International Journal of Membrane Science and Technology, 2023, Vol. 10, No. 5, pp 375-390

The Detection of Brain Cancer Using Machine Learning: A Systematic Analysis of Methodology, Comparisons, Results and Challenges

MD Ashif Raja[1], Anzar Hussain Lone[2*], Manpreet Kaur[3], Preet Kaur [4], Rajinder Singh Sodhi [5], Neha[6]

[1,4] Om Sterling Global University, Hisar, India,

[5]J C Bose University of Science and Technology, YMCA, Faridabad, India,

[1,2,3,6]Lovely Professional University, Phagwara, PunjabIndia; E-mail: anzarhussainlone@gmail.com

Abstract: Among the deadliest illnesses that is not initially recognized in the context of cancer is brain cancer. Cancerous cells are created when cells proliferate quickly and uncontrollably. The changes in tumour location, size, and shape severely impair the ability to detect brain cancers. The wrong diagnosis of a brain tumour can have terrible and fatal consequences. So there is need of high level accuracy to find the tumor classification. The categorization, segmentation, analysis, and detection of brain cancer are the main topics of this work. In order to aid researchers, This study intends to offer an extensive exploration of the existing literature regarding brain tumor identification through the utilization of magnetic resonance imaging. Three different types of medical imaging for brain cancer were subjected to machine learning approaches (feature extraction, augmentation methods, segmentation, and anatomy of brain tumours) and identifies current issues that must be resolved for various machine learning algorithms to be applied widely in the treatment of personalised brain cancer. Ultimately, this comprehensive review compiles relevant scholarly works concerning brain tumor detection, accentuating its advantages, limitations, progressions, and challenges, thus paving the way for potential forthcoming investigations.

Keywords: Brain Cancer, Feature Extraction, Machine Learning Algorithm, Magnetic Resonance Imaging**,** Segmentation

1. INTRODUCTION

In our body brain is the one of the most important and complicated organs which work with billions of cells. The brainstem, which is predominantly shielded by the skull, is made up of the cerebrum, cerebellum, and brainstem [1, 3, 4]. Uncontrolled cell division causes an abnormal cell cluster to form in proximity to or within the brain., which show how a brain tumour grows. There are numerous ways to categorise brain tumours, such as primary, secondary, or metastatic tumours.

The size, outer later, or origin of the brain tumour are typically considered when evaluating it. Primary and secondary tumours are two different categories for tumours. As a result of the primary cancer tissue's tendency to begin in the brain and remain there, the brain. From other sections of the body, the secondary tumour may impact the brain. The classification model is ranked according to the rate of cell proliferation at which it occurs. Technical names for some brain tumours include meningioma, glioblastoma, and astrcytomas. About 70% of all brain tumours are primary tumours, with the remaining 30% being secondary tumours. Just as primary tumours, which are those that first develop in the brain, are classified according to their origin, so are other tumour types. The majority of secondary tumours, on the other hand, are malignant tumours that initially develop in any other organ of the body before spreading to the brain.

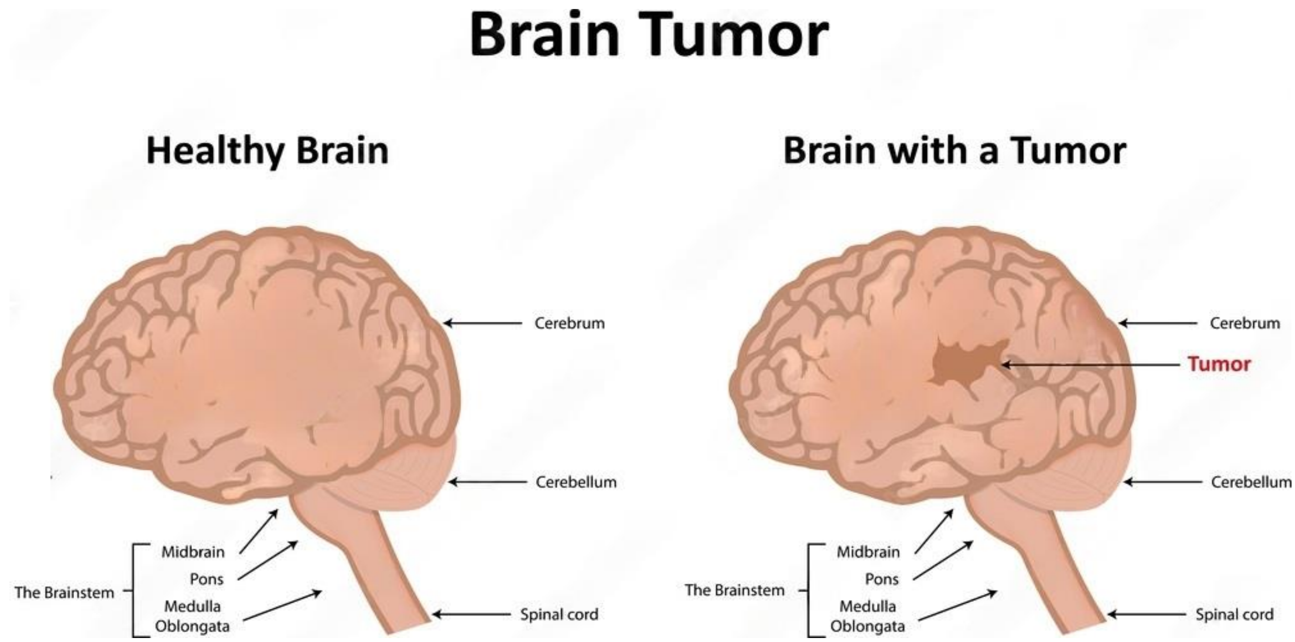

Fig1: Healthy and Brain with Tumor

Reference: https://www.thehealthsite.com/diseases-conditions/brain-tumour/

These tumours may be benign or malignant (cancerous) (benign). When compared to benign tumours, malignant brain tumours may be more dangerous because they grow quickly, invade nearby brain and spinal tissues, and provide a greater risk of death. It may be primary or secondary type. A more detailed categorization have classified these tumors into four grades. According to the WHO's grading system, gliomas are classified from I through IV and are the most prevalent category of brain tumour in adults. ‘Grade I tumours consist primarily of benign, normal-looking cells. Tumors classified as "Grade II" seem to be slightly atypical. Tumors classified as "Grade III" contain malignant and blatantly aberrant cells. Grade IV brain tumours are the most dangerous variety and contain rapidly proliferating and aberrant cells. The patient's treatment and recovery are greatly aided by early identification. Brain tumour diagnosis and grade determination is typically a difficult and drawn-out process.

Most clinical diagnoses, such as ischemic stroke, hematoma, and tumour, have reduced accuracy, which has been a problem, especially with sores. An important role in the early detection and management of such results is played by clinical imaging. It provides clinicians with information essential for a successful and convincing diagnosis of various illnesses. In light of division of ischemic stroke, discharge, hematoma, and tumour sores from cerebral MR and CT samples, some of the present approaches need to be upgraded in accordance with the emergence of new techniques in order to promote the accurate, quick process, and fully automated diagnosis.

The bulk of studies demonstrate how machine learning has been applied for detection, prognosis, and classification of diseases in agriculture [1] and the health sector [2,3]. Many different fields have made use of machine learning. Lung and colon cancer segmentation and classification [3], breast cancer segmentation and classification [4–7], and brain tumour detection and segmentation are the health topics that have garnered the most attention [8–10]. Using various cellular (histologic examination) procedures, resection is a component of a biopsy, which also includes pathological investigation. is the gold standard in the diagnosis of brain tumours. However, a biopsy is an intrusive diagnostic procedure that could cause bleeding or possibly damage and functional loss [9]. Because of this, non-invasive brain cancer identification by applying MRI has become an essential component of modern neuroimaging, allowing medical professionals to assess the morphological, molecular, metabolic, and functional characteristics of brain tumours [9,10]. It is crucial to divide the pixels from the provided sample for diagnosing cancer cells. The main picture sources are CT scan, X-rays, MRI, and others. The information that can be observed to determine if a process is aberrant or normal is provided by the collected picture sources.As a result, image processing is crucial in locating the human body's cancerous regions. The primary benefit of such a system will be the pre-handling of stage.

In a structural MRI, the grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF) of a healthy brain identified [11]. The majority of the differences observed during a structural MRI scan is caused by the water content of these tissues. The cerebral cortex is connected to other regions of the brain by a myelinated axon known as white matter (WM), which is composed of 70% water. It connects the brain's left and right hemispheres and transports data between neurons. the deep white matter region where the basal nuclei are located, also found in the grey matter, which is 80% water and comprises neuronal and glial cells that regulate brain activity. Although the ventricular system in the brain, the brain and skull, and the spaces between them are all filled with cerebrospinal fluid, which is virtually entirely water [11,12].

Brain Tumor Classification Methods:

According to the WHO's, there are more than 150 different forms of tumours that affect the central nervous system (CNS), these are primarily divided into primary and metastatic (secondary) cancers [13]. The brain or the tissues immediately surrounding it is where the first cancers develop. Metastatic tumours, on the other hand, develop in other body organs and travel through the circulation to the brain. While original tumours might be benign or malignant, metastatic tumours are regarded as diseased or malignant. The current de facto method of choice for classifying brain tumours is a biopsy. To obtain a sample, however, needs definitive brain surgery most of the time [14,15]. Yet, an automatic brain tumour categorization from an MRI is non-invasive, avoiding the need to take tumour samples and being safer. Furthermore, the diagnosis and planning of the appropriate course of therapy can be enhanced by the machine learning-based brain tumour classification from an MRI scan [16]. Because of this, automatic brain tumour categorization from MRI scans using machine or deep learning approaches is a current field of research, and encouraging results have been attained [17,18].

Machine Learning-Based Approach:

In ML approach, a task is given to a machine, and as it completes more of them, it gets better at it. Supervised, unsupervised, and reinforcement learning are the three main categories into which machine learning approaches are typically divided [19].

Unsupervised learning, on the other hand, includes training a data sample from a data source with the correct classification already provided by domain experts. Unsupervised learning makes use of an algorithm to find hidden patterns in unlabeled data. In contrast,, reward signals are used to direct a series of decisions in reinforcement learning. As a result, the algorithm learns by receiving rewards or penalties for its behaviour [19,20]. Machine learning has been used to classify brain tumours from MRI images, and promising classification performance has been reported [20–22].

In traditional machine learning-based brain tumour classification systems, preprocessing, segmentation, feature extraction, and classification steps are commonly present. Brain MRI images are significantly affected by the pre-processing of several noises, including salt-and-pepper, Gaussian, Rician, and speckle noise [23,24]. Applications based on machine learning have difficulties as a result of these sounds [25,26]. Consequently. A variety of approaches have been developed for noise reduction based on statistical features and frequency spectrum distribution [26].

The radiomics analysis process starts with tumour segmentation, which transforms the original medical image into an extractable image. Although the segmentation method has been extensively studied for a very long time, there is still a need for improvement, particularly in the field of medical picture analysis. removing tags, smoothing the foreground, adjusting intensity inhomogeneity, maintaining important edges, scaling, cropping, and skull-stripping are all included in pre-processing. [27].At the moment, there are three categories that may be used to categorise the segmentation techniques used to identify tumours in images: manual, semiautomatic, and automatic. The most widely used segmentation methods include threshold segmentation, fuzzy theory-based image segmentation, region-based image segmentation, and edge-based image segmentation. There are many tumour image segmentation algorithms, but there is no agreement on how to pick the best one for each situation.

Table 1 Summary of the ML based Approach

Reference	Dataset & its Reference	Algorithm	Image processing Technique	Tumor Types	Performance
[28]	SPES and SISS 2015	Expectation maximization	Expectation Maximization (EM)	Normal and abnormal	0.78±0.08 DSC on SPES and 0.53±0.26 DSC on SISS
[29]	BRATS 2015 Challenge	BA and RG	LS,PCA, DRLS and WS	Benign and malignant	Acc= RG 0.9753 DRLS 0.9716 PCA 0.9747 WA 0.9782
[30]	BRATS 2019 challenge	CNN	3D semantic segmentation,Relu GN	Benign and malignant	results 0.882 and 0.837 whole tumor and tumor core,
[31]	Private data	SVM	PCC, PCA, and ICA	Benign and malignant	0.82 ACC at PCC, 0.85 ACC at PCA, 0.79 ACC
[32]	14 normal and 87 abnormal images	ANN	Feedback PCNN (FPCNN), wavelet transform, PCA	Normal and abnormal	0.99 ACC
[33]	Private images collected from ShirdiSai Cancer Hospital	(SVM,KNN, and ANN)	Wavelet, shape, texture, and boundary features, ICA	Benign and malignant	0.99 ACC, 1.00 SE, 0.98 SP
[34]	Harvard	SVM	2D-DWT, Wavelet-energy	Normal and abnormal	0.97 ACC, 0.99 precision,0.92 SP, 0.98 SE
[35]	BRATS 2013 synthetic	RF	Multi-level Otsu threshold, HOG-TOP	Complete, core and enhance	0.93±0.04 HG DSC, 0.90±0.02 LG DSC
[36]	Harvard Medical School	Twin SVM	HMI	Benign and malignant	0.98 ACC, 0.99 SE, 0.92 SP
[37]	Harvard Medical School	Kernel support vector machine (KSVM)	Stationary wavelet entropy (SWE)	Benign and malignant	0.98 ACC, 0.99 precision, 0.96 SP, 0.98 SE
[38]	BRATS 2013 challenge	SVM	Fractional Sobel filter, statistical features	Healthy and un-healthy tissues	0.98 ACC, 0.86 SE, 0.98 SP
[39]	2012, 2013, 2014, and	Softmax	Stacked sparse	Benign and malignant	100% on 2012, 90% on

	2015 BRATS		autoencoder (SSAE)		2012 synthetic, 95% on 2013, 100% on Leaderboard 2013, 97% 2014 and 95%
[40]	Local data	SVM	CNN	Grade I, II, III and IV	100%
[41]	Harvard Medical School	SVM	BWT,GLCM ,GA	Benign and malignant	Accuracy 90 97.3 98.5 Error 10 2.7 1.5 Sensitivity 86.6 98.6 98.6 Specificity 84 96.1 97 Precision 93.3 96 98

Deep Learning Based Approach:

Fuzzy sets, artificial neural networks, and expert systems are a few of the cutting-edge classification methods that have gained popularity recently, but each one has drawbacks and has a lower accuracy level than others. Using the deep (CNN) architecture of deep learning, which achieves effective results in handling various machine learning issues, is one of the sophisticated categorization methods. GPU technology enables parallel processing while deep convolutional neural networks are employed for categorization. This approach assesses categorization and GPU technologies. Despite positive advancements in the field of shallow supervised machine learning algorithms for the categorization of brain cancers into their many categories, detecting brain tumours from an MRI image is still challenging. The main cause of these difficulties is the ROI detection, and typical handmade feature extraction algorithms are ineffective at efficiently extracting descriptive data [42].

The intricacies of brain anatomy and the substantial density of neural matter are the primary factors contributing to this lack of efficiency. In contrast to surface-level machine learning methods, deep learning relies on acquiring layered feature representations. In the context of brain cancer classification through deep learning, the models ascertain the most suitable descriptive details for characterizing diverse brain tumors. Due to the inherent characteristics of deep learning, the categorization of brain tumours is now a data-driven problem rather than a challenge based on manually created features [42,43]. The enormous amounts of MRI-based image data can be processed and evaluated objectively with the help of deep learning techniques. Many review papers have already been published that concentrate on the conventional techniques for segmenting MRI-based brain tumour images. A prominent deep learning model frequently applied in brain tumor classification tasks and bearing significant influence is the convolutional neural network (CNN). [43].

Per a suggestion put forth by Xue et al. [44], an adversarial encoder network should have the capacity to assess both the input image and the projected segmentation, as well as the input image and the reference segmentation. The scalar adversarial loss for the segmentation CNN was determined by the L1-loss between the two feature sets. This approach proved beneficial for the segmentation of brain tumors in MR images, with features being extracted at various scales for both input types. Adversarial training could also find application in weakly supervised anomaly segmentation, particularly in cases where image-level labels are available but voxel-level labels are not.The methods utilised for classifying brain tumours in the reviewed literature differ from one another

Some glioma segmentation strategies merged CNN application with other clustering or classification algorithms. One strategy suggests using CNN to make a localised structured prediction. Label patch dictionaries of size N are created by first extracting label patches from ground truth pictures and then clustering them using the k-means method to divide them into N groups. This technique substitutes the utilization of CNNs to categorize the central voxels within input image patches into different brain tissue classes. Subsequently, a 2D CNN is employed to classify multimodal input image patches into one of these defined clusters [45]. The BRATS dice scores for the overall tumour, core tumour, and active tumour zones are reported to be 83%, 75%, and 77%, respectively, regarding the segmentation effectiveness of the method.

However, Rao et al. [46] pursued an alternative approach by extracting multi-plane patches encompassing individual pixels. They proceeded to train four separate CNNs, each utilizing input patches derived from a distinct MRI modality image. The combined outputs from the final hidden layers of these CNNs were employed to train a Random Forest (RF) classifier through the use of feature maps. Unfortunately, the specifics of pre- and post-processing methodologies are undisclosed, resulting in an accuracy level of merely 67%.

A recommended T1-weighted MRI scan for brain cancers was offered by Minz et al. [50]. The dataset encompasses scans of various brain tumor types—glioma, meningioma, and pituitary tumors—across three distinct anatomical views: axial, sagittal, and coronal. Preprocessing involved two techniques: scaling and normalization applied to the images. To augment the training dataset, images were further enhanced through 90-degree rotation and vertical flipping. In their approach, a proprietary CNN model was employed, which underwent training using the Adam optimizer. Validation was conducted using 10-fold cross-validation, employing a mini-batch size of 16. The convolution layer weights are initialised using a Glorot initializer. The results of an MRI can be computationally analysed using the K-Nearest Neighbour methodology, a basic scientific application and classification method of image processing.

Ramdlon et al. [51] presented a paper in which classifier identify the different types of tumours by labelling them and detecting tumours and edoema in T1 and T2 picture sequences. This approach uses only the Axial region of the MRI results, which are categorised into the three groups of Astrocytoma, Glioblastoma, and Oligodendroglioma. The location of the tumour is determined using fundamental image processing techniques such image enhancement, image binarization, morphological image, and watershed. Following the segmentation of the Shape Extration Feature, tumour categorization is implemented. The tumour categorization findings were 89.5 percent, which can give more precise and detailed information about tumour detection.

In semantic segmentation, adversarial learning has been shown to be successful in collecting long-range and high-level label consistencies. A challenge that is specific to medical imaging is how to effectively and efficiently capture 3D semantics. A brand-new projective adversarial network, known as PAN, is being proposed by Khosravan et al. [52] that uses 2D projections to incorporate high-level 3D data. With the aid of this module, our segmentor can integrate certain global data into our adversarial network directly. We decided on pancreatic segmentation using CT scans for the clinical application. The suggested approach delivered cutting-edge performance without increasing the segmentor's complexity.The tumours are found using a computer-based diagnosis to analyse a specific magnetic resonance image. The tumour region is located using simple image processing methods.

In 2021, Ayadi and colleagues [53] introduced a computer-assisted diagnosis (CAD) system that harnessed the capabilities of a Convolutional Neural Network (CNN) algorithm to classify brain cancers. Their methodology was executed through the utilization of an 18-weighted layer CNN classifier, and the outcomes derived from this approach were evaluated across three distinct and independent datasets. Remarkably, their results demonstrated a high level of accuracy, with the CNN classifier achieving an impressive accuracy rate of 94.74% in accurately identifying brain tumors within the examined samples. This pioneering study not only underscores the potential of deep learning methods but also underscores the practical application of such techniques in enhancing brain cancer diagnosis and detection.

Dilip et al. [54] proposed a model of Image morphological procedures, image bianarization, and picture enhancement. For the computation of texture features uses the Grey Level Co-occurrence Matrix. There are five different features that make up the texture. The class of the query image determined using specific features, either alone or in combination. Images of brain cancer patients with the astrocyte type are only used for simplicity.

The core of evidence-based medicine, according to a concept put forth by Amisha et al. [55], is the creation of links and patterns from an existing body of data in order to generate clinical correlations and insights. In the past, we have relied on statistical techniques to identify these patterns and relationships.

In the pursuit of advancing early diagnosis for brain tumors, İrmak and colleagues [56] put forth a novel approach that harnessed the potential of deep learning through a Convolutional Neural Network (CNN) model. Their primary objective revolved around the task of categorizing brain tumors into multiple distinct categories, thus enabling a more precise and early detection process.

Notably, their strategy involved the development of three distinct CNN models, each tailored to address a specific categorization task. This approach underscored the recognition of the intricate variations present within different types of brain tumors, demonstrating the authors' dedication to comprehensively addressing the complexities of brain tumor classification.

The initial CNN model, meticulously designed and rigorously trained, yielded remarkably promising outcomes. With a staggering accuracy rate of 99.33%, this model showcased an impressive ability to identify brain tumors with exceptional precision. Such a remarkable achievement reaffirms the potential of deep learning-driven methodologies in revolutionizing the landscape of early brain tumor diagnosis, fostering a new era of medical advancements that hold the promise of significantly improving patient outcomes.

A CAD system was created by Sultan et al. [57] for the single-research classification of brain cancer MR images into three groups. A newly created deep neural network structure was also used to further categorise gliomas into several class (Grade II, III & IV). A 16-layer convolution network is proposed, with the input layer containing the preprocessed images as the first layer and the convolution layers and their activation functions as the following levels. In order to prevent overfitting, two dropout layers are also utilised, as well as a softmax layer, a fully connected layer with classification layer that generates the predicted class.

Sajjad et al. [58] created a revolutionary multi-grade brain tumour classification system based on deep learning. Our system has three components: Following three steps, a pre-trained VGG-19 CNN model is defined for multi-grade brain tumour classification. The dataset's tumour regions are segmented by a CNN model in steps 1, 2, and 3. The segmented data is then further augmented using a number of factors to enhance the amount of data samples. According to the experimental findings, the suggested CNN-based CAD system is effective at assisting the radiologist in making an accurate classification decision for multi-grade brain tumours into four categories.

By categorising brain tumours as benign or malignant, O¨ zyurt et al. [59] proposed a model is being used to build an effective automatic method for brain tumour segmentation. NS-EMFSE was used for brain tumours segmentation. Alexnet collected the characteristics of the segmented images using KNN, SVM and CNN architectures were used to determine the classification. SVM classifier produced the best results, scoring 95.62%. If more photos are used in the database, it is predicted that this accuracy rate would rise. The popular and effective segmentation and classification techniques CNN and Neutrosophy will be used, and this will significantly advance image processing.

A CNN-based approach is suggested by Kabir Anaraki et al. [60] for categorising MR images of glioma brain tumours. The use of a genetic algorithm was used to look for a CNN structure that delivers superior outcomes. The suggested technique can be used as a backup alternative for early detection during a non-invasive surgery. As a result, depending on the severity of the tumour, the appropriate action can be done at the appropriate moment.

The classification technique, feature selection, manual feature extraction, and region-of-interest definition are the most common steps in the suggested techniques in this field. In contrast, the suggested deep learning method automatically extracts useful features, negating the need to provide a feature extraction method. Utilising a network architecture that works well for one piece of data may produce subpar results for another.

The author Zacharaki et al. [61] provides a classification system for identifying adult brain tumours utilising perfusion MRI and rCBV maps in addition to standard MRI. Shape traits, picture intensity statistics, and rotation-invariant

The tumoral, edematous, and necrotic region's centre and marginal areas are used to extract gabor texture features. With the exception of tracing the ROIs, the technique is completely automated, therefore expert assistance is not needed. Overall, employing Support Vector Machines (SVM) for texture pattern classification holds significant potential in achieving an accurate and quantitative evaluation of brain tumors. Nonetheless, there's a need to expand the analysis to incorporate additional datasets. This step is crucial not only for assessing the method's applicability across a broader spectrum but also for refining its performance. The effectiveness of such classification systems tends to improve with more comprehensive training, thus amplifying their capabilities in practical scenarios.

Using digital pathology pictures, Ertosun and Rubin [62] suggest a deep learning-based, modular classification pipeline for automated glioma grading. The Cancer Genome Atlas (TCGA)'s whole tissue digitised images of pathology slides were used to train the deep learning modules. For the validation data set, convolutional neural networks were trained with more than 90% classification accuracy, and they attained 96% classification accuracy for the task of classifying GBM vs. LGG. They also succeeded in classifying LGG into Grade II or Grade III with a classification accuracy of 71%.

Seetha et al. [63] suggested a model depending on FCM segmentation, feature extraction for texture and shape, and Traditional brain tumor classification involves the application of classification methods centered around Support Vector Machines (SVM) and Deep Neural Networks (DNN). Images of a healthy brain and cancer are used to represent the classification results. Python is used to implement the system. It is a part of the category of trained models. As a consequence of this, just the top layer is trained. Also extracted from CNN are raw pixel values with feature values for depth, width, and height. Following that, the Gradient Decent based loss function is used to achieve high precision. Calculations are done for the validation accuracy, validation loss, and training accuracy. The training's accuracy rate is 97.5%. In a related vein, validation accuracy is good and validation loss is quite low.

In identifying the healthy and brain patient, the medical decision-making system El-Dahshan et al.[64] constructed using the supervised learning techniques (FP-ANN and k-NN) and the unsupervised learning techniques like wavelet transform, principal component analysis produced highly encouraging results. The worst sensitivity and specificity rates were achieved by the ANN technique. Our approach is applicable to all MR image types, including proton density (T1-T2-PD) and T1-T2-weighted images. In order to classify the MR images of the human brain, this study created two hybrid techniques: DWT + PCA + FP-ANN and DWT + PCA + k-NN. According to the results, the suggested strategy can produce a reliable classifier that is accurate.

Paul et al. [65] suggested segmentation method to overcomes the limitations of the traditional K-means algorithm and produces results that are both qualitatively and quantitatively highly satisfying. The segmentation results mentioned above are in line with current medical standards. Additionally, the rate of segmentation success in brain MRI images obtained from all three perspectives is quite high and satisfactory. Nearly majority of the test cases' real-time execution times are under 9 seconds.

A technique to improve classification performance was proposed by Cheng et al. [66]. First, instead of using the original tumour region as the ROI, the augmented tumour region created by image dilation is used since tumour surrounding tissues can also provide crucial information about the type of tumour. Increasingly smaller ring-shaped subregions are created within the enlarged tumour region. We assess the efficacy of the suggested approach through the examination of three distinct feature extraction techniques: the intensity histogram, the grey level co-occurrence matrix (GLCM), and the bag-of-words (BoW) model, employing an extensive dataset. Notably, our methodology involves an enhancement wherein the augmented tumor region, as opposed to the conventional tumor region, is employed as the Region of Interest (ROI). As a result of this augmentation, we observe an improvement in accuracy across the intensity histogram, GLCM, and BoW model. This results in improvements in accuracy of 82.31% from 71.39%, 84.75% from 78.18%, and 88.19% from 83.54%, respectively. Ring-form partition and region augmentation both have the potential to improve accuracy by up to 87.54%, 89.72%, and 91.28%, respectively.

Papageorgiou et al.[67] suggested FCM grading model which is capable of providing diagnostic results with a respectably high degree of accuracy. More specifically, classification accuracy for low-grade and high-grade brain tumours was 92.68% (38/41) and 93.22% (55/59) respectively. FCM is based on human expertise, as opposed to data-driven models. Furthermore, it is not dependent on any training method that is biassed against the size of the available data sets for it to be robust. When diagnosing new cases, it can accurately explain decisions and provides some transparency. The latter is of special relevance since it offers ways to improve inter- and/or intra-observer agreement, lower uncertainty, and gain a better grasp of the diagnostic criteria for tumour grading.

Huang, Z et al. [68] introduces CNNBCN, a convolutional neural network created by ER, WS, and BA algorithms and depend on complicated networks with altered activation function for picture classification of brain tumours. According to experimental findings, the CNNBCN original model and updated model perform better in terms of classification accuracy than several manually created neural networks. Additionally, it performs on par with one of the most effective picture categorization models available right now. The CNNBCN classifier not only produced acceptable outcome in the area of classifying images of brain tumours, but it also served as a guide for creating network topologies.

Ge et al. [69] devised an innovative approach involving both actual and pairwise Generative Adversarial Network (GAN)-enhanced MRIs for training purposes. The efficacy and reliability of this approach were convincingly demonstrated through outcomes on the testing dataset. By integrating two extensive datasets comprising authentic and GAN-augmented MRIs, the proposed strategy showcased an enhanced capability for the classifier to generalize when confronted with the testing set. The multi-faceted impact of this approach extends to the post-processing stage, which holds significance in diagnosing conditions based on volumetric 3D imaging. The two-stage training methodology, combined with the amalgamation of real and GAN-augmented MRIs, promises benefits for post-processing procedures. Comparisons conducted against existing methodologies unveiled that the proposed technique, employing a fusion of genuine and GAN-augmented training datasets, delivered results that are on par with the current state-of-the-art standards, even when dealing with diverse datasets.

Noreen et al. [70] has proposed a model in which two distinct possibilities were evaluated. First, the features were taken from multiple DensNet blocks using a pre-trained DensNet201 deep learning model. These features were concatenated, and the brain tumour subsequently categorised using the softmax model. The attributes from different Inception modules were pulled from the pre-trained Inception-v3 model, concatenated, and then sent to the softmax in order to categorise brain tumours. For the classification of brain tumours, the ensemble method, which concatenates dense blocks using the pre-trained DensNet201 model, performed better than the other research methods. With a testing accuracy of 99.51% on test samples, the suggested procedure produced the best results in the diagnosis of brain tumours.

Kurup et al. [71] proposed a paper in which examine how data pre-processing methods affect disease classification. The ailment taken into consideration for this paper is a brain tumour. There are various approaches that address the challenge of disease categorization from the perspective of image processing. CNN is a modern and widely used deep learning method, are mostly employed for image categorization applications. The traditional CNN requires an enormous amount of labelled data, which is difficult for the medical industry. This problem can be solved via capsulenet. As a result, the capsulenet is used in the current study to classify brain tumours. The suggested approach demonstrates how crucial data pre-processing is to improving the capsulenet architecture used for classifying brain tumours.

Sharif et al. [72] introduce a novel automated deep learning approach designed for the classification of multiclass brain tumors. Their proposed methodology involves adapting and training the Densenet201 Pre-Trained Deep Learning Model through a process of deep transfer learning, especially suited for handling imbalanced datasets. The distinguishing characteristics of the trained model are extracted from the average pool layer, which encapsulates precise information specific to each type of cancer.Two distinct techniques are employed in this study. The first technique, named Entropy-Kurtosis-based High Feature Values (EKbHFV), relies on high feature values derived from the entropy and kurtosis statistics. The second technique involves a modified genetic algorithm (MGA) based on metaheuristics.This comprehensive approach represents an innovative stride towards more accurate and refined multiclass brain tumor classification, leveraging a combination of deep learning, statistical measures, and genetic algorithm techniques.

Emrah Irmak [73] proposed an innovative CNN model geared towards the multi-classification of brain tumors with the primary goal of early detection. Notably, this model's hyperparameters are systematically fine-tuned via a grid search, thus optimizing its performance. The study leverages three distinct and reputable CNN models, each applied to separate medical image datasets that have been publicly released for the purpose of brain tumor classification. Remarkably, this approach achieves exceptional accuracy levels. The detection of brain tumors, for instance, is accomplished with an impressive accuracy rate of 99.33%. Moreover, when classifying brain magnetic resonance images into categories such as glioma, meningioma, pituitary, normal brain, and metastatic, a satisfactory accuracy of 92.66% is attained. Notably, the model excels in accurately categorizing glioma brain tumors into grades II, III, and IV, achieving a remarkable accuracy of 98.14%.

Çinarer et al. [74] propose a DNN-driven framework for the classification of brain cancers. The adept identification of glioma grades is achieved through the integration of high-dimensional 3D imaging features, an intricate method for feature selection, and the utilization of a deep learning classifier. This recommended model has demonstrated notable effectiveness in glioma grading, exhibiting an F1 score of 96.97% using wavelet filters. The precision and recall rates stand at 94.12% and 100%, respectively, while the area under the ROC curve is 98.75%, reflecting the model's robust performance. Remarkably, the accuracy reaches 96.15%. Employing the DNN model proves particularly valuable in identifying wavelet filters that offer the highest accuracy for classifying Grade II and Grade III cancers. This underscores the model's capability to distinguish nuanced variations in glioma grades, showcasing its potential to aid in accurate and reliable cancer grading processes.

Convolutional neural networks and computer-aided tumour detection systems have made significant advancements in machine learning and offered success stories. Rehman et al. [75] put forth a comprehensive framework designed for the classification of brain tumors, encompassing pituitary, glioma, and meningioma types. Leveraging the MRI slices from the brain tumor dataset available on Figshare, each architecture explores the application of transfer learning techniques, specifically fine-tuning and freezing.In order to enhance the dataset's size and mitigate the risk of overfitting, the study incorporates data augmentation techniques applied to the MRI slices. Through meticulous experimentation, the fine-tuned VGG16 architecture emerged as the most successful, achieving a remarkable accuracy level of up to 98.69% in both classification and detection tasks. This achievement underscores the effectiveness of their proposed framework and the potential of transfer learning in enhancing brain tumor classification accuracy.

Table 2 Summary of the DL based Approach

Reference	Dataset & its Reference	Algorithm	Image processing Technique	Tumor Types	Performance
[14]	Online Available [76]	CNN	reduction, enlargement, and normalisation	Pituitary, Meningioma, and Glioma	ACC 91.9%, precision 94.81%
[47]	Online Available	CNN	AlexNet and GoogLeNet	Pituitary, Meningioma, and Glioma	80%
[48]	ADNI	multi-scale convolutional neural network (MSCNN)	denoising, Skull stripping, sub-sampling	Benign, Malignant	ACC 90.1%
[49]	Local dataset [76]	SVM	Image fusion with contourlet transform	Meningioma, Glioma,	ACC 93%
[50]	Local dataset [76]	Adaboost	resizing enhancement	Benign, Malignant	ACC 89.90%
[51]	TCIA	KNN	resizing, cropping, median filtering	Astrocytoma Oligodendroglioma	ACC 89.5%
[57]	Tianjing Medical University REMBRANDT	CNN	down-sampling (convolution, Rectified Linear Unit (ReLU),	Glioma, meningioma and pituitary classification	98.7%
[58]	Radiopaedia dataset Brain tumor dataset	Deep CNN with Extensive Data Augmentation	multi-grade brain tumor classification and segmentation	Glioma grade classification	90.67%
[59]	TCGA-GBM	Neutrosophy and Convolutional Neural Network (NS-CNN)	Neutrosophic Expert Maximum Fuzzy-Sure Entropy Set – CNN (NS-EMFSE-CNN)	Brain tumor and brain non-tumor classification	95.62%
[60]	TCGA-LGG REMBRANDT Hazrat-e Rasool General Hospital	convolutional neural networks and genetic algorithms	data rescaling method	Glioma grade classification	90.9%
[61]	3.0-T MRI scanner system image	binary support vector machine	FSL library of analysis tools	Benign, Malignant type of tumor	88%

[62]	TCGA-GBM TCGA-LGG	CNN	deep learning pipeline	Glioma grade classification	96%
[63]	IMAGENET	CNN , SVM	Fuzzy C Means	Benign, Malignant type of tumor	97.5%
[64]	Harvard Medical School Website	FP-ANN and k-NN	PCA & ICA	Glioma grade classification	98%
[65]	Local dataset	K – Means with advanced Dual Localization	OTSU, K – Means	Glioma, meningioma and pituitary classification	91.43%
[66]	Publicly available dataset	GLCM	Intensity histogram, GLCM, and raw patch-based BoW	Glioma, meningioma and pituitary classification	91.28%
[67]	University Hospital of Patras	fuzzy cognitive maps (FCMs)	weight matrix of FCM	Glioma grade classification	92%
[68]	Available online	CNNBCN	Erdos-Renyi (ER) algorithm, Watts-Strogatz (WS) algorithm and Barabasi-Albert (BA) algorithm	Meningioma, Glioma& Pituitary	ACC 95.49%
[69]	The Cancer Genome Atlas (TCGA) [77]	Multi-stream 2D-CNN	Augmentation using GAN	low-, mid- and high-grade of Glioma	SPE 92.17%
[70]	Available online	Iception-V3 DensNet201	AdaGrad and RMSProp algorithms	Pituitary, Meningioma & Glioma&	ACC 99.51% of DensNet201 & ACC 99.34% of Iception-V3
[71]	Available online	CapsulNet	flipping, patching	Pituitary, Meningioma & Glioma&	MG: PR 85%, RE 94%, F1-Score 94, %GL: PR 85%, RE 94%, F1-Score 94%, PT: PR 85%, RE 94%, F1-Score 94%
[72]	BraTS 2018 & 2019	Pre-trained DenseNet201	Transfer learning- & Entropy-kurtosis based	low-grade glioma & high-grade glioma	low-grade glioma Accuracy :99.3% and high-grade glioma Accuracy: 99.8%
[73]	RIDER [79]	Custom CNN model	ReLU, normalization, max pooling	Class 1: Normal, Metastatic, Meningioma, Glioma& Pitiutary Class 2: Grade II, III & IV	Class 1: ACC 92.66% Class 2: ACC 98.14%
[74]	The Cancer Imaging Archive (TCIA) [78]	DNN	DWT	Pituitary, Glioma, and meningioma classification	Accuracy 96.15%,
[75]	Available online [76]	AlexNet, GoogleNet & VGG16	augmentation, contraststretching	Pituitary, Glioma, and meningioma classification	AlexNet-accuracy 95.46% GoogleNet-accuracy 98.04%
[80]	Private Data	Savitzky-Golay denoising	GLCM, 3DCNN-BTC, DAEN-BTC	Benign, Malignant type of tumor	31.14%, 16.09% and 11.48% during benign; during malignant higher

					accuracy 35.18%, 19.17% and 22.80%;

Table 2. A summary of methods for classifying brain tumours based on machine learning.

CONCLUSIONS

In the last few decades, there has been a revolution in the use of technology to diagnose and treat cancer. In light of how seriously brain tumours influence human health, this research has provided a systematic evaluation of current methods for detection and treatment. This article's main objective is to evaluate, analyse, classify, and identify current limitations in the approaches used to diagnose various forms of brain cancer. The image pre-processing, noise removal, feature extraction, tumour fragmentation, and classification stages of automated cancer diagnosis have been demonstrated in this paper with standard datasets. This study's primary objective is to give new researchers who want to start their research activities in this sector with a knowledgeable basis.

Redesigning the research pipeline, comprehending cancer growth phenomena, developing preclinical models, accurately handling complicated cancers, early detection, and treatment, innovative approaches to designing and delivering clinical investigations, and improving accuracy.

The appearance, shifting size, shape, and structure of brain tumours continue to make accurate tumour detection extremely difficult. Despite the significant strides made by tumor segmentation algorithms in the evaluation and identification of tumors within MR images, it's imperative to acknowledge that there remains a considerable room for advancement. While these algorithms have shown promising potential, their effectiveness in accurately segmenting and classifying tumor regions requires further refinement and enhancement to achieve optimal outcomes.

The intricate nature of brain tumors and the variability in their appearance within imaging data underline the complexity of the segmentation task. Notably, the challenge lies in capturing the diversity of tumor shapes, sizes, and appearances across different patients, imaging modalities, and pathological conditions. Moreover, factors such as image quality, noise, and artifacts can introduce additional complexities that demand sophisticated solutions.

Efforts should be directed toward developing algorithms that are robust, adaptive, and capable of handling these complexities. This involves harnessing advancements in machine learning, deep learning, and image processing techniques to create algorithms that can effectively capture the nuances of tumor boundaries and internal structures. Enhanced data augmentation strategies, integration of multimodal information, and the incorporation of domain-specific knowledge can all contribute to the improvement of segmentation accuracy and generalizability.

Furthermore, the translation of algorithmic developments into clinical practice necessitates rigorous validation and integration into existing medical workflows. Collaborations between computer scientists, medical experts, and imaging specialists are crucial to ensure that these algorithms align with the needs of clinical practitioners and lead to meaningful improvements in patient care.

In conclusion, this review covers all relevant concerns, the most recent research, as well as its shortcomings and challenges. The researchers will find it helpful to have the expertise necessary to quickly and successfully conduct new study.

REFERENCES

[1] Afework, Y.K.; Debelee, T.G. Detection of Bacterial Wilt on Enset Crop Using Deep Learning Approach. Int. J. Eng. Res. Afr. 2020, 51, 131–146.

[2] Debelee, T.G.; Schwenker, F.; Ibenthal, A.; Yohannes, D. Survey of deep learning in breast cancer image analysis. Evol. Syst. 2019, 11, 143–163.

[3] Debelee, T.G.; Kebede, S.R.; Schwenker, F.; Shewarega, Z.M. Deep Learning in Selected Cancers' Image Analysis—A Survey. J. Imaging 2020, 6, 121. [PubMed]

[4] Debelee, T.G.; Amirian, M.; Ibenthal, A.; Palm, G.; Schwenker, F. Classification of Mammograms Using Convolutional Neural Network Based Feature Extraction. In Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering; Springer International Publishing: Berlin/Heidelberg, Germany,2018; pp. 89–98.

[5] Debelee, T.G.; Gebreselasie, A.; Schwenker, F.; Amirian, M.; Yohannes, D. Classification of Mammograms Using Texture and CNN Based Extracted Features. J. Biomimetics Biomater. Biomed. Eng. 2019, 42, 79–97.

[6] Debelee, T.G.; Schwenker, F.; Rahimeto, S.; Yohannes, D. Evaluation of modified adaptive k-means segmentation algorithm. Comput. Vis. Media 2019, 5, 347–361.

[7] Kebede, S.R.; Debelee, T.G.; Schwenker, F.; Yohannes, D. Classifier Based Breast Cancer Segmentation. J. Biomimetics Biomater. Biomed. Eng. 2020, 47, 41–61.

[8] Megersa, Y.; Alemu, G. Brain tumor detection and segmentation using hybrid intelligent algorithms. In Proceedings of the AFRICON 2015, Addis Ababa, Ethiopia, 14–17 September 2015.

[9] Roberts, T.A.; Hyare, H.; Agliardi, G.; Hipwell, B.; d'Esposito, A.; Ianus, A.; Breen-Norris, J.O.; Ramasawmy, R.; Taylor, V.; Atkinson, D.; et al. Noninvasive diffusion magnetic resonance imaging of brain tumour cell size for the early detection of therapeutic response. Sci. Rep. 2020, 10.

[10] Villanueva-Meyer, J.E.; Mabray, M.C.; Cha, S. Current Clinical Brain Tumor Imaging. Neurosurgery 2017, 81, 397–415.

[11] Rosenbloom, M.J.; Pfefferbaum, A. Magnetic resonance imaging of the living brain: evidence for brain degeneration among alcoholics and recovery with abstinence. Alcohol Res. Health J. Natl. Inst. Alcohol Abus. Alcohol. 2008, 31, 362–37.

[12] Charles R. Noback, Norman L. Strominger, R.J.; A. Ruggiero, D. The Human Nervous System: Structure and Function; Humana Press: Totowa, NJ, USA,2005.

[13] Kleihues, P.; Louis, D.N.; Scheithauer, B.W.; Rorke, L.B.; Reifenberger, G.; Burger, P.C.; Cavenee, W.K. The WHO Classification of Tumors of the Nervous System. J. Neuropathol. Exp. Neurol. 2002, 61, 215–225.

[14] Badža, M.M.; Barjaktarovi´c, M.C. Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network. ˇ Appl.Sci. 2020, 10, 1999.

[15] Tandel, G.S.; Biswas, M.; Kakde, O.G.; Tiwari, A.; Suri, H.S.; Turk, M.; Laird, J.; Asare, C.; Ankrah, A.A.; Khanna, N.N.; et al. A Review on a Deep Learning Perspective in Brain Cancer Classification. Cancers 2019, 11, 111. [PubMed]

[16] Quon, J.; Bala, W.; Chen, L.; Wright, J.; Kim, L.; Han, M.; Shpanskaya, K.; Lee, E.; Tong, E.; Iv, M.; et al. Deep Learning for Pediatric Posterior Fossa Tumor Detection and Classification: A Multi-Institutional Study. Am. J. Neuroradiol. 2020.

[17] Díaz-Pernas, F.J.; Martínez-Zarzuela, M.; Antón-Rodríguez, M.; González-Ortega, D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network.Healthcare 2021, 9, 153. [PubMed]

[18] Deepak, S.; Ameer, P. Brain tumor classification using deep CNN features via transfer learning. Comput. Biol. Med. 2019, 111, 103345.

[19] Dangeti, P. Statistics for Machine Learning; Packt Publishing: Birmingham, UK,2017.

[20] Ahmmed, R.; Swakshar, A.S.; Hossain, M.F.; Rafiq, M.A. Classification of tumors and it stages in brain MRI using support vector machine and artificial neural network. In Proceedings of the 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox's Bazar, Bangladesh,16–18 Feb. 2017, pp. 229–234.

[21] Ismael, M.R.; Abdel-Qader, I. Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network, .Rochester, MI, USA, 3–5 May 2018, pp. 0252–0257.

[22] Sathi, K.A.; Islam, M.S. Hybrid Feature Extraction Based Brain Tumor Classification using an Artificial Neural Network, In Proceedings of the 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA), Greater Noida, India,30–31 October 2020, pp. 155–160.

[23] Liu, L.; Yang, H.; Fan, J.; Liu, R.W.; Duan, Y. Rician noise and intensity nonuniformity correction (NNC) model for MRI data. Biomed. Signal Process. Control 2019, 49, 506–519.

[24] Ramesh, S.; Sasikala, S.; Paramanandham, N. Segmentation and classification of brain tumors using modified median noise filter and deep learning approaches. Multimed. Tools Appl. 2021, 80, 11789–11813.

[25] Ravikumar Gurusamy, D.V.S. A Machine Learning Approach for MRI Brain Tumor Classification. Comput. Mater. Contin. 2017, 53, 91–108.

[26] Li, M.; Wang, H.; Shang, Z.; Yang, Z.; Zhang, Y.; Wan, H. Ependymoma and pilocytic astrocytoma: Differentiation using radiomics approach based on machine learning. J. Clin. Neurosci. 2020, 78, 175–180. [PubMed]

[27] Kaplan, K.; Kaya, Y.; Kuncan, M.; Ertunç, H.M. Brain tumor classification using modified local binary patterns (LBP) feature extraction methods. Med. Hypotheses 2020, 139, 109696. [PubMed]

[28] Haeck T, Maes F, Suetens P (2015) ISLES challenge 2015: Automated model-based segmentation of ischemic stroke in MR images. BrainLes 2015:246–253

[29] Raja NSM, Fernandes SL, Dey N, Satapathy SC, Rajinikanth V (2018) Contrast enhanced medical MRI evaluation using Tsallis entropy and region growing segmentation. J Ambient Intell Human Comput:1–12

[30] Myronenko A, Hatamizadeh A (2020) Robust semantic segmentation of brain tumor regions from 3D MRIs. arXiv:2001.02040

[31] Zöllner FG, Emblem KE, Schad LR (2012) SVM-based glioma grading: optimization by feature reduction analysis. Z Med Phys 22:205–214

[32] El-Dahshan E-SA, Mohsen HM, Revett K, Salem A-BM (2014) Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. Expert Syst Appl 41:5526–5545

[33] Arakeri MP, Reddy GRM (2015) Computer-aided diagnosis system for tissue characterization of brain tumor on magnetic resonance images. SIViP 9:409–425

[34] Yang G, Zhang Y, Yang J, Ji G, Dong Z, Wang S et al (2016) Automated classification of brain images using wavelet-energy and biogeography-based optimization. Multimedia Tools Appl 75:15601–15617

[35] Abbasi S, Tajeripour F (2017) Detection of brain tumor in 3D MRI images using local binary patterns and histogram orientation gradient. Neurocomputing 219:526–535

[36] Zhang Y, Yang J, Wang S, Dong Z, Phillips P (2017) Pathological brain detection in MRI scanning via Hu moment invariants and machine learning. J Exp Theor Artif Intell 29:299–312

[37] Wang S, Du S, Atangana A, Liu A, Lu Z (2018) Application of stationary wavelet entropy in pathological brain detection. Multimedia Tools Appl 77:3701–3714

[38] Padlia M, Sharma J (2019) Fractional Sobel filter based brain tumor detection and segmentation using statistical features and SVM. In: Nanoelectronics, circuits and communication systems, pp 161–175

[39] Amin J, Sharif M, Gul N, Raza M, Anjum MA, Nisar MW et al (2020) Brain tumor detection by using stacked autoencoders in deep learning. J Med Syst 44:32

[40] Ayadi W, Elhamzi W, Charfi I, Atri M (2021) Deep CNN for brain tumor classification. Neural Process Lett 53:671–700

[41] Arif M, F. Ajesh, Shermin Shamsudheen , Oana Geman , Diana Izdrui , and Dragos Vicoveanu Hindawi Journal of Healthcare Engineering Volume 2022, Article ID 2693621, 18 pages https://doi.org/10.1155/2022/2693621

[42] Kang, J.; Ullah, Z.; Gwak, J. MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers. Sensors 2021, 21, 2222. [PubMed]

[43] Amin, J.; Sharif, M.; Raza, M.; Saba, T.; Rehman, A. Brain Tumor Classification: Feature Fusion. In Proceedings of the 2019 International Conference on Computer and Information Sciences (ICCIS), Sakaka, Saudi Arabia, 3–4 April 2019, pp. 1–6.

[44] Xue Y, Xu T, Zhang H, Long LR, Huang X. SegAN: Adversarial Network with Multi-scale L_1 Loss for Medical Image Segmentation. Neuroinformatics. 2018 Oct;16(3-4):383-392. doi: 10.1007/s12021-018-9377-x. PMID: 29725916.

[45] Dvorak P, Menze B. Structured prediction with convolutional neural networks for multimodal brain tumor segmentation. MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS) 2015:13–24.

[46] Rao V, Sarabi M S, Jaiswal A. Brain tumor segmentation with deep learning. MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS) 2015:56–59.

[47] Cheng, J. Brain Tumor Dataset. 2017. Available online: https://figshare.com/articles/dataset/brain_tumor_dataset/1512427.

[48] Hao, J.; Li, X.; Hou, Y. Magnetic Resonance Image Segmentation Based on Multi-Scale Convolutional Neural Network. IEEE Access 2020, 8, 65758–65768.

[49] Prabha, S.; Raghav, R.; Moulya, C.; Preethi, K.G.; Sankaran, K. Fusion based Brain Tumor Classification using MultiscaleTransform Methods. In Proceedings of the 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 28–30 July 2020, pp. 1390–1393. \

[50] Minz, A.; Mahobiya, C. MR Image Classification Using Adaboost for Brain Tumor Type. In Proceedings of the 2017 IEEE 7th International Advance Computing Conference (IACC), Hyderabad, India, 5–7 January 2017, pp. 701–705.

[51] Ramdlon, R. H., Martiana Kusumaningtyas, E., & Karlita, T. (2019). *Brain Tumor Classification Using MRI Images with K-Nearest Neighbor Method. 2019 International Electronics Symposium (IES).* doi:10.1109/elecsym.2019.8901560

[52] Khosravan N, Mortazi A, Wallace M, Bagci U. PAN: Projective Adversarial Network for Medical Image Segmentation. Med Image Comput Comput Assist Interv. 2019 Oct;11769:68-76. doi: 10.1007/978-3-030-32226-7_8. Epub 2019 Oct 10. PMID: 37011270; PMCID: PMC10062392.

[53] SEER. SEER Research Data 1975–2017—Surveillance, Epidemiology, and End Results (SEER) Program. 2019. Available online: www.seer.cancer.gov

[54] Dilip Kumar Gandhi, “Detection of Brain Tumor and Extraction of Texture Features using Magnetic Resonance Images,” International Journal of Engineering Innovation & Research, vol. 1, no. 5, 2012.

[55] Amisha, Malik, P., Pathania, M., & Rathaur, V. K. (2019). Overview of artificial intelligence in medicine. *Journal of family medicine and primary care*, *8*(7), 2328–2331.

[56] ırmak, Emrah. (2021). Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework. Iranian Journal of Science and Technology, Transactions of Electrical Engineering. 45. 1-22. 10.1007/s40998-021-00426-9.

[57] Sultan HH, Salem NM, Al-Atabany W (2019) Multi-classification of brain tumor images using deep neural network. IEEE Access 7:69215–69225. https://doi.org/10.1109/ACCESS.2019.2919122

[58] Sajjad M, Khan S, Muhammad K, Wu W, Ullah A, Baik SW (2019) Multi-grade brain tumor classification using deep CNN with extensive data augmentation. J Comput Sci 30:174–182. https:// doi.org/10.1016/j.jocs.2018.12.003

[59] O¨ zyurt F, Sert E, Avci E, Dogantekin E (2019) Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy. Measurement 147(106803):1–7. https://doi.org/10.1016/j.measurement.2019. 07.058

[60] Kabir Anaraki A, Ayati M, Kazemi F (2019) Magnetic Resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms. Biocybern Biomed Eng 39(1):63–74. https://doi.org/10.1016/j.bbe. 2018.10.004

[61] Zacharaki EI, Wang S, Chawla S, Soo Yoo D, Wolf R, Melhem ER, Davatzikos C. Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magn Reson Med. 2009 Dec;62(6):1609-18. doi: 10.1002/mrm.22147. PMID: 19859947; PMCID: PMC2863141.

[62] Ertosun, M. G., & Rubin, D. L. (2015). Automated Grading of Gliomas using Deep Learning in Digital Pathology Images: A modular approach with ensemble of convolutional neural networks. *AMIA ... Annual Symposium proceedings. AMIA Symposium*, *2015*, 1899–1908.

[63] Seetha J, Raja SS (2018) Brain tumor classification using convolutional neural networks. Biomed Pharmacol J 11(3):1457–1461

[64] El-Dahshan ESA, Hosny T, Salem ABM (2010) Hybrid intelligent techniques for MRI brain images classification. Digital Signal Process 20(2):433–441. https://doi.org/10.1016/j.dsp.2009.07. 002

[65] Paul, T. U., & Bandhyopadhyay, S. K. (2012). Segmentation of brain tumor from brain MRI images reintroducing K–means with advanced dual localization method. International Journal of Engineering Research and Applications, 2(3), 226-231.

[66] Cheng J, Huang W, Cao S, Yang R, Yang W, Yun Z, Wang Z, Feng Q (2015) Enhanced performance of brain tumor classification via tumor region augmentation and partition. PLoS ONE 10(10):1–13.

[67] Papageorgiou EI, Spyridonos PP, Glotsos DT, Stylios CD, Ravazoula P, Nikiforidis GN, Groumpos PP (2008) Brain tumor characterization using the soft computing technique of fuzzy cognitive maps. Appl Soft Comput J 8(1):820–828.

[68] Huang, Z.; Du, X.; Chen, L.; Li, Y.; Liu, M.; Chou, Y.; Jin, L. Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification With a Modified Activation Function. IEEE Access 2020, 8, 89281–89290.

[69] Ge, C.; Gu, I.Y.H.; Jakola, A.S.; Yang, J. Enlarged Training Dataset by Pairwise GANs for Molecular-Based Brain Tumor Classification. IEEE Access 2020, 8, 22560–22570.

[70] Noreen, N.; Palaniappan, S.; Qayyum, A.; Ahmad, I.; Imran, M.; Shoaib, M. A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor. IEEE Access 2020, 8, 55135–55144.

[71] Kurup, R.V.; Sowmya, V.; Soman, K.P. Effect of Data Pre-processing on Brain Tumor Classification Using Capsulenet. In ICICCT 2019 – System Reliability, Quality Control, Safety, Maintenance and Management; Springer: Singapore, 2019; pp. 110–119.

[72] Sharif, M.I.; Khan, M.A.; Alhussein, M.; Aurangzeb, K.; Raza, M. A decision support system for multimodal brain tumor classification using deep learning. Complex Intell. Syst. 2021.

[73] Irmak, E. Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework. Iran. J. Sci. Technol. Trans. Electr. Eng. 2021.

[74] Çinarer, G.; Emiro ˘glu, B.G.; Yurttakal, A.H. Prediction of Glioma Grades Using Deep Learning with Wavelet Radiomic Features. Appl. Sci. 2020, 10, 6296.

[75] Rehman, A.; Naz, S.; Razzak, M.I.; Akram, F.; Imran, M. A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning. Circuits Syst. Signal Process. 2019, 39, 757–775.

[76] Cheng, J. Brain Tumor Dataset. 2017. Available online: https://figshare.com/articles/dataset/brain_tumor_dataset/1512427

[77] Bakas, S.; Akbari, H.; Sotiras, A.; Bilello, M.; Rozycki, M.; Kirby, J.; Freymann, J.; Farahani, K.; Davatzikos, C. Segmentation Labels for the Pre-operative Scans of the TCGA-GBM collection. Cancer Imaging Arch. *2017*.

[78] Erickson, B.; Akkus, Z.; Sedlar, J.; Korfiatis, P. Data from LGG-1p19qDeletion. 2017. Available online: **https://wiki**. cancerimagingarchive.net/display/Public/LGG-1p19qDeletion (accessed on 3 May 2021).

[79] Scarpace, L.; Flanders, A.E.; Jain, R.; Mikkelsen, T.; Andrews, D.W. Data from Rembrandt. 2019. Available online: https://wiki.cancerimagingarchive.net/display/Public/ REMBRANDT

[80] S. K. Binu Siva Singh, K. V. Karthikeyan. (2023) Multiple-Controlled Toffoli and Multiple-Controlled Fredkin Reversible Logic Gates-Based Reversible Synchronous Counter Design. IETE Journal of Research 0:0, pages 1-14.

DOI: https://doi.org/10.15379/ijmst.v10i5.2506