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Role of Deep Learning in Brain Tumor Detection and Classification (2015 to 2020): A Review

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Abstract— During the last decade, computer vision and machine learning have revolutionized the world in every way possible. Deep Learning is a sub field of machine learning that has shown remarkable results in every field especially biomedical field due to its ability of handling huge amount of data. Its potential and ability have also been applied and tested in the detection of brain tumor using MRI images for effective prognosis and has shown remarkable performance. The main objective of this research work is to present a detailed critical analysis of the research and findings already done to detect and classify brain tumor through MRI images in the recent past. This analysis is specifically beneficial for the researchers who are experts of deep learning and are interested to apply their expertise for brain tumor detection and classification. As a first step, a brief review of the past research papers using Deep Learning for brain tumor classification and detection is carried out. Afterwards, a critical analysis of Deep Learning techniques proposed in these research papers (2015 to 2020) is being carried out in the form of a Table. Finally, the conclusion highlights the merits and demerits of deep neural networks. The results formulated in this paper will provide a thorough comparison of recent studies to the future researchers, along with the idea of the effectiveness of various deep learning approaches. We are confident that this study would greatly assist in advancement of brain tumor research.

Index Terms—Brain Tumor, Deep Learning, Machine Learning, Neural Networks

1. Introduction

THE revolution in machine learning and computer vision has opened new ways and paths for groundbreaking inventions and algorithm development [1][2]. It has shown remarkable performance and has application in many areas like self-driving cars, health, education and IoT (Internet of Things) [3]. Biomedical applications of machine learning and artificial intelligence are recently gripping the researchers specially the area of anomaly detection has taken much attention [4].

Brain tumor is considered as one of the deadliest diseases [5] [6] in the world due to its increased affect and mortality rate in all age groups [7] [8] [9][10] [11] **.** It is mentioned in [9] that it is the second leading cause of cancer in India. According to recent report "Cancer Statistics 2020" published by the American Cancer Society ,around 24000 people will get infected from brain tumor while estimated 19000 deaths will happen in 2020 in U.S [12]. This disease is now getting equally common in kids as well due to increase in the use of technology like cell phones, Tablets etc.[13]**.** Around 120 types of tumors [5] have been found till date and they all appear in different shape and size[14] [6] [15] which makes the detection more difficult due to the complex structure of the brain [16]. Many medical imaging modalities are being utilized for many years to detect the brain anomalies i.e. Computed Tomography (CT scan), Positron Emission Tomography (PET) scan, Magnetoencephalography (MEG) and Magnetic Resonance Imaging (MRI) etc.[2][8]. Among them, MRI multimodality imaging technique is the most popular and efficient technique frequently used in the detection of brain tumor because of its ability to differentiate between structure and tissue on the basis of contrast levels [14] [8] [9] [17] [18] [19]. Currently, anomaly detection through MRI is manual mostly and clinicians have to spend a lot of time to detect and segment the tumor for treatment and surgical purpose[1] [2] [20]**.** This manual technique is also prone to errors and can compromise life. In order to resolve these issues, studies have started to focus on various machine learning and Deep Learning techniques for computer-based tumor detection and segmentation.

Deep Learning is a subfield of machine learning that has been widely used since the past few years to make an automatic, semi-automatic or hybrid model that can efficiently classify and segment the tumor in less time and with maximum accuracy [2] [4]**.** Early detection of brain tumor helps the radiologists for effective prognosis and increase the chance of long-term survival [8] but it's still a challenging task due to the variable appearance , location , shape and size of the tumor[5] [10]**.** A lot of work has already been done in this area to assist doctors, patients as well as researchers. Numerous Computer Aided Diagnostic (CAD) systems are developed so far that detect the anomaly in brain automatically[17] [8] and classify it but still lack in many areas [18]**.** Many reviews have been published in this regard but still none of them highlighted the deficiencies in the work already done and provided any significant insight for the future directions. Hybrid models lack interoperability while deep models suffer from gradient vanishing problem. Similarly, data pre-processing standardization is lacking.

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Deep Learning optimization algorithms are required to make a bridge between different techniques, algorithms and domains. The biggest drawback of Deep Learning is that it requires huge amount of annotated data [3] [21] [2]**.** The solution to these problems can only be found by carrying out a thorough review of the existing techniques that are present in the literature. While giving an idea of the advantages and disadvantages, reviews also give you an idea of a new algorithm or architecture that can be developed to cope up with the ongoing problem and that is the main aim of this paper.

Recent research papers related to detection and classification of brain tumors using deep learning between 2015-2020 were considered in this review. We wanted to explore the state-of-art current research related to both detection and classification of brain tumor. The main reason of doing this type of review is that we plan to work on a particular Multi-task learning model of deep learning and we want to explore the existing deep learning models to get an insight into the loopholes and gaps that can be filled using our proposed deep learning scheme. Multi-task learning architectures combine multiple models into one model having a single learning mechanism and can be trained end to end for multiple tasks [22]. These types of models usually have one input and multiple outputs. Usually, conference papers are not given much importance, but we used both journal and conference papers for writing this review because surprisingly a huge amount of newly developed deep learning models have been presented in the conference papers in the last five years. It was also noticed that very informative and intuitive reviews were published in journals which really helped us in devising and shaping our paper.

No specific publisher was targeted but we took papers from multiple sources as can be seen in Table 1. below to cater for diverse knowledge in a single domain. Multiple online scientific research article repositories were used for gathering relevant papers. IEEE explore, Medline, Google Scholar, ScienceDirect and ResearchGate were used for searching the relevant papers. The filter option for the year (2015 to 2020) was selected every time so that only papers in the selected time period came out. We mainly used the words like detection of MRI images using deep learning, classification of brain tumor from MRI images using deep learning, detection and classification of brain tumor using deep learning etc. A review of 53 selective papers is presented in this paper. The breakup of these articles with publication source is shown in Table 1. below.

Table 1. Breakup of paper sources considered for the review

Publication Source	Number of Papers
Journals	
IEEE Access	4
Springer	15
Elsevier	11
Hindawi	3
WARSE	1
SCIRP	1
Tejass Publishers	1
Oriental Scientific Publishing Company	1
Maxwell Scientific Publishing Corporation	1
Indian Society Of Education and Environment	1
IJRASET	1
Conferences	
IEEE Conferences	13
Total	53

All papers cover the aspect of detection of brain tumor or classification of brain tumor or both using deep learning. Although machine learning is a huge domain which encapsulates deep learning, still research work done using machine learning models have not been made part of the review because of the huge number of reviews already present in that domain. To carry out some research work in a specific domain, reviews are very critical and efficient stage to start with. We are confident that our review would assist the researchers focused on integration of brain tumor detection and classification in future.

The underlined objective in carrying out this detailed survey is to give the researchers an insight into what has already been done in the area of classification of brain MRI images including the pros and cons of already developed techniques and algorithms of Deep Learning. Figure 1 shows the outline of key concepts presented in this review paper. The first part provides a detailed description of MRI imaging modality. It also provides some insight into the basics of brain tumor and the role of MRI in detecting brain tumors. The second part highlights the progress of existing methodologies and algorithms in making a CAD system in the form of literature review. A critical analysis of research papers from 2015 to 2020 is being done in the form of a Table in this part. The third part gives some of the factors that degrades the performance of existing CAD systems. The fourth part gives some of the key ideas that can be implemented to boost the classification model and make it a robust one. Finally, the conclusion summarizes the whole review. In the end, some key future directions are also presented for aspiring researchers to make them explore the unknown areas. Some valuable suggestions on the basis of studies presented in this paper are provided so that it can help in designing an efficient and fully automated classification algorithm.

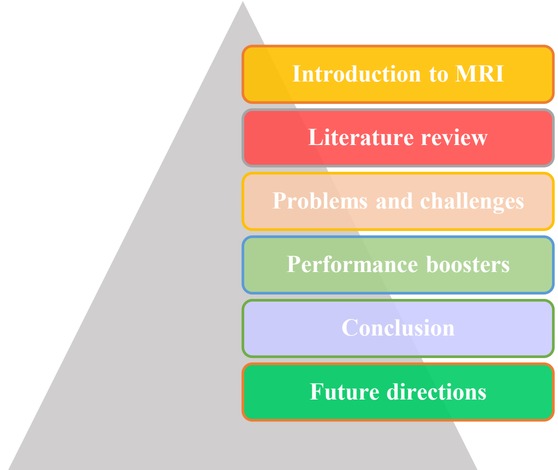

Figure 1. Outline of the Literature Review

2. MAGNETIC RESONANCE IMAGING

Different medical imaging techniques have surfaced over the past few years that assist the medical practitioners in detecting the type of disease and its location. The imaging modality also helps the doctors to predict the well-being and overall survival of patients. CT-scan, X-ray, MRI, MRS,PET scan etc. are some of the techniques used currently for detecting the anomaly in any part of the body [23] [5] [21]. MRI has attained considerable attention and praise in the sense that it is a non-invasive and 3D imaging technique that can locate the anomaly in the soft tissues or non-bony area in a very effective manner[8] [9] [1] [24]. It gives the best contrast in terms of tissue structure because it has the capability to show images up to 65535 grey levels which is impossible to be visualized by a naked eye [25] [9] [1]. MRI machine can take multiple images of the subject under observation from different views as can be seen in the Figure 2 below with different contrast and physical properties and due to this reason it is known as multiple modality imaging [26].

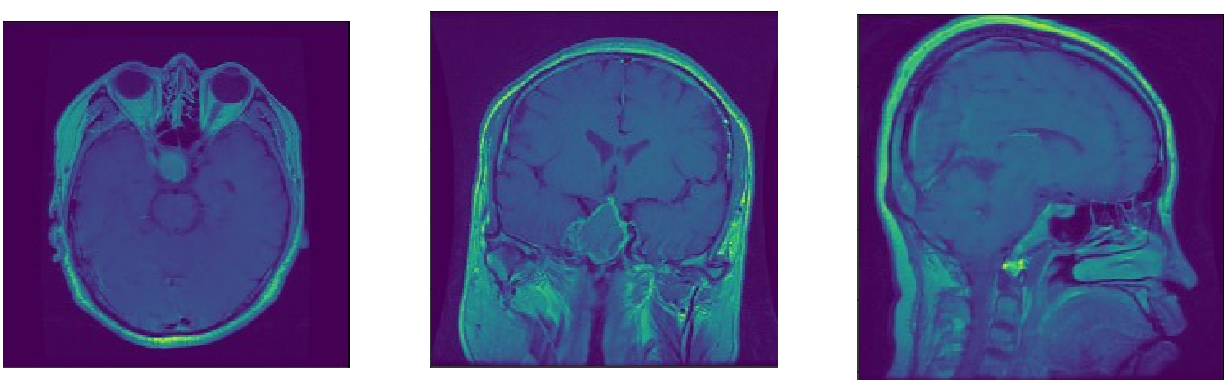

Figure 2. Three views of an MRI image (Axial, Sagittal and Coronal)

2.1 Methodology:

MRI is a non-invasive technique that uses non-ionizing and harmless radiation [16] to show the 3D anatomical structure for any part of the body without the need to cut open the area [27]. It uses RF pulses and strong magnetic field to acquire images [16] [28]. The idea is to place the body inside a strong magnetic field. Initially the magnets are off and the water molecules inside the human body are at their equilibrium position. The magnets are then operated to turn on the magnetic field. Under the influence of this strong magnetic field, the water molecules of the body align themselves in the direction of the magnetic field [29]. A strong RF energy pulse is applied to the body in the direction of the magnetic field which stimulates the protons to spin against the magnetic force and realign. When the RF energy pulse is turned off, the water molecules come to their equilibrium position and align themselves again with the magnetic field [29]. In doing so, the water molecules emit RF energy which is detected by the scanner and is converted into viewable images [5] [10]**.** The amount of RF energy released by the water molecules depends upon the tissue structure. The intensity of the emitted RF energy can be varied by varying the scanner parameters and in this way, multiple modality images through the MRI machine can be obtained. Two most important factors that controls the MRI images are TE and TR times [30] that are explained as under:

- TE time (time to echo): It's the time between the delivery of the RF pulse and the receipt of the echo signal [29].
- TR time (repetition time): It is the amount of time between successive pulse sequences applied to the same slice [29].

3. BRAIN TUMOR

Brain tumor is basically a mass like structure of alive and dead cells that start to grow uncontrollably inside the brain [28] [14] [5]. Brain tumor patients have different survival rate depending upon the size and severity of the disease [31]. Brain tumor consists of two types: primary and secondary, according to their site of origination. Primary brain tumors originate inside the brain while secondary tumors develop elsewhere inside the body and then travel towards the brain [6] [15] [20].

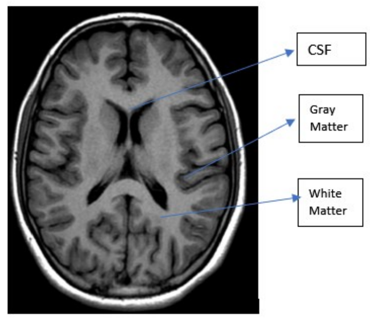

Figure 3. Brain MRI image taken from Kaggle dataset showing three parts of the brain

Human brain has three important parts in terms of tissue structure i.e. grey matter, white matter and cerebrospinal fluid (CSF) as can be seen in Figure 3 above [9] [30]. These three parts along with the tumor show different contrast when imaged under different physical characteristics and play the key role in MRI imaging for brain tumor detection as they consist of soft tissues. The water molecules inside these tissues largely depend upon the TE and TR times which have already been explained in the previous section. The four popularly used and easily available types of MRI images are T1, T2, T1-CE and Flair [17] [9] [26]. These images are obtained by varying the TE and TR times as explained below:

- T1 Weighted Images: These images are obtained by keeping short TE and TR times [7]. CSF appears dark in T1 weighted images [20]**.** T1 images highlight fat tissue inside the body [23] [29].
- T2 Weighted Images: These images are obtained by keeping long TE and TR times [7] which makes the CSF brighter [20]**.** These images highlight fat tissue and water inside the body [23] [29].
- T1- CE Images: These images have same TE and TR time as of T1 images except that they are obtained by first injecting gadolinium to the patient which is a non-toxic paramagnetic contrast enhanced agent. The agent has the property to illuminate the areas when imaged [23] [29].
- Flair Images: These images are obtained by keeping TE and TR times very long [20]. By doing so, abnormalities remain bright but normal CSF fluid is attenuated and made dark. This sequence is very sensitive to pathology and makes the differentiation between CSF and an abnormality much easier [23] [28] [29].

Figure 4 shows the four types of MRI images as explained above. It can be seen clearly that all the four images give rich information about the appearances of the brain tissues [19]. Each MRI image explained previously show a very different and prominent information about the hidden entities inside the brain. This is briefly shown in Table 2. Other than these four commonly known sequences, Diffusion Weighted Imaging (DWI), Diffusion Tensor Imaging (DTI) and Perfusion MRI has also appeared as powerful MRI sequences in detecting brain anomalies [23].

Table 2. Properties of Different MRI Sequences [20][29]

Brain Entity	T1w (TR< 1000ms, TE <30ms)	T2w (TR>2000, TE>80ms)	Flair (large TE and TR times)	T1-Gd
Grey Matter	Grey	Dark	Dark	Dark
White Matter	Bright	Dark	Dark	Grey
CSF	Dark	Bright	Dark	Dark
Tumor	Dark	Bright	Bright	Bright

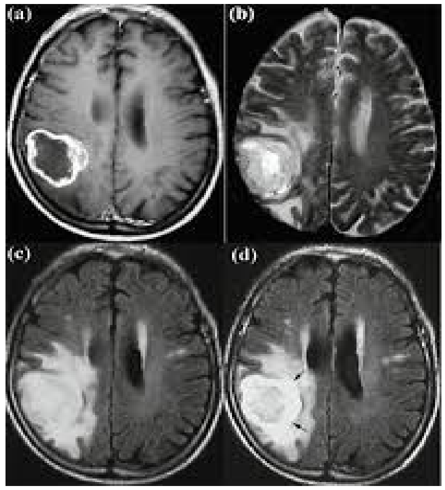

Figure 4. (a) T1 weighted (b) T2 weighted (c) Flair (d) Flair- contrast enhanced [23]

According to the severity, brain tumor is classified into two categories namely benign and malignant [9] [4]**.** Benign tumors are less aggressive in the sense that they are slow growing [16], normal in appearance and have regular boundaries while malignant tumors are aggressive in the sense that they can be life-threatening as their growth is very fast [5] and they have very irregular shape [32]. World health organization (WHO) has placed the malignant tumors into four different grades considering the chemical and physical properties of the tumor [26] [27]. The grading criteria is explained in Figure 3 below [21]**.**

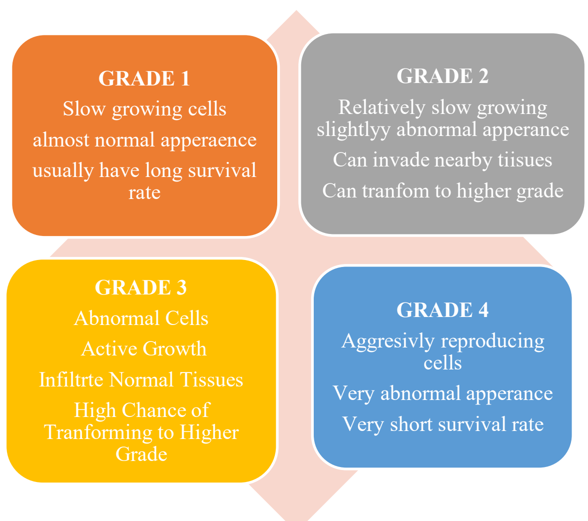

Figure 5. Grading Criteria of Brain Tumor [18]

4. LITERATURE REVIEW OF CLASSIFICATION

This section presents a detailed overview of the research papers dealing with classification of brain tumor MRI images using Deep Learning techniques published during the period 2015 to 2020. This section is formulated as follows: section A presents a brief overview of the existing methodology adopted in majority of the papers for detection and classification of MRI images using Deep Learning techniques. Section B presents a description of the popular datasets that have been used in the research papers reviewed in the form of a Table. Section C presents a brief overview of the literature on brain tumor classification using deep learning presented in the past six years with quantitative analysis while section D presents a summarized qualitative comparison of the proposed techniques covered in the literature section. Finally, section E presents the critical analysis in the form of a table.

4.1 Existing methodology

The existing state-of-the-art techniques follow some pre-defined steps to classify brain MRI images[5] [10] [32] [17]**.** Figure 6 shows the steps mainly followed in detecting and classifying tumor and non-tumor tissues in brain MRI images [33] [9]. A brief description of the possible steps and approaches is as follows:

- Input Images: The input images used are mainly the MRI brain scans [5] [19]. The input can be 2D or 3D depending upon the architecture and memory limits.
- Pre-processing: It is one of the major steps being followed extensively in the literature in state-of-the-art models. It has proven to be as critical as any other step due to its efficiency in enhancing the input images in considerable ways[5] [24] [34].
- Segmentation: It mainly partitions the input image into similar sections based on some criteria so that only valuable information can be taken out and rest is discarded [19] [11]. Some researchers segment the exact tumor [34] while some segments the portion of the image containing the tumor [5]. Multiple approaches exist.
- Classification: The aim of classification is to categorize the input data into multiple categories depending on some behavioral patterns that are similar within the group.

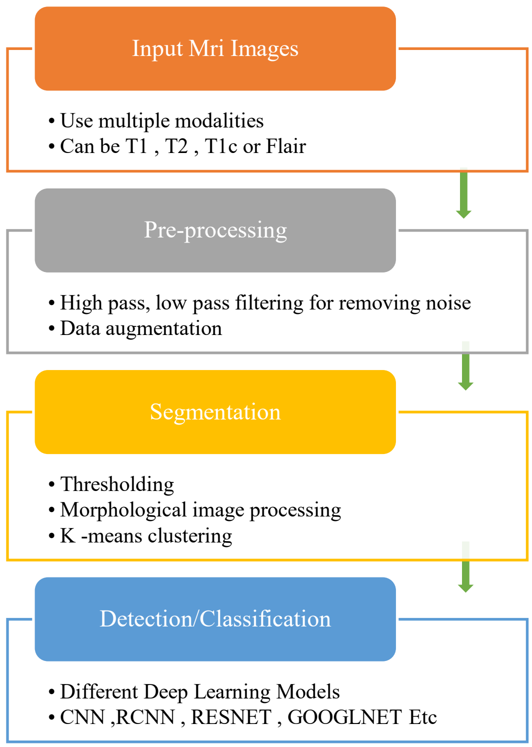

Figure 6. Existing classification methodology

Multimodality MRI has been widely accepted as a standard imaging technique for diagnosing brain tumors in almost all the literature work cited in this paper because of its enormous capabilities [23] [17][19]. Almost 70 % researchers first pre-process the MRI images for enhancement and noise removal [9] [25]**.** Some authors also use data augmentation in conjunction with pre-processing stage to increase the dataset. Afterwards, they segment the tumor area using any of the image processing techniques available so far. After segmentation, the segmented area is given as input to a Deep Learning algorithm for training purpose [9]. Another technique usually practiced is to input the pre-processed images directly without segmentation to Deep Learning algorithm [9]**.** Segmentation is not a critical part for classification due to which mostly people do not use it for classification task [9]. The model learns the features itself from the input image and train on these features. Finally, the trained model is tested for classification.

Although there is no need for feature extraction in Deep Learning algorithms [26] but research has shown that feature extraction using machine learning or metaheuristic approaches is still used with deep learning as hybrid models for incorporating efficient and robust features for classification [35] [36]. The features are extracted using statistical tools or machine learning approaches. Then this feature vector is used to train the Deep Learning algorithm. The last procedure that is observed to be followed in the literature is to input the brain MRI images directly to a Deep Learning algorithm without pre-processing for classification.

The main aim of every approach is to modify the layers of the Deep Learning model according to the requirement for experimental purpose and then choose the model that gives the best performance. People have also used hybrid models by concatenating machine and Deep Learning models for building efficient systems. Before starting any of the above-mentioned procedures, the dataset is divided into training, testing and validation sets accordingly.

In Deep Learning, significant amount of praise and acknowledgment has been given to Convolutional Neural Network (CNN) in the sense that it has the capability to automatically extract deep features by adapting to small changings in the images[4] [20] [37]. It also has the capability to handle ample amount of data. So far CNN has achieved very challenging results in detection and classification of brain tumors using MRI [4][37].

4.2 Datasets

Table 3. Publicly Available Datasets

Datasets Name	*Source*	*Reference*
IBSR	[38]	[96]
OASIS	[39]	[62]
THE WHOLE BRAIN ATLAS	[40]	[10]
BRATS (2012-2019)	[41]	[49][50][51][56][58][58][62]
RIDER	[42]	-
RADIOPEDIA	[43]	[33]
TCIA	[44]	[30][54][61]
FIGSHARE CJDATA	[45]	[48][53][55][60][64]
ISLES	[46]	[14]
CANCER GENOME ATLAS	[47]	[11][54][65]
KAGGLE	[48]	[46][47][52][61][66][67]

A CAD system based on Deep Learning requires a large amount of data for training purpose [37]. In this regard, sufficient number of datasets are made available for research purpose[8] [4] [1] [49]**.** Table 2. briefly lists the names of some of the datasets. All of these datasets have been used by the research work reviewed in this paper but BRATS dataset is the one that has been used the most due to its large size and better visualization properties. Figure 7 shows two MRI images (High grade and Low grade) extracted from BRATS 2012 dataset. The references column in the table points to the papers that has used it while the second column points to the web address of the online repository of the specific dataset**.**

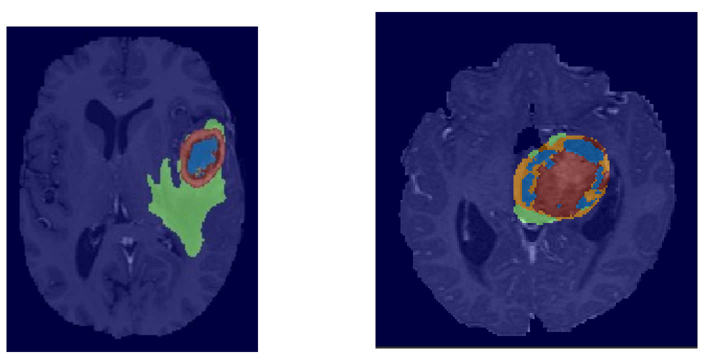

Figure 7. Left image (High grade glioma overlay image with axial view shown in 95th slice) Right image (Low grade glioma overlay image with axial view shown in 85Th slice

4.3 Performance Measures

Performance metrics are specialized formulas that give us the evidence about the type of working and credibility of a specific algorithm / model. The performance metrics that are largely being used in the literature are listed in the Table 4. below with formula and functionality to give more insight into the working of a specific type of measure and its significance. It must be kept in mind that only those metrics that are significant for classification are listed.

Table 4. Performance Metrics

Performance Metric	Formula	Definition/Functionality
Sensitivity/Recall	TP/(TP+FN)	The ratio of correctly predicted positive observations to the all-Positive observations in respective class
Precision	TP/(TP+FP)	Precision is the ratio of correctly predicted positive observations to the total predicted positive observations
Specificity	TN/(TN+FP)	The ratio of correctly predicted negative observations to the all-negative observations in respective class
Accuracy	(TP+TN)/(TP+TN+FP+FN)	It is the total number of observations predicted correctly in percentage
Training/ Validation Loss	$(\text{Actual- Predicted})^2$	Training loss is the error on the training set of data. Validation loss is the error after running the validation set of data through the trained network.
Execution Time		The Total time taken by the program or model to run on a trained machine
Learning rate		It defines how quickly the neural network updates the concepts it has learned.
PPV	TP/(TP+FP)	It is the proportion of the positive results that are truly positive
False Acceptance Rate (FAR)/ False Positive Rate /False Alarms	FAR = FP/(FP+TN) FA = Number of False Acceptances TA = Total Number of Attempts	The percent of negative observations that are wrongly predicted as positive
False Rejection Rate (FRR) / Missed Alarms	FRR = FN/(FN+TP)	The percent of positive observations that are wrongly rejected or predicted as negative
Equal Error Rate (EER)	FAR = FRR	When FAR equals to FRR
F1 Score	2*TP/(2*TP+FP+FN)	F1 Score is the weighted average of precision and recall.
Area under the ROC Curve (AUC)		The area under the ROC curve (AUC) is a measure of how well the model is distinguishing between different classes. An area of 1 is considered to be the best in evaluating test cases.
Cross validation		Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample

4.4 Related works:

Several research papers have surfaced since the popularity of the Deep Learning techniques. Deep neural networks have lessened the burden of feature extraction and selection due to their self-learning capability. Different Deep Learning models from simplest to complex are evolved with time and have shown marvelous results in the domain of medical imaging [21].

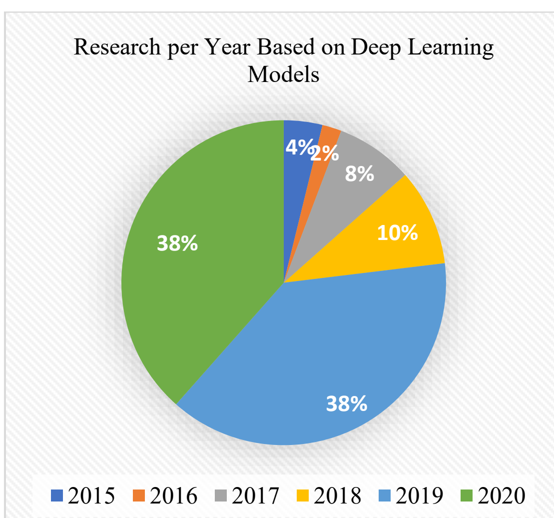

Figure 8. Year wise statistics of research papers reviewed

In the current study, almost 53 research papers are critically reviewed to account for the efficiency of Deep Learning in brain tumor classification using MRI images. The use of Deep Learning algorithms for brain tumor classification has doubled since the last year. Figure 8 shows a pie chart of year wise distribution of research papers. We can clearly see that the use of Deep Learning has increased 10 folds in 2019 and is expected to increase further this year because of the advantages it holds in terms of data handling capabilities and automation.

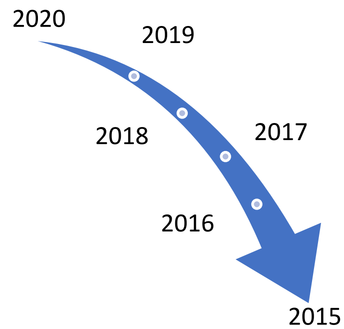

Figure 9. Order of the Qualitative Review

Below is a detailed overview of the research papers published in the last six years that have used Deep Learning models for brain tumor detection and classification in MRI images. The brief review of each paper is organized on year wise basis to help the researchers in better understanding and grasping of knowledge. We have discussed various aspects of studies in each year such as deep learning models, datasets, and pre-processing and data augmentation etc. Figure 9 briefly show the order of the literature survey.

4.4.1 Technical studies carried out in 2020

We are starting our review with the discussion of studies published in 2020. We selected 20 publications of 2020 for our study and a detailed review is provided in this section.

In a recent publication by T. Kalaiselvi, S. T. Padmapriya the authors have constructed six CNN models for the classification of brain tumor [50]. All the six CNN models mainly differ in the number of layers. Drop out layer is incorporated in 2 CNN models for regularization and 2 models are also using stopping criteria and batch normalization in addition to the drop out layer. the remaining 2 models are used without these layers. The training is done on BRATS 2013 Dataset while testing is done on World Brain Atlas (WBA). The results show that model 4 shows optimum results in the sense that it showed decreased false alarm rate for non-tumor images while model 6 yields the best results and achieved an overall accuracy of 96%.

In another paper, data pre-processing is used to increase the efficiency of the CNN architecture for brain tumor classification [51]. Two main pre-processing i.e., rotation and patch extraction are used as classical data augmentation techniques and are applied to the dataset of 3064 images to increase the dataset. Then the images are resized to 28*28 to reduce the model complexity. Finally, capsule-net is utilized to verify the effectiveness of data augmentation and to classify the brain tumor images into three types i.e., glioma, meningioma and pituitary tumor. The results show that pre-processing greatly effects the performance.

A binary classification problem of brain tumor MRI images has been discussed by the authors in [52]. They have used ALEXnet and VGG16 for feature extraction. Their idea is to first enhance the prominent features using hyper column technique and then fuse the features extracted using both the architectures. Recurrent feature elimination (RFE) is used for selecting fittest features. Finally, Support Vector Machine (SVM) was involved for classification and gave 96% overall accuracy.

The authors in [53] have established a procedure by combining Deep Learning and statistical model to discriminate between tumor and non-tumor images. The authors first pre-process the images using a non-local mean filter to suppress noise. Bayesian Fuzzy C-means algorithm is then utilized for segmentation. Information-theoretic measures, wavelet packet Tsallis entropy (WPTE) and scattering transforms (ST) are utilized for the feature extraction process. Finally, classification is done using Deep Autoencoder (DAE) based JOA (Jaya optimization algorithm) and SoftMax regression. The results show 98.5 % accuracy using the proposed technique.

The authors in [54] have pointed out the importance of pre-processing and segmentation of MRI images before giving it as input to a deep learning algorithm. Their idea is to sharpen the MRI images then apply median filtering for noise smoothing. Afterwards, tumor area is segmented using region growing for giving it as input to a fine-tuned stacked sparse autoencoder (SSAE) model. The model was trained and tested on BRATS dataset for 2012, 2013, 2014, and 2015. The results show improved accuracy and sensitivity of the proposed technique.

The authors in [55] present a modified and improved version of RESnet50 which gives better response for classifying brain MRI images into tumor and non-tumor. 8 layers have been added to the original architecture of RESnet 50 and then trained using MRI dataset from Kaggle. The results are also compared with renowned CNN architectures like Googlenet, Alexnet, DENSEnet etc. The results show that the proposed system gives improved accuracy of 97% as compared to the other Deep Learning models.

A novel BrainMRNET convolutional neural network has been designed and discussed in [56]. The model consists of 3 main parts. The first part consists of Convolution Block Attention Module (CBAM) which makes the network learn channel and spatial information. The second part consists of residual block that helps the network learn more prominent features and finally there is hyper Column technique implemented before the fully connected layer. This technique concatenates the feature map from all the convolution layer for better generalizability and efficient classification. the classification success achieved with the BrainMRNet model was 96.05%.

In [57], the authors have exploited the significance of data pre-processing on the classification accuracy and error rate. Mainly the techniques implement data augmentation to increase generalizability and decrease gradient vanishing problem. At first the data is resized and cropped from the center to remove the background information as much as possible as it doesn't help in classification. Afterwards, 7 augmentation techniques were applied to increase the dataset for reduction in overfitting. Finally, the augmented dataset of MRI scans is used as input to Resnt50 architecture for training as well as testing. The results show 98% accuracy.

The authors in [58] present a novel technique that fuses together 4 MRI modalities into one MRI image using dwt technology. The technique generates one fused MRI sequence for each patient. CNN model is then trained using the five MRI datasets with fused MRI sequences. The results show an increase in accuracy for fused images

A novel approach on deep learning based Generative Adversarial Networks (GANs) architecture is proposed in [59]. Their idea was to use CNN as a discriminator of GAN and pre-train it using the two datasets. Data augmentation helped the generative part of GAN to output more realistic images of brain MRI scans. The last layer of CNN discriminator in GAN is replaced with SoftMax for classification. Later on, this deep CNN discriminator is fine-tuned on the Figshare dataset. The results show 88% accuracy.

A hybrid approach SR-FCM-CNN has been proposed by authors in [60]. They first performed the pre-processing using SR CNN network. The low-resolution images are converted to high resolution using this approach and then segmented using FCM approach. The images are then augmented by rotating and zooming to incorporate generalization ability of the classifier. Afterwards, that Squeeze-net architecture was applied to extract features and classified using ELM approach. the results show 98 % accuracy.

The authors in [61] use faster R-CNN for brain tumor detection and classification. For effective implementation of Faster R-CNN, VGG-16 architecture was used as the base-line mathematical model. Region proposal network was utilized for accurate marking of the tumor area. Figshare data set was used for classification into three classes. The results show that the proposed algorithm demonstrates an improved Mean Average Precision of 77.60% for all the three classes.

The study in [62] discusses transfer learning as an important element to cope with the problems of small datasets. The authors of the paper have proposed a complex algorithm using VGGnet as the base-line architecture. The architecture uses pre-trained VGGnet and does block-wise fine tuning of 6 blocks. Each block has different number of layers. The authors formulated six different models by tuning different blocks in each model and studying the effects. Two publicly available datasets (BRATS and CE-MRI) were investigated. The results show 97.28% and 98.69% accuracy on the respective datasets.

The authors in [63] have exploited the features of Kaggle MRI brain tumor dataset using the famous CNN architecture. The CNN model takes in the input MRI image, pre-processes it, segments it and then extracts the features using CNN. Finally, it classifies the output as either a tumorous or non-tumorous image. The authors made a Graphical User Interface (GUI) for effective interaction with the algorithm. The designed algorithm shows 90 to 99% accuracy on the Kaggle dataset.

The study in [64] focuses on multi-level segmentation for efficient feature extraction and classification of brain tumor from MRI scans. The authors first pre-process the MRI images data and then used thresholding, watershed algorithm and morphological operation for segmentation. Features are extracted through CNN and then finally K-SVM classified the images of tumor as cancerous or non-cancerous. The proposed algorithm shows 87.4% accuracy overall.

In another study in [13] the authors have used Haar wavelet transform for feature extraction of the brain MRI images. The Haar wavelet transforms the input image into two sets of features: approximation coefficients and detail coefficients. The authors then used the approximation coefficients to train the deep CNN model. The results show 99.3 % accuracy for CNN and 98 % accuracy for the SVM case.

The authors have presented multiple feature fusion-based classification method in [65]. The authors have proposed two network architectures: one for segmentation and one for classification. Pre-trained inception V3 model was fine-tuned using the BRATS training dataset. Deep features were concatenated with Dominant Rotated Local Binary Patterns (DRLBP) using simple array-based concatenation. The features are then reduced using the Particle Swarm Optimization (PSO). The results show 92% accuracy on BRATS dataset.

The study in [66] presents another efficient algorithm for brain tumor classification and segmentation using statistical features. The proposed algorithm first pre-processes the MRI images for removing noise and extracts statistical features using run length texture features and GLCM matrix. The features are then reduced using Oppositional Gravitational Search Algorithm (OGSA) and fed to RNN which then classified the image as either tumor or non-tumor. The tumor images are then sent to the second phase for segmentation of ROI. The proposed algorithm shows 96% classification accuracy on the used dataset.

Data augmentation plays an important role in medical imaging where we have limited datasets available. The importance of data augmentation is highlighted in another paper at [67] . The authors have used the capabilities of Progressively Growing Generative Adversarial Networks (PG-GANS) to increase the BRATS-2016 data set for effective tumor detection using RESNET-50. Comparisons have been made between the classical data augmentation techniques and PG-GAN based data augmentation. Results have shown 91% accuracy when the detection is performed by combining the classical as well as the PG-GAN based data augmentation.

The authors in [68] have proposed a novel algorithm for MRI image analysis which they named as BRAINnet. The algorithm efficiently detects if the tumor is present or not and if it is present then the second BRAINnet architecture classifies the tumor into respective category by doing segmentation. Results show 98% accuracy in case of detection while 99% in case of classification and is comparable with the state-of-the-art approaches.

In another paper in [69], the efficiency of optimization algorithms has been evaluated by modelling a novel Computer aided diagnosis system for classification of brain MRI into tumor/non-tumor images using CNN. The systems Graphical user interface is built to work with two types of datasets (Kaggle and TCIA). 3 different optimizers were used to account for the best one. The results show that RMSprop gives the best accuracy of almost 98% and helps in fast execution of the algorithm in testing and training phase.

4.4.1.1 Quantitative analysis of 2020 algorithms

In the current year (2020), the focus of many researchers, scientists, and mathematicians is on opening the black box of Deep Learning and resolve all the ongoing problems of deep architectures. Huge amount of research is being carried out in this year with a focus on the pre-processing of MRI images as can be seen in Figure 10. Furthermore, the data augmentation techniques have been shifted from classical to automatic using GANs as can be seen in the Figure 11 below. Research is now more oriented towards the enhancement of images rather Deep Learning algorithms and some researchers have shown promising results in this case.

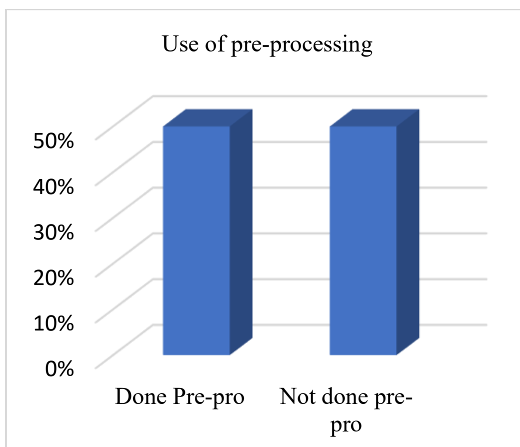

Figure 10. Use of pre-processing in 2020

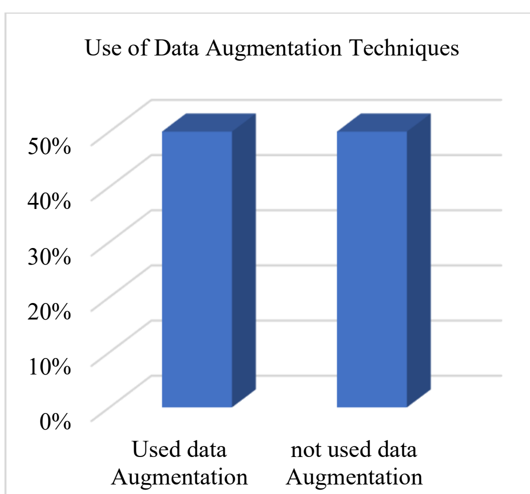

Figure 11. Use of data Augmentation in 2020

It can also be seen in Figure 12 that people have used CNN the most during 2020, even though other prominent and efficient architectures exist in the literature. This is because of the high generalizability, stability and accuracy rate of CNN. It can be observed from Figure 12 that researchers have developed numerous Deep Learning models that did not exist in the literature before 2019. Feature extraction was used previously mainly with machine learning architectures to reduce the dimensionality and also to take into account only the valuable information and discard the extra information. It can be seen in Figure 13 that scientists are still experimenting with different feature extraction techniques although Deep Learning does not require it specifically.

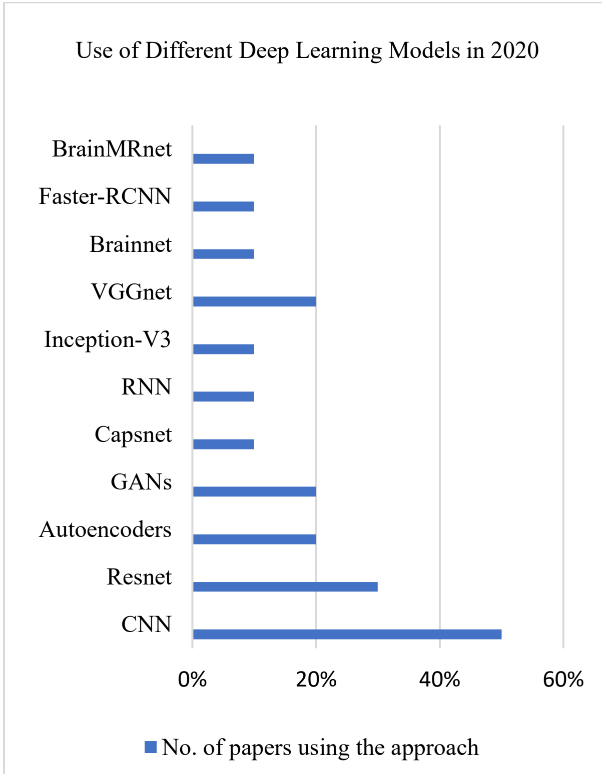

Figure 12. Use of Deep Learning Algorithms during 2020

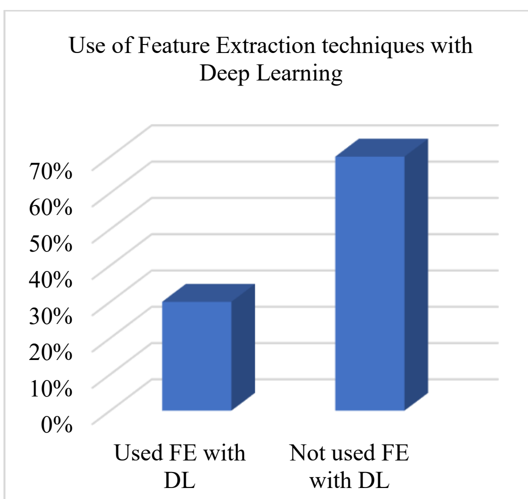

Figure 13. Use of feature extraction in 2020

4.4.2 Technical studies carried out in 2019

We selected 20 papers from 2019 that are mainly using Deep Learning as the main tool in their proposed algorithms and detailed survey of these studies is provided in this section.

In one of the studies in [70], the authors have utilized the efficiency of compression techniques to maximize the accuracy and execution time of CNN in brain MRI classification. They proposed a novel pre-processing step before classification. The method first segments the Region of Interest (ROI) (mainly brain tissue area) using Probabilistic Neural Network (PNN) and then compresses the ROI using two Back Propagation Neural Networks (BPNN). Finally, the compressed images are used as input to CNN for classification. The results were obtained for 3 different types of optimizer for comparison purpose and has shown accuracy rates higher than 90%.

The efficiency of newly developed Capsule network is exploited in another study in [71]. The authors developed a new model of Capsulenet with the name Convcaps. They have used two inputs to the network i.e., tumor image and segmented tumor region. A new loss function is also introduced to optimize the network in all respects. Six different types of experiments have been performed by varying the input and results show that the optimized algorithm gives highest accuracy of 93% when compared with other state-of-the-art models.

The efficient usability of the density of RESNET34 architecture is evaluated in [72]. The authors have utilized the basic deep RESNET34 for modeling and construction of a new algorithm G-RESNET. In this new algorithm, flattened layer is replaced with global max pooling layer and new loss function is introduced. Separate experiments were conducted to account for the effects of global max pooling layer and the loss function on the classification accuracy. Finally, an experiment is also conducted by feature fusion of low-level and high-level features. Results have shown that the newly proposed G-RESnet with optimized loss function and feature fusion achieves 95% accuracy.

Similarly, in another study in [73] the authors have presented a novel approach for detecting tumor and classifying it into benign and malignant category. The proposed method uses score level fusion of the output vectors from pre-trained Alexnet and Googlenet to classify the segmented tumor region into the respective categories. Their algorithm first pre-process the input MRI images by using linear and log transformations. After that the tumor part is segmented using thresholding and morphological operation and finally the segmented area is used to classify the tumor as high grade or low grade on BRATS dataset. The results show an increase in the accuracy of the proposed techniques. The authors also compared the training time and loss curve with the state-of-the-art techniques.

The authors of another publication have proposed Faster R-CNN algorithm for efficient detection and classification of brain tumor MRI images [74]. At first, the images are given as input to a simple CNN through which a convolutional feature map is obtained and this map is then converted to region proposals which are then reshaped in to a feature vector through ROI pooling layer. Finally, this ROI feature vector is given as input to faster R-CNN for classification. SVM was also employed for creating maximum margin between classes so that the algorithm can classify the images with maximum accuracy. Their algorithm achieved 95% accuracy.

Another study in [75] presents a modified form of model already proposed by Ari and Hanbay [76]. The proposed solution modifies the pre-processing and classification stage of the old model. The system uses median filtering for pre-processing because it preserves the edges while removing the noise. Secondly, the model uses modified SoftMax and loss function in convolution layer instead of the sigmoid function because it is inefficient for multi-class classification problem. The last stage segments the tumor using watershed algorithm and morphological operations. Finally, results have been presented. The model achieves 97% accuracy and reduce processing time.

In [77] the authors have used the conventional CNN with 8 layers to classify the brain MRI images as tumor or non-tumor using a private dataset . The algorithm first classifies the images using the proposed CNN. If the image is detected with tumor, then it is segmented. At first global thresholding is applied for binarization of the image and after that watershed algorithm followed with morphological operations extracts the tumor. Finally, tumor area is also calculated. The results show that the proposed algorithm achieves 98% accuracy.

Deep Learning has evolved as a grinding machine of big data in the recent years and have superseded many conventional algorithms. The authors in [78] have developed a novel web-based Deep Learning software for T1-weighted contrast enhanced images in python using keras library. The software first performs the pre-processing of the input images i.e. rotation, rescaling and truncation. The software accepts multiple formats of the images like jpeg, jpg and png. Finally, it classifies the input MRI image dataset into three classes i.e. meningioma glioma and pituitary tumors using CNN. The experimental results show 99% accuracy for all the three classes.

CNNs have many disadvantages. The most important and the critical one is that it does not take into consideration the spatial relationship between the object and its surroundings. This problem is overcome in a recently proposed CAPSNET model by K. Adu, Y. Yu [79]. The authors proposed dilated capsule network which is an extension of the conventional CNN. The pooling layer in the existing CNN architecture is replaced by “routing by agreement” layer in the dilated CAPSNET architecture. The method first pre-processes the images to make them fit and acceptable for the algorithm. The dilated CAPSNET uses dilated convolution in convolutional layers for better image resolution. The results have shown 95% accuracy of the proposed technique.

The authors in [80] have proposed a Deep Learning approach for brain tumor segmentation and classification. The proposed system first evaluates the performance of CNN with three different classifiers namely SoftMax layer, Radial Basis Function and Decision Trees. The best accuracy was achieved using SoftMax layer. Later on, this model is used with the central clustering algorithm for feature extraction. Finally, the extracted features are given to the proposed CNN algorithm with fully connected SoftMax layer for classification. The experimental results show that the adopted methodology has the ability to give 96% accuracy.

The most critical drawback of CNN is that it requires a large amount of data which is currently not available in all domains of research. So this problem was addressed in a recent study by C.Han et al [81]. The authors proposed a technique in which noise to image and image to image GANS are used for data augmentation. At first progressively growing GANS generate random realistic brain images. In the second stage Multimodal UNsupervised Image-to-image Translation (MUNIT) refines the generated images for further improvement. After data augmentation, RESNET-50 was used to classify the images into tumor or non-tumor categories. Multiple models varying in the number of training and testing images were constructed. The results show that the proposed data augmentation technique outperforms the conventional data augmentation methods and give 96% accuracy and boost the performance when combined with conventional data augmentation.

In another study in [82] the authors have shed some light on the importance of multimodalities of brain MRI images. They showed that multimodal information if fused together can give better results in terms of the accuracy. BRATS 2018 dataset was utilized in this research. The authors first pre-processed the images using grey-level normalization and contrast adjustment. The data was also augmented using conventional techniques. Afterwards, the pre-processed images of all the four modalities are given as input to 3D CNN for classification. The authors have used instant normalization to speed up the convergence. Modified loss function was also incorporated. Final results show that by fusing information from multiple modalities, the model achieves a dice score of 92%.

One of the drawbacks of CNN is the need to have labelled dataset. This problem was dealt in one of the studies in [83]. The main idea of this paper was to consider 3D MRI images as 2D slices and use them as input sequences. Three models were designed using deep leaning for comparisons i.e., DENSEnet-RNN, DENSEnet-LSTM and DENSEnet-DENSEnet. In the first model DENSEnet is used as a feature extractor while Recurrent Neural Network (RNN) is used for classification. In the second model DENSEnet was used as feature extractor while Long Short-Term Memory (LSTM) was used as a classifier. Similarly, in the third model DENSEnet is used as a feature extractor as well as classifier. Experimental results show that the three models give accuracies of 87%, 91% and 92% respectively.

In another study by Hossain, M Ashraf in [84], the authors used the conventional CNN for brain tumor MRI classification. The system classifies the images into three classes. The images are first passed through a pre-processing stage. Each image is resized, smoothed using Gaussian filter and then histogram equalized. The pre-processed images are then given as input to the CNN architecture having 5 layers. The final results show that the proposed algorithm achieves an accuracy of 94.39% and an average precision of 93.33%. The authors also compared the results with some state-of-the-art models and plotted graphs for training accuracy and training loss which also showed satisfactory performances.

In [85] the authors have presented a modified version of CAPSNET for classification of brain MRI images into three classes depending upon their type. The authors suggest that CNN lacks the capability to cater the information about the spatial relationship from the tumor surrounding area. This drawback is addressed with the proposed CAPSNET architecture by adding the surrounding information along with the image itself. At first the images are given as input to CAPSNET for classification. The segmented tumor boundary box is concatenated with the calculated output vector at the final fully connected layer to assist in classification. In this way the surrounding information also adds up and helps in more accurate classification. The proposed methodology shows 88% accuracy rate without the need of large and labelled dataset.

The authors in [86] have proposed pre-trained ALEXNET as the promising architecture for brain MRI image classification provided appropriate features are given to it. The method first extracts the features using curvelet transform and Gray Level Co-Occurrence Matrix (GLCM) matrix. Curvelet transform is basically used to get multiscale geometric analysis in the frequency domain. GLCM is a statistical approach that gives us the texture-based features. Finally, all the features are concatenated and given as input to ALEXNET. The model shows 100 % accuracy for the given dataset.

In another paper [87], the authors have proposed modified version of the two CNN models namely ALEXNET and VGG-16. The proposed methodology first pre-processes the images by removing noise and resizing them. After that the images are given as input to train the two models. A GUI is also designed in the classification stage to visualize the results. The number of feature maps and convolutional layers are increased in both models. The authors have designed 3 models each for both architectures. Final results show that model no 3 of ALEXnet shows 96% accuracy while model no 1 of VGG-16 shows 98% accuracy and were best of all six models.

The authors of the publication in [88] have presented a modified version of Googlenet for designing a fully automatic system that can classify brain tumor into three types i.e. glioma, meningioma and pituitary tumor. The proposed methodology uses transfer learning technique to deal with the limitation of small dataset. First, the model of Googlenet is modified for multi-class classification problem then it is fine-tuned on training dataset. The transfer learned and fine-tuned model is then used for classification of the tumor type. Results were also compared with the existing techniques. Patient level fivefold cross-validation scheme was applied on the dataset. Experiments show 98% accuracy of the proposed architecture which outperforms all state-of-the-art methodologies.

In another study by H.H Sultan, N.M Saleem at [89], the authors have proposed a deep architecture of CNN to classify two datasets of brain MRI images accurately. The proposed model classifies the first dataset into three classes (meningioma, glioma and pituitary) and provides tumor grade to the second dataset (grade 2, 3 ,4). The method first pre-processes the images by resizing them and then performs augmentation for better generalizability and less overfitting. The authors have also used two dropout layers in a model of 16 layers to reduce overfitting. The experiment was conducted separately for the two datasets. The results how 96%

accuracy for the first data and 98% accuracy for the second dataset.

The authors of [90] used five different CNN models to classify tumor into three categories meningioma, glioma and pituitary tumor. All five different models were modified in terms of their depth while the hyperparameters remain constant. The authors have just changed the depth of the architecture in all the 5 models and recorded the results. The best model was model no 2 with two hidden layers. The maximum accuracy achieved by this model is 98%.

4.4.2.1 Quantitative analysis of 2019 algorithms

Unlike the previous years, a huge amount of work in detecting and classifying brain tumor in MRI images was carried out in 2019. Researches once again shifted their attention towards image enhancement techniques by doing different pre-processing on the input brain MRI datasets as can be seen in Figure 14. They started developing hybrid models by concatenating different machine and deep learning techniques. Surprisingly less work was found in case of data augmentation as shown in Figure 15.

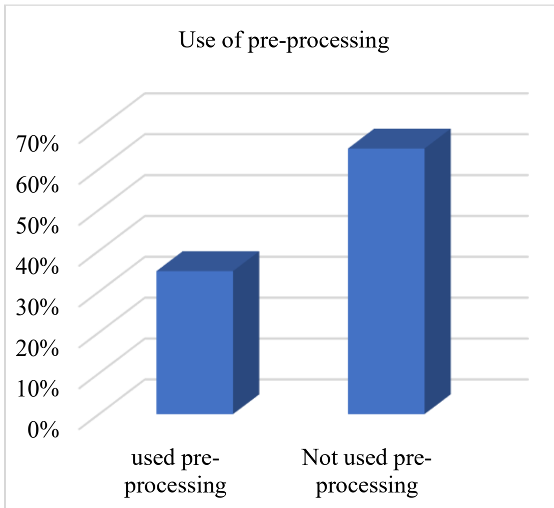

Figure 14. Usage of pre-processing in 2019

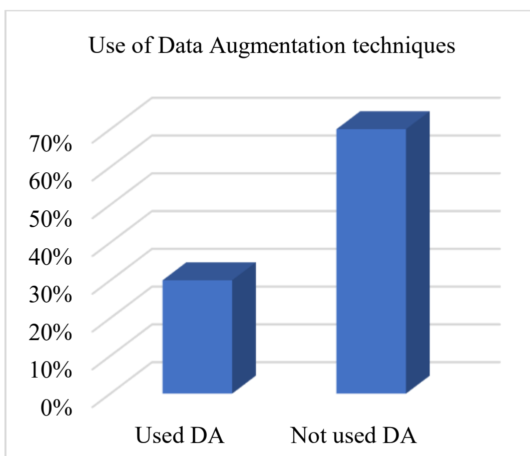

Figure 15. Usage of data augmentation in 2019

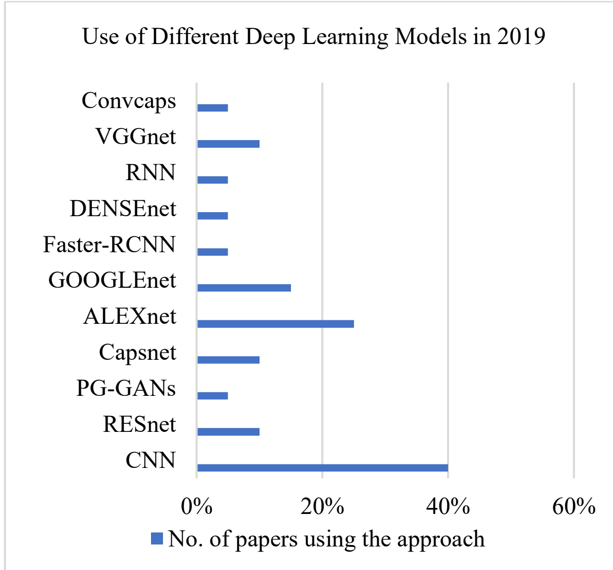

Figure 16. Usage of Deep Learning Algorithms in 2019

Similarly, it can be seen in Figure 16 that a lot of new models i.e., PG-GANs, Convcaps, Capsnet etc. arise which showed great results and were used by other studies for experimentation. Since deep learning does not depends on feature extraction so the features remained undiscovered while researchers were busy in developing new algorithms and making hybrid models using machine and deep learning techniques for multi-task learning. Figure 17 highlights the usage of feature extraction in 2019 models.

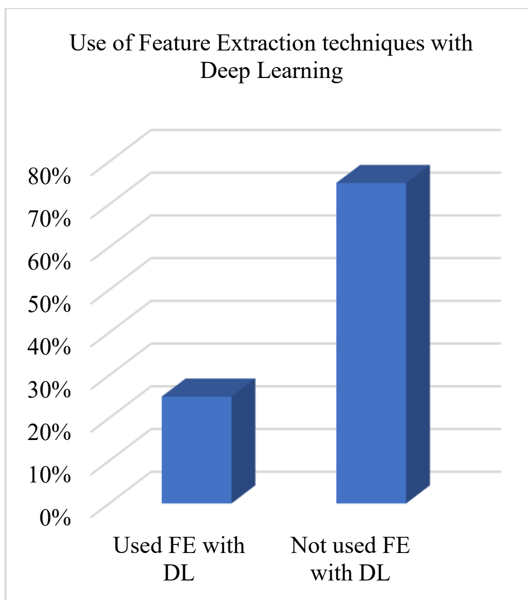

Figure 17. Use of feature extraction in 2019

4.4.3 Technical studies carried out in 2018

We reviewed 5 most related studies published in 2018 and a detailed survey of these studies is provided in this section.

The results presented in [91] describes Faster R-CNN as an efficient tool to increase the accuracy for tumor detection. The proposed algorithm used pre-trained Alexnet along with Region Proposal Network (RPN). At first, model pre-processes the private dataset. Afterwards, the convolutional feature map from ALEXNET is used as the input to RPN for calculating ROI. These ROIs are used to train the F-RCNN. The authors have used both end-to-end and 4 stage training for the proposed architecture. The results show 99% accuracy for end-to-end training.

The authors have utilized CNN in [92] for classifying between tumor and non-tumor images from BRATS 2015 and radiopedia dataset. Their idea was to only train the final layer of the CNN model and used the extracted features of the ImageNet. Gradient decent algorithm was used for back propagation to calculate the loss. The authors have only found the accuracy and have compared it with SVM and DNN. Their proposed technique achieved 97% accuracy.

In another article [93], the authors have used a modified architecture of ALEXnet and ZFnet for the detection and classification of brain MRI and lung CT scans into tumor / non-tumor images. Ten layers deep architectures of Alexnet and ZFnet are employed in the proposed technique. Images were resized to 227*227 and input to the respective algorithm for classification. Results show 97% accuracy for both datasets.

The authors in another study [94] have described U-Net as an efficient method for brain tumor segmentation and CNN as classification technique. The authors utilized U-Net first for segmentation and then CNN for classification. Authors first pre-process the images from BRATS 2015 dataset and then used the pre-processed data as input to the U-Net architecture for segmentation. The segmented images are then used for classification from CNN. The images are finally classified as normal, benign and malignant. The proposed architecture worked better from the existing techniques as per the study however, no experimental data or results were shared.

The authors of [95] have proposed Deep Neural Network (DNN) for classification of brain tumor into three types namely glioblastoma, sarcoma and metastatic bronchogenic carcinoma. The authors first segment the brain tumor using Fuzzy C-Means clustering and then extract the features using Discrete Wavelet Transform (DWT). The features are then reduced using Principal Component Analysis (PCA). Finally, classification is done using 6-layered DNN. The proposed scheme shows 98% accuracy and has been compared with other state-of-the-art methodologies.

4.4.3.1 Quantitative analysis of 2018 algorithms

In 2018, researchers started experimenting with the Deep Learning models by making modifications in the architectures to see the performance and shifted their attention from pre-processing and data augmentation algorithms as can be seen in Figure 18 and 19 below. A good number of new algorithms i.e. ZFnet, Alexnet and Faster R-CNN were created from the state-of-the-art models that showed promising results. The algorithms used in 2018 are categorically shown in Figure 20.

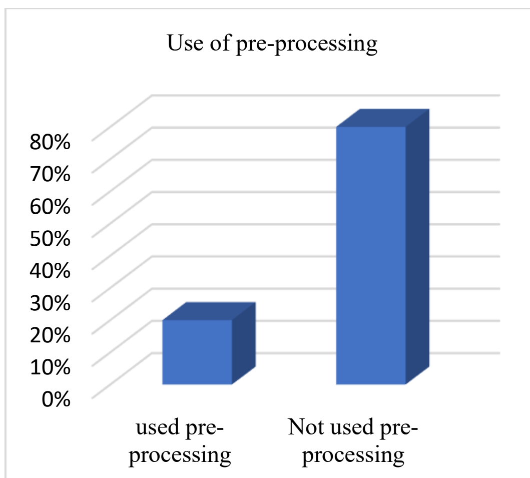

Figure 18. Use of pre-processing in 2018

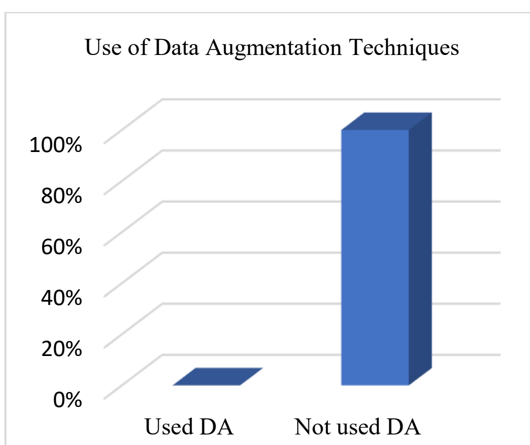

Figure 19. Use of data augmentation in 2018

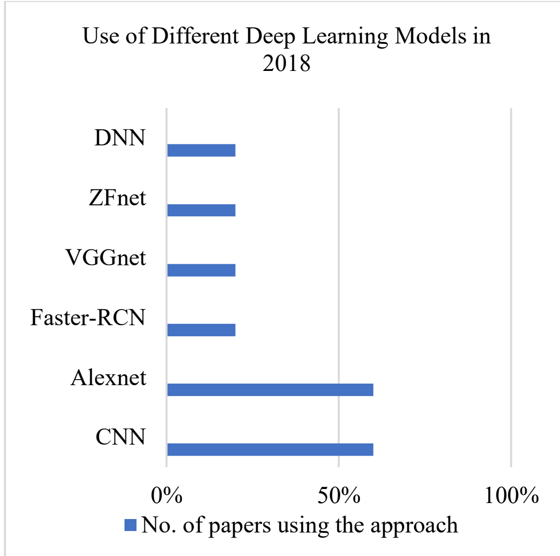

Figure 20. Use of Deep Learning Algorithms in 2018

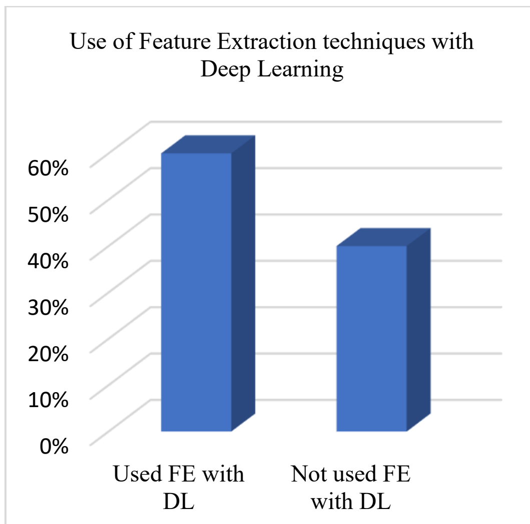

Figure 21. Use of feature extraction in 2018

The researchers once again started focusing on the importance of concatenating hand-crafted features with Deep Learning algorithms and have shown results that are way better than the ones listed in previous years. Figure 21 shed some light on this aspect of these studies.

4.4.4 Technical studies carried out in 2017

We reviewed four studies from 2017 Considering Deep Learning as the main algorithm and detailed survey of these studies is provided in this section.

In one of the studies of 2017 [96], authors have utilized deep CNN model with Gated Multimodal Units (GMU) fusion to integrate the multimodal information from all the three modalities for brain tumor classification. At first, the 3D CNN model is used to extract features from all the three MRI modalities i.e., T1, T2, Flair of BRATS 2015 dataset along with gated multimodal units to fuse the information. Afterwards, distilled CNN is used to classify the tumor using privileged learning. The fused information is used as teacher in the final layer of training of this distilled network. Different types of results are formulated in this research. The main results of the distilled network using privileged learning show improvement in the accuracies.

The authors in [97] proposed CNN for classification and segmentation of tumor into its parts (necrosis, enhancing and non-enhancing tumor). The proposed methodology first does the pre-processing using NI4TK software. Bias field correction and intensity normalization was performed. Then classification was done using CNN into four parts of tumor. Data augmentation was carried out to overcome overfitting. The results show that the proposed methodology has the potential to classify tumor accurately.

The authors in [98] proposed a novel approach in this paper. Three convolutional neural networks were proposed i.e., patchnet, slicenet, and volumenet. As the name implies, the three models were designed to take input as patches, slices and 3D volumetric MRI images separately. Apart from these three models, the researchers also proposed two already trained models VGGNET and RESNET for testing the prepared dataset using fine-tuning. The results have proved that volumenet surpasses all in terms of accuracy. The experiments showed 97% accuracy for volumenet.

The authors in [95] used CNN to classify the brain MRI images into five classes namely; Astrocytoma, Glioblastoma, Oligodendroglioma, unidentified tumor and healthy brain. The authors proposed an 8-layer CNN for this work. Three different datasets namely Rembrandt, Brains and Miraid were utilized in this work. The images were first resized to decrease the computational complexity then they were given as input to CNN. The deep CNN architecture was efficient enough and provided 99.98% average efficiency for all the five classes.

4.4.4.1 Quantitative analysis of 2017 algorithms

The immense research on Deep Learning algorithms actually started in 2017 and rose higher afterwards. Efficient and deep models like VGGnet, Resnet and Convnet appeared as promising architecture in this year. Researchers mainly focused to experiment with the Deep Learning models by first pre-processing the MRI brain images and see the performance. The increased use of pre-processing is clear from Figure 22. The reason behind this was that people were increasingly using pre-processing with machine learning techniques so they started experimenting the same procedures with Deep Learning.

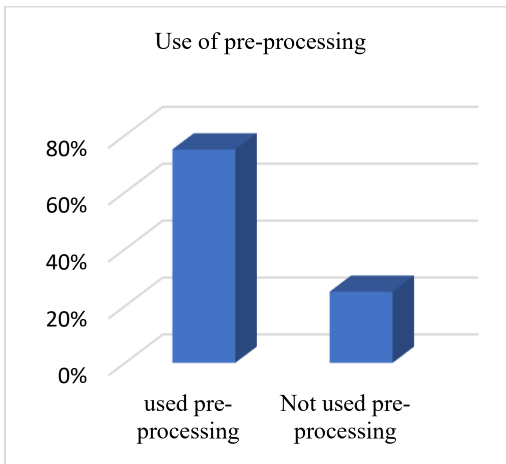

Figure 22. Use of pre-processing in 2017

Similarly, less importance was given to the data augmentation techniques as its importance was not much clear at that time as it is now. Less use of data augmentation is clear from Figure 23. Deep Learning algorithms that were used extensively are listed in Figure 24. As it was the year when research in Deep Learning models started booming so only limited models were developed and used again and again. Researches were reluctant to shift their attention to other deep leaning models and liked to experiment with the state-of-the-art models with limited modifications.

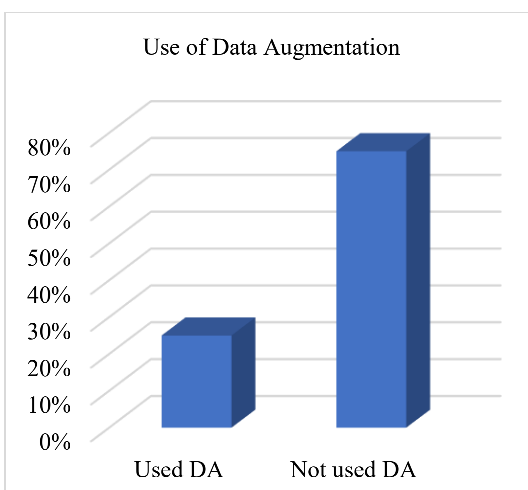

Figure 23. Use of Data Augmentation in 2017

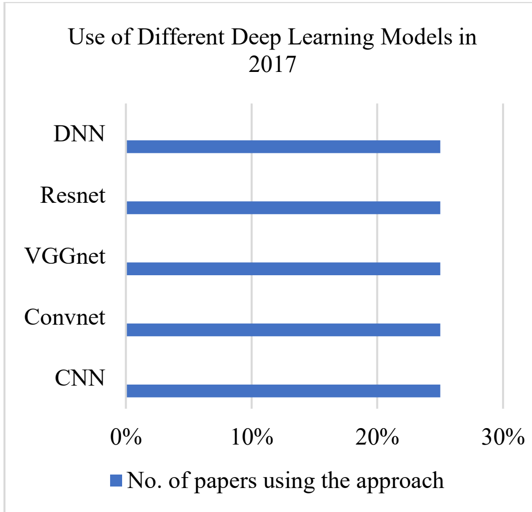

Figure 24. Use of Deep Learning Algorithms in 2017

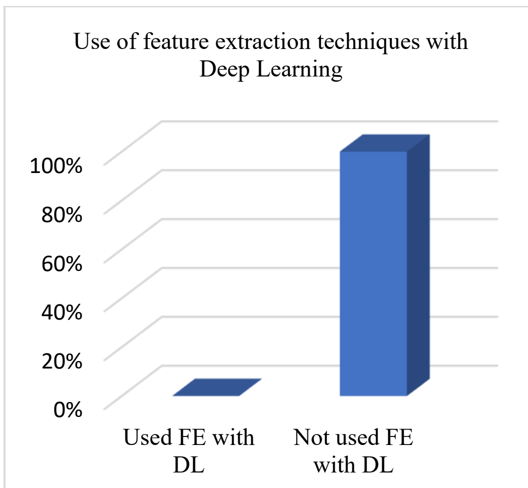

Figure 25. Use of feature extraction in 2017

Figure 25 highlights the usage of feature extraction techniques with Deep Learning algorithms and it can be seen that feature extraction was minimally used in 2017 and studies were only interested to see and learn the dynamics of Deep Learning at that stage.

4.4.5 Technical studies carried out in 2015-2016

Since the majority of studies for brain tumor classification involving Deep Learning started in 2017, so there were not many significant studies done before 2017. Consequently, we are providing survey of just few representative studies from 2016 and 2015. The survey of these studies is provided below.

The authors in [99] suggested fusion of texture and shape features for content-based image retrieval and classification of brain MRI images. Initially the images were contrast enhanced for better visual perception. After that texture-based features were extracted using Zernike moments while shape features were extracted using contourlet transform. Genetic algorithm and particle swarm optimization was employed to select best features. Finally, deep neural network and extreme learning machine was used to classify the brain tumor MRI images. Results showed that DNN achieved 88% while ELM showed 96% accuracy.

In [100] the authors exploited different features and used their significance to classify tumor and non-tumor regions using some Deep Learning algorithm. The images are first pre-processed using median filtering to remove noise. Then segments are extracted using Multiple Kernel based Probabilistic Clustering (MKPC). Shape, intensity and texture features are then extracted and selected using Linear Discriminant Analysis (LDA). Finally, the features are fed into Deep Learning model for classification. Results show 83% accuracy.

The authors of [101] proposed a single layer CNN model for grading of brain tumor MRI images in this study. The proposed method first pre-processes the images from BRATS 2014 dataset in the sense that it only takes the cuboidal area in the middle of the three-dimensional volumetric brain MRI images. Furthermore, the dataset is increased by using more slices of the tumor region and taking their rotated versions. The findings are compared with the state-of-the-art neural network model and shows promising results. The model shows 67% accuracy and specificity which is more than the simple neural network model.

4.4.5.1 Quantitative analysis of 2015-16 algorithms

It can be concluded from the technical review of the studies carried out in 2015 and 2016 above that not enough attention was paid in this era on Deep Learning. People were reluctant to use them and paid more attention on machine learning based algorithms. They still extracted the features using statistical and machine learning techniques. Very little work was found in case of brain MRI image analysis using Deep Learning in the period from 2015-2016 due to which further statistical analysis is not possible for this period.

4.5 Summarized Algorithm Development from 2015-2020

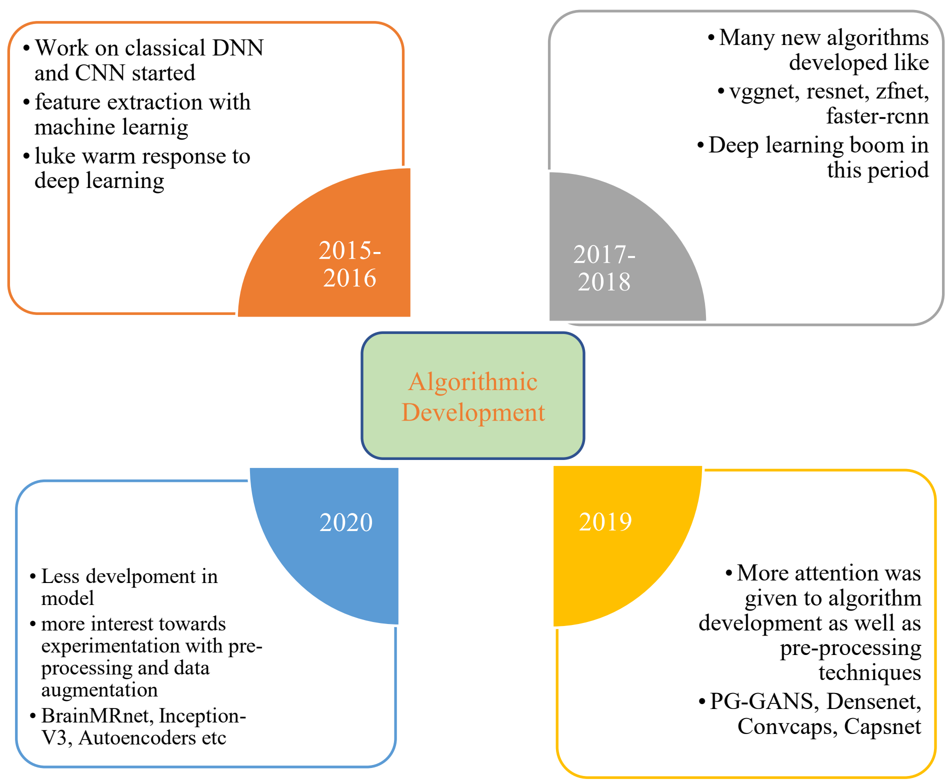

Figure 26. Algorithmic development from 2015-2020

There were two types of algorithmic developments noticed for the research range considered for this review, one was the deep learning algorithms for classification and detection of MRI images, while the other was deep learning algorithms for pre-processing of MRI images. As can be seen in Figure 26. above, 2015 was the slowest growth era for deep learning. There was very lukewarm response from people towards deep learning. They were quite comfortable with machine learning algorithms and did not want to shift their attention towards deep learning. Much work in algorithm development started in the mid 2017 till 2019. In between, people readily experimented with these algorithms. In 2019, the attention of researchers shifted towards pre-processing of MRI images so new deep learning algorithms were developed for this cause. Data augmentation also shifted paradigm from conventional to automatic. Year 2020 was totally based on experimentation with techniques and algorithms for pre-processing, feature extraction and data augmentation. Algorithmic development was slow and no major improvements in architectures surfaced in this period. Conventional or existing models were utilized with minor changes during the year 2020.

4.6 Summarized Qualitative Analysis

From the above-mentioned detailed analysis of studies in terms of content and quantitative analysis, it can be concluded easily that researchers are now focusing more towards the enhancement of 3D MRI images rather than optimizing the algorithms as noise free images play a vital role in better prognosis. Initially the demand and interest were towards machine learning but now this paradigm has shifted towards Deep Learning almost completely. We can see this trend summarized in the wheel in Figure 27.

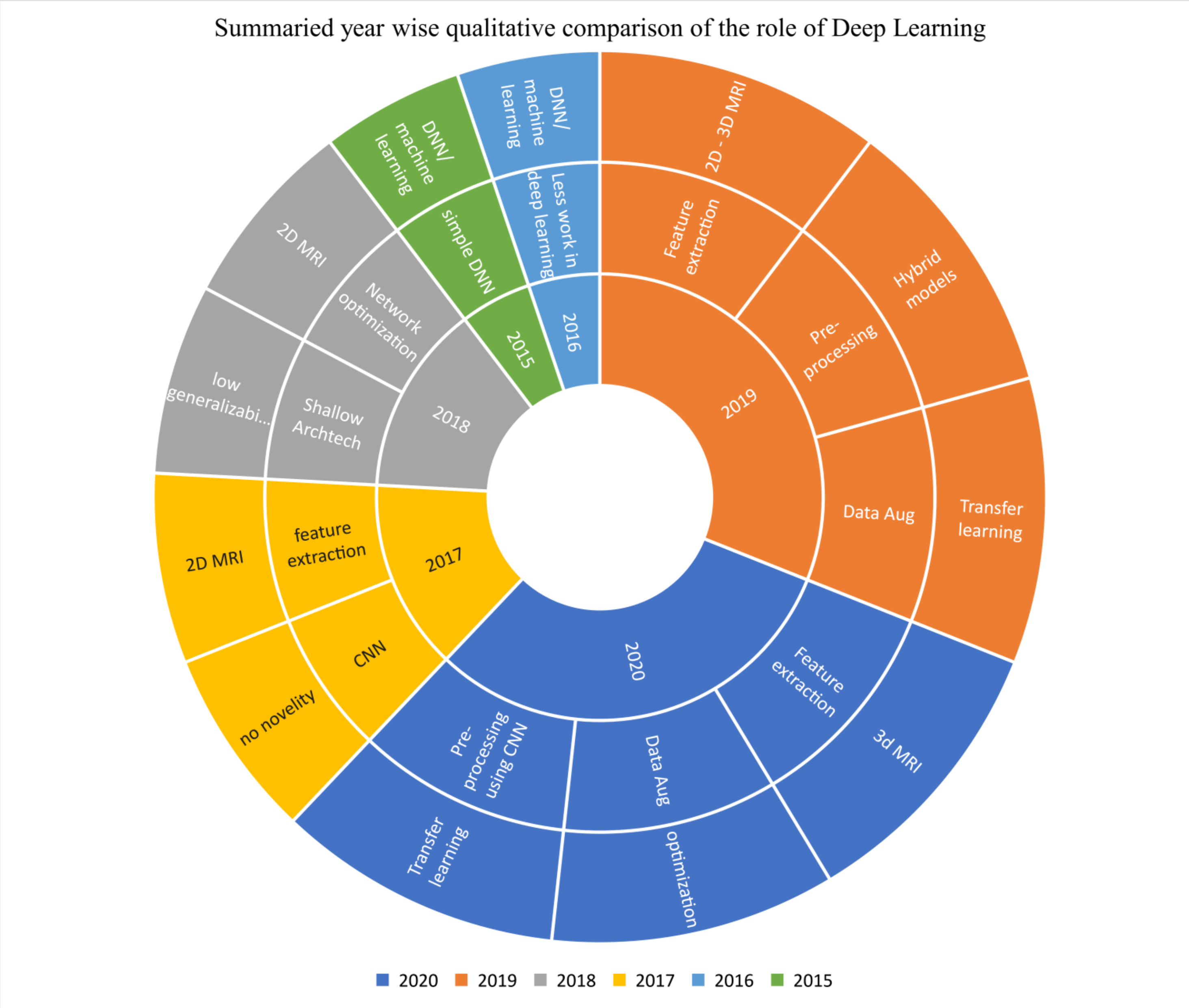

Figure 27. Six years progress of Deep Learning summarized in a wheel

Fine tuning and transfer learning have completely changed the way people were thinking about the black box of Deep Learning. Now researchers are using these learning models along with data augmentation to enhance the generalizability and efficiency of the Deep Learning models. Scientists are now focusing more on hybrid models with multi-task learning. The main aim is to make a model learn multiple tasks from single input so that a more efficient and fully automatic system with less complexity can be achieved.

4.7 Performance Comparison and Critical Analysis

A comparison table is formulated that gives a brief overview of all the important key elements of each research paper reviewed above. Table 5. essentially shows a brief summary of the techniques followed uptill now. Some drawbacks and achieved results have also been mentioned for quick analysis.

Table 5. Critical Analysis of the Literature Review

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software used	Pre-Processing
1.	[50]	2020	Classify + Detect	BRATS 2013, Whole Brain Atlas (WBA) (8 volumes)	No info	6 CNN models	Accuracy, False alarm and Missed alarm	96-99% all Model 6 yields optimum Results	No information regarding data preprocessing Complex model received best results Time complexity	CNN	Keras and Tensorflow in Python	No info
2.	[51]	2020	Classify	Figshare (3,064 images from 233 patients)	T1-wCE	Capsule net	Accuracy, Precision, recall, F1 score	Without pre-p 87% With pre-p 92%	Training time not mentioned, shallow architecture	CNN	TensorFlow	Flipping and patching, resized to a size of 28 * 28
3.	[52]	2020	Classify into tumor and non-tumor	Dataset by Chakraborty, 2019 from Kaggle (155 tumor and 98 normal images)	No info shared	CNN/ SVM for classification	Accuracy, sensitivity, specificity, F1 score	Overall accuracy was found to be 96.77%	Complex and time-consuming method adopted for feature enhancement (hyper column) and selection	Alexnet and VGG16 were used for feature extraction using hyper column while RFE was used for feature selection	Matlab (R2018b)	Data augmentation to balance the normal class with abnormal class
4.	[53]	2020	Classify into tumor and non-tumor	BRATS 2015	T1c, T1, T2, Flair	Deep autoencoder based JOA (java optimization algorithm) with a SoftMax regression	Accuracy	High classification accuracy (98.5 %)	Complexity of feature extraction	Bayesian fuzzy clustering (BFC) for segmentation and scattering transform (ST) and wavelet packet tsallis entropy (WPTE) methods for feature extraction	Matlab	Non-local mean filter for denoising
5.	[54]	2020	Classify into tumor or non-tumor	BRATs 2012, 2013, 2014,2015	T1c, T1, T2, Flair	Stacked sparse Autoencoder (SSAE)	Accuracy, sensitivity, specificity	Improved accuracy average 98% in case of all datasets	Shallow architecture of SSAE Not much improvement in accuracy and computational time	Stacked sparse Autoencoder (SSAE)	Matlab (R2018b)	Fusion of high pass filtered images and then median filtering was applied

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software used	Pre-Processing
6.	[55]	2020	Classify into tumor and non-tumor	Brain tumor detection dataset from the Kaggle Site (2 folders)	No info shared	Resnt50 as baseline network	Accuracy, sensitivity, specificity, precision, recall	The increase in the accuracy 97%	Complex architecture because of added 8 layers No innovative approach	CNN, Resnet50, Alexnet, Googlenet	Matlab	No info
7.	[56]	2020	Detect tumor and non-tumor images	Kaggle (Dataset made by Chakraborty)	No info	Brain MRNET (CBAM, residual blocks and hyper column technique)	Accuracy, sensitivity, specificity	Brain MRNET model gave 96.05% accuracy	Complex Architecture	Brain-MRNET (CNN)	Matlab (R2019a)	One to one augmentation
8.	[57]	2020	Classify into 3 types	Figshare (3064 images)	T1c	Residual networks	Accuracy, precision, recall, F1-score and balanced accuracy.	We have achieved the highest accuracy of 99%	No novelty. Same architecture Increased parameters because of augmentation	Resnet50	Python 3.6, using Keras library with Tensor Flow	Resize, crop and augmentation
9.	[58]	2020	Tumor and non-tumor	BRATS 2012 2013 ,2015, 2018	T1-CE, T1, T2 Flair	DWT-for feature fusion CNN for classification	Accuracy, sensitivity, specificity	Improved accuracy, sensitivity on each dataset	Complex method due to increase number of parameters because of fusion Good accuracy for fused images mainly	CNN	Didn't Mention	Noise removal using Partial differential diffusion filter (PDDF)
10.	[59]	2020	Classify into three types	Figshare (3064 images from 233 patients) Whole brain MR volumes with and without dementia (373 images from 150 subjects)	T1-CE	CNN-GAN	Accuracy, precision, sensitivity, F1 score	88% Accuracy	Complex methodology No comparisons	CNN - GAN	Keras with Python 3.6.6	Normalization between -1 to 1 Data augment (rotate + mirror)

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
11.	[60]	2020	Detect+ classify into benign and malignant	Cancer genome atlas glioblastoma multiform (TCGA-GBM) and database in the cancer imaging archive (TCIA) (500 samples)	T1-GD enhanced MRI images	SR-FCM-(CNN) for segmentation and feature extraction Classified using ELM	Accuracy	98.33 %	Complex and lengthy process No comparisons made with state of the art	CNN (squeeze-net) Segmented using SR-FCM	Didn't mention	Gray scale + super resolution + data augmentation (rotate + enlarge)
12.	[61]	2020	Detect + classify	Figshare by Cheng	T1-CE	F-RCNN and region proposal uses VGG-16 as the base network	Precision	Average precision of 75.18% for glioma, 89.45% for meningioma and 68.18% for pituitary tumor.	Testing time is not illustrated Complexity of region proposal network	F-RCNN	Did' not mention	Normalized using min-max method
13.	[62]	2020	classification	BRATS, CE-MRI	Flair images from BRATS and T1C from CE-MRI	Block-wise fine tuning and transfer learning on VGGnet and KNN as classifier	Sensitivity, specificity, precision, F1-Score	97.28% accuracy on the BTDS-2 and and 98.69% on CE-MRI datasets respectively.	Complex architecture, No info of training and testing time, No convergence graphs are shown	Deep VGGnet	Didn't mention	De-noising, data augmentationon and intensity normalization
14.	[63]	2020	Classify + detect	Kaggle	No info shared	CNN	Accuracy	90 to 99% Accuracy	No technical info of the CNN architecture No info on the type of pre-processing Training and testing time not shared No graphs of algo convergence	CNN (GUI was also designed)	Tensor flow and python	Yes, but didn't mention any methodology

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software used	Pre-Processing
15.	[64]	2020	Detect and classify as cancerous or non-cancerous	Harvard medical school (128 images with multiple brain tumors)	No info shared	Seg using thresholding and watershed and then classification using KSVM	Accuracy, precision, recall	97.4% accuracy overall	No info regarding the used CNN architecture used No info regarding training testing time, Complexity of prior segmentation	CNN	Didn't mention	Smoothing, sharpening and reducing the noise of input
16.	[13]	2020	Detection and Classification into three types	Figshare by Cheng (only 170 for each class)	T1-CE	Deep CNN 5 layers	Accuracy, Sensitivity, specificity	Accuracy 99.3% for CNN and 98.5% for SVM	No comparisons with state-of-the-art method except SVM Simple CNN model with no innovation	Wavelet transform	Didn't mention	No info about pre-processing
17.	[65]	2020	Segmentation + classification	BRATS 13,14,17,18	T1, T2, T1C, FLAIR	Inception V3 pre-trained CNN	Accuracy	92% for classification	Complexity and time-consuming model in terms of FE and concatenation Increased computational time because of feature fusion	Using SBDL for seg Deep Feature extraction using Inception V3 and DRLBP and selected using PSO	Matlab 2018b	Contrast stretching using pixel increase along line (PIAL)
18.	[66]	2020	Detect + classify	Private and publicly available dataset (Total 1000 images used)	No info given	RNN	Accuracy, specificity, sensitivity	96% classification accuracy 98% specificity, 97% sensitivity	No detailed info about the imaging modalities considered (2D or 3D) Complex and tiring due to the headache of FE	Feature extraction using wavelet statistical approach and selected using oppositional gravitational search algorithm (OGSA)	Matlab version (7.12)	Noise removal using gaussian filtering

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
19.	[67]	2020	Detection of tumor/nontumor images	BRATS 2016	T1c-brain axial MRI images	PG-GANs for DA and Resnet-50 for detection	Accuracy, sensitivity, specificity	91% accuracy 86% sensitivity , 97% specificity	Further comparisons can be made with state-of-the-art method No info of training and testing time No graphs showing convergence	Resnet-50	Didn't mention	30-130 slices were taken and then DA was performed Center crop the image slices to 224*224 for detection
20.	[68]	2020	Detect and classify	OASIS, pre-post tumor dataset (BITE), Figshare (total of 4689 for detection and 613 for classification)	T1c	2 BRAIN NETs for detect and Classification	Accuracy, sensitivity, specificity	98% accuracy for detection and 99% for classification in case of BRAINnet	No info regarding testing and training time, Complex 22-layer architecture	No, Brainnet	Matlab 2018b.	Not done except for Alexnet and VGGnet only for comparison purpose
21.	[69]	2020	Classify	Kaggle, TCIA	1000 axial MRI images	CNN	Accuracy, loss and execution time	RMSprop is the best optimizer with 98% accuracy and fast execution	No comparisons with state-of-the-art method Cannot work with 3D MRI	Segmented using thresholding and Feature extraction using CNN	Python using Keras and Tensor Flow	Noise filtering, adjusting luminosity
22.	[70]	2019	Classify	Kaggle (tumor, non-tumor images), TCIA	1000 axial MRI images	Seg using PNN while classification using CNN	Accuracy	Accuracy greater than 90% for 3 different optimizers	No comparisons with state-of-the-art technique	CNN	Python using Keras and Tensor Flow	Extraction of ROI for compression to reduce the data size
23.	[71]	2019	Classification	Figshare by cheng (3064 images)	T1-CE	CNN Convcaps	Accuracy	Classification accuracy increases to 93.5%, and the training speed is also improved.	Complex architecture with excessive parameters No comparisons with other algos	Convcaps	TensorFlow	No

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software are used	Pre-Processing
24.	[72]	2019	Classification	Figshare by cheng (3064 images)	T1-CE	Global Average Pooling Residual Network (G-RESnet)	Accuracy	95%	Deep and complex architecture, No listing of training and testing time, No info regarding any pre-processing The setup cannot be used for 3D MRI volumes	Resnet34	Pytorch framework	No info
25.	[73]	2019	Detect (benign /malignant) + seg	Miccai BRATS (2013-2017) ISLES strokes dataset	Flair, T1, T1-CE and T2 DWI, CBV and CBF	Thresholding for segmentation Alex and Google net for Feature fusion	Dice, sensitivity, specificity, accuracy, AUC curve	99% accuracy in the case of BRATS 2017 dataset using fusion architecture	Complex architecture of feature fusion So, error can accumulate Not much difference in accuracy using score level fusion from Alexnet and google net No literature review presented in the paper	Feature extraction using Alexnet and Google net	Matlab	Log transformation for intensity normalization and morphological operations for segmentation
26.	[74]	2019	Detect + seg (benign+ malignant)	Didn't mention 20 patient's data were used for training	No info shared	Faster R-CNN and SVM	Accuracy	95% on private dataset	No dataset info, No info about the annotations of the dataset No clear methodology No comparisons were made Training data was very small	Faster R-CNN For converting convolutional feature map into region proposals	Tensorflow with python	Converted the image data into .xml file and then to .csv file. Csv file Contains the name, class and bounding box coordinates for each image.
27.	[75]	2019	Detect + classify into three classes	Figshare dataset (3064 images)	T1-CE	Enhanced SoftMax and los function with ELM-LRF CNN	Accuracy, training time, training loss	97% accuracy is achieved with 2 to 6s reduction in the processing time	very little improvement in accuracy and processing time No comparisons with state-of-the-art models	ELM-LRF to Extract features	Python 3.6 with keras	Gray scale conversion, median filtering, enhancement

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software are used	Pre-Processing
28.	[76]	2019	Classify (tumor or non-tumor) + segment	Private data set of 330 images	No info shared	CNN	Training accuracy, validation accuracy	CNN archives rate of 98 % accuracy with low Complexity	Ambiguity about the data set No clear observations (very brief results)	Feature extraction using CNN while seg using global thresholding and watershed algo	Didn't mention	Only for segmentation (noise removal + sharpening)
29.	[77]	2019	Classify into three types Also developed GUI	Figshare dataset (3064 images)	T1-w images	CNN (auto-keras)	Accuracy, sensitivity, specificity, F1-score	96% accuracy	No comparisons have been made with state-of-the-art models, No confusion matrices have been made	CNN (auto-keras)	Keras with python	Pre-processing (image rotation, changing width and Length, truncating images, rescaling, etc.)
30.	[78]	2019	Detect + classify	Figshare dataset (3064 images)	T1-CE	Capsnet (dilated capsule net)	Accuracy	95% accuracy	No significant model novelty of Capsnet Not enough comparisons and experiments with confusion matrix	CNN (dilated capsule net)	Pytorch	Down sampled to 64*64
31.	[79]	2019	Detect (normal + tumor brain)	Private dataset containing 153 patients, 1892 images	No info Shared	Alexnet (CNN) (SoftMax, RBF and DT)	Accuracy, sensitivity, specificity, precision	99% with the proposed algo (the SoftMax classifier has the best accuracy in the CNN)	No clear methodology, No comparisons have been made with state-of-the-art approaches No info regarding pre-processing	Features extracted using center clustering algorithm	Didn't mention	Image resizing but no clear info

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software used	Pre-Processing
32.	[80]	2019	Detect (tumor/non-tumor)	BRATS 2016	T1-CE	PG-GANs for data augmentation, MUNIT - SIMGANs for refinement and RESnet-50 for detection	Accuracy, sensitivity, specificity	87% accuracy with PG-GAN, 92% with MUNIT and 94% with SIMGAN	Very complex and time-consuming methodology No literature reviews	GANs	Didn't mention	Resizing before data augmentation and refinement
33.	[81]	2019	Detection	Miccai BRATS 2018	Flair, T1, T1-C, and T2.	3D-Multi CNNs	Dice correlation coeficient, sensitivityy, and specificityy.	Dice correlation coefficient 84% Sensitivity 82% Specificity 99%	Not enough literature review Not enough and novel experimental results were carried out Not enough difference in single modal and multi modal is presented	3D Multi-CNNs	Didn't mention	Image cropping, enlargement and data augmentation (rotation, flip, mirror)
34.	[82]	2019	Detect + classify into four types	Figshare dataset (3064 images) and 422 images of private datasets of normal, gliomas, meningiomas and metastatic brain tumors	T1-C and T1, T2 , Flair	DENSE net - LSTM DENSE net-DENSE net, DENSE net-RNN	Accuracy	92% for public and 71% for private data DENSEnet-DENSEnet presentt the best performance for the proprietary dataset. For the public dataset, DENSEnet-LSTM outperforms all the previous work on this dataset	Takes too much long (5h) for auto-encoder like dense-net (feature extraction)	DENSEnet (auto-encoder)	TensorFlow	No pre-processing

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Softwares used	Pre-Processing
35.	[83]	2019	Classify into three types of tumor	Figshare dataset (3064 images)	T1-CE	CNN	Accuracy (F1 score), precision, Recall	Accuracy of 94%, average precision of 93.33% and an average recall of 93%	The model can be compared with more state-of-the-art models Very Brief results No innovation in CNN	CNN	Didn't mention	Resize, smoothed, and histogram equalize
36.	[84]	2019	Classify into three types of tumor	Figshare dataset (3064 images)	T1-CE	Capsnet (CNN)	Only accuracy	90.89% accuracy is achieved	No methodology of boundary extracting is shared Very limited results and comparisons have been done No pre-processing info	Capsnet	Python 2.7, using Keras library	Down sampled to 128 *128)
37.	[85]	2019	Classify + seg	Public dataset (no info)	No info shared	Alexnet	Accuracy	100% accuracy in training and validation The model has flexibility for modification, able to train faster and the Capability to overcome over fitting using drop outs etc.	No comparisons with state-of-the-art models No testing performance No performance metrics involved and discussed	Features extracted using curvelet transform and GLCM matrix Segmentation using K-means	Didn't mention	Not shared

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
38.	[86]	2019	Classify (Normal, Benign, Malignant)	BRATS 2015	Flair	Alexnet, VGG-16	Equal error rate (EER), false acceptance rate (FAR), and false Rejection rate (FRR).	VGG16 gives 98% accuracy	Better results could be achieved using all 4 modalities No info regarding enhancement except normalization	CNN	Didn't mention but constructed GUI python	Enhancement, cropping, resize 3D to 2D
39.	[87]	2019	Classify (3 types)	Figshare Dataset (3064 images)	T1-CE	Pre-trained Googlenet (using transfer learning) SVM KNN	Accuracy, precision, recall, F1 score, specificity, roc curve and Five-fold cross validation	Googlenet (92 %) SVM (97%) KNN (98%)	Training time is still high (55 mins with best results)	Features extracted using pre-trained Googlenet using transfer learning	Matlab 2018b	Normalization between 0 to 1, Rescale to 224*224 and third dimension was created for Googlenet
40.	[88]	2019	Classify + grading	Two different data sets (Figshare by Cheng and REMBRANDT) (3064 and 516 images)	T1-CE images of both datasets	One CNN to classify type of tumor and one CNN for grading	Pre, sensitivity, specificity, accuracy	Accuracy of 96 % and 98%	Complex architecture of 16 layers Learning rate is high	CNN	Matlab 2018b and Python	Downsizing and data augmentation
41.	[89]	2019	Classify into 3 types	Figshare dataset (3064 images)	T1-CE	Alexnet, Googlenet, and VGGnet using transfer learning (classify with either SoftMax or SVM)	Acc, sensitivity, specificity, precision	The fine-tune VGG16 architecture attained highest accuracy up to 98.69% in terms of classification aand detection	Complexity of pre-processing Time-complexity	CNN for feature extraction using Transfer learning (fine-tune and freeze)	Caffee library 7	Enhanced using contrast stretching technique Data augmentation to increase dataset to reduce overfitting

Sr. No.	Ref	Year	Purpose	Dataset	Imaging Modality	Algo	Performance Metrics	Findings	Draw Back	Features Extracted	Tools/ Software used	Pre-Processing
42.	[90]	2018	Detect into four types of tumor (benign, Malignant, glial and astrocytoma)	50 brain MRI images	No info shared	Alexnet is used for classification along with RPN by faster R-CNN	Overall precision, accuracy	End to End gives better result and reduce inference time per image as compared to 4 stage training The Bounding box score accuracy for e2e is more than 99% whereas 4 stage gives only 98%.	No comparison has been done with the state-of-the-art approaches Limited results Limited literature review Incomplete data set information Software was used for pre-processing of the dataset	Feature map extraction using Alexnet as the base network and RPN network Used faster RCNN for training	Python with keras, tensor flow	Data augmentation using (image flipping)
43.	[91]	2018	Detect (tumor and non-tumor)	BRATS 2015 and images from Radiopedia	No info shared	CNN	Validation accuracy, training accuracy	97.5% accuracy	No clear info about the modalities used (dataset) No clear methodology No comparisons with state-of-the-art models Not much improved results	Feature were taken from ImageNet database	Python	Image resize
44.	[92]	2018	Classify into tumor/non-tumor	Rembrandt and 'SPIE-AAPM-CT Challenge	Front, coronal, sagittal views but no info regarding the modality	CNN (Alexnet and ZFnet) with 10 layers each	Accuracy	97% accuracy in both cases	No comparison with state of the art The network is unable to learn from mixed type of data (axial, coronal, sagittal) No mentioning of training and testing time	CNN (Alexnet and ZFnet)	Didn't mention	Only resized the images to 227*227

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
45.	[93]	2018	Classify into normal, benign or malignant images	The 2015 Miccai BRATS challenge,	T1, T2, Flair, T1-CE	U-Net for seg and CNN for classification	Nothing mentioned	Not a single result	No specificity results were shared Normal tissues were also categorized as tumor tissues (that was a flaw) Very less literature review No comparison Vague methodology	U-net was used for feature extraction and CNN was used for classification	Tensor flow and keras	Resizing and renaming Histogram equalization of T1, T2 and standard normalization and scaling of T1-CE and Flair images
46.	[94]	2018	Segmentation + classification into three types	Harvard dataset (66 real human brain MRIs with 22 Normal and 44 abnormal images)	Axial Plane, T2-weighted and 256* 256 pixel	Deep neural network for classification and fuzzy C-means clustering for segmentation	Accuracy, precision, recall, F-score, ROC curve	98% Accuracy	No enough literature review, Technique employed was also not unique Very small dataset can lead to overfitting of the model	Feature extraction using DWT and reduced using PCA	Matlab R2015 a and weka 3.9	No info shared
47.	[95]	2017	Classification into benign and malignant (tumor grading)	BRATS 2015	T1, T2, T1-CE and Flair	3D CNN with gated multimodal units (GMU) information fusion of all 3 modalities	Mean accuracy (acc), sensitivity, Specificity and positive predictive value (PPV)	75.4 % for Flair with 1.3% improvement 74.2% with 3.3 % improvement	Not enough literature review No comparisons with state-of-the-art approaches Only compared with variations of itself	GMU fusion of feature information using 3D CNN	Didn't mention	Resizing or down sampling and crop
48.	[96]	2017	Classify and segment tum	No info	No info	CNN	No info	Classify using CNN and segment	No results and comparisons No methodology discussed No info about the dataset	CNN	Matlab	Bias field correction and intensity normalization using NI4TK Data augmentation to reduce overfitting

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
49.	[97]	2017	Classify into HG and LG	BRATS 2017 And TCIA	T1, T1-CE, T2, Flair	3 models of convnet (patchnet, slicenet, volumenet) Two other models VGGnet and RESnet using transfer learning	Accuracy, F1 score	Testing accuracy of 97% for volumenet Novel approach	Complexity of the proposed scheme + high training time	Feature extraction using convolutional neural network	TensorFlow, with Keras in Python.	Already done but made three data sets for three models
50.	[98]	2017	Classify into 4 types of brain tumors	Rembrandt (65427 images of 100 patients). (BRAINS) image bank repository of university of Edinburgh and from Miraid, a dataset from TCIA	No info shared Except (MRI scans of axial, coronal and sagittal planes are used)	Deep CNN with 8 layers	F1-score and accuracy	The model performs with an average F1-score of 99.46%. Also, the accuracy of the proposed model is 99.68%	There is no comparison made with state-of-the-art methodologies Also, the approach is not novel. Its repeated	CNN	TensorFlow, TFLearn, scikit-learn and other python libraries	Format changed and resize
51.	[99]	2016	Classify + seg (five types)	1000 images of private dataset from some Indian hospital	Axial T1 weighted and sagittal T2 weighted images	DNN and ELM	Sensitivity, specificity, accuracy, Error Rate, Jaccard coefficient (j) and F-measure	DNN achieves 88% accuracy while ELM achieves 96% Accuracy	Complexity of extracting features No comparisons or results on public datasets Too much un-necessary details	Contourlet transform and Zernike moments were used to extract feature and then GA, PSO is used for feature selection	Matlab 2013	Contrast enhancement

Sr. No.	**Ref**	**Year**	**Purpose**	**Dataset**	**Imaging Modality**	**Algo**	**Performance Metrics**	**Findings**	**Draw Back**	**Features Extracted**	**Tools/ Software used**	**Pre-Processing**
52.	[100]	2015	Classify into tumor and non-tumor	No info	No info	Segmentation using multiple kernels based probabilistic clustering (MKPC) and classify using Deep Learning	Sensitivity, specificity, Accuracy	Specificity 0.80, 0.83 % accuracy and 0.88 sensitivity As cluster Size is increased the sensitivity, specificity and accuracy has increased	No clear methodology of the classification . Complexity of feature extraction	Shape, texture and intensity features are extracted and selected using LDA	Matlab	De-noising using median filtering
53.	[101]	2015	Tumor grading	BRATS 2014 195 (HG) 25(LG)	T1, T2, T1-CE, Flair	CNN	Sensitivity, Specificity	Sensitivity and specificity of 0.67%	No experimental results shown No innovative methodology No improved results Only compared with NN	CNN	Didn't mention	Central cuboid is extracted Increase data using more slices and taking rotated versions

It can be concluded from the Table 5. above that many robust and efficient deep learning models were developed from time to time. Some papers didn't mention the dataset as well as the modality used while some didn't mention the type of tool or software used for simulation purpose which is not a good approach. Research papers that have used private dataset must also validate their results using some public dataset so that comparison on a same standard can be made.

Similarly, it can also be noticed that no performance metric is a standard for all studies. Researchers have used variety of performance metrics but it was deduced from the definitions and mathematical formulas of performance metrics in Table 3. as well as from the findings of Table 4 that all of them are somehow linked to the accuracy of the proposed models. If sensitivity and specificity are high then obviously accuracy will be high and vice versa. Consequently, it was concluded that accuracy was still the main focus of majority of the researchers. However, we know that MRI images suffer from class imbalance issue so accuracy doesn't help much in this scenario. Precision and Recall works best when we have class imbalance issues. Almost all of the researchers have used these along with accuracy. Precision accounts for the accuracy of the minority class while recall gives us an idea about coverage of the minority class or the positive class. In this sense, both metrics are as important as the accuracy.

5 PERFORMANCE DEGRADING FACTORS

The profound analysis of existing techniques helped us in devising a list of some key elements that directly or indirectly effects the performance of the CAD system. Multiple factors are involved which degrades the performance of a specific Deep Learning algorithm designed for classification. These factors affect other tasks equally. They can be categorized as shown in the Figure 28.

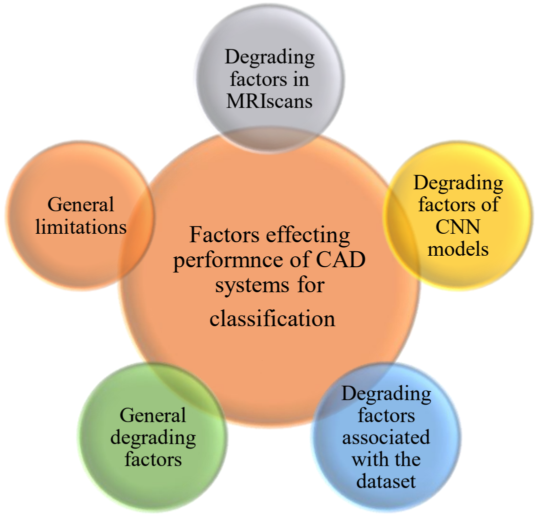

Figure 28: Performance degrading factors

Some of the above mentioned key problematic factors can be mitigated while other cause a tradeoff. So, one has to balance the architecture in every sense to take the full advantage of the CAD systems. All of the above-mentioned factors are explained in detail below.

5.1 Degrading factors in MRI images:

- *Physical artifacts due to Mechanical operation:*

The equipment involved in generating MRI scans produce a noise which creates disturbance in the image acquisition process. Because of the sound, the MRI images incorporate noise in the form of physical artifacts [25]. Motion artifacts are also introduced if the subject under examination moves during image acquisition. These noises are inevitable and requires some standard way of removing them.

- *Class imbalance:*

In image processing, we refer to the area of interest as the foreground and rest of the area as the background. The images of brain tumor mostly have a large background with respect to the foreground. This creates class imbalance which arises when the groups to be classified have unequal voxel distribution [21]**.**

- *Heterogeneity in the tumor structure*

Brain tumor basically has 3 heterogenous parts that may or may not be connected. The three parts differ in the physical and chemical properties [23]**.** There heterogenous appearance at times makes it difficult to predict if the pixel under consideration belongs to foreground or background [102]**.**

- *Inter-class variability in tumors*

When physically and chemically two different classes have very less or no anatomical difference, then this phenomenon is called as inter-class variability and it should be high between different classes and minimal between same class. For example, high grade and low grade (grade 2 and grade 3) show less accuracy due to less inter-class variability as seen by the extracted features [18].

5.2 Degrading factors in CNN models

- *Multiclass classification:*

Deep Learning models designed so far are still not able to deal with multiclass classification problem. Models usually work best for binary classification but reduce their accuracy when dealing with multi-classification problem.

- *Fusion of MRI modalities in all the three views*

Deep Learning models have evolved much in recent years from 2D to 3D. Brain tumor MRI data is a multiple modality data. Each patient has three views and each view can have four images namely T1c, T1, T2 and Flair. When this type of mixed data is considered then the existing architectures are not able to learn and exploit the features completely from all the views. Consequently, there is a need to design a system capable of fusing information intelligently from multiple modalities [2].

- *Interoperability and automation*

The deep models lack in their ability of interoperability and automation. Very few architectures are available till date that are fully automated and can adapt to model changes etc. Automation requires that a system must be an end-to-end, robust and must require minimal or no human interaction.

5.3 Degrading factors associated with the Datasets

- *Standard dataset availability*

BRATS is a very famous challenge that happens every year and makes available a good amount of dataset that is being used for classification as well. Other than that, very few reliable datasets on brain imaging are freely available. Furthermore, the private data available is also not in a standard format with extreme noise. There is a strong need of a freely available standard datasets that can be confidently used for research purposes [1]**.**

- *Data augmentation*

We already know that Deep Learning models work efficiently with large amount of data [37] but unfortunately, we lack quality datasets. Data augmentation helps in increasing the small datasets and making an efficient generalized model so that the model can learn from data taken from any source with low misclassification rate. So far there is no standard augmentation technique devised for MRI images. Researchers have proposed different algorithms but their main idea is to increase the data. They usually do not take into account the spatial and textural relationships. There is a need for standardized augmentation technique so that comparative analysis can be made on its basis.

- *Standard Pre-processing Technique*

Pre-processing is required to make a data clean from every type of noise and more acceptable for the required task in hand [37]. All available datasets have pre-processing issues [8] [102]**.** Even BRATS datasets have issues like noise and motion artifacts etc. So far there is no know standard for pre-processing available. People use low standard application software which degrade the image quality instead of improving.

5.4 General problems and challenges

- *Integration of medical imaging modalities*

The Deep Learning models designed so far consider the features fusion of MRI modality alone. If features from DTI, MRS, perfusion MRI and Functional MRI data is also incorporated with the standard MRI then further increase in performance can be observed. Other data based on microscopic imaging or histopathological examinations could also be included to increase the efficiency of the models and help in accurate and timely predictions [2]**.**

- *One system for all tasks*

There is a strong need of a computer aided system that can-do data augmentation, pre-processing, feature extraction, selection, detection and classification in one go. An end-to-end fully automatic system is the need and solution of the problems associated with the existing architectures [1]**.**

- *Intelligent feature selection mechanism*

Deep Learning does feature extraction and selection on its own by learning different parameters and optimizing them. Still the system is not intelligent in feature selection and usually does pooling which although reduce the parameters but in turn also removes the features that can be an efficient entity for the whole system.

5.5 General limitations

- *Hardware requirements*

As Deep Learning models require large amount of data [37] which is associated with millions and trillions of parameters so GPU based systems with large amount of memory are a need of the current situation [10]. But these systems are not easily available to everybody due to their high price. As a result, many researchers are bound to design models within their financial scope and limits which greatly effects their research production [1].

- *Tradeoff between shallow architecture and convergence speed*

Shallow architectures have high convergence but low accuracy as the system is unable to learn more promising and deep features. This problem can only be optimized but cannot be removed.

- *Tradeoff between deep architecture and convergence speed*

Deep architectures mostly show high accuracy but their convergence speed is low because of the large number of parameters that they have to learn.

- *Tradeoff between pooling and accuracy*

The pooling layer acts as a feature selection layer and removes unimportant features according to the way it is programmed. But it affects the accuracy as it is not an intelligent layer and works on mathematical basis which degrades the accuracy.

- *Gradient explode and gradient vanishing*

For high accuracy, researches try to have a deep architecture but it suffers from gradient vanishing problem which means the error which has to be propagated starts vanishing. Similarly, gradient explode is the increase in the value of the propagating gradient due to the selection of a wrong optimizer.

6. PERFORMANCE ENHANCEMENT TECHNIQUES

Based on the detailed critical review provided above, some performance enhancement techniques are presented that are used by some studies and some proposed them as valuable factors for effective performance. All the scattered solutions provided in all the studies have been combined in this section to help the researchers and scientists working in this field to take advantage and make efficient CAD systems with robust characteristics.

- *Multiple modalities*

If all of the four MRI modalities (T1, T2, T1-c, Flair) are employed in training process then accuracy can be improved further and overfitting can be reduced.

- *Addition of pooling layer*

The overload of processing millions and trillions of parameters can be reduced by adding modified and efficient pooling layers which help in dimensionality reduction.

- *Skip connections*

Skip connections as the name implies, skip some layers/connections in neural networks and feed the output of one layer as input to another layer instead of just forwarding the output to next layer [103]. Skip connections really help in optimizing the error that propagates through the network plus they also help in increasing the generalizability by adding features from previous layers as well. Basically, what we are trying to do using these skip connections is that we want to make our model robust and dynamic. The model will be more generalized in a way that each layer having a skip connection will be able to learn features that are not picked by the previous layers [104]. Secondly, the most important factor reduced by skip connections is gradient vanishing problem as the skip connections are being added as input to other layers so they do not allow a gradient to be as low as zero [105]. In short, it can be concluded that skip connections stabilize the training process, helps in convergence, and enable feature reusability [105].

➢ *Regularization*

Different regularization schemes and algorithm can be employed in the deep learning models to improve their efficiency and robustness e.g., early stop and dropout layer are two ways that can be used to prevent the effects like overfitting. Similarly, batch normalization can also be used for improving the convergence speed of the network model.

➢ *Transfer learning*

Transfer learning is an efficient approach for training network when less dataset is available. It is very powerful tool which is yet to be discovered completely.

➢ *Optimization Algorithms*

Efficient and intelligent optimization algorithms are required that can help in proper error propagation. They really help in increasing the robustness and speedy convergence [2].

➢ *Multi-task Deep Learning (MTL)*

Multi-task Deep Learning (MTL) is relatively a new idea which actually combines the power of multiple architectures and concatenates them together to make one system for multiple tasks. It really helps in making a fully automatic systems saving computational cost and improving robustness against overfitting.

➢ *Ensemble learning*

Ensemble learning averages the classification accuracies of multiple classifiers and then gives the final results. It has shown promising results but it has not been used and exploited completely. Research has shown that it can prove to be as good as the existing complex architectures [2].

7. CONCLUSION

The paper presents a thorough review of the research work about detection and classification of brain tumor MRI images into tumor and non-tumor classes using Deep Learning, presented over the period from 2015 to 2020. A lot of meaningful and efficient algorithms have been developed so far but still each algorithm lacks in one way or the other due to the lack of standardization. Critical analysis of the pros and cons of each methodology surfaced until is provided in detail in this study. Some performance degrading factors and their solutions are also listed to give an idea to potential researchers for developing some optimized CAD systems. From comparative analysis, it is clear that Deep Learning techniques and algorithms have great power and ability to handle large amount of data. Still their benefits are not exploited completely in the study of brain tumor. From the above-mentioned detailed review, it can be concluded that there is a strong need of fully automatic unified framework that can efficiently detect and classify the brain tumor into multiple classes with less complexity.

8. FUTURE DIRECTIONS

In light of the above-mentioned limitations and challenges that are encountered by the existing researchers and scientists, few key ideas are presented that can be given importance while designing future models. The most important idea is to have a pre-processing system that can-do color balancing in textured MRI images so that new and improved features can be exploited. A lot of research has been done for tumor classification and segmentation but fewer studies have been carried out for tumor detection [1].

Detection is the most important step and must be given equal priority in future studies and research. There is a strong need to bring MRI image registration and compression techniques under one roof. Only through this way we can take full advantage of the 3D features and hidden information inside an MRI image. An interoperable system needs to be designed that can easily work with 2D or 3D images. New ways and means must be devised to concatenate the powers of shallow and deep architectures into one unified framework [1]. Hybridization must be used to combine promising architectures and algorithms with an aim to integrate advantages [31]. Another future enhancement can be the use of optimization techniques for Deep Learning models that are lacking in the existing models. Transfer learning has performed well but is yet to be explored completely in the realm of brain tumor studies.

Most importantly, a single fully automatic system for all tasks is missing. Since one of the main objectives of deep-learning based brain tumor studies is to assist neurosurgeons in automation of tumor classification and segmentation, it is important to move towards development of such frame work. There is a need to develop a unified framework that would combine various tasks starting from pre-processing till the final stages of tumor type identification. In short, the future of deep- learning based brain tumor studies is very optimistic and focusing on the right direction would move these studies from research labs to hospitals. We believe that our review would provide the researchers an insight about the directions to take in future for this purpose.

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REFERENCES

[1] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, ‘A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned’, *Magn. Reson. Imaging*, vol. 61, no. May, pp. 300–318, Sep. 2019, doi: 10.1016/j.mri.2019.05.028.
[2] K. R. Bhatele and S. S. Bhadauria, ‘Brain structural disorders detection and classification approaches: a review’, *Artif. Intell. Rev.*, 2019, doi: 10.1007/s10462-019-09766-9.
[3] D. Nanware, S. Taras, and S. Navale, ‘Brain Tumor Detection Using Deep Learning’, *Int. J. Sci. Res. Eng. Dev.*, vol. 3, pp. 391–395, 2020.
[4] Muhmmad Irfan Sharif, ‘Recent Advancements in Brain Tumor Segmentation and Classification using Deep Learning: A Review’, *Int. J. Eng. Res.*, vol. V8, no. 12, pp. 319–325, 2019, doi: 10.17577/ijertv8is120190.
[5] H. Kaur and A. K. Gill, ‘Review of Brain Tumor Detection Using Various Techniques’, *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 7, no. 5, pp. 867–870, 2017, doi: 10.23956/ijarcsse/v7i4/0221.
[6] M. Sharif, J. Amin, M. Raza, M. Yasmin, and S. C. Satapathy, ‘An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor’, *Pattern Recognit. Lett.*, vol. 129, pp. 150–157, Jan. 2020, doi: 10.1016/j.patrec.2019.11.017.
[7] M. Jayali, V. Bhagat, and B. Dhaigude, ‘A Survey on Brain tumor Detection Techniques’, *Int. Res. J. Eng. Technol.*, vol. 8, no. 4, pp. 28–32, 2017.
[8] M. I. Sharif, J. P. Li, J. Naz, and I. Rashid, ‘A comprehensive review on multi-organs tumor detection based on machine learning’, *Pattern Recognit. Lett.*, vol. 131, pp. 30–37, Mar. 2020, doi: 10.1016/j.patrec.2019.12.006.
[9] B. Panda and C. S. Panda, ‘A Review on Brain Tumor Classification Methodologies’, *Int. J. Sci. Res. Sci. Technol.*, vol. 6, no. 6, pp. 346–359, 2019, doi: 10.32628/ijsrst20717.
[10] R. Kaur and A. Doegar, ‘Localization and Classification of Brain Tumor using Machine Learning & Deep Learning Techniques’, *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 9S, pp. 59–66, Aug. 2019, doi: 10.35940/ijitee.I1010.0789S19.
[11] M. Nazir, M. A. Khan, T. Saba, and A. Rehman, ‘Brain tumor detection from MRI images using multi-level wavelets’, *2019 Int. Conf. Comput. Inf. Sci. ICCIS 2019*, pp. 1–5, 2019, doi: 10.1109/ICCISci.2019.8716413.
[12] R. L. Siegel, K. D. Miller, and A. Jemal, ‘Cancer statistics, 2020’, *CA. Cancer J. Clin.*, vol. 70, no. 1, pp. 7–30, Jan. 2020, doi: 10.3322/caac.21590.
[13] A. M. Sarhan, ‘Brain Tumor Classification in Magnetic Resonance Images Using Deep Learning and Wavelet Transform’, *J. Biomed. Sci. Eng.*, vol. 13, no. 06, pp. 102–112, 2020, doi: 10.4236/jbise.2020.136010.
[14] M. Mudda, R. Manjunath, and N. Krishnamurthy, ‘Brain Tumor Classification Using Enhanced Statistical Texture Features’, *IETE J. Res.*, vol. 0, no. 0, pp. 1–12, 2020, doi: 10.1080/03772063.2020.1775501.
[15] S. A. Swapnil and V. S. Girish, ‘Image Mining Methodology for Detection of Brain Tumor: A Review’, in *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, 2020, no. Iccmc, pp. 232–237, doi: 10.1109/ICCMC48092.2020.ICCMC-00044.
[16] L. Kapoor and S. Thakur, ‘A survey on brain tumor detection using image processing techniques’, in *2017 7th International Conference on Cloud Computing, Data Science & Engineering - Confluence*, 2017, pp. 582–585, doi: 10.1109/CONFLUENCE.2017.7943218.
[17] A. R. Deepa and W. R. Sam Emmanuel, ‘A comprehensive review and analysis on mri based brain tumor segmentation’, *Int. J. Sci. Technol. Res.*, vol. 8, no. 10, pp. 2140–2154, 2019.
[18] G. S. Tandel *et al.*, ‘A review on a deep learning perspective in brain cancer classification’, *Cancers (Basel).*, vol. 11, no. 1, 2019, doi: 10.3390/cancers11010111.
[19] N S Zulpe and V P Pawar, ‘Review on Brain Tumor Segmentation and Classification Techniques’, *Int. J. Eng. Res.*, vol. V6, no. 11, pp. 7–11, 2017, doi: 10.17577/ijertv6is110008.
[20] N. Kumari and S. Saxena, ‘Review of Brain Tumor Segmentation and Classification’, *Proc. 2018 Int. Conf. Curr. Trends Towar. Converging Technol. ICCTCT 2018*, pp. 1–6, 2018, doi: 10.1109/ICCTCT.2018.8551004.
[21] M. W. Nadeem *et al.*, ‘Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges’,

Brain Sci., vol. 10, no. 2, pp. 1–33, 2020, doi: 10.3390/brainsci10020118.
[22] F. Gao, H. Yoon, T. Wu, and X. Chu, 'A feature transfer enabled multi-task deep learning model on medical imaging', *Expert Syst. Appl.*, vol. 143, p. 112957, 2020, doi: 10.1016/j.eswa.2019.112957.
[23] J. Liu, M. Li, J. Wang, F. Wu, T. Liu, and Y. Pan, 'A survey of MRI-based brain tumor segmentation methods', *Tsinghua Sci. Technol.*, vol. 19, no. 6, pp. 578–595, 2014, doi: 10.1109/TST.2014.6961028.
[24] D. S. S. K. Vipin Y. Borole, Sunil S. Nimbhore, 'Image Processing Techniques for Brain Tumor Detection: A Review', *Int. J. Emerg. Trends Technol. Comput. Sci. Web*, vol. 4, no. 5, pp. 28–32, 2015.
[25] G. Mohan and M. M. Subashini, 'MRI based medical image analysis: Survey on brain tumor grade classification', *Biomed. Signal Process. Control*, vol. 39, pp. 139–161, 2018, doi: 10.1016/j.bspc.2017.07.007.
[26] M. Sharif, J. Amin, M. Raza, M. A. Anjum, H. Afzal, and S. A. Shad, 'Brain tumor detection based on extreme learning', *Neural Comput. Appl.*, vol. 8, 2020, doi: 10.1007/s00521-019-04679-8.
[27] M. A. Kabir, 'AUTOMATIC BRAIN TUMOR DETECTION AND FEATURE EXTRACTION FROM MRI IMAGE', *Sci. World J.*, vol. 8, pp. 695–711.
[28] L. Sahoo, L. Sarangi, B. R. Dash, and H. K. Palo, 'Detection and Classification of Brain Tumor Using Magnetic Resonance Images', Springer, Singapore, 2020, pp. 429–441.
[29] 'Magnetic Resonance Imaging (MRI) of the Brain and Spine: Basics', 2006. [Online]. Available: https://casemed.case.edu/clerkships/neurology/Web Neurorad/MRI Basics.htm.
[30] M. S. H. Al-Tamimi and G. Sulong, 'Tumor brain detection through MR images: A review of literature', *J. Theor. Appl. Inf. Technol.*, vol. 62, no. 2, pp. 387–403, 2014.
[31] T. P. Pries, R. Jahan, and P. Suman, 'Review of Brain Tumor Segmentation, Detection and Classification Algorithms in fMRI Images', *2018 Int. Conf. Comput. Charact. Tech. Eng. Sci. CCTES 2018*, pp. 300–303, 2019, doi: 10.1109/CCTES.2018.8674150.
[32] L. Kapoor and S. Thakur, 'A survey on brain tumor detection using image processing techniques', *Proc. 7th Int. Conf. Conflu. 2017 Cloud Comput. Data Sci. Eng.*, no. November 2016, pp. 582–585, 2017, doi: 10.1109/CONFLUENCE.2017.7943218.
[33] A. S. Remya Ajai and S. Gopalan, 'Analysis of Active Contours Without Edge-Based Segmentation Technique for Brain Tumor Classification Using SVM and KNN Classifiers', Springer Singapore, 2020, pp. 1–10.
[34] A. S. Remya Ajai and S. Gopalan, 'Analysis of Active Contours Without Edge-Based Segmentation Technique for Brain Tumor Classification Using SVM and KNN Classifiers', 2020, pp. 1–10.
[35] M. I. Sharif, J. P. Li, J. Naz, and I. Rashid, 'A comprehensive review on multi-organs tumor detection based on machine learning', *Pattern Recognit. Lett.*, vol. 131, pp. 30–37, 2020, doi: 10.1016/j.patrec.2019.12.006.
[36] A. Tiwari, S. Srivastava, and M. Pant, 'Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019', *Pattern Recognit. Lett.*, vol. 131, pp. 244–260, 2020, doi: 10.1016/j.patrec.2019.11.020.
[37] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, 'A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned', *Magn. Reson. Imaging*, vol. 61, no. May, pp. 300–318, 2019, doi: 10.1016/j.mri.2019.05.028.
[38] 'IBSR Dataset'. [Online]. Available: https://www.nitrc.org/projects/ibsr.
[39] 'oasis (open access series of imaging studies)'. [Online]. Available: https://www.oasis-brains.org/.
[40] M. D. Keith A. Johnson and P. D. J. Alex Becker, 'the whole brain atlas'. [Online]. Available: http://www.med.harvard.edu/AANLIB/.
[41] 'Multimodal Brain Tumor Segmentation Challenge 2020: Previous BraTS Instances'. [Online]. Available: http://braintumorsegmentation.org/.
[42] 'Rider neuro MRI'. [Online]. Available: https://wiki.cancerimagingarchive.net/display/Public/RIDER+NEURO+MRI.
[43] 'Radiopedia , cases'. [Online]. Available: https://radiopaedia.org/encyclopaedia/cases/all?lang=us.
[44] 'THE CANCER IMAGING ARCHIVE (TCIA)'. [Online]. Available: https://www.cancerimagingarchive.net/collections/.
[45] 'Brain tumor dataset'. [Online]. Available: https://figshare.com/articles/brain_tumor_dataset/1512427.
[46] 'ISCHEMIC STROKE LESION SEGMENTATION CHALENGE'. [Online]. Available: http://www.isles-challenge.org/ISLES2016/.
[47] 'THE CANCER GENOME ATLAS', *National cancer institute*, 2006. [Online]. Available: https://www.cancer.gov/about-nci/organization/ccg/research/structural-genomics/tcga.
[48] 'Brain MRI Images for Brain Tumor Detection'. [Online]. Available: https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection.
[49] L. Sahoo, L. Sarangi, B. R. Dash, and H. K. Palo, 'Detection and Classification of Brain Tumor Using Magnetic Resonance Images', Springer Singapore, 2020, pp. 429–441.
[50] T. Kalaiselvi, S. T. Padmapriya, P. Sriramakrishnan, and K. Somasundaram, 'Deriving tumor detection models using convolutional neural networks from MRI of human brain scans', *Int. J. Inf. Technol.*, pp. 2–7, 2020, doi: 10.1007/s41870-020-00438-4.
[51] R. V. Kurup, V. Sowmya, and K. P. Soman, *Effect of Data Pre-processing on Brain Tumor Classification Using*

Capsulenet. Singapore: Springer Singapore, 2020.
[52] M. Toğaçar, Z. Cömert, and B. Ergen, 'Classification of brain MRI using hyper column technique with convolutional neural network and feature selection method', *Expert Syst. Appl.*, vol. 149, p. 113274, Jul. 2020, doi: 10.1016/j.eswa.2020.113274.
[53] P. M. S. Raja and A. Viswasa, 'ScienceDirect Brain tumor classification using a hybrid deep autoencoder with Bayesian fuzzy clustering-based segmentation approach', *Integr. Med. Res.*, pp. 1–14, doi: 10.1016/j.bbe.2020.01.006.
[54] J. Amin *et al.*, 'Brain Tumor Detection by Using Stacked Autoencoders in Deep Learning', 2020.
[55] A. Çinar and M. Yildirim, 'Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture', *Med. Hypotheses*, vol. 139, no. March, p. 109684, 2020, doi: 10.1016/j.mehy.2020.109684.
[56] M. Toğaçar, B. Ergen, and Z. Cömert, 'BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model', *Med. Hypotheses*, vol. 134, p. 109531, Jan. 2020, doi: 10.1016/j.mehy.2019.109531.
[57] S. A. Abdelaziz Ismael, A. Mohammed, and H. Hefny, 'An enhanced deep learning approach for brain cancer MRI images classification using residual networks', *Artif. Intell. Med.*, vol. 102, p. 101779, Jan. 2020, doi: 10.1016/j.artmed.2019.101779.
[58] J. Amin, M. Sharif, N. Gul, M. Yasmin, and S. Ali, 'Brain tumor classification based on DWT fusion of MRI sequences using convolutional neural network ☆', vol. 129, pp. 115–122, 2020, doi: 10.1016/j.patrec.2019.11.016.
[59] N. Ghassemi, A. Shoeibi, and M. Rouhani, 'Biomedical Signal Processing and Control Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images', *Biomed. Signal Process. Control*, vol. 57, p. 101678, 2020, doi: 10.1016/j.bspc.2019.101678.
[60] F. Özyurt, E. Sert, and D. Avcı, 'An expert system for brain tumor detection: Fuzzy C-means with super resolution and convolutional neural network with extreme learning machine', *Med. Hypotheses*, vol. 134, no. September 2019, p. 109433, Jan. 2020, doi: 10.1016/j.mehy.2019.109433.
[61] Y. Bhanothu, A. Kamalakannan, and G. Rajamanickam, 'Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network', *2020 6th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2020*, pp. 248–252, 2020, doi: 10.1109/ICACCS48705.2020.9074375.
[62] B. Anilkumar and P. Rajesh Kumar, 'Tumor classification using block wise fine tuning and transfer learning of deep neural network and KNN classifier on MR brain images', *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 2, pp. 574–583, 2020, doi: 10.30534/ijeter/2020/48822020.
[63] M. H C, 'Evaluation of Brain Tumor MRI Imaging Test Detection and Classification', *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 8, no. 6, pp. 124–131, 2020, doi: 10.22214/ijraset.2020.6019.
[64] R. Islam, S. Imran, M. Ashikuzzaman, and M. M. A. Khan, 'Detection and Classification of Brain Tumor Based on Multilevel Segmentation with Convolutional Neural Network', *J. Biomed. Sci. Eng.*, vol. 13, no. 04, pp. 45–53, 2020, doi: 10.4236/jbise.2020.134004.
[65] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, 'Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images', *Pattern Recognit. Lett.*, vol. 129, pp. 181–189, 2020, doi: 10.1016/j.patrec.2019.11.019.
[66] S. S. Begum and D. R. Lakshmi, 'Combining optimal wavelet statistical texture and recurrent neural network for tumour detection and classification over MRI', *Multimed. Tools Appl.*, vol. 79, no. 19–20, pp. 14009–14030, 2020, doi: 10.1007/s11042-020-08643-w.
[67] C. Han *et al.*, 'Infinite Brain MR Images: PGGAN-Based Data Augmentation for Tumor Detection', Springer, Singapore, 2020, pp. 291–303.
[68] A. Raj, A. Anil, P. L. Deepa, H. Aravind Sarma, and R. Naveen Chandran, 'BrainNET: A Deep Learning Network for Brain Tumor Detection and Classification', Springer, Singapore, 2020, pp. 577–589.
[69] A. El Boustani, M. Aatila, E. El Bachari, and A. El Oirrak, 'MRI Brain Images Classification Using Convolutional Neural Networks', Springer, Cham, 2020, pp. 308–320.
[70] A. El Boustani and E. El Bachari, 'MRI Brain Images Compression and Classification Using Different Classes of Neural Networks', Springer, Cham, 2019, pp. 122–134.
[71] Y. Cheng, G. Qin, R. Zhao, Y. Liang, and M. Sun, 'ConvCaps: Multi-input Capsule Network for Brain Tumor Classification', Springer, Cham, 2019, pp. 524–534.
[72] D. Liu, Y. Liu, and L. Dong, 'G-ResNet: Improved ResNet for Brain Tumor Classification', Springer, Cham, 2019, pp. 535–545.
[73] J. Amin, M. Sharif, M. Yasmin, T. Saba, M. A. Anjum, and S. L. Fernandes, 'A New Approach for Brain Tumor Segmentation and Classification Based on Score Level Fusion Using Transfer Learning', *J. Med. Syst.*, vol. 43, no. 11, 2019, doi: 10.1007/s10916-019-1453-8.
[74] N. Poonguzhali, K. R. Rajendra, T. Mageswari, and T. Pavithra, 'Heterogeneous deep neural network for healthcare using metric learning', *2019 IEEE Int. Conf. Syst. Comput. Autom. Networking, ICSCAN 2019*, pp. 1–4, 2019, doi: 10.1109/ICSCAN.2019.8878728.
[75] S. Maharjan, A. Alsadoon, P. W. C. Prasad, T. Al-Dalain, and O. H. Alsadoon, 'A novel enhanced softmax loss function

for brain tumour detection using deep learning', *J. Neurosci. Methods*, vol. 330, p. 108520, 2020, doi: 10.1016/j.jneumeth.2019.108520.

[76] A. Ari and D. Hanbay, 'Deep learning based brain tumor classification and detection system', *Turkish J. Electr. Eng. Comput. Sci.*, vol. 26, no. 5, pp. 2275–2286, 2018, doi: 10.3906/elk-1801-8.

[77] S. R. Joshi, D. B. Headley, K. C. Ho, D. Paré, and S. S. Nair, 'Classification of brainwaves using convolutional neural network', *Eur. Signal Process. Conf.*, vol. 2019-Septe, pp. 128–132, 2019, doi: 10.23919/EUSIPCO.2019.8902952.

[78] H. Ucuzal, S. Yasar, and C. Colak, 'Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface', *3rd Int. Symp. Multidiscip. Stud. Innov. Technol. ISMSIT 2019 - Proc.*, pp. 1–5, 2019, doi: 10.1109/ISMSIT.2019.8932761.

[79] K. Adu, Y. Yu, J. Cai, and N. Tashi, 'Dilated Capsule Network for Brain Tumor Type Classification Via MRI Segmented Tumor Region', in *2019 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2019, no. December, pp. 942–947, doi: 10.1109/ROBIO49542.2019.8961610.

[80] M. Siar and M. Teshnehlab, 'Brain tumor detection using deep neural network and machine learning algorithm', *2019 9th Int. Conf. Comput. Knowl. Eng. ICCKE 2019*, no. Iccke, pp. 363–368, 2019, doi: 10.1109/ICCKE48569.2019.8964846.

[81] C. Han *et al.*, 'Combining noise-to-image and image-to-image GANs: Brain MR image augmentation for tumor detection', *IEEE Access*, vol. 7, pp. 156966–156977, 2019, doi: 10.1109/ACCESS.2019.2947606.

[82] M. Li, L. Kuang, S. Xu, and Z. Sha, 'Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network', *IEEE Access*, vol. 7, pp. 180134–180146, 2019, doi: 10.1109/ACCESS.2019.2958370.

[83] Y. Zhou *et al.*, 'Holistic Brain Tumor Screening and Classification Based on DenseNet and Recurrent Neural Network', Springer, Cham, 2019, pp. 208–217.

[84] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim, and F. Muhammad Shah, 'Brain Tumor Detection Using Convolutional Neural Network', *1st Int. Conf. Adv. Sci. Eng. Robot. Technol. 2019, ICASERT 2019*, vol. 2019, no. Icasert, pp. 1–5, 2019, doi: 10.1109/ICASERT.2019.8934561.

[85] P. Afshar, K. N. Plataniotis, and A. Mohammadi, 'Capsule Networks' Interpretability for Brain Tumor Classification Via Radiomics Analyses', in *2019 IEEE International Conference on Image Processing (ICIP)*, 2019, pp. 3816–3820, doi: 10.1109/ICIP.2019.8803615.

[86] P. Muthu Krishnammal and S. Selvakumar Raja, 'Convolutional neural network based image classification and detection of abnormalities in MRI brain images', *Proc. 2019 IEEE Int. Conf. Commun. Signal Process. ICCSP 2019*, pp. 548–553, 2019, doi: 10.1109/ICCSP.2019.8697915.

[87] N. A. Ali, A. R. Syafeeza, L. J. Geok, Y. C. Wong, N. A. Hamid, and A. S. Jaafar, 'Design of Automated Computer-Aided Classification of Brain Tumor Using Deep Learning', Springer, Singapore, 2019, pp. 285–291.

[88] S. Deepak and P. M. Ameer, 'Brain tumor classification using deep CNN features via transfer learning', *Comput. Biol. Med.*, vol. 111, no. March, p. 103345, 2019, doi: 10.1016/j.compbiomed.2019.103345.

[89] H. H. Sultan, N. M. Salem, and W. Al-Atabany, 'Multi-Classification of Brain Tumor Images Using Deep Neural Network', *IEEE Access*, vol. 7, pp. 69215–69225, 2019, doi: 10.1109/ACCESS.2019.2919122.

[90] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, and T. R. Mengko, 'Brain Tumor Classification Using Convolutional Neural Network', in *IFMBE Proceedings*, Springer, Singapore, 2019, pp. 183–189.

[91] R. Ezhilarasi and P. Varalakshmi, 'Tumor detection in the brain using faster R-CNN', *Proc. Int. Conf. I-SMAC (IoT Soc. Mobile, Anal. Cloud), I-SMAC 2018*, pp. 388–392, 2019, doi: 10.1109/I-SMAC.2018.8653705.

[92] J. Seetha and S. S. Raja, 'Brain tumor classification using Convolutional Neural Networks', *Biomed. Pharmacol. J.*, vol. 11, no. 3, pp. 1457–1461, 2018, doi: 10.13005/bpj/1511.

[93] P. S. Vipin Makde, Jenice Bhavsar, Swati Jain, 'Deep Neural Network Based Classification of Tumourous and Non-tumorous Medical Images', in *Smart Innovation, Systems and Technologies*, 84th ed., vol. 84, S. C. Satapathy and A. Joshi, Eds. Cham: Springer International Publishing, 2018, pp. 199–205.

[94] M. Kachwalla, M. P. Shinde, R. Katare, A. Agrawal, V. M. Wadhai, and M. S. Jadhav, 'Classification of Brain MRI Images For Cancer Detection Using Deep Learning', vol. 3, no. 10, pp. 635–637, 2017, doi: 10.17148/IJARCCE.2018.7454.

[95] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, 'Classification using deep learning neural networks for brain tumors', *Futur. Comput. Informatics J.*, vol. 3, no. 1, pp. 68–71, 2018, doi: 10.1016/j.fcij.2017.12.001.

[96] F. Ye, J. Pu, J. Wang, Y. Li, and H. Zha, 'Glioma grading based on 3D multimodal convolutional neural network and privileged learning', *Proc. - 2017 IEEE Int. Conf. Bioinforma. Biomed. BIBM 2017*, vol. 2017-Janua, pp. 759–763, 2017, doi: 10.1109/BIBM.2017.8217751.

[97] A. Antony, K. A. Fathima, D. Raju, and M. C. Binish, 'Brain Tumor Detection and Classification in MRI Images', vol. 6, no. 5, pp. 84–89, 2017.

[98] Subhashis Banerjee and Francesco Masulli and Sushmita, 'Brain Tumor Detection and Classification from Multi-Channel MRIs using Deep Learning and Transfer Learning', *IEEE Access*, pp. 1–9, 2017.

[99] A. Anbarasa Pandian and R. Balasubramanian, 'Fusion of contourlet transform and zernike moments using content based image retrieval for MRI brain tumor images', *Indian J. Sci. Technol.*, vol. 9, no. 29, pp. 1–8, 2016, doi:

10.17485/ijst/2016/v9i29/93837.

[100] A. Sciences, M. Scientific, and P. Corp, ‘Brain Tumor Detection and Classification Using Deep Learning Classifier on MRI Images V . P . Gladis Pushpa Rathi and 2 S . Palani Department of Computer Science and Engineering , Sudharsan Engineering College , Sudharsan Engineering College , Sathiyamang’, *Appl. Sci. Eng. Technol.*, vol. 10, no. 2, pp. 177–187, 2015, doi: 10.19026/rjaset.10.2570.

[101] Y. Pan *et al.*, ‘Brain tumor grading based on Neural Networks and Convolutional Neural Networks’, *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2015-Novem, pp. 699–702, 2015, doi: 10.1109/EMBC.2015.7318458.

[102] K. Meena and E. Murali, ‘Study on Various Machine Learning Algorithms for Brain Tumor Detection’, *Int. J. pure Appl. Math.*, vol. 117, no. 8, pp. 139–143, 2017, doi: 10.12732/ijpam.v117i8.28.

[103] Nikolas Adaloglou, ‘Intuitive Explanation of Skip Connections in Deep Learning’, *AI SUMMER*. 2020.

[104] H. Liu, Q. Li, and I.-C. Wang, ‘A Deep-Learning Model with Learnable Group Convolution and Deep Supervision for Brain Tumor Segmentation’, *Math. Probl. Eng.*, vol. 2021, pp. 1–11, Feb. 2021, doi: 10.1155/2021/6661083.

[105] S. Alaraimi, K. E. Okedu, H. Tianfield, R. Holden, and O. Uthmani, ‘Transfer learning networks with skip connections for classification of brain tumors’, *Int. J. Imaging Syst. Technol.*, p. ima.22546, Feb. 2021, doi: 10.1002/ima.22546.

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