Classification of brain tumor images using enhanced deep learning based methodologies

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Abstract. Brain tumor is abnormal increase in number of cells present inside brain. The tumor can be classified into various types like Glioma, Meningioma and Pituitary based on their location and severity. If the brain tumour is detected in the early stages, it makes it easier for a patient to get a proper treatment. Deep learning especially in the field of CNNs have performed really well in detecting brain tumour. In this paper, a pretrained CNN model RESNET-50 is implemented using the technique of transfer learning on the Figshare dataset. Contrast stretching and Histogram Equalization techniques separately were implemented on the input images and their performances have been compared in terms of precision and recall with similar techniques Kaur et al. [9]. RESNET-50 with Contrast Stretching attained the highest accuracy of 99.15% for classification.

Keywords: Brain tumor · Transfer Learning · Deep Learning · CNN · Classification · RESNET.

1 Introduction

Brain tumor is one of the most fatal and fast-growing diseases Dong et al. [2]. Tumors that develop in the brain cause life-threatening disease and thus early diagnosis proves to be really important in these cases. Glioma is a fast-growing, aggressive type of tumor that forms on the supportive tissue of the brain. Glioblastoma is the most common grade IV brain cancer Hanif et al. [6]. Meningioma develops in the cells of the membrane that surround the brain and spinal cord. Most of these tumors are benign and are typically removed with surgery. Pituitary tumors are lumps that form in the pituitary, a small gland about the size of a pea that sits inside the skull, just below the brain and above the nasal passages.

A major challenge in brain tumor treatment planning and quantitative evaluation is determining the extent of the tumor. Even after novel advancements in partially and wholly automatic methods for brain tumor segmentation and detection, yet, various significant problems are there in this task majorly because

of the dissimilarities in the shape, size, location, regularity of the brain tumor heterogeneous appearance.
Magnetic resonance imaging (MRI) furnishes detailed information about brain tumor anatomy and acts as a necessary pre-processing step for tumor detection GB et al. [3]. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) Lee et al. [10]. Superior and finer 2D or 3D brain images are produced in case of MRI using magnetic resonance and not ionizing radiation or radioactive tracers.
In recent years, deep learning has really outperformed the conventional image processing techniques. When compared to older and traditional image processing methods, the most eminent advantage of deep learning algorithms is the elimination of the need for feature extraction and image segmentation Dong et al. [2].
Transfer learning, a new and efficient technique in deep learning, is basically reusing a pre-trained model on a new problem which may or may not have new and different data Rehman et al. [18]. In transfer learning, the machine exploits knowledge gained from a previous task to improve generalization about another. Top performing models can be imported and applied directly, or integrated to create a hybrid model for your own computer vision problems Torrey et al. [26].
In this paper we have used the RESNET-50 model for the purpose pf classifying numerous brain tumor images into the three classes. The RESNET-50 model can be divided into five stages each with a convolution and identity block. All convolution blocks have 3 convolution layers and each identity block also has three convolution layers. The RESNET-50 has more than 23 million trainable parameters.
The major contribution of the current study can be directed as in the following manner. A deep network based methodology is enhanced using techniques like contrast stretching for image pre-processing. The classification performance in terms of precision Goutte et al. [4] and accuracy is then analysed for different deep learning techniques for different sets of data distribution. Pre-trained CNN architecture (ResNet-50) is used as a classifier to avoid manual feature extraction. The classification performance of Brain Tumor images with ResNet-50 on contrast enhanced images is higher compared to histogram equalisation. Also accuracy for different distributions of data is used to visualize results and to get a clearer picture of our task and its validity. The paper is organised as : Section - 2 engages in long and careful consideration of related works. Section 3 demonstrates the methodologies involved in the image pre-processing steps. Also classification using ResNet 50 in detail, its architecture, flow diagram of the entire process and the proposed classifier in specific and its structure. Experimental results and along with comparisons between the methodologies is explained in Section 4 using graphs and tabular data. The conclusion is drawn in Section 5.

2 Related Work

Various algorithms have been implemented on brain tumour detection. Some techniques are based on pixels, regions and edges, some are texture segmented based methods, and some are template matching methods.

In Dong et al. [2] a U-Net based deep convolutional network Ronneberger et al. [19] with soft dice loss functions Milletari et al. [13] for fully automatic brain tumor segmentation and detection technique is proposed. Based on the experiments on a well-established benchmarking (BRATS 2015) public dataset. This study makes it possible to generate a patient-specific brain tumor segmentation model without manual interference, and this allows important assessment for clinical tasks like diagnosis, planning of treatment and monitoring of patient.

A hybrid technique constituting LSVM classifier with Multi-Layer perceptron based kernel functions and RBF kernel functions for classification, and Fast Bounding Box for segmentation has been proposed in GB et al. [3]. Noise removal is done as a pre-processing step by median filtering followed by statistical based feature extraction using GLCM Singh et al. [24]. The classification accuracy is claimed to be 96.63% which is quite promising.

Ming-Ni Wu et al. [28] proposed a method which combined K-MEANS clustering, a color translation technique and histogram clustering hence creating the method more efficient and very easy to implement. The given gray-level MR images were converted into a color space image and the experiment conducted demonstrates encouraging results.

In [7] A dataset of 1500 brain MRI images is used in this paper. There are 1200 tumour affected and 300 healthy brain MRI images. Four types of brain tumor CNS Lymphoma, Glioblastoma, Meningioma and Metastases are successfully detected using the method in this paper. Otsu segmentation along with 2D adaptive filtering is used to segment the tumor region from normal tissues. After detection of tumour, size of tumour is also calculated. The accuracy of 93% is achieved in the proposed model.

The main purpose of Özyurt et al. [16] is to provide an efficient automatic brain tumor segmentation system with help of classification of brain tumors into benign and malignant. Features of segmented images were extracted using CNN architectures and then were classified with SVM and KNN classifiers. An accuracy of 95.62% is yielded by SVM classifier in the proposed work. This accuracy rate is also expected to increase if a bigger dataset is used.

A stepwise methodology was followed in Sajjad et al. [21]. First the the tumors were segmented in the input MR images using a fully automatic deep learning based technique called InputCascadeCNN to extract the local as well as the global features then due to the scarcity of data the available data was augmented using various techniques creating 30 images out of one. Lastly VGG-19 model was used to classify the tumors because of its 3*3 kernels with 1 stride to recognize important features of MRIs with less no. of parameters.

In Sultan et al. [25], a Convolutional Neural Network architecture was implemented to classify different types and grades of brain tumors. The architecture of the network was evolved using different configurations to attain the most ap-

propriate of the structures. Here two different datasets from two different sources were used achieving the highest accuracies of about 96.13% and 98.7% concerning the two datasets used in this paper.
In the study of Rehman et al. [18], they conducted a study of three architectures of CNN namely AlexNet, GoogLeNet, and VGGNet. They used the CNN to classify brain tumors in various types. They use the technique of the tranfer learning to use pretrained models on MRI images of brain tumor dataset of Figshare. They also used data augumentation technique for enhancing the dataset. In this study, use of VGG-16 architecture provided with highest accuracy of 98.69%.
Due to the lack of available annotated medical images, accurate computer-assisted diagnosis requires various Data Augmentation (DA) techniques, such as geometric/intensity transformations however, those transformed images have a similar distribution to the original ones, leading to limited performance improvement. In Han et al. [5], This study uses Progressive Growing of GANs, a multi-stage generative training method, to generate original-sized 256X256 MRI images. Results show that this PGGAN-based DA method can achieve promising performance improvement in tumor detection and also in other medical imaging tasks.
The study in Özyurt et al. [15] proposes a hybrid method using Neutrosophy and Convolutional Neural Network. This study classifies tumor region areas into benign and malignant. They segmented MRI images using the neutrosophic set - expert maximum fuzzy-sure entropy. They extracted the features of the segmented brain images in the classification stage by using CNN and these were then classified using SVM and KNN classifiers. Experimental results indicate that CNN features displayed a better classification performance with SVM with an average success of 95.62%.

3 Materials and Methodology

In this section, we present a brief description of the Figshare dataset. Secondly describe the two approaches for pre-processing of the images and lastly introduce the architecture of the CNN used i.e RESNET-50.

3.1 Data Acquisition:

In this study, we have utilised the publicly available brain tumor dataset - Figshare for proposed framework to classify brain tumors. The dataset consists of 3064 total MRI images out of which 708 are meningioma, 1426 are glioma and 930 are pituitary tumors. This data is organized in matlab data format (.mat file) Saini et al. [20]. Each MAT file contains following fields for every image: a patient ID, label for every image that represents the type of brain tumor, 512 X 512 images in uint16 format, array containing tumor border, and ground truth in binary mask image Singh et al. [23]. We mainly used 512×512 image data in uint16 format (MRI images) of brain tumors and labels for classification.

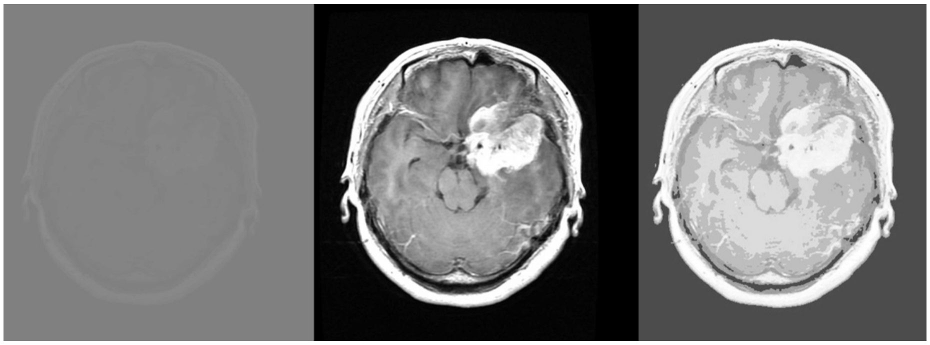

Fig. 1. a.Original image present in dataset. b.Image after contrast stretching. c.Image after histogram equalization.

3.2 Preprocessing:

In this phase, finer details of the images are refined and noise is removed from the images. The foremost task of medical imaging analysis is cleaning of the MRI images and to enhance the contrast. Since the MRI images are procured from different techniques thus cause false intensity levels Liu et al. [11]. The images are made suitable for further study by image enhancement techniques. Thus, different image processing algorithms as followed were deployed to enhance the contrast of MRI images Lu et al. [12].

Contrast stretching: High-resolution contrast images were produced using the contrast stretching algorithm. In contrast stretching, the contrast is enhanced by stretching the range of intensity values. It widens the range of gray levels for poorly-contrasted MRI images.

Histogram Equalization: We also used histogram equalization to improve the results of our model. This makes the areas of lower local contrast values gain the high contrast. In this technique image intensity values are adjusted to increase the contrast of images by efficiently spreading out the most frequent intensity values.

3.3 Classification using deep learning:

Transfer learning is the idea of overcoming the isolated learning paradigm and utilizing knowledge acquired for one task to solve related ones Reddy et al. [17]. Basically it is a technique in which a model developed for a problem is reused in another problem as a starting point. Learning a new task relies on the previous learned tasks.
A brief and comprehensive framework of architectures of RESNET50 as illustrated. **RESNET50:** RESNET50 has 48 Convolution layers and is a variant of

the RESNET model with 1 MaxPool and 1 Average Pool layer. This pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. In this way, the network has learned rich feature representations for a wide range of images.
The network has an image input size of 224 X 224 and 3.8 x 10$\hat{9}$ Floating points operations. Fig. 2 demonstrates the architecture of RESNET50 Shin et al. [22].

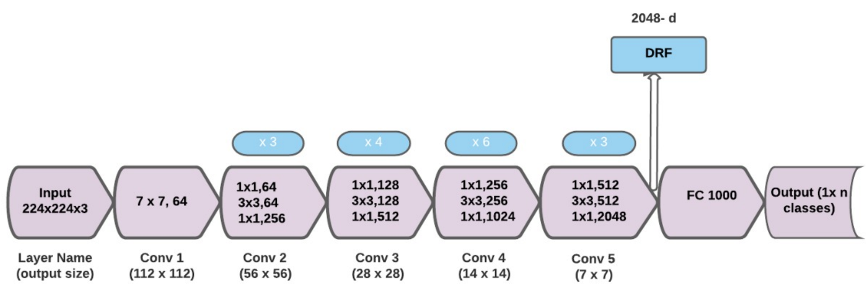

Fig. 2. RESNET50 architecture

the two major situations in the transfer learning are - fine-tuning of the convNet and freeze the convNet layers the first scenario, replacement and retainment of the pre trained ConvNet is done on the target dataset for continuing backpropagation Werbos et al. [27] and finally, the last fully connected layer classifies the target dataset containing 3064 total MRI images out of which 708 are meningioma, 1426 are glioma and 930 are pituitary tumors.
In the present study we are deploying the first situation. Through the flow chart given in fig. 3, a short illustration of major techniques used for the tasks of classification and detection of the brain tumors. The T1-weighted contrast-enhanced images are trained for 233 patients with three kinds of brain tumors. The proposed work employs a pre-trained architecture of CNN, i.e. RESNET50. The framework of the proposed system contains three main phases: preprocessing, fine-tuning of the entire network, and classification/detection as illustrated in fig. 3.
In the first part, two contrast enhancement methods are used on the MRI image namely histogram equalization and contrast stretching technique.
In the next step, RESNET 50 is employed on a target brain tumor dataset—Figshare. In this phase, the fine-tuning strategies of transfer learning are deployed Kamble et al. [8]. In the final phase, automated features are classified in the last step using the proposed classifiers softmax layer and binary_crossentropy as the loss function.

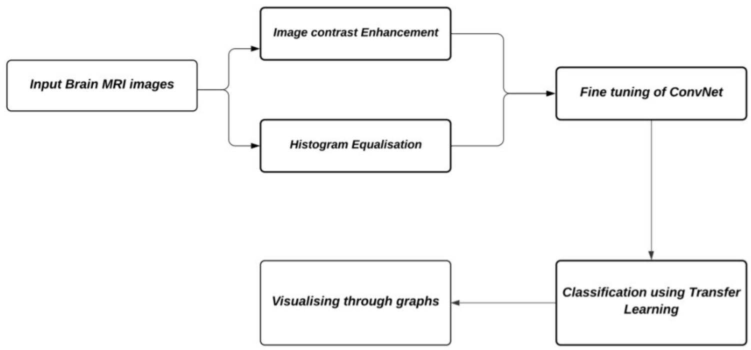

Fig. 3. Methodology flow diagram.

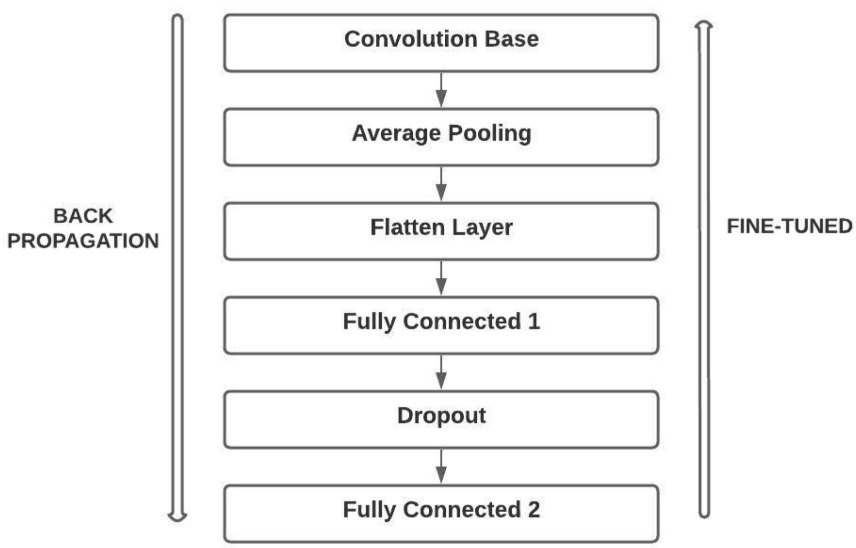

Fig. 4. Proposed Classifier

Proposed Classifier: As the dataset we used is large enough and different from the base dataset so all the layers of the dataset are finetuned. We followed the following steps:

- Firstly the last fully connected layers of pretrained network is removed and is replaced with our proposed classifier with a number of classes equal to classes present in the target dataset that is 3.
- Randomly initialized the weights of our classifier.
- Initialise the weights of other layers using pretrained weights.
- Train the entire network.
- Test the network and obtain the evaluation matrices.

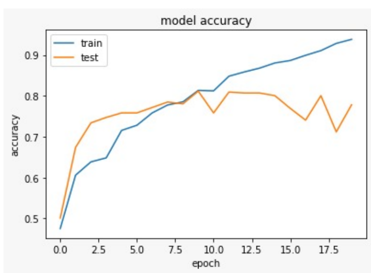

Fig. 5. Accuracy per Epoch with train test split of 75-25

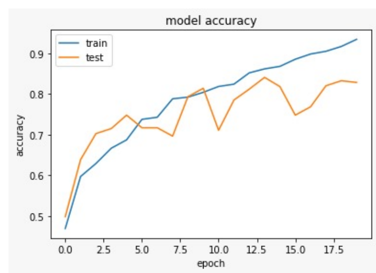

Fig. 6. Accuracy per Epoch with train test split of 80-20

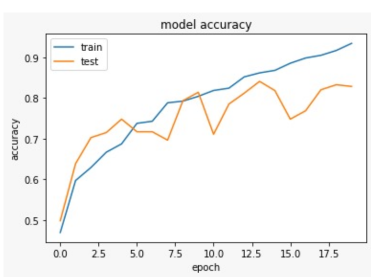

Fig. 7. Accuracy per Epoch with train test split of 80-20

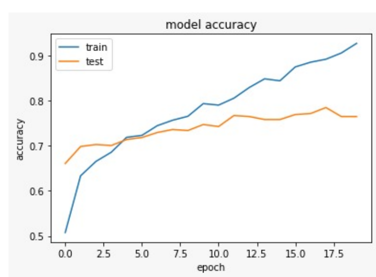

Fig. 8. Accuracy per Epoch with train test split of 75-25 with histogram equaization.

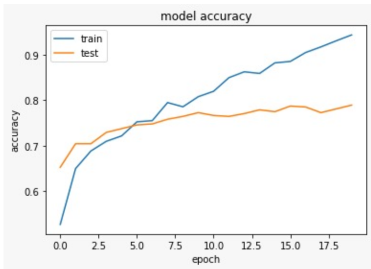

Fig. 9. Accuracy per Epoch with train test split of 80-20 with histogram equalization.

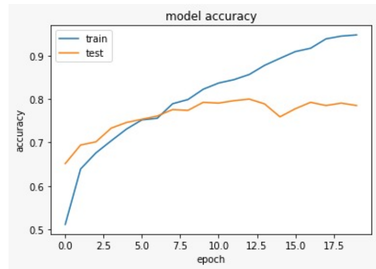

Fig. 10. Accuracy per Epoch with train test split of 90-10 with histogram equalization.

4 RESULTS AND DISCUSSION

Our study is done using the brain tumor dataset Figshare which is freely available for the public. It provides 3064 brain MRI images with 708 slices for meningioma tumor, 1426 for glioma tumor, and 930 for pituitary tumor. The first task was to convert (512 x 512) 2D images into 3D images so that they can be passed to the RESNET Model. For that we had to drop a few pixels from the edges of the image thus making suitable 3D images without dropping the quality of the images.
In the study, dataset is divided in various split ratios- 90:10, 80:20 and 75:25 for training and testing respectively. The testing accuracy along precision recall and other metrics for both contrast-stretching and histogram equalization techniques are then compared. We used Batch size of 10, maximum epochs of 20 and SGD

CLASS	Train-Test Split Percentage					
	75-25		80-20		90-10	
	Precision	Recall	Precision	Recall	Precision	Recall
meningioma	0.80	0.90	0.82	0.87	0.84	0.80
glioma	0.85	0.83	0.85	0.84	0.82	0.77
pituitary	0.83	0.70	0.84	0.81	0.72	0.80

Table 1. RESNET-50 Classifier Results with Contrast stretching.

optimizer Bottou et al. [1] for training purposes. Binary Cross Entropy as loss function was used.
The above graphs shows the accuracy per epoch in various train-test splits. In Table 1 and Table 2 classes are divided into 3 types of brain tumors that are meningioma, glioma and pituitary with their respective precision and recall

CLASS	Train-Test Split Percentage					
	75-25		80-20		90-10	
	Precision	Recall	Precision	Recall	Precision	Recall
meningioma	0.63	0.64	0.69	0.54	0.71	0.51
glioma	0.79	0.81	0.80	0.87	0.81	0.90
pituitary	0.94	0.89	0.90	0.94	0.90	0.93

Table 2. RESNET-50 Classifier Results with Histogram Equilization.

values for train and test splits of 75%-25%, 80%-20% and 90%-10%. The resulting values show that contrast stretching gave more consistent results for all the classes whereas in the case of histogram equalization, the values are high for some classes but low for others thus making the resulting values irregular.
Figures in our dataset needed contrast enhancement therefore we used contrast stretching and histogram equalization techniques , but clearly from results it can be seen that contrast stretching was able to enhance the features more adequately thus performing better overall.Our model gave varying results for different train-test ratios. Out of the three, split of 80-20 gave most balanced result as it gave similar results for all the three classes and accounted for the least difference between final traing and test accuracy percentages.

5 Conclusion

In our study, Brain tumors MR images are classified with the help of transfer Learning using a pretrained CNN network RESNET-50. RESNET-50 gave promising results for every variation with little fine tuning. Histogram Equalization and Contrast Stretching Techniques are used for pre-processing the image data and it has been found that Contrast Stretching gave more stable results as compared to Histogram equalization. The highest accuracy of 99.15% was attained in the case of Contrast Stretching and it gained an increase of 0.46% from the previous works.
One important factor of indication for curability and severity of a tumor is the stage of the cancer. increasing stages of cancer indicate increasing severity of the tumor and thus reducing its chances of getting cured. This Study successfully detects the type of tumor in the brain but does not determine the stage of the cancer. This study classifies tumors based on the location of the tumor for eg. if the tumor is in the pituitary gland it is classified as pituitary tumor. This study does not classify tumor as cancerous(benign) or non cancerous(malignant). With modern 3d brain scans, brain tumors can be detected at earlier more curable stage stage easily giving physicians a better idea about the location of the tumor and keeping a track of its growth. Nowadays special deep learning models are being created to give better performances in specific niches like finance,

geosciences etc. Neural Network architectures can be build specially for the task of biomedical imaging can prove to be very helpful in studies like ours because of the pretraned weights and the specific functioning of the model.

References

1. Bottou, Léon. "Large-scale machine learning with stochastic gradient descent." Proceedings of COMPSTAT'2010. Physica-Verlag HD, 2010. 177-186.
2. Dong H., Yang G., Liu F., Mo Y., Guo Y. (2017) Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks.
3. Praveen G B, Agrawal A. Hybrid approach for brain tumor detection and classification in magnetic resonance images. Communication, Control and Intelligent Systems (CCIS). 2015. p. 162–6.
4. Goutte, Cyril, and Eric Gaussier. "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation." European conference on information retrieval. Springer, Berlin, Heidelberg, 2005.
5. Han C, Rundo L, Araki R, Furukawa Y, Mauri G, Nakayama H, Hayashi H. Infinite brain MR images: PGGAN-based data augmentation for tumor detection. InNeural approaches to dynamics of signal exchanges 2020 (pp. 291-303). Springer, Singapore.
6. Hanif, Farina et al. "Glioblastoma Multiforme: A Review of its Epidemiology and Pathogenesis through Clinical Presentation and Treatment." Asian Pacific journal of cancer prevention : APJCP vol. 18,1 3-9. 1 Jan. 2017, doi:10.22034/APJCP.2017.18.1.3
7. Ahmed I, Nida-Ur-Rehman Q, Masood G, Nawaz M. Analysis of brain mri for tumor detection segmentation. In Proceedings of the World Congress on Engineering 2016 (Vol. 1, p. 25).
8. Kamble, Ravi M., et al. "Automated diabetic macular edema (DME) analysis using fine tuning with inception-resnet-v2 on OCT images." 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES). IEEE, 2018.
9. Kaur, Hardeep, and Jyoti Rani. "MRI brain image enhancement using Histogram equalization Techniques." 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET). IEEE, 2016.
10. Lee, Joseph KT, ed. Computed body tomography with MRI correlation. Vol.1. Lippincott Williams Wilkins, 2006.
11. Liu, Jin, et al. "Applications of deep learning to MRI images: A survey." Big Data Mining and Analytics 1.1 (2018): 1-18.
12. Lu, Jian, Dennis M. Healy Jr, and John B. Weaver. "Contrast enhancement of medical images using multiscale edge representation." Optical engineering 33.7 (1994): 2151-2161.
13. Milletari, F., Navab, N., Ahmadi, S.-A.: V-Net: Fully Convolutional Neural Networks for Volumetric Medical Image Segmentation. arXiv. 1–11 (2016).
14. Menze et al., The Multimodal Brain TumorImage Segmentation Benchmark (BRATS), IEEE Trans. Med. Imaging, 2015.
15. Fatih Özyurt a, Eser Sert b, Engin Avci c, Esin Dogantekin . Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy.
16. Özyurt F, Sert E, Avci E, Dogantekin E. Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy. Measurement. 2019 Dec 1;147:106830

17. Reddy, A. Sai Bharadwaj, and D. Sujitha Juliet. "Transfer learning with ResNet-50 for malaria cell-image classification." 2019 International Conference on Communication and Signal Processing (ICCSP). IEEE, 2019.
18. Arshia Rehman , Saeeda Naz , Muhammad Imran Razzak, Faiza Akram , Muhammad Imran .A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning
19. Ronneberger, O., Fischer, P., Brox, T.: U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Medical Image Computing and Computer-Assisted Intervention. pp. 234–241 (2015)
20. Saini, Pankaj Kr, and Mohinder Singh. "Brain tumor detection in medical imaging using MATLAB." International Research Journal of Engineering and Technology 2.02 (2015): 191-196.
21. Sajjad, Muhammad Khan, Salman Muhammad, Khan Wu, Wanqing Ullah, Amin Baik, Sung. (2018). Multi-Grade Brain Tumor Classification using Deep CNN with Extensive Data Augmentation. Journal of Computational Science. 30. 10.1016/j.jocs.2018.12.003.
22. Shin, Hoo-Chang, et al. "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning." IEEE transactions on medical imaging 35.5 (2016): 1285-1298.
23. Singh, Jatinder. "FigShare." Journal of Pharmacology and Pharmacotherapeutics 2.2 (2011): 138.
24. Singh, Shruti Srivastava, Divya S. Agarwal. (2017). GLCM and its application in pattern recognition. 20-25. 10.1109/ISCBI.2017.8053537.
25. H. H. Sultan, N. M. Salem and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network," in IEEE Access, vol. 7, pp. 69215-69225, 2019, doi: 10.1109/ACCESS.2019.2919122.
26. Torrey, Lisa, and Jude Shavlik. "Transfer learning." Handbook of research on machine learning applications and trends: algorithms, methods, and techniques. IGI global, 2010. 242-264.
27. Werbos, Paul J. "Backpropagation through time: what it does and how to do it." Proceedings of the IEEE 78.10 (1990): 1550-1560.
28. M. Wu, C. Lin and C. Chang, "Brain Tumor Detection Using Color-Based K-Means Clustering Segmentation," Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP 2007), Kaohsiung, 2007, pp. 245-250, doi: 10.1109/IIHMSP.2007.4457697.