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A Systematic Review of Deep Learning and Machine Learning Methods in Diagnosis of Brain Tumor

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Abstract: Brain tumour diagnosis is a major challenge for the medical professionals now a days. Due to their inexorable growth, brain tumors require early detection to improve patient survival rates. Due to the abundance of important diagnostic information, it offers, magnetic resonance imaging (MRI) has become the de facto medical imaging technology. Brain tumours are detected in MRI images using machine learning and deep learning, two forms of artificial intelligence. This study aims to provide a thorough examination of the categorization methods based on artificial intelligence (AI) that are currently used to forecast brain cancers. (Machine and Deep Learning). The purpose of this study is to identify the best successful methods for identifying brain malignancies using deep learning, machine learning, and optimization. These include CNN, UNET, supervised machine learning, etc. The achievements and failures of the current models are emphasized, along with the potential for future research to increase the patient survival rate. Further, a comparative analysis of various existing brain tumor classification techniques according to the publication year, published journals, techniques, and performance measures is also done in this paper.

Keywords: Deep learning, Brain tumor classification, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Machine learning.

1. Introduction:

Brain tumours are among the most dangerous illnesses affecting the neurological system because they result from an uncontrolled expansion of brain cells [9], which is contrary to the normal cellular growth cycle [10]. The term "tumor" is referred to a neoplasm that is formed when abnormal cells grow out of control [51]. Because the tumour develops so rapidly in such a small area, it disrupts normal brain function and greatly increases the mortality risk for both children and adults with brain tumours [3]. The central nervous system is severely compromised by gliomas, the primary brain tumour that most frequently affects adults. Low-grade (LGG) and high-grade (HGG) gliomas are two different ways that glial cells in the brain can grow into gliomas [52]. Due to its fast development, the HGG is more dangerous than the LGG, and patients with such issues have a two-year life expectancy [10]. Based on their malignancy and pace of growth, brain tumours are divided into two major groups. From the primary tumour in the brain, malignant cells travel throughout the body to create secondary tumours [3].

Diagnosis of malignancies and assessments of the effectiveness of treatment rely heavily on medical imaging technologies. The major types of medical imaging are computed tomography (CT), ultrasounds, X-rays, and MRI [14]. Since radiologists have found it more challenging to identify subtle structural changes using CT-based imaging, magnetic resonance imaging (MRI) has emerged as the preferred non-invasive scanning technique. With time constraints taken into account during the forecast stage of AI-based systems, tumor type identification is a laborious task. The ability to distinguish between different tumor sub-regions is aided by the MRI scans' images, which feature variable contrasts and brightness emphasizing various regions of the brain. These scans, which are sometimes referred to as MRI modalities or sequences, capture various tumour characteristics at various lengths and intensities. T1-weighted (T1w), T2-weighted (T2w), and T1-weighted MRI with contrast enhancement (T1ce) are the three most popular imaging techniques. Different tumour sub-regions may be identified using different MRI sequences, and each sequence is regarded to be significant [24].

Using segmented MRI brain imaging data, software-based medical image processing may provide more precise diagnosis. However, MRI images are notoriously difficult to segment due to noise and artefacts introduced by image-collecting devices [53] [23]. Since each imaging modality provides distinctive information on target regions, combining data from many modalities might enhance segmentation [54]. Therefore, multi-modal medical image segmentation may provide more reliable and accurate segmentation results. There are numerous computer-assisted strategies for segmenting medical images, including approaches using artificial neural networks (ANN), regions, thresholds, and models [56]. However, effectively integrating such information is still difficult [55][20].

Due to the lack of a universal decision system for diagnosing brain tumours with greater accuracy regardless of the shape of the brain tumour [58], the major aim of the research is to compare and contrast different approaches for making such predictions. Segmentation and feature extraction are traditional techniques for classifying brain tumours as gliomas or meningiomas. Deep learning techniques, which employ techniques like the fisher vector and the grey level co-occurrence matrix, overcome the shortcomings of traditional techniques. Hence, in this research, deep learning, optimization-based methods, machine learning, CNN, UNET, and supervised machine learning used for the classification is considered for review and the advantages and challenges associated with the deep learning in acquiring the required classification accuracy is enumerated. This research encourages the development of novel approaches by facilitating their automated feature extraction and categorization without resorting to tried-and-true models.

One of the deep learning techniques, convolutional neural networks (CNN), has recently been demonstrated to be especially useful in the segmentation of medical pictures [57] due to its high segmentation accuracy. To accomplish deep learning, we use convolutional multi-layer neural networks, which have a convoluted design consisting of numerous hidden layers and free parameters. After MRI input signals have been handled with convolution layers, pooling layers, filters/kernels, and fully-connected layers, a function is employed to make a decision [23]. While 3D convolutional neural networks (CNNs) require more processing power, they are widely regarded as superior to 2D CNNs when it comes to volumetric segmentation [10]. The Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), Artificial Neural Network (ANN), and ensemble approaches are a few examples of machine learning techniques. However, many of the existing machine learning methods that make up a system rely on computationally expensive and time-consuming features, such as preprocessing, ROI segmentation, and classical feature extraction. The extraction of feature maps from the input brain picture collected from the MRI database is shown in the architecture of the deep classifier in brain tumour classification shown in Figure 1.

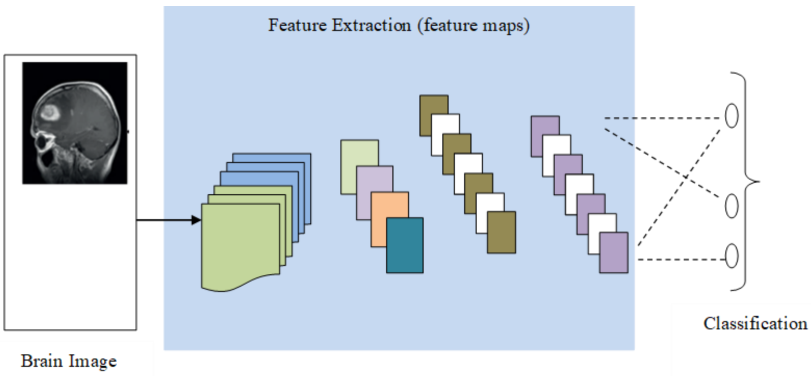

Figure 1. Brain Tumor classification using deep learning

2. Contribution and Organization of Paper:

We conduct a thorough literature analysis in this work to highlight the drawbacks of both deep learning and conventional machine learning techniques. We detail the available issues, clinical implications, and limitations from the studies, the vast majority of which are in the deep learning domain. The review is conducted by collecting the methods published in good Journals from 2018 that accepted the contributions from researchers for classification.

The remaining sections of the study are as follows:

Section 2 of the research details the categorization of the existing brain tumor classification techniques.

Section 3 of the article provides the analysis of the conventional methods in terms of performance measures, year, techniques and journal of publication.

Section 4 provides the research gaps in the existing models.

Finally, the article is concluded in section 5.

3. Conventional Methods for Brain Tumor Classification:

Here, we dissect figure 2 to illustrate how the current brain tumour classification model used in the research publications is broken down into its several categories.

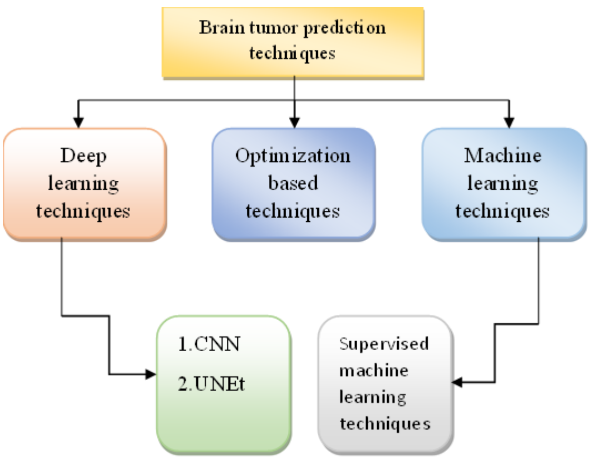

Figure 2. Categorization of brain tumor classification techniques

3.1. Deep learning techniques:

The deep model's basic architecture is shown in Figure 3, which highlights how it outperforms more conventional feature extraction methods. The NeuroXAI framework for producing 2D and 3D explainable sensitivity maps was developed in [16]. Seven cutting-edge explanation techniques are included in NeuroXAI that, via the use of visualization maps, help to make deep learning models understandable. For the purpose of identifying and classifying brain malignancies, hierarchical deep learning-based brain tumour (HDL2BT) classification using convolutional neural networks (CNN) was described in [19]. For a quick and effective course of treatment, it is essential to identify and segregate tumours, and convolutional neural network (CNN)-based medical image processing is producing good working order. In [32], a deep learning network was used to determine whether or not given tissue samples were tumours. (healthy). The homogeneity field effect of the MR slices was also used to highlight the predicted slices, which were then merged with the input slices with the use of a high-pass filter image. Median filtering is applied to the combined slices as well. The quality of the output slices improves when the input slices have their sharp corners softened and highlighted. Next, we employ a 4-connected seed growth algorithm that combines comparable pixels from the input slices depending on their intensities. After that, a tuned two-layer stacked sparse autoencoder (SSAE) model receives the segmented slices. It has been discovered that the multi-level feature extraction and concatenation method, as described in [35], is useful for the early identification of brain tumours. We increased the model's dependability by using Inception-v3 and DensNet201, two previously trained deep learning models. These two methods for identifying and classifying brain tumours were tested in two different contexts. The presented procedure outperformed all others in detecting brain tumours and yielded the best testing accuracy on test samples. To simultaneously segment, detect, and grade LGG tumors using MRI images, deep learning segmentation, and grading models were described in [36]. These models were based on CNN. The automated grading of tumour MRI images using the segmentation model's projected tumour masks served as a non-invasive, automated tool for LGG diagnosis and treatment planning. The unsupervised fuzzy set technique is used to enhance pictures and help in accurate segmentation utilising triangular fuzzy median filtering, as shown in [37]. The texture (ST) characteristics of each candidate's lesions are comparable based on analysis of the recovered Gabor features. The regression ELM omits one of these ST properties, whereas the extreme learning machine (ELM) receives all of them. The proposed method is quite slow to converge. When analyzing MR images for the detection of stroke and gliomas. In [38], the authors provide a learning model based on LSTMs that improves the results of training on temporal data. The sequential nature of MR imaging makes LSTM well suited to learning the sequences of this data. The subtumoral area also did not fit any of the categories predicted by the LSTM model. In [40], we saw two patching techniques and a brain-wise normalization. The use of variables derived from predicted tumour labels in a network appears to be a constraint on the model's ability to estimate overall survival days for patients who had undergone gross complete resection surgery. An automated multimodal classification method for brain tumours based on deep learning was suggested in [41]. The feature selection process improved classification performance and reduced computational overhead. The shown findings allowed for the inference that the given approach yielded steady accuracy outcomes. The identification and segmentation of brain tumours is addressed in [49], where a cascaded deep-learning network technique is shown. This approach takes use of both local and global knowledge using 3D arous convolution with varying kernel sizes. In addition, it enables feedback-connected direct gradient propagation from deep to shallow layers.

3.1.1. Based on Convolutional Neural Network:

In [1], use of a deep neural network to glean tractographic information from tumours of the brain was outlined. For the purpose of segmenting and classifying brain tumours depending on survival, our method coupled parcellation with human brain connectomics. This technique uses a patch-based neural network in which location data is explicitly included as a parameter. When compared to the proposed method, the patch-based neural network performed better.

The authors of [2] suggest an automated CNN-based tumour identification strategy to assess if areas suggesting cancer grade are the most pertinent ones for classification, to spot any structural problems, and to develop plans for getting more accurate classifiers. With CNNs, tumor grading could be learned directly from imaging data without the need for manually set ROIs. These techniques could overfit the data and uncover fictitious patterns. As a result, it would be ideal to implement these procedures after a quality assurance phase. In [3], the authors describe a dynamic DL approach for monitoring GB brain tumours over time. With this method, we use a dimensionality reduction algorithm to isolate relevant picture characteristics, classify images as high- or low-grade, and eliminate extraneous features by adjusting the correlation thresholds between features. The current approach can predict survival rate using classification and required less segmentation time—roughly 10 seconds for the full system to analyze it. This study [4] used Random Forest, SVM, XgBoost, and LGBM to forecast the OS period using radiometric features, which reflect combined deep data and hand-crafted characteristics of the tumour. The suggested strategy consists of three main parts: automatic tumour segmentation, feature extraction using both manual and deep learning methods, and survival time classification. Similarly, deep features are extracted using the CNN model by stacking segmented cores, augmenting, and full tumors. Thus, the goal of forecasting survival rates is accomplished with more precision and efficiency than with another state-of-the-art approach, which suffers from a limited dataset. For identifying the multiclass classification of brain tumors using MRI, an automated strategy based on deep CNN was presented by [7] to provide a better classification result while learning more quickly than conventional DL models. The CNN model consists of six layers: two input layers, two activation levels, two hidden layers (for convolution and output), and one fully connected layer. This design has a total of twelve layers, including an activation (ReLU) layer, a flattening layer, three dropout layers, six BN levels, and layers for max-pooling and activation. The provided model also makes use of many hidden layers to automatically train for hierarchical characteristics. It was advised to incorporate 3D spherical coordinates transform in the pre-processing stage, as indicated in [8], to increase the DCNN models' accuracy and generate more generalizable results, even when the model was trained on tiny and varied datasets and translated into other domains. The spherical coordinate system gets around many standardization problems because it works regardless of sharpness and imaging settings. Two different DCNN models were used to compare Cartesian and Spherical volumes using the same network topology and different dice scores. These models may be utilised with various datasets without further training since they are resolution independent. According to the study [9], deep pretrained convolutional neural networks trained utilizing transfer learning architectures can automatically classify brain MRI scan tumours as benign or malignant. In the image classification step, VGG16, Inception-v3, and ResNet50 are specifically utilized as classifiers since, when applied to the problem of recognizing brain tumours on the training and testing datasets, they produce superior results. Additionally, the recognition rate is significantly closer to that of loss and validation accuracy with less loss. As a result, it is constrained to focus on a certain set of training data and is unable to produce accurate identification for a new dataset. In order to identify brain tumours in specific individuals, [12] suggested a deep learning-based cancer classification method for evaluating T1Gd and FLAIR MRI data. When the Learn-Morph-Infer approach is applied using widely accessible technology, tumour models of complicated series, like as reaction-diffusion and reaction advection-diffusion models, exhibit considerable improvements on the scale of minutes while maintaining computation time. In [20], a deep learning method for segmenting brain tumours was demonstrated using fictitious MRI and CT data. Multi-modal 3-D picture categorization has several medical applications, including disease diagnosis, therapeutic planning, and image-guided surgery. Insights that cannot be obtained from a single image treatment can be revealed by multimodal images, notwithstanding the segmentation constraints. [21] published a Deep Convolutional Neural Network that classifies and distinguishes between different types of brain pictures using a Res net 152 Transfer Learning model. The data is pre-processed using the Otsu binarization approach to achieve these objectives. The proposed approach greatly reduced the amount of time needed to compute while also significantly improving accuracy.The 3D Brain Tumor Segmentation (BraTS) files contain four different types of imaging data. (T1, T1C, T2, and Flair). The creators of an automated semantic segmentation system for brain tumours provide a convolutional neural network-based approach in [23]. The suggested method has been proven to be extremely effective and promising for imaging and diagnosing brain tumours. A Deep Convolutional Neural Network (CNN) was used to segment brain tumors, and the results were reported in [26]. To enlarge the training dataset and avoid overfitting, data augmentation by elastic transformation was used. Meningioma, glioma, and pituitary tumors were successfully segmented and classified using the multi-scale CNN technique, which employs three different processing routes. This method provided good segmentation performance metrics and may be used to address other medical imaging challenges, despite the fact that the diversity of the three tumour types led to false positives in certain pictures and that pieces of the skull and spinal column are left in place. We created the best possible CNN model and adjusted its hyper-parameters with a grid search optimizer. In [27], a multi-classification of brain tumours was published with the purpose of establishing early treatment objectives. The classification, which made use of a sizable clinical dataset that is freely accessible, produced some excellent findings. The area under the receiver operating characteristic curve was used to assess the model's performance. (AUC of the ROC). A Mask Region-based Convolution neural network (Mask RCNN) with a densenet-41 backbone architecture was introduced in [28] with the goal of accurately localizing, segmenting, and classifying brain tumours as well as automatically separating the brain cancer from a complex background without user intervention. Artefacts and noise created during MRI capture must be removed before preprocessing the raw images may start. The model is then trained using the ground-truth segmentation masks that are developed. The method that is being explored uses deep characteristics that are more reliable and discriminating. Region-based CNN also does classification after first locating the tumour region (RoI), which improves accuracy. Using the enormous volumes of data produced by convolution blocks of deep pre-trained models, the authors of [29] propose a two-channel deep neural network architecture for cancer classification. The empirical results from two separate benchmark datasets are used to inform a technique for directing attention that gives priority to tumour-affected areas while giving less weight to non-tumor parts. The two-channel DNN model has exceptional generalisation abilities, and the given pooling and attention techniques provide a suitable abstract representation. In [39], the CNN design was first proposed for use in detecting brain tumours from MRI scans. The non-linear value obtained from deep learning studies is transformed using activation functions. Activation functions were employed to carry out non-linear transformation operations when training the 3D U-Net to tackle the tumour segmentation challenge. A dual-force training method is put out in [42] to actively encourage deep models to gather high-quality multi-level features. Extensive testing on the two most current brain tumour segmentation datasets provides evidence for the applicability and efficiency of the offered approaches. The MLP-based post-processing strategy does not employ an end-to-end framework because its training methodology is distinct from that of the DFN. Using convolutional neural networks (CNNs), [44] presents a method for classifying brain tumours into the three most common types: gliomas, meningiomas, and pituitary tumours. To extract features from brain MRI data, the proposed classification approach uses a pre-trained GoogLeNet and the deep transfer learning concept. Deep convolutional neural networks' (CNNs') many applications are outlined in [45]. Since the training data set is so limited, data augmentation is frequently used to improve CNN performance. Recent studies have also shown the value of data augmentation for making more accurate classifications throughout both training and testing. Using Deep Convolutional Neural Networks, three automatic approaches for segmenting brain tumors were given in [46]. These methods combine the strength of CNNs with the ensemble learning method, creating a novel model that we have named “EnsembleNet.”EnsembleNet models have produced highly accurate findings. The MRI brain tumour segmentation using 3D FCN was initially described in [47]. As a consequence, the approach excels at separating the WT area, but it has a way to go before it fully achieves its full potential in separating the ET and TC regions. The frog leap optimization strategy is utilized to reduce classifier error and the Adaptive Flying Squirrel (AFS) segmentation algorithm is used to boost classification accuracy in, where the hybrid AFDNN with frog leap technique is used to find anomalies in vase images. By having the best convergence speed, this segmentation increases the segmentation accuracy. Because of the intricacy of the brain, finding the tumor in brain imaging is a laborious task. It was suggested in [50] to segment and identify brain tumors using an active deep learning-based feature selection technique. The first stage involves enhancing the contrast, which is then sent to SbDL for the building of a saliency map. SbDL next applies simple thresholding to turn the saliency map into a binarized form. The stage in the proposed strategy that selects the best characteristics reduces classification time while simultaneously improving accuracy.

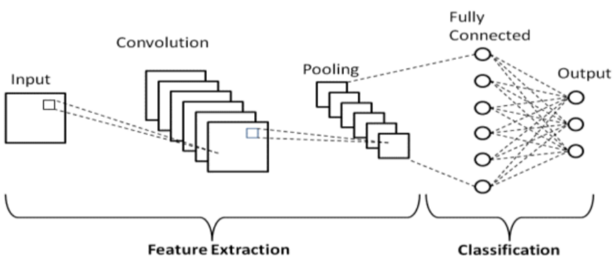

Figure 3. Deep architecture

3.1.2. Based on U-Net techniques:

UNet evolved from the basic CNN, which not only classifies the disease, but also locates the abnormality in the input brain image due to the pixel-based function as presented in figure 4. In [10], a technique was described for the purpose of segmenting brain tumours and identifying them as either entire, enhanced, or core tumour regions. A series of multi-scale residual attention convolutional neural networks (MRA-UNet) with a configurable region of interest is used in the proposed method. (A-ROI). By using three successive slices as the input, the approach incorporates sequential information and considerably improves the precision with which complete tumours are segmented. When used to both the enhanced and core tumour segmentation procedures, adaptive ROI yields considerable benefits. Using multi-modal MRI data, Swin UNETR, a revolutionary architecture for semantic segmentation of brain tumors, was introduced in [11]. For encoding and decoding, the provided model uses a Swin transformer and a CNN-based decoder with skip connections of various resolutions. As a result, Swin UNETR performs superbly and earns top ratings during the certification procedure. The local feature reaction is retained and transported via activation from the appropriate level on the encoder side to the decoder side via skip connections in [14]'s 3D Deep dResU-Net approach, which enhances training. The accuracy of removing cancers from brain MRI images was improved as a consequence. The suggested approach aims to enhance processing generally and tackle the issue of fading gradients specifically. Attention ARU-GD, a deep learning architecture, was created in [18] for the semantic segmentation of brain tumours. Here, a focus gate and an enhanced guided decoder are used. By generating more reliable feature maps at the decoder and limiting activations to regions that were really pertinent to the task at hand, these changes to the original Res-UNet network improved learning. They were able to boost the recognition rate when combined. The model's computationally intensive training process did not reduce the amount of memory needed or the amount of time it takes to compute. It was initially shown in [30] to automatically segregate brain tumours from MRI images using UNet-based designs. The UNet was built with two-pathway-residual (TPR) blocks to facilitate the development of such models. Two-pathway residual blocks may benefit from more local and global characteristics at once. The UNet structure's TPR blocks have improved assessment criteria like DSC and sensitivity while also lowering the amount of parameters in the provided models. In conclusion, the proposed models' benefits include lower computing costs, faster segmentation, and a lack of post-processing.

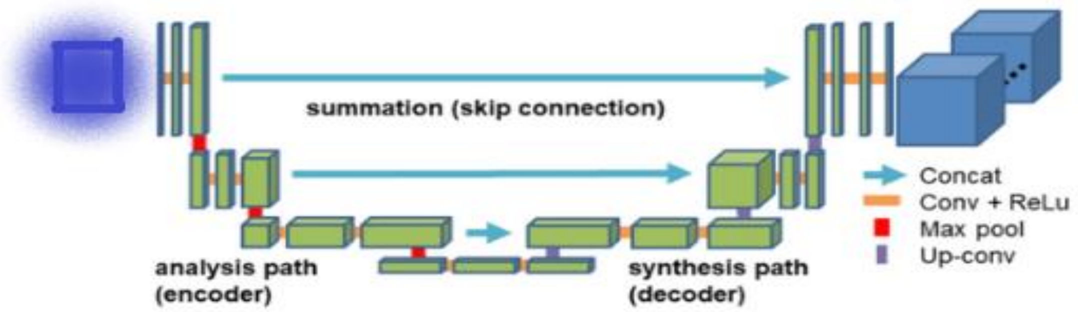

Figure 4. UNET model in brain tumor segmentation and classification

3.2. Machine learning techniques:

In [17], a stochastic strategy for automated diagnosis of brain tumours based on IoT was described using the brain's physical processes. With the new method, magnetic resonance imaging (MRI) is no longer necessary, which reduces computing complexity and improves the accuracy of predicting the possibility of brain tumours. Temperature, blood pressure, and monitoring sensors are connected to the wearable wristband known as the Mi Band 2 and are supplied by an Arduino-Uno CPU. Because of this, even though the suggested method is simple to use and inexpensive, it is unable to pinpoint the precise position and size of brain tumours. A segmentation network based on the quantum variation classifier (QVR) was developed in [22] to assess the malignancy of tumours. The characteristics were gathered using the inceptionv3 model, and the softmax approach produced a score vector that was passed into the variation quantum classifier to aid in the categorization of brain tumours. Using segmented ground masks, a better Seg-Network was created and trained with a few changed parameters. It enables a more precise division of the tumour. A post-hoc interpretability approach built on CAM was proposed in [24] to clarify the network classifications and analyze the segmentation model's behaviour for the input MRI images. This technique looked into the classification strategy of the model. The method that was used to illustrate this point demonstrated how well the model's information was in line with the subject-matter expertise of real experts. In addition, a deletion metric was employed to demonstrate that the outcomes are more accurate in terms of the coverage of the class region, so overcoming the drawback of quantitatively assessing visual explanations. In [31], a new data-driven method, GP-GAN, was reported for the growth categorization of gliomas; this method makes use of stacked 3D generative adversarial networks (GANs). It uses a stacked conditional GAN with a new objective function incorporating l1 and Dice losses to arrive at its results. Because the generator was directed by a segmented feature map, the photos were enhanced. In order to better integrate hierarchical components and provide more realistic results, a modified 3D U-Net architecture was used to build the generator. The given GP-GAN does improve performance, however there are still issues with the present method. Uneven evolution of some component types is possible. Because doing so would greatly increase the number of parameters required to characterize the malignancy, the tumour was simulated as a whole without differentiating between its many components. A new OM-Net model for segmenting brain tumours was released in [33] to solve the issue of class imbalance. Contrary to the conventional MC design, OM-Net just needs one compute pass to go from coarse to fine segmentation. By sharing parameters, training data, and even classification results, OM-Net completely benefits the link between the tasks, outperforming MC in terms of model size and processing power. In [43], the Nave Bayes classification was used to correctly identify a tumour zone that includes all malignant tissues that are spreading, to identify the tumour region from different brain MRI images, and to determine whether or not the discovered area is a tumor. The technique achieves a high tumor picture detection rate.

3.2.1. Supervised Machine Learning:

The automated Ultra-Light Brain Tumor Detection (UL-BTD) method is based on a revolutionary Ultra-Light Deep Learning Architecture combined with extremely distinctive textural properties [5]. This design enables significant fine-tuning to assist surgical intervention inside the operating room. The UL-BTD system may be simply deployed on even a current PC system with standard GPU capability, with detection limits of 11.69 milliseconds for each picture. The suggested technique could make real-time brain tumour surgery quicker and easier. The contrast-limited adaptive histogram equalization (CLAHE) preprocessing method was created in [15]. After that, we created the merged pictures using a DCT-based fusion approach. Image fusion helps enhance the standard of the final images, which will enhance the performance of classifiers. The high-quality fused images will produce greater accuracy in classification than using individual input images. The contrast-limited adaptive histogram equalization method begins by preprocessing input pictures like MRI and SPECT images. A technique for effective MRG and ASVM-based brain tumour segmentation and classification was published in [25]. This method utilizes the grasshopper optimization algorithm (GOA). The five steps of the proposed research include preprocessing, segmentation, feature extraction, feature selection, and classification. First, noise effects are removed using the median filter, and then the skull is manually stripped to preserve the region of interest (ROI). The ROI region must then be divided using the MRG approach. Segmentation is followed by the extraction of features from the GLCM. The GOA is then used to pick the crucial features. The classifier is then given the chosen features to categorize the image as positive or negative.

3.3. Based on optimization techniques for hyperparameter tuning in classifiers:

To categorize FLAIR, T1, T2, and T1CE tumors, the approach described in [6] employs the top deep learning characteristics. The dataset was normalized before transfer learning using the ResNet101 pretrained system was performed. In order to employ the ResNet101 pretrained model for illness diagnosis, we gave it a last polish using the transfer learning method. The fusing of optimal features increased accuracy, although there was a large reduction in classification time. This work's main flaw was the fusion procedure, which lengthens the evaluation system's processing period. [13] created the Enhanced Watershed Segmentation (EWS) approach, which uses a ResNet50 model with a modified layer architecture consisting of five convolutional layers and three fully connected layers, for the classification of brain tumours and the extraction of deep data. The current model learns a wide variety of deep features from the ResNet50 deep learning model and feeds them as input to the classifier, which allows it to maintain the fastest practical convergence time with large deep features. Both the modified ResNet50 model trained with deep features and the modified ResNet50 model trained with EWS captured images of brain cancer cells that were remarkably accurate. The brain surface extraction (BSE) procedure must be used before the skull may be removed. Particle swarm optimization (PSO) is then used to the remaining picture to improve segmentation after the skull has been removed. Following the extraction of local binary patterns (LBP) and deep features from the segmented pictures, the best features are chosen using a genetic algorithm (GA). Artificial neural networks (ANNs) and other classifiers are employed to categorise the cancer grades. The method that was presented took more time, but the results were superior.

4. Comparative Analysis

In this section various brain tumor classification techniques are analyzed by considering the publication year, published journals, techniques, and performance measures.

4.1. Analysis based on publication year

The categorization of brain tumours according to publication year analysis is shown in Table 1. The research papers considered for analysis are from 2018 to 2022, and most of the researchers published the papers during the year 2022 for personality trait classification. The chart analysis of the reviewed papers based on the year of publication is revealed in figure 5.

Table 1. Year of publication

Year of Publication	Reviewed papers
2018	[1][2][45][46]
2019	[40][42][43][44]
2020	[31][32][33][34][35][36][37][38][39][41][50]
2021	[23][24][25][26][27][28][29][30][47][48][49]
2022	[3][4][5][6][7][8][9][10][11][12][13][14][15][16][17][18][19][20][21][22]

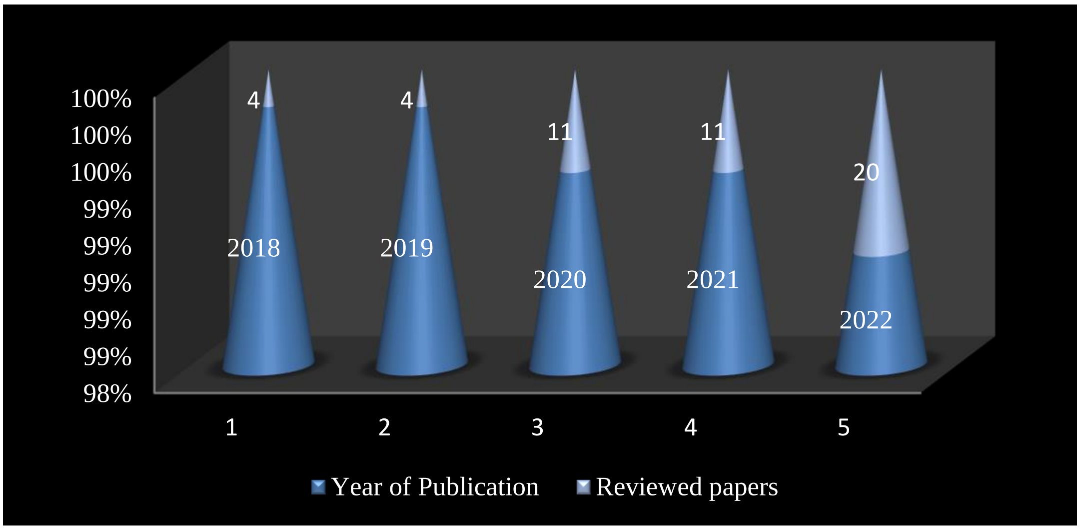

Figure 5. Chart analysis based on year of publication

4.2. Analysis based on published journals

Table 2 reveals the analysis of the reviewed papers based on the journals published, the reviewed papers are published in the journals IEEE, Springer, Elsevier, MDPI, Hindawi, Wiley online library, and Research Gate. Figure 6 reveals the chart analysis based on the published journals along with the reviewed papers.

Table 2. Published Journals

Published Journals	Reviewed papers
Elsevier	[3][10][12][14][18][21][23][24][30][31][34][36][39][42][44][46][47][50]
Springer	[1][2][8][11][16][25][27][29][32][37][38][40][45][48]
Hindawi	[6][7][9][13][15][19][22]
MDPI	[5][20][26][28][41]
IEEE	[33][35][43][49]
Research Gate	[17]
Wiley online library	[4]

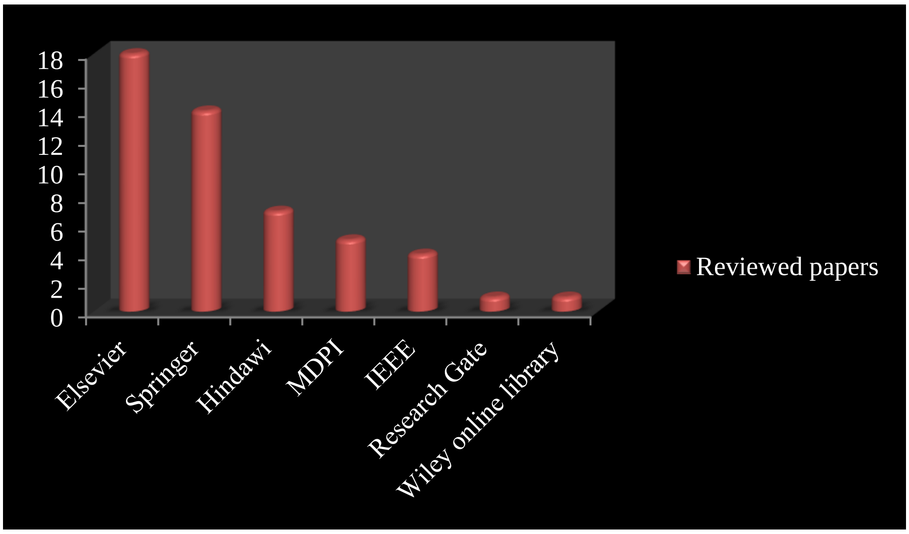

Figure 6. Chart analysis based on Published Journals

4.3. Analysis based on techniques

Table 3 displays the results of a technique-based analysis of the evaluated publications; this analysis demonstrates that majority of the most current studies use the deep learning approach of CNN and SVM for brain tumour classification. The reviewed articles' chart analysis and the different reviewed brain tumour classification techniques are shown in Figure 7.

Table 3.Various techniques

Techniques	Reviewed papers
CNN	[1][2][4][7][8][9][20][21][23][26][27][39][42][44][45][46][50]
Faster RCNN	[3]
SVM	[5][15][25]
PSO	[6]
MRA-Unet	[10]
SwinUNEtTRansformers	[11]
Learn-Morph-Infer	[12]
EWS	[13]
ResU-Net	[14][18][30]
NeuroXAI	[16]

stochastic method	[17]
deep learning	[19][32][35][36][40][41][49]
QVR	[22]
post-hoc interpretability technique.	[24]
Mask RCNN	[28]
DNN	[29]
GAN	[31]
OM-Net	[33]
GAPSO based ANN	[34]
extreme learning	[37]
LSTM	[38]
Naïve Bayes Classification	[43]
3D FCN	[47]
AFDNN	[48]

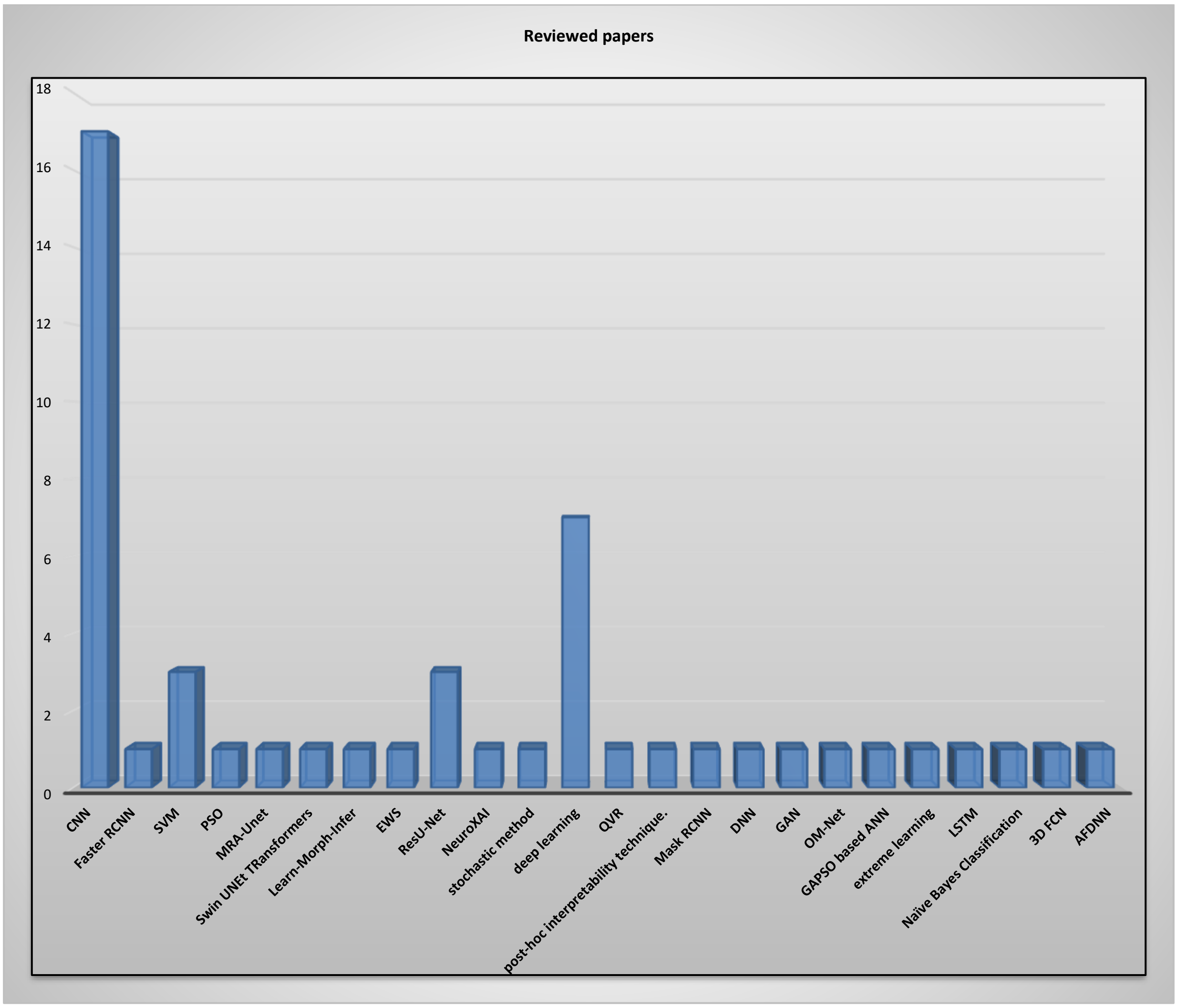

Figure 7. Chart analysis based on various techniques

4.4. Analysis based on the performance measures

In Table 4, we see an evaluation of the various kinds of brain tumour classification studies using a variety of performance metrics. Figure 8 reveals the chart analysis of the reviewed papers based on the utilized performance measures.

Table 4. Performance measures

Performance measures	Reviewed papers
Accuracy	[1][2][4][5][6][7][8][9][10][12][13][15][16][17][20][21][22][23][24][25][27][28][29][30][31][32][34][36][37][38][39][41][43][44][48][50]
Sensitivity	[13][21][25][26][28][30][33][34][36][37][38][40][42][43][46][47][48][49]
Specificity	[13][15][21][25][30][34][36][37][38][40][43][44][46][47][48]
Precision	[7][9][13][15][19][21][22][35][44]
F1-measure	[6][9][15][21][22][23][35]
Recall	[7][9][15][22][35][44]
FPR	[39][38][37][48]
FNR	[39][38][37][41][48]
others	[3][11][14][18][45]

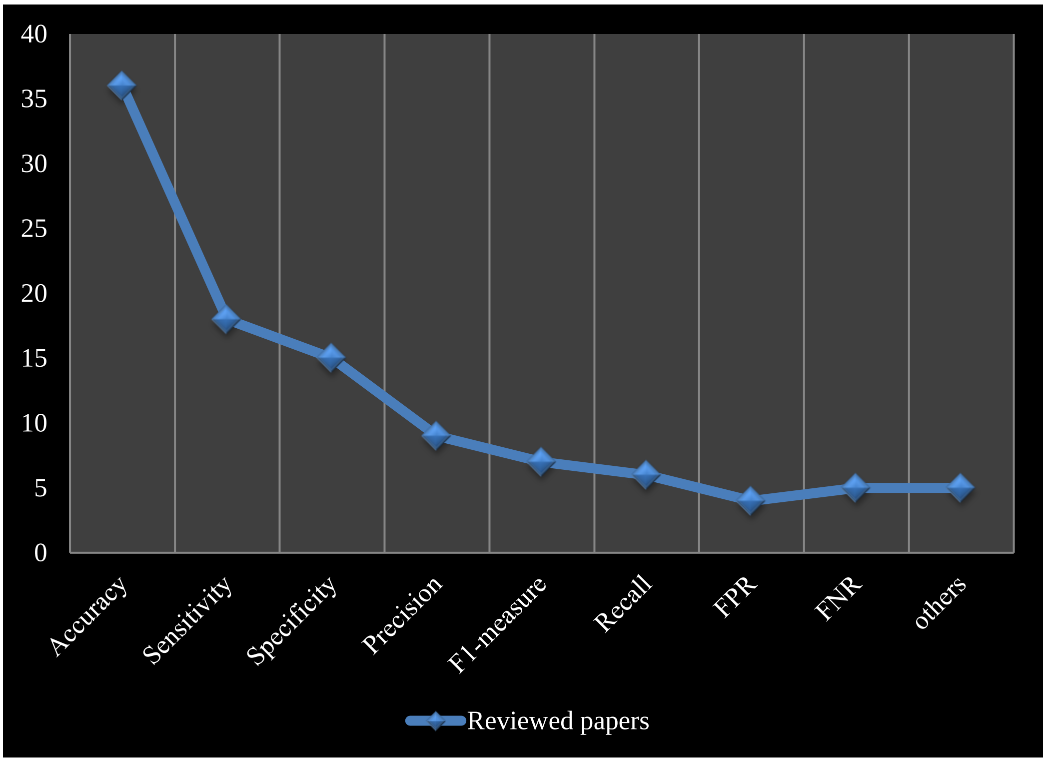

Figure 8. Chart analysis based on performance measures

5. Research gaps of the conventional methods

The following are the difficulties that were examined during the investigation of several strategies for classifying brain tumours:

- The inability of DL models to generalize is a major limitation that might provide unexpected results in segmentation/classification accuracy when used with data from other organizations [8].
- Failures of real-world models on imaging methods are exacerbated by inconsistencies in input pictures across domains and a lack of sufficient datasets

for training a DL model in a new domain [8].

- The method for real-time diagnosis is slowed down when large sets of Brain MRI images are used; this is because it takes a long time to discover and categorize the brain tumour [21].
- CNN makes the mistake of overfitting and discovers fake patterns among the data. Consequently, it would be ideal to implement these procedures after a quality assurance phase. [2]
- Accuracy in deep learning-based approaches relies significantly on a wide parametric space and efficient algorithms [5]. However, the classification phase or decision-making is complex and opaque.
- It is anticipated that the pretrained CNN model will have overfitting problems, particularly when classification error decreases while training accuracy rises. Overfitting occurs when the model's predictive abilities are restricted to the data used during training [9].
- High-level semantic information extraction is typically the primary goal of CNN's last convolutional layer. Deep Medic's performance is constrained because of a lack of low- and middle-level data [42].
- Several deep-learning models, both 2D and 3D, are available for segmenting brain tumours; as computational power increases, the models' architectures get more sophisticated, and their segmentation findings become more trustworthy [47].

Conclusion

CNN has a major impact on the rapidly growing field of deep learning, with applications spanning from platform development to brain tumour classification. This article provides a comprehensive overview of the classification method used in 50 studies addressing the topic of brain tumours. Articles published between 2018 and 2022 on the subject of brain tumour classification using deep learning and similar approaches were reviewed for this study. The study demonstrated that optimization-based deep learning algorithms outperformed the conventional methods used in the included research publications in terms of accuracy, recall, precision, F1 measure, FPR, FNR, specificity, and sensitivity. The analysis of brain tumor classification takes into account several deep learning algorithms with successes, published journals, year of publication, and performance metrics.

References

[1] Kao, P.Y., Ngo, T., Zhang, A., Chen, J.W. and Manjunath, B.S.,"Brain tumor segmentation and tractographic feature extraction from structural MR images for overall survival prediction," In International MICCAI Brainlesion Workshop (pp. 128-141). Springer, Cham, 2018, September.

[2] Pereira, S., Meier, R., Alves, V., Reyes, M. and Silva, C.A.,"Automatic brain tumor grading from MRI data using convolutional neural networks and quality assessment," In Understanding and interpreting machine learning in medical image computing applications (pp. 106-114). Springer, Cham, 2018.

[3] Wankhede, D.S. and Rangasamy, S.,"Dynamic architecture based deep learning approach for glioblastoma brain tumor survival prediction," Neuroscience Informatics, p.100062, 2022.

[4] Das, S., Bose, S., Nayak, G.K., Satapathy, S.C. and Saxena, S.,"Brain tumor segmentation and overall survival period prediction in glioblastoma multiforme using radiomic features," Concurrency and Computation: Practice and Experience, 34(20), p.e6501, 2022.

[5] Qureshi, S.A., Raza, S.E.A., Hussain, L., Malibari, A.A., Nour, M.K., Rehman, A.U., Al-Wesabi, F.N. and Hilal, A.M.,"Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection," Applied Sciences, 12(8), p.3715, 2022.

[6] Zahid, U., Ashraf, I., Khan, M.A., Alhaisoni, M., Yahya, K.M., Hussein, H.S. and Alshazly, H.,"BrainNet: optimal deep learning feature fusion for brain tumor classification," Computational Intelligence and Neuroscience, 2022.

[7] Tiwari, P., Pant, B., Elarabawy, M.M., Abd-Elnaby, M., Mohd, N., Dhiman, G. and Sharma, S.,"Cnn based multiclass brain tumor detection using medical imaging," Computational Intelligence and Neuroscience, 2022.

[8] Russo, C., Liu, S. and Di Ieva, A.,"Spherical coordinates transformation pre-processing in Deep Convolution Neural Networks for brain tumor segmentation in MRI," Medical & Biological Engineering & Computing, 60(1), pp.121-134, 2022.

[9] Srinivas, C., KS, N.P., Zakariah, M., Alothaibi, Y.A., Shaukat, K., Partibane, B. and Awal, H.,"Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images," Journal of Healthcare Engineering, 2022.

[10] Ullah, Z., Usman, M., Jeon, M. and Gwak, J.,"Cascade multiscale residual attention cnns with adaptive roi for automatic brain tumor segmentation," Information Sciences, 608, pp.1541-1556, 2022.

[11] Hatamizadeh, A., Nath, V., Tang, Y., Yang, D., Roth, H.R. and Xu, D.,"Swinunetr: Swin transformers for semantic segmentation of brain tumors in mri images" In International MICCAI Brainlesion Workshop (pp. 272-284). Springer, Cham, 2022.

[12] Ezhov, I., Scibilia, K., Franitza, K., Steinbauer, F., Shit, S., Zimmer, L., Lipkova, J., Kofler, F., Paetzold, J., Canalini, L. and Waldmannstetter, D.,"Learn-Morph-Infer: a new way of solving the inverse problem for brain tumor modeling," Medical Image Analysis, p.102672, 2022.

[13] Sharma, A.K., Nandal, A., Dhaka, A., Koundal, D., Bogatinoska, D.C. and Alyami, H.,"Enhanced watershed segmentation algorithm-based modified ResNet50 model for brain tumor detection," BioMed Research International, 2022.

[14] Raza, R., Bajwa, U.I., Mehmood, Y., Anwar, M.W. and Jamal, M.H.,"dResU-Net: 3D deep residual U-Net based brain tumor segmentation from multimodal MRI," Biomedical Signal Processing and Control, 79, p.103861, 2023.

[15] Nanmaran, R., Srimathi, S., Yamuna, G., Thanigaivel, S., Vickram, A.S., Priya, A.K., Karthick, A., Karpagam, J., Mohanavel, V. and Muhibbullah, M.,"Investigating the role of image fusion in brain tumor classification models based on machine learning algorithm for personalized medicine," Computational and Mathematical Methods in Medicine, 2022.

[16] Zeineldin, R.A., Karar, M.E., Elshaer, Z., Wirtz, C.R., Burgert, O. and Mathis-Ullrich, F.,"Explainability of deep neural networks for MRI analysis of brain tumors," International Journal of Computer Assisted Radiology and Surgery, pp.1-11, 2022.

[17] Rahman, M.L., Reza, A.W. and Shabuj, S.I.,"An internet of things-based automatic brain tumor detection system," Indonesian Journal of Electrical Engineering and Computer Science, 25(1), pp.214-222, 2022.

[18] Maji, D., Sigedar, P. and Singh, M.,"Attention Res-UNet with Guided Decoder for semantic segmentation of brain tumors," Biomedical Signal Processing and Control, 71, p.103077, 2022.

[19] Khan, A.H., Abbas, S., Khan, M.A., Farooq, U., Khan, W.A., Siddiqui, S.Y. and Ahmad, A.,"Intelligent model for brain tumor identification using deep learning,"Applied Computational Intelligence and Soft Computing, 2022.

[20] Islam, K.T., Wijewickrema, S. and O'Leary, S.,"A Deep Learning Framework for Segmenting Brain Tumors Using MRI and Synthetically Generated CT Images," Sensors, 22(2), p.523, 2022.

[21] Kumar, K.A., Prasad, A.Y. and Metan, J.,"A hybrid deep CNN-Cov-19-Res-Net Transfer learning architype for an enhanced Brain tumor Detection and Classification scheme in medical image processing," Biomedical Signal Processing and Control, 76, p.103631, 2022.

[22] Amin, J., Anjum, M.A., Sharif, M., Jabeen, S., Kadry, S. and Moreno Ger, P.,"A New Model for Brain Tumor Detection Using Ensemble Transfer Learning and Quantum Variational Classifier," Computational Intelligence and Neuroscience, 2022.

[23] Karayegen, G. and Aksahin, M.F.,"Brain tumor prediction on MR images with semantic segmentation by using deep learning network and 3D imaging of tumor region," Biomedical Signal Processing and Control, 66, p.102458, 2021.

[24] Saleem, H., Shahid, A.R. and Raza, B.,"Visual interpretability in 3D brain tumor segmentation network," Computers in Biology and Medicine, 133, p.104410, 2021.

[25] Srinivasa Reddy, A. and Chenna Reddy, P.,"MRI brain tumor segmentation and prediction using modified region growing and adaptive SVM," Soft Computing, 25(5), pp.4135-4148, 2021.

[26] Díaz-Pernas, F.J., Martínez-Zarzuela, M., Antón-Rodríguez, M. and González-Ortega, D.,"A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network," In Healthcare (Vol. 9, No. 2, p. 153). MDPI, 2021, February.

[27] Irmak, E.," 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(3), pp.1015-1036, 2021.

[28] Masood, M., Nazir, T., Nawaz, M., Mehmood, A., Rashid, J., Kwon, H.Y., Mahmood, T. and Hussain, A."A novel deep learning method for recognition and classification of brain tumors from MRI images," Diagnostics, 11(5), p.744, 2021.

[29] Bodapati, J.D., Shaik, N.S., Naralasetti, V. and Mundukur, N.B.,"Joint training of two-channel deep neural network for brain tumor classification," Signal, Image and Video Processing, 15(4), pp.753-760, 2021.

[30] 30]Aghalari, M., Aghagolzadeh, A. and Ezoji, M.,"Brain tumor image segmentation via

asymmetric/symmetric UNet based on two-pathway-residual blocks," Biomedical Signal Processing and Control, 69, p.102841, 2021.

[31] Elazab, A., Wang, C., Gardezi, S.J.S., Bai, H., Hu, Q., Wang, T., Chang, C. and Lei, B., "GP-GAN: Brain tumor growth prediction using stacked 3D generative adversarial networks from longitudinal MR Images," Neural Networks, 132, pp.321-332, 2020.

[32] Amin, J., Sharif, M., Gul, N., Raza, M., Anjum, M.A., Nisar, M.W. and Bukhari, S.A.C.,"Brain tumor detection by using stacked autoencoders in deep learning," Journal of medical systems, 44(2), pp.1-12, 2020.

[33] Zhou, C., Ding, C., Wang, X., Lu, Z. and Tao, D.,"One-pass multi-task networks with cross-task guided attention for brain tumor segmentation," IEEE Transactions on Image Processing, 29, pp.4516-4529, 2020.

[34] Sharif, M., Amin, J., Raza, M., Yasmin, M. and Satapathy, S.C.,"An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor," Pattern Recognition Letters, 129, pp.150-157, 2020.

[35] Noreen, N., Palaniappan, S., Qayyum, A., Ahmad, I., Imran, M. and Shoaib, M.,"A deep learning model based on concatenation approach for the diagnosis of brain tumor," IEEE Access, 8, pp.55135-55144, 2020.

[36] Naser, M.A. and Deen, M.J.,"Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images," Computers in biology and medicine, 121, p.103758, 2020.

[37] Sharif, M., Amin, J., Raza, M., Anjum, M.A., Afzal, H. and Shad, S.A.,"Brain tumor detection based on extreme learning," Neural Computing and Applications, 32(20), pp.15975-15987, 2020.

[38] Amin, J., Sharif, M., Raza, M., Saba, T., Sial, R. and Shad, S.A.,"Brain tumor detection: a long short-term memory (LSTM)-based learning model," Neural Computing and Applications, 32(20), pp.15965-15973, 2020.

[39] Çinar, A. and Yildirim, M.,"Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture," Medical hypotheses, 139, p.109684, 2020.

[40] Wang, F., Jiang, R., Zheng, L., Meng, C. and Biswal, B.,"3d u-net based brain tumor segmentation and survival days prediction," In International MICCAI Brainlesion Workshop (pp. 131-141). Springer, Cham, 2019, October.

[41] Khan, M.A., Ashraf, I., Alhaisoni, M., Damaševičius, R., Scherer, R., Rehman, A. and Bukhari, S.A.C.," Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," Diagnostics, 10(8), p.565, 2020.

[42] Chen, S., Ding, C. and Liu, M.,"Dual-force convolutional neural networks for accurate brain tumor segmentation," Pattern Recognition, 88, pp.90-100, 2019.

[43] Zaw, H.T., Maneerat, N. and Win, K.Y.,"Brain tumor detection based on Naïve Bayes Classification," In 2019 5th International Conference on engineering, applied sciences and technology (ICEAST) (pp. 1-4). IEEE, 2019.

[44] Deepak, S. and Ameer, P.M.,"Brain tumor classification using deep CNN features via transfer learning," Computers in biology and medicine, 111, p.103345, 2019.

[45] Wang, G., Li, W., Ourselin, S. and Vercauteren, T.,"Automatic brain tumor segmentation using convolutional neural networks with test-time augmentation.,"In International MICCAI Brainlesion Workshop (pp. 61-72). Springer, Cham, 2018.

[46] Saouli, R., Akil, M. and Kachouri, R.,"Fully automatic brain tumor segmentation using end-to-end incremental deep neural networks in MRI images," Computer methods and programs in biomedicine, 166, pp.39-49, 2018.

[47] Sun, J., Peng, Y., Guo, Y. and Li, D.,"Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN," Neurocomputing, 423, pp.34-45, 2021.

[48] Deb, D. and Roy, S.,"Brain tumor detection based on hybrid deep neural network in MRI by adaptive squirrel search optimization," Multimedia tools and applications, 80(2), pp.2621-2645, 2021.

[49] Le, N., Yamazaki, K., Quach, K.G., Truong, D. and Savvides, M.,"A multi-task contextual atrous residual network for brain tumor detection & segmentation," In 2020 25th International Conference on Pattern Recognition (ICPR) (pp. 5943-5950). IEEE, 2021.

[50] Sharif, M.I., Li, J.P., Khan, M.A. and Saleem, M.A.,"Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images," Pattern Recognition Letters, 129, pp.181-189, 2020.

[51] G. B. JanardhanaSwamy, Anusha, Lavanya, Meghashree, and Sangeetha, "Brain tumor detection using convolutional neural network," International Journal for Research in Applied Science and Engineering Technology, vol. 8, no. VI, 2020.

[52] R. R. Agravat, M. S. Raval,"3d semantic segmentation of brain tumor for overall survival prediction", in: International MICCAI Brainlesion Workshop, Springer, 2020, pp. 215–227.

[53] Kahali, S., Adhikari, S.K. and Sing, J.K.,"A two-stage fuzzy multi-objective framework for segmentation of 3D MRI brain image data," Applied Soft Computing, 60, pp.312-327, 2017.

[54] Sun, J., Peng, Y., Guo, Y. and Li, D.,"Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN," Neurocomputing, 423, pp.34-45, 2021.

[55] Tan, W., Tiwari, P., Pandey, H.M., Moreira, C. and Jaiswal, A.K.,"Multimodal medical image fusion algorithm in the era of big data," Neural Computing and Applications, pp.1-21, 2020.

[56] Pham, D.L., Xu, C. and Prince, J.L.,"A survey of current methods in medical image segmentation," Annual review of biomedical engineering, 2(3), pp.315-337, 2000.

[57] Fu, X., Liu, T., Xiong, Z., Smaill, B.H., Stiles, M.K. and Zhao, J.,"Segmentation of histological images and fibrosis identification with a convolutional neural network," Computers in biology and medicine, 98, pp.147-158, 2018.

[58] Sunanda Das; O. F. M. Riaz Rahman Aranya; Nishat Nayla Labiba, "Brain Tumor Classification Using Convolutional Neural Network", In Proceedings of 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, May 2019.