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Brain Tumor Detection Using Hybride Models.

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Abstract—T Tumor detection in the brain is considered a crucial effort in imaging techniques where the diagnosis made precisely and early can change the scenario in healthcare. Driving into their applications, deep learning effectiveness comes from systems where convolutional networks, under the generals of recurrent models, are well-articulated, such as long short-term memory. Thereby in the study, we came up with a hybrid model for deep learning that integrates CNN-LSTM as a base model and VGG 16 feature extractor to improve on the performance of brain tumor classification; the CNN-LSTM model is spatial and temporal dependencies extraction from MRI images while deep feature representation is facilitated by VGG16. The ensemble model improves classification accuracy by jointly preparing spatial hierarchies and sequential dependencies for data. Testing and training was accomplished from a brain tumor dataset on a very high accuracy and robust performance. Experimental results therefore show that the hybrid VGG-LSTM model is superior in brain tumor detection over conventional CNN. Thus, clinicians dealing with diagnosis could be assisted with a very easy tool by radiologists.

Keywords— Brain Tumor detection, deep learning, image processing, CNN.

1.Introduction

Now a days Much has been said about brain tumours, and this has made it a tall order in terms of the height of the wall medical professionals face in trying to build mortality in their patients. Indirectly, survival rates also rely on having the right early and accurate diagnosis of brain tumours for proper treatment. Standard diagnostic approaches, such as MRI, can easily be employed to detect brain tumours, providing very high resolution of images. Their ability to give information to the radiologists on types and locations of tumours makes them effective [21-23]. Unfortunately, even this is subject to drawbacks, like the long time taken for manual diagnosis and human error, and, finally, it demands a very productive talent.

Now, with deep learning technology, much of the work done in feature extraction and classification processes has been automated in medical image analysis. Deep learning has dramatically changed the medical image analysis paradigm because it automates both feature extraction and classification processes. Among all the techniques discussed, convolutional neural networks (CNNs) have been most popular for the classification of brain tumors, exploiting their innate capability of learning spatial hierarchies of features. But using CNNs would not be enough because spatial hierarchy does not capture sequential dependencies in that data, therefore requiring combining these models with sequential models such as LSTM [31].

This work proposes a hybrid deep learning model to combine the CNN-LSTM-fast feature extractor VGG16 to improve brain tumor classification. The base model in this case is CNN-LSTM, which captures spatial and temporal features, while the features extracted from VGG16 boost the capability of the latter. Features are learned better, leading to an improvement in performance.

Training and validation of the proposed model with the brain tumor dataset will be done against available conventional CNN architectures. The results indicate that the hybrid model outperforms against the existing benchmark in terms of classification accuracy and hence promises to find real-world applicability in clinical scenarios. This also connects the advancements in deep learning to the applicability of clinical practice in medical imaging in this ongoing attempt at health care solutions driven by artificial intelligence and Deep network.

2,.LITERATURE REVIEW

The brain tumor classification in MRI images has seen its fair share of deep learning-based approaches proposed. Krizhevsky et al. (2012) proposed AlexNet for image classification, which completely changed the picture and initiated research into medical imaging via CNNs. We subsequently saw VGG16 developed by Simonyan and Zisserman (2015) with an even deeper architecture to further enhance classification accuracy by utilizing smaller convolutional filters. These architectures became highly popular in medical image analysis, achieving very good accuracy in tumor classifications. However, CNN models target their energy more in the spatial domain and fail to consider the complex nuances involved in medical image variations.

To further improve classification performance, the researchers incorporated recurrent neural networks (RNNs) with CNNs. Long short-term memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), are the ones that have widely modeled any kind of sequential dependencies. Islam et al. (2020) proved that CNN-LSTM models are more effective in identifying tumor progression across time compared to standalone CNNs in medical imaging. But CNN-LSTMs must need efficient feature-extraction mechanisms in order to yield their best.

VGG16, an established CNN model, is an obvious choice for many researchers as a feature extractor since it has a much deeper architecture and some pre-trained knowledge from large-scale datasets like ImageNet (Deng et al. 2009). Gupta et al. (2021) and Kumar et al. (2022) proved that coupling VGG16 with LSTM allows the model to utilize both spatial and temporal information, improving its classification accuracy. This study strengthens those findings by fusing CNN-LSTM and VGG16 to create a potent hybrid framework for tumor detection.

Recent efforts into medical image classification have also explored transformer architectures. In ViTs, feature extraction and classification tasks outperform classical CNNs, according to Dosovitskiy et al. (2020). Due to the dependence of ViTs on large datasets and computational resources, they find fewer practical applications in real-time clinical usage. The proposed alternative hybrid model intends to be fast and less resource-intensive by merging CNN and LSTM networks.

Several studies have shown that even data augmentation and transfer learning could give impetus to medical imaging via improved performance of the deep learning model. As reported by Shorten and Khoshgoftaar (2019), augmenting MRI images [3,4] via rotation, flipping, scaling, etc. improves generalizability and reduces overfitting. Transfer learning is an efficient model when feature extraction from small medical datasets via pre-trained models like VGG16 is included, keeping in mind the practical clinical applications of deep learning.

However, explainability and interpretability are still challenges with deep learning models successfully achieving miracles in medical image analysis. Attention mechanisms were looked into by Ribeiro et al. (2016) [6-7,13].

3.DATASET DESCRIPTION

The Dataset used to make and complet the model is the image dataset

The image dataset is splitted into 2 class “TRAIN” and “TEST” data.

There are 4 types of brain tumors classified classes in each TRAIN and TEST dataset as showed in fig1 “Glioma, Meningioma, Nontumor, Pituitary”.

The MRI images are placed in their respective folder for supervised learning the sample images are displayed below in.

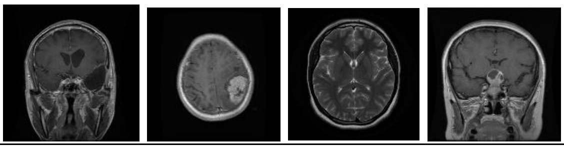


Fig (1): Images in each class

The model is trained with 80% of images and tested with 20% of images in the data set as showed in table1

Class	Images
Train	5712
Validation	1311
Image Size	244*244
Total images	7023

4.METHDOLOGY

The methodology involves in setting up the environments to building model involves in multiple process like image processing, model training and testing.

Image Preprocessing:

Preprocessing, founded the most key step in Brain tumor disease detection tasks because of the fact that MRI images have to be transformed into a form that is appealing and recognized easily by deep learning models.[9] The preprocessing pipeline typically encompasses several key steps: The preprocessing pipeline typically encompasses several key steps:

Image Detection and Localization: Apply the latest Image detection algorithms and all the images are resized to 224*224 and normalized

$$Inorm = \frac{I - \mu}{\sigma} \quad \text{----- (1)}$$

Where I is the original pixel intensity

μ is the mean and σ is the standard deviation.

Image Landmark Detection and Alignment: To be able to find the disease part landmarks precisely map them with landmark recognition methods [2]. The subsequent procedure of using geometric transformations to align the defected landmarks permits the creation of a consistent orientational view across the pictures.

Image Enhancement and Normalization: Apply image adjustments like histogram equalization or contrast stretching to better the image and to make the features crisp enough for a detailed analysis. Besides that, normalize intensity values to standard unit range (e.g., [0, 1]) and it will help the model converge during training process.

CNN LSTM Basement Model consists of a convolutional and max-pooling layers extracting spatial features from MRI images into feature maps, which is then flattened, reshaped, and fed into an LSTM hub. This makes it better in its robustness character for classification since this LSTM layer captures the sequential dependencies in the spatial features.

The Convolutional neural networks understand the local space of the image they notice the hierarchy of features, and provides the translation invariant feature detection. Feature extraction is the function of this step, a part of training process to identify features in input images.

$$F(i,j) = m\sum n\sum I(m,n) \cdot K(i-m, j-n) \quad \text{---(2)}$$

- I(m,n) represents the input image,
- K is the convolutional kernel (filter),
- F(i,j) is the resulting feature map.

This VGG16 model is used to extract its deep features for MRI images, which are passed into an LSTM layer for further sequential modeling. Softmax finally classifies the output.

$$FGAP = \frac{1}{H \times W1} \sum_{i=1}^{H} \sum_{j=0}^{W} F(i,j) \text{ -------(3)}$$

Thus, CNN LSTM base models consist of convolutional layers followed by max-pooling, after which the network flattens data before input to an LSTM hub for capturing sequential dependencies in fig2.

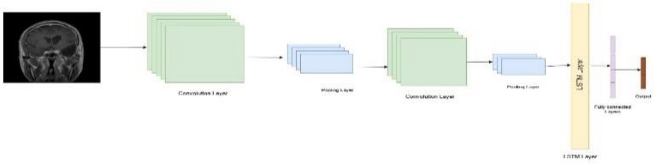


Fig (2): System architecture of CNN

The VGG16 LSTM based models consist of convolutional layers followed by max-pooling and followed by flatten layer and processed to LSTM layer and finally to dens layer as showed in fig3.

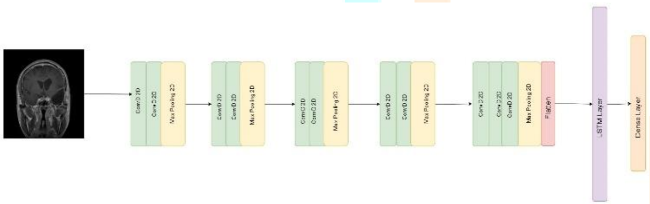
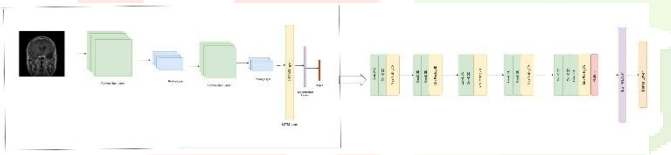


Fig (3): System architecture of Vgg16-LSTM

The model are trained individually give a better result but to get the best result I proposed the hybrid model CNN-LSTM + Vgg16-LSTM the model architecture given in fig4.



Model Train and Testing:

The development of the hybrid CNN-LSTM and VGG16-LSTM model takes place across several stages. The CNN-LSTM model serves as the ground model while the VGG16-LSTM is considered the frontal model [24] and the training is done systematically such that healthy learning is achieved.

There are several expression and formulas used to train the Once the image is processed the training phase MRI images are pre-processed, then fed into the CNN component. Features are extracted using convolutional layers and max pooling.

They are flattened and fed to the LSTM layers for sequential modeling. Feature Learning and Training

The CNN part learns spatial features using convolutional layers. The LSTM part learns temporal dependencies across the extracted features.

It trains the model using categorical cross-entropy loss and optimizes to Adam. The SoftMax layer gives the class probabilities as output passing through the equation (4).

$$L = -i\sum yilog(y\hat{}i) \text{ ------- (4)}$$

Using the CNN-LSTM Model within the VGG16-LSTM Front Model

Feature Extraction:

Rather than training from scratch, the trained CNN-LSTM model extracts feature maps from MRI images [26].

The same images are processed by the VGG16 model in parallel to obtain representations of deep features.

Fusion of Features and LSTM Training:

The output feature vectors from CNN-LST are thus concatenated by the equation (5).

$$ht = ot \odot \tanh(ct) \text{ ------ } (5)$$

These features go through an LSTM layer that learns patterns across the different representations in equation (6).

$$P(y = k \mid x) = \frac{e^{zk}}{\sum_j e^{zj}} \text{ ---------- } (6)$$

The initial freeze applies to the CNN-LST and VGG16 layers when training the LSTM and fully connected layers.

Then, all the layers which had earlier been frozen were unfreezes, and fine-tuning took place at a later date.

Finally, an effort is made towards early stopping and learning rate scheduling.

The max pooling Cuts down a spatial dimension, renders the model less sensitive with to data variations, degrades the risk of overfitting. This is a type of operation which the neural network mostly uses for training by decreasing the size of feature maps.

$$Max\ Pooling(x) = max(pooling\_window)$$

The Fully Connected layers and the SoftMax Activation Function used to Combines features from convolutional layers, captures global relationships, produces output logits. This layer is a crucial part of the training phase for classification tasks and Normalizes logits to class probabilities, facilitates multi-class classification. SoftMax is part of the output layer used during training to compute class probabilities. By using the expressions

$$Z = X \cdot W + b \text{ --------- } (7)$$

Where Z is the SoftMax Activation as given in equation (8):

$$(Zi) = eZi / \sum j = 1CeZj \text{ ------------- } (8)$$

After the completion of Softmax Activation function then it under goes with the backword pass method involves computing the gradients of the loss function with respect to the parameters of the model calculated with the help of equation (9,10).

$$\partial W[l]/\partial L = \partial a[l]/\partial L \cdot \partial z[l]/\partial a[l] \cdot \partial W[l]/\partial z[l] \text{ --------} (9)$$

$$\partial b[l]/\partial L = \partial a[l]/\partial L \cdot \partial z[l]/\partial a[l] \cdot \partial b[l]/\partial z[l] \text{ ------} (10)$$

Once the model is trained the testing phase of the model is started which calculates the loss function and the accuracy of the model using formula at equation 11

$$L = loss\_function\ (ytrue, ypred) \text{ ----------- } \mathbf{(11)}$$

5.RESULTS AND DISCUSSION

- The results and the accuracy of the model is represented by their receptive accuracy and loss function of each model is given in the table.

Model	Accuracy	loss
CNN	75.11	40.31
VGG16	80.44	49.35
CNN-LSTM	91.66	31.44
VGG16-LSTM	92.55	36.96

- The accuracy and loss function Varys with the epochs and visualized through the graph as shown in Fig5, Fig6, Fig7, Fig8.

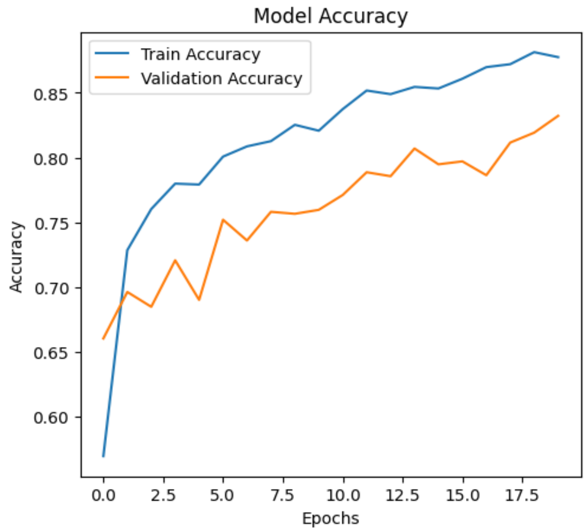


Fig5: Accuracy graph of cnn-Lstm

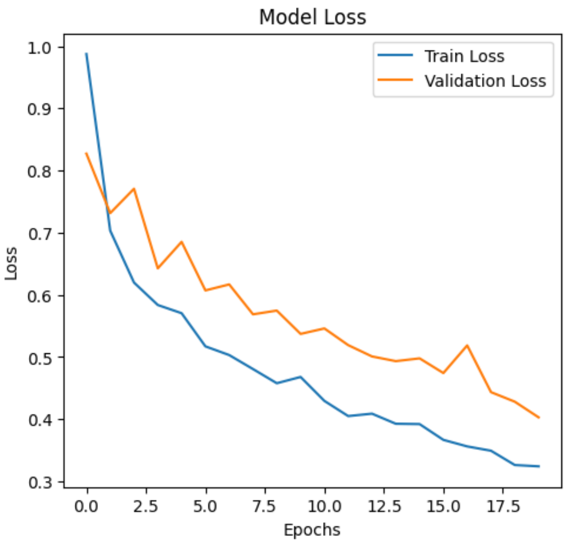


Fig6: Loss Graph of CNN-LSTM

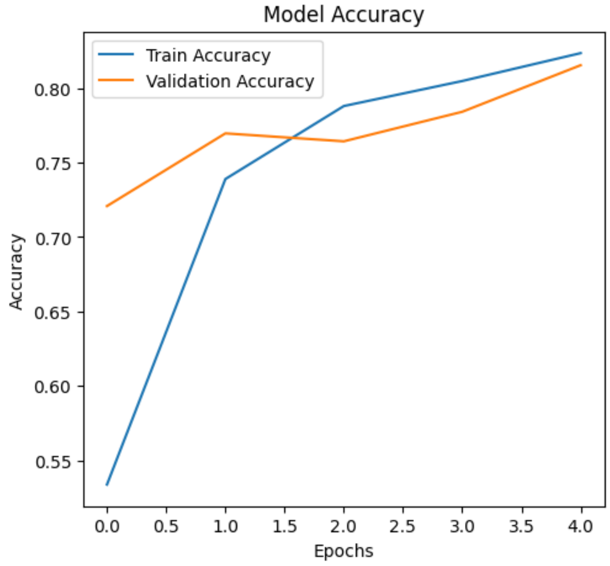


Fig7: Accuracy graph of VGG16-LSTM

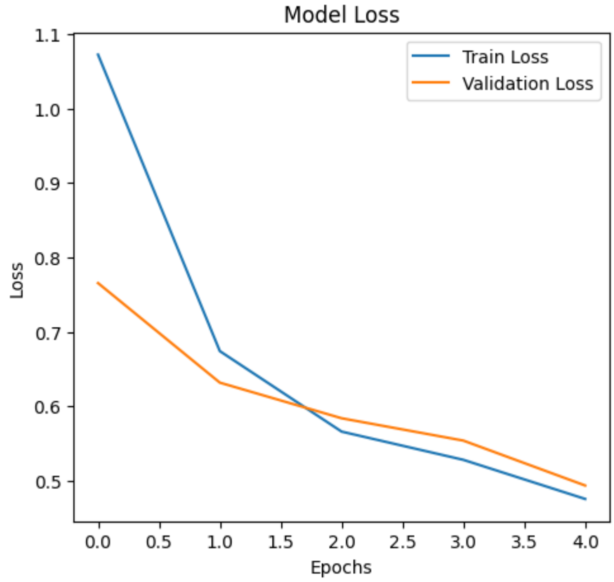


Fig8: Loss Graph of VGG16-LSTM

To know the in-detail performance and the losses of the model known by the predating the classes in the dataset is visualized by the confusion matrix of model in Fig9, Fig10.

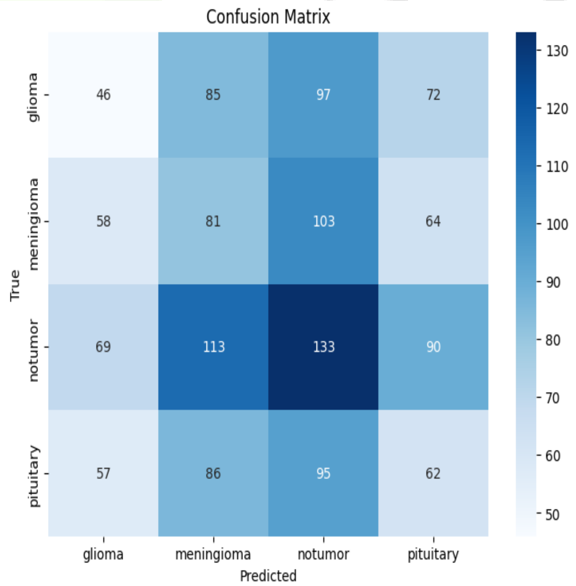


Fig9: Confusion matrix of CNN-LSTM

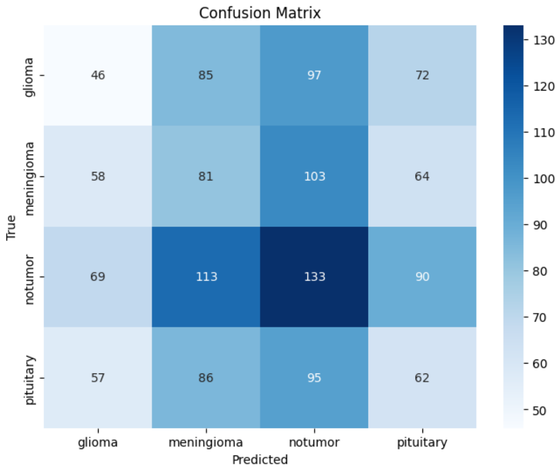


Fig10: Confusion matrix of VGG16-LSTM

6.Conclusion and Future work

With the above graphs and the matrix of the models prepared clearly shows the best performance showcasing with high accuracy and low loss function with respective to other models

From the results and model working we can conclude that the combination of a deep learning and machine learning model called the hybrid models performs well that all other individual models

These model finally with high accuracy and best prediction helping in the real-world problem to identify the type of brain tumor and treat it faster improving treatment speed.

The improvement or upgradation that can be done in future scope by the implanting the build model with the micro controls keeping the model applicable and to solve the real time world problems to speed up the treating ration in the health sector

References

1. **Sandeep Shiraskar; Dominick Rizk,**2024 2nd International Conference on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings).
2. **G. Sajiv and G. Ramkuma**r, "Multiple Class Breast Cancer Detection Method Based on Deep Learning and MIRRCNN Model", 2022 International Conference on Inventive Computation Technologies (ICICT), pp. 981-987, 2022.
3. **S Anjanayya, V. M. Gayathri and R. Pitchai,** "Brain Tumor Segmentation and Survival Prediction using Multimodal MRI Scans with Deep learning Algorithms", IEEE International Conference on Innovative Computing Intelligent Communication and Smart Electrical Systems, 2022.
4. **Mohd Faizaan Khan et al.,** "Detection of Brain Tumor from the MRI Images using Deep Hybrid Boosted based on Ensemble Techniques", IEEE International Conference on Smart Electronics and Communication, 2022.
5. **D. Jin et al.,** "AI-powered cancer detection: Advances and challenges", Cancer Letters, vol. 475, pp. 28-36, 2020.
6. **Gajendra Raut**, Deep Learning Approach for Brain Tumor Detection and Segmentation, IEEE, January 2021**.**
7. **Puneet Jain and S. Santhanalakshmi,** "Early Detection of Brain Tumor and Survival Prediction Using Deep Learning and An Ensemble Learning from Radiomics Images", IEEE 3rd Global Conference for Advancement in Technology, 2022.
    A. **Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq and N. Ayesha,** "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture", Microsc. Res. Techn., vol. 84, no. 1, pp. 133-149, 2021.
8. **M. N. Islam, T. Mahmud, N. I. Khan, S. N. Mustafina and A. K. M. N. Islam,** "Exploring machine learning algorithms to find the best features for predicting modes of childbirth", IEEE Access, vol. 9, pp. 1680-1692, 2021.
9. **S. Irsheidat and R. Duwairi,** "Brain Tumor Detection Using Artificial Convolutional Neural Networks", ICICS, 2020.
10. **R. Sreelakshmy et al.,** "An Automated Deep Learning Model for the Cerebellum Segmentation from Fetal Brain Images", BioMed Research International, vol. 2022, pp. 1-13, Jun. 2022.

11. **Baid, U., Ghodasara, S., Mohan, S., et al.** (2021). The RSNA-ASNR-MICCAI BraTS 2021 benchmark on brain tumor segmentation and radiogenomic classification. *arXiv preprint arXiv:2107.02314*.
12. **"Brain Tumor: Statistics Cancer", Net Editorial Board, 02 2022.**
13. **Ghaffari, M., Sowmya, A., & Oliver, R.** (2020). Automated brain tumor segmentation using deep learning: A review of models, methods, and challenges. *Medical Image Analysis*, 65, 101797.
14. **Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H.** (2021). nnU-Net: A self-adapting framework for U-Net-based medical image segmentation. *Nature Methods*, 18(2), 203-211.
15. **Vangireddy Vishnu, Vardhan Reddy et al.,** "Brain Tumor Detection using Novel Kernel Extreme Learning with Deep Belief Network and Compare Prediction Accuracy with Fuzzy C-means Clustering", IEEE 2nd International Conference on Technological Advancements in Computational Sciences, 2022.
16. **V. Konde, P. Ayush, T. Kalita, S. Shyam and S. Suchitra,** "Brain Tumor Detection Based on Deep Learning Neural Network Using MRI", 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), pp. 1-5, 2024.
17. **G. Wang et al.,** "Deep learning in medical image analysis: Challenges and applications", Computerized Medical Imaging and Graphics, vol. 89, no. 101654, 2021
18. **Y. Liu et al., "**Deep learning for automatic diagnosis of brain tumors on magnetic resonance imaging", Journal of Neural Engineering, vol. 17, no. 4, 2020**.**
19. **Jin, W., Zheng, W., Tang, Y., et al.** (2020). Deep learning with relation attention for brain tumor segmentation. *Pattern Recognition*, 107, 107457.
20. **Z. Liu, L. Tong, L. Chen et al**., "Deep learning based brain tumor segmentation: a survey", *Complex Intell. Syst.*, vol. 9, pp. 1001-1026, 2023,
21. [online] Available: https://doi.org/10.1007/s40747-022-00815-5.
22. **Wang, H., Zhou, Z., Li, Y., et al.** (2021). Mixed transformer U-Net for medical image segmentation. *Medical Image Analysis*, 73, 102134.
23. **Karim, R., Dutta, A., Bhuiyan, A., et al.** (2021). Deep learning-based brain tumor classification using transfer learning and data augmentation. *Biomedical Signal Processing and Control*, 68, 102708.
24. **Arslan, S., Jiang, Z., Zheng, J., & Xu, Y.** (2021). A hybrid deep learning approach for brain tumor classification. *IEEE Access*, 9, 10383-10391.
25. **Rehman, A., Naz, S., Razzak, M. I., et al.** (2020). A deep learning-based framework for automatic brain tumors classification using transfer learning. *Pattern Recognition Letters*, 131, 256-262.
26. **W. El Elhola and K. Bozed,** "Performance Analysis of Brain Tumor Detection Based on Gradient Boosting Machine -CNN model", 2022 IEEE 2nd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), pp. 544-547, 2022
27. **Saba, T., Mohamed, A. S., Ahmadi, S., et al.** (2021). Brain tumor detection using fusion of hand-crafted and deep learning features. *Cognitive Computation*, 13(2), 267-282.
28. **Mohammad Shahjahan Majib,** "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images", IEEE, 2021.
29. **R. Tamilselvi, BRAMSIT:** A Database for Brain Tumor Diagnosis and Detection, IEEE, August 2020**.**
30. **C. L. Choudhury, C. Mahanty and R. Kumar,** "Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network", ICCSEA, 2020..
31. **Mishra, A. K., Raghav, S., & Garg, R.** (2021). Attention guided CNN-LSTM hybrid network for image classification. *IEEE Access*, 9, 113201-113210.