provides the VGG16 with extra density information when training with MRI images. After being trained using the Adam optimizer and 10-fold cross-validation, the suggested technique is evaluated with a T1-weighted contrast-enhanced imaging brain tumour dataset. An accuracy of 96.01% was attained when the performance was assessed using macro sensitivity; the study finds that the hybrid method is the most suited for medical picture applications. One big problem with VGG-16 is how slowly it trains on datasets. This is because the input data is so large, which uses much space on storage and bandwidth, rendering the model useless. [28]

2.6 DWT Technique

A brain tumour develops when cells in the brain undergo abnormal and unregulated cell division. Researchers are eager to discover strategies to slow the spread of brain tumours, which have recently emerged as a significant cause of mortality in today's society. Image processing and signal-based analysis are two approaches used for brain tumour detection. This study applies a strategy based on robust image processing to MRI pictures. MRI pictures are highly favoured because of their clarity and lack of background noise. Before applying SVM for tumour detection, this work employs a clustering-based approach for picture segmentation. The classifiers took seven features into account and evaluated them. SVM produced a substantial outcome with an accuracy rate of 94.6%. [29]

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Brain tumours are collections of abnormal cells. As a result, the mortality rate among people rises. Hence, this publication suggests a fusion procedure to detect brain tumours by combining structural and texture data from four MRI sequences: T1C, T1, Flair, and T2. The fusion technique employs a discrete wavelet transform (DWT) in conjunction with Daubechies's kernel, yielding a more informative tumour region than a single MRI sequence. A PDDF, or partial differential diffusion filter, eliminates background noise following the fusion procedure. A proposed convolutional neural network (CNN) model is fed to the segmented tumour region using a global thresholding strategy to distinguish between tumour and non-tumour regions. To evaluate the suggested method, five publicly available datasets are utilized: BRATS 2012, BRATS 2013, BRATS 2015, BRATS 2013 Leader board, and BRATS 2018. On benchmark datasets, the results demonstrate that fused images outperform isolated sequences. [30]

To pick features from the high-dimensional clinical brain image datasets being investigated, this proposal employs an EGSO. In essence, VOI leads to more extensive characteristics being extracted. However, certain aspects are irrelevant and can be left out. The feature sub-selection approach used in this paper uses EGSO to achieve this. The separated features were inputs to the RBFNN classifier model after the suggested EGSO retrieved the relevant sub-features. In addition, while training the RBFNN, the Enhanced GSO optimizes its weight values. This novel strategy achieved better classification accuracy with a lower error rate by employing a faster convergence process. Due to the elimination of the local minima problem and subsequent reduction in calculation time, the suggested classifier is assuredly stable. Compared to earlier classifiers—PSVM and SVM—proposed in this research and the literature, the simulation results show that the RBFNN classifier based on EGSO is superior. This paper's study will help medical professionals make more consistent diagnoses by analyzing diseases. Using the best attributes that better characterize MRI, the suggested model generates an automated method for brain cancer detection. Brain tumours can be either benign or malignant.[31]

Brain tumour infection localization, segmentation, and detection It takes much time and effort to process MRI pictures. Image processing ideas allow us to see the many human anatomical structures. Simple imaging techniques have difficulty providing insight into the aberrant human brain. Magnetic resonance imaging is used to understand better and discern the brain's neuronal architecture. Magnetic resonance imaging (MRI) is a suite of imaging techniques that can scan and record the brain's inner workings. The primary goals of this research were to simplify and enhance the performance of DWT-based brain tumour region growth segmentation, a method for removing noise, and the extraction of grey-level co-occurrence matrix (GLCM) features. Morphological filtering, which eliminates post-segmentation noise, was the next step. The experimental results proved that the suggested method successfully distinguished between normal and pathological brain tissues from MR images, with an accuracy rate of approximately 100%. [32]

2.7 Different Techniques

Regarding small datasets, like medical imaging ones, capsule networks (CapsNets) are incredibly effective designs because of their routing by agreement approach, allowing them to leverage such information. Because brain cancer is so fatal and because misclassification of tumours can have devastating effects, accurate tumour classification is a top priority in the field of medical imaging. Recent work demonstrated the feasibility of designing a CapsNet architecture to classify different types of brain tumours. While other deep learning models do an excellent job of returning uncertain samples to human experts, CapsNets fails to do the same by failing to incorporate forecast uncertainty (resulting from uncertainty in the model weights). The is a Bayesian CapsNet framework present in this paper. It can calculate both the mean predictions and the entropy, which measures the uncertainty in those predictions. The results validate that returning the uncertain predictions is a suitable technique for increasing the network's interpretability, and they also show that filtering out the uncertain predictions can enhance the accuracy. [33]

Brain tumour identification and segmentation utilizing the superpixel technique based on transfer learning is presented in the proposed work. Depending on the presence or absence of tumour, the first step is categorizing brain scans as either usual, Low-Grade Glioma (LGG), or High-Grade Glioma (HGG). The 2019 Brain Tumor Segmentation (BraTS) competition database tests the suggested methods. The VGG-19 transfer learning model is used to perform the tumour identification job with training data from the VGG-19 transfer learning model at epoch 6, a training accuracy of 99.82%, a validation accuracy of 96.32%, and a testing accuracy of 99.30%. An AUC of 0.99, a sensitivity of 97.81%, and a specificity of 100% were all achieved. Step two involves applying the superpixel segmentation to isolate the tumour to the LGG and HGG pictures. An average detection dice index of 0.932 was achieved using the ground truth data in conjunction with the superpixel segmentation technique. Evidence from experiments shows that the proposed [34]

A tumour in the brain is an abnormal mass of cells that has grown there. One way to detect a brain tumour is by obtaining images of the brain tissue using magnetic resonance imaging (MRI). Then, a radiologist can manually segment the tumour boundaries on these images. Manual segmentation might be complex when dealing with a high volume of photos. More efficient and objective findings can be achieved by designing a computer-aided diagnosis (CAD) system to automate the segmentation of tumour boundaries. The purpose of this study was to evaluate and compare three segmentation algorithms—morphological geodesic active contour (MGAC), snake active contour (SAC), and morphological active contour without edge (MACWE)—on thirty-four brain MRI T1-weighted images that contained pituitary tumours, meningiomas, or gliomas. The performance of these methods using the Hausdorff Distance and the Jaccard Similarity Index (JSI) (HD). With an average JSI of 71.18% and an HD of 4.04 pixels, the MGAC achieved the best segmentation results. After the shift, the JSI for MGAC segmentation was 76.42% for gliomas, 76.84% for pituitary tumours, and 85.98% for meningiomas, respectively. This suggests that a random shift in contour initialization had a more significant impact on gliomas and pituitary tumours than meningiomas. The meningioma JSI was 77.94%, while the glioma JSI was 66.31 percent.[35]

Classifying brain tumours is a complex problem in medical image analysis. A shorter human lifespan might be the consequence of errors made in the diagnosis of brain tumours. There might be fewer mistakes made by humans if tumour diagnosis were automated. Due to recent technical breakthroughs, the research community has extensively used visual attention for medical image analysis tasks in creating computer-aided diagnosis systems. A multi-level attention method is presented here for brain tumour identification. In addition to prioritizing the tumour location, the suggested multi-level attention network (MANet) keeps track of the cross-channel temporal dependencies in the semantic feature sequence derived from the Xception backbone. Test how well the suggested method works on the Figshare and BraTS benchmark datasets. These experiments show that combining spatial and cross-channel attention improves generalizability and yields better results with fewer model parameters. This proposed MANet surpassed multiple previous models in the tumour recognition test. [36]

III. CONCLUSION

This research paper thoroughly reviews diverse techniques applied to classify brain MRI images, offering a comprehensive understanding of the field's current state. The literature survey highlights the evolution from traditional machine learning to the prominence of deep learning models, particularly convolutional neural networks, in achieving remarkable accuracy in brain tumor classification. The analysis underscores the significance of feature extraction and selection methods, emphasizing their crucial role in enhancing classification performance. While acknowledging the strides made in the field, the review also identifies areas for improvement, such as the need for standardization in datasets and continued exploration of hybrid models. Overall, this paper contributes a nuanced perspective to the existing body of knowledge, guiding researchers and practitioners in the ongoing pursuit of refining brain MRI classification methodologies for enhanced clinical applications

REFERENCES

[1]. Sharif, Muhammad & Li, Jian & Amin, Javeria & Sharif, Abida, Brain Mri Feature Extraction and Classification." 2020 11th International Conference on Computing, Communication and Networking Technologies (Icccnt). Ieee, 2020.

[2]. Ameer Hussian Morad and Hadeel Moutaz Al-Dabbas, "Classification of Brain Tumor Area for Mri Images", Journal of Physics: Conference Series, 2020

[3]. Kate Himmelmann, Veronika Horber, Javier De La Cruz, Karen Horridge, Vlatka Mejaski-Bosnjak, Katalin Hollody, "Mri Classification System (Mrics) For Children with Cerebral Palsy: Development, Reliability, And Recommendations", Developmental Medicine & Child Neurology, 2016

[4]. Sravan, V., Swaraja, K., Meenakshi, K., Kora, P., Samson, M, "Magnetic Resonance Images Based Brain Tumor Segmentation-A Critical Survey." In 2020 4th International Conference on Trends In Electronics And Informatics (Icoei) (48184), 2020

[5]. Krisna Nuresa Qodri, Indah Soesanti, Hanung Adi Nugroho, "Image Analysis for Mri-Based Brain Tumor Classification Using Deep Learning", Ijitee, Vol 5, 2021

[6]. Soumick Chatterjee, Farazahmed Nizamani, Andreas Nürnberge & Oliver Speck, "Classifcation of Brain Tumours in Mr Images Using Deep Spatiospatial Models", Scientific Reports, 2022

[7]. Imayanmosha Wahlang, Arnab Kumar Maji, Goutam Saha, Prasun Chakrabarti, Michal Jasinski, Zbigniew Leonowicz and Elzbieta Jasinska, "Brain Magnetic Resonance Imaging Classification Using Deep Learning Architectures with Gender and Age", Mdpi Sensors 2022

[8]. Mittal, Mamta, "Deep Learning Based Enhanced Tumor Segmentation Approach for Mr Brain Images." Applied Soft Computing 78, 2019

[9]. Mohsen, Heba, Et Al. Classification Using Deep Learning Neural Networks for Brain Tumors. Future Computing and Informatics Journal, Vol 3, Pp 68-71, 2018

[10]. Hajar Cherguif, Jamal Riffi, Mohamed Adnane Mahrez, Ali Yahaouy, And Hamid Tairi, "Brain Tumor Segmentation Based On Deep Learning," In International Conference On Intelligent Systems And Advanced Computing Sciences (Isacs), Ieee, 2019.

[11]. Alok Sarkar, Md. Maniruzzaman, Mohammad Ashik Alahe, And Mohiuddin Ahmad, "An Effective and Novel Approach for Brain Tumor Classification Using Alexnet Cnn Feature Extractor and Multiple Eminent Machine Learning Classifiers in Mris," Journal of Sensors, Hindawi, 2023

[12]. Sunita M. Kulkarni*, G. Sundari, "Comparative Analysis of Performance of Deep Cnn Based Framework for Brain Mri Classification Using Transfer Learning", Journal of Engineering Science And Technology Vol. 16, No. 4 (2021

[13]. Aggarwal, M., Tiwari, A.K., Sarathi, M. Et Al. An Early Detection And Segmentation Of Brain Tumor Using Deep Neural Network. Bmc Med Inform Decis Mak 23, 78 (2023).

[14]. N. Ghassemi, A. Shoeibi, And M. Rouhani, "Deep Neural Network with Generative Adversarial Networks Pre-Training for Brain Tumor Classification Based on Mr Images", Biomed. Signal Process. Control, Vol. 57, P. 101678, Mar. 2020.

[15]. Malla Pp, Sahu S, Alutaibi Ai. Classification Of Tumor in Brain Mr Images Using Deep Convolutional Neural Network and Global Average Pooling. *Processes*. 2023

[16]. Someswararao, Chinta & Reddy, Shiva & Appaji, Sangapu & Gupta, V, "Brain Tumor Detection Model From Mr Images Using Convolutional Neural Network", . Icscan49426, 2020

[17]. Seetha, J., And S. S. Raja. "Brain Tumor Classification Using Convolutional Neural Networks." Biomedical & Pharmacology Journal, Vol 11, 2018

[18]. Ozyurt F, Sert E, Avci E, Dogantekin E. "Brain Tumor Detection Based On Convolutional Neural Network With Neutrosophic Expert Maximum Fuzzy Sure Entropy. Measurement", Vol 147, J.Measurement.2019

[19]. Chirodip Lodh Choudhary, Chandrakanta Mahanty, Raghvendra Kumar, And Borjo Kishore Mishra, "Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network," In International Conference on Computer Science, Engineering and Applications (Iccsea), Ieee, 2020

[20]. Jia And Deyun Chen, "Brain Tumor Detection and Classification of Mri Images Using Deep Neural Network," In Ieee Access, Ieee 2020

[21]. Badza, M.; Barjaktarovic, C. "Classification Of Brain Tumors From Mri Images Using A Convolutional Neural Network". Journal Of Applied Science, 10(6),2020

[22]. Jayachandran And R. Dhanasekaran, "Multi Class Brain Tumor Classification of Mri Images Using Hybrid Structure Descriptor and Fuzzy Logic Based Rbf Kernel Svm", Iranian Journal of Fuzzy Systems Vol. 14, No. 3, (2017

[23]. Anil Kumar Mandle, Satya Prakash Sahu and Govind Gupta, "Brain Tumor Segmentation and Classification in Mri Using Clustering and Kernel-Based Svm", Biomedical & Pharmacology Journal, June 2022

[24]. Sowrirajan, S. R., Balasubramanian, S., & Raj, R. S. P." Mri Brain Tumor Classification Using A Hybrid Vgg16-Nade Model"., Brazilian Archives Of Biology And Technology, 66, E23220071, 2023

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[25]. Vijay Wasule, Poonam Sonar, "Classification of Brain Mri Using Svm and Knn Classifier", Third International Conference on Sensing, Signal Processing and Security (Icsss), 2017

[26]. Sanjeev Kumar, Chetna Dabas, Sunila Godara, "Classification of Brain Mri Tumor Images: A Hybrid Approach", Information Technology and Quantitative Management, 2017

[27]. Ms. Swati Jayade, D. T. Ingole, And Manik D. Ingole, "Mri Brain Tumor Classification Using Hybrid Classifier," In International Conference On Innovative Trends And Advances In Engineering And Technology, Ieeee, 2019.

[28]. Saran Raj Sowrirajan, Surendiran Balasubramanian, Raja Soosaimarian Peter Raj, "Mri Brain Tumor Classification Using a Hybrid Vgg16- Nade Model", Brazilian Archives of Biology and Technology. Vol.66, 2023

[29]. Chaudhary A, Bhattacharjee V. An Efficient Method for Brain Tumor Detection and Categorization Using Mri Images By K-Means Clustering & Dwt. Int J Inform Technol. 2020

[30]. Amin J, Sharif M, Gul N, Yasmin M, Shad Sa. Brain Tumor Classification Based on Dwt Fusion of Mri Sequences Using Convolutional Neural Network. Pattern Recognit Lett. 2020

[31]. Sungheetha, Akey, And Rajesh Sharma. "Gtikf-Gabor-Transform In Corporated K-Means And Fuzzy C Means Clustering For Edge Detection In Ct And Mri." Journal Of Soft Computing Paradigm (Jscp) 2, 2020

[32]. N. Varuna Shree, T. N. R. Kumar, "Identification and Classification of Brain Tumor Mri Images with Feature Extraction Using Dwt and Probabilistic Neural Network", Brain Informatics, 2018

[33]. Pranian Afshar, Arash Mohammadi, And Konstantinos N.Plataniotis, "Bayescap: A Bayesian Approach To Brain Tumor Classification Using Capsule Networks," Ieee Signal Processing Letters(Volume 27),2020.

[34]. Akshi Ahuja, B.K Panigrahi, And Tapan Gandhi, "Transfer Learning Based Brain Tumor Detection And Segmentation Using Superpixel Technique," In International Conference On Contemporary Computing And Applications, Ieee, 2020.

[35]. Ahmad Habbie Thias, Donny Danudirdjo, Abdullah Faqih Al Mubarok, Tati Erawati Rajab, And Astri Handayani, "Brain Tumor Semi-Automatic Segmentation On Mri T1-Weighted Images Using Active Contour Models," In International Conference On Mechatronics, Robotics And Systems Engineering (Morse), Ieeee, 2019.

[36]. Shaik, Nagur & Cherukuri, Teja, "Multi-Level Attention Network: Application to Brain Tumor Classification". Signal, Image and Video Processing.,2022