Brain Tumor Classification from MRI Images: A Hybrid Approach with Pre-processing and Feature Extraction

[1*]Satyam Singh, [2] Praveen Kumar Mohane

[1,2] CSE, Millennium Institute of Technology Bhopal, M.P, India.

[1]satyameyt@gmail.com,[2]pkmohane9910@gmail.com,

Abstract - The article proposes a framework of CNN and RFC to classify brain tumors by using MRI images, which combines CNN (Convolution Neural Networks) and RFC (Random forest classification). Pre-processing, Feature bring-out, and Categorization are the three phases of the proposed framework. We use the Gaussian Filter Method on the dataset then we combine the original dataset with processed data in parallel. The feature extraction of magnetic resonance imaging was performed automatically by CNN in the second step. Several classification algorithms, including RFC, KNN, D, SVM and NB, are used in theend. The extracted features from the CNN model are given to the classifier algorithms, which predict Glioma, Pituitary, Meningioma tumors, and no tumor as a result of the testing dataset. Experiments are carried out on an open dataset of images selected for classification from the Kaggle databases. A separate CSV file is maintained that contains testing images name and their specification. The proposed approach is able to achieve 99.61% accuracy on the training dataset, 92.16% on the validation data, and 71.2% on the CSV/testing data.

Keywords— Brain Tumor Classification, CNN, RFC, hybrid model CNN-RFC, MRI.

I. Introduction

The cell is the building block of any living body. The abnormal growth of the cell initiates tumor which may be classified as brain and subordinate tumors. Human body contains the brain, a very complex organ which is responsible for intelligence, translation, movement initiation and controlling actions and speech. Brain tumor occurs in brain whereas subordinate tumor occurs in body. Benign and Cancerous are brain tumor types whereas subordinate tumor is Cancerous only [19, 22, 23, 24]. The CBTRUS (Central Brain Tumor Registry of the US) has reported that cancer of the brain has 10th rank for reasons which causes death and suggested 5 year, 10 year survival statistics that 36% and 31% can survive after the detection of cancer, respectively [25, 26, 28, 29]. MRI is used to reveal brain tumor and examines the biopsy and operation to assess the tumor grade [30]. The grade indicates the growth size and its spread, and MRI is used to investigate this due to the reason for its Non-Invade nature and having no established Biological risks [31]. MRI images represent scale, variance, and position of objects along an axis coordinate and can be T1_weighted, T2_weighted and FLAIR (Fluid-Attenuated-Inversion-Recovery), and divided into TE and TR. For T1_weighted, TE and TR are short whereas FLAIR is similar with

P. Johri et al. (eds.), *Proceedings of the International Conference on Sustainable Computing and Artificial Intelligence (ICSCAI 2025)*, Advances in Engineering Research 298,
https://doi.org/10.2991/978-94-6239-674-6_27

T2_weighted with TE and TR long [32]. Brain tumors may be classified as Glioma, Pituitary Tumor, and Meningioma Tumor. Primary tumors are considered in the study, glioma tumors and meningiomas tumors are common and develop from glial cells often in adults [33]. Automated and Semi-automated classification techniques are used to identify brain tumor categorization due to the reason of criticalness and compactness as reducing the misclassification and to identify the brain tumor type. [5,35]. CNN has two advantages as sparse communication among neurons between layers and weight sharing. In order to solve classification problem, the CNN based automated model has been used. The CNN+RFC model selects the most relevant element with less complexity as compared with other models like CNN, CNN+SVM ,CNN+KNN, CNN+NB and CNN+DT.

The article is structured into five sections. The first section deals with the basics of tumors, Section 2 contains the recent technologies description. Section 3 discusses dataset description methodology and feature selection, Experimental results and discussion are described into section IV followed by conclusion and future work in section V.

II. Related Work

Automatic or semiautomatic methods for the categorization of brain tumors have been proposed over the years, which are summarized below.

Kharat et al. [1] have presented two deep neural network techniques for the organization of MR imaging of brain tumors. Feature dissociation, dimensionality depletion and organization are three stages of this deep neural network. Feed-forward ANN and Back-Propagation NN are two classification algorithms. This network is created for image processing, differentiation, validation, extraction of features, object detection, and classification. Zulpe, N., & Pawar, V. [2] have suggested a brain tumor classification method based on automatic recognition. Sachdeva et al. [3] have proposed a model PCA-ANN to classify six classes namely glioblastoma-multiforme, normal regions, childhood tumor medulloblastoma, secondary tumor metastatic, meningioma, and astrocytoma. They have archived the classification accuracy from 77% to 91%. Suganthe et al. [4] have suggested a RNN (Recurrent Neural Network) method for the identification of tumor cells with a 90% accuracy. Ari, A., & Hanbay, D. [5] have proposed an automated tumor detection system, here, the local-receptive-fields based extreme-learning-machine method produces 97.1% classification accuracy. Arasi et al. [6] have proposed a method for determining and classifying brain tumors. For classification, a LOB (Lion Optimized Boosting) algorithm with SVM (Support Vector Machine Classifier) model is applied to classify brain tumors.

Gaikwad et al. [7] have used a PNN (Probabilistic Neural Network) method. With the help of the proposed system, they have categorized the brain tumor into 3 categories as Normal, Benign and Malignant with an accuracy of 97.14% and 100% with spread values 10^7 and 10^6. For brain tumor classification, Simonett et al. [8] have combined MRSI and MRI data features and obtained better results by MRSI data only. Biller et al. [9] have used Na-MR imaging for PFS prediction with better than IDH mutation and improved the accuracy of brain tumor categorization. Roy et al.[10] have used the ANFIS (Adaptive Neuro Fuzzy Inference System) and compared the results with other classifiers namely, ANN with Backpropagation and KNN with an accuracy of 98.25%. Sapra,& et al. [11] have used a revised PNN (Probabilistic NN) model which is based on LVQ (Learning Vector Quantization) with 100% accuracy. Madhusudhana Reddy, P., & Prabha, I. S. [12] have utilized histogram equalization, image correction, and thresholding functions. They used the BW label feature to determine the tumor's centroid and the Dilate operator to draw the tumor's boundaries and deployed a feed-forward network with the backpropagation method. Gauvain,& et al. [13] have suggested that the diffusion coefficient can be used to predict tumor classification as well as to characterize Tumor Cellularity and Total Nuclear Region. These boundaries aren't accessible in regular MRI images and resulted, diffusion-tensor imaging can help with diagnosis. Rajesh Sharma, R., & Marikkannu, P. [14] have proposed a 3D (Three Dimensional) novel brain tumor categorization model that uses MR imaging with both micro and macroscale features to distinguish between benign and malignant brain MRI. VOI (Volume of Interest) of an image has been noticed by applying 3D volumetric (SCLGM) and 3D run length and co-occurrence matrix with the aid of a 3D-Gaussian filter.

Pathak, A. N., & Sunkaria, R. K. [20] have proposed a hybrid of PCA-SVM that gives an accuracy of 100%. Pathak, A. N., & Sunkaria, R. K. [20] have applied DWT (Discrete Wavelet Transform) using Haarwavelet to bring out features then feature reduction has been done using PCA. These selected features feed into SVM for categorization of various types of brain tumor. Srinivas, B., & Rao, G. S. [21] have proposed a compound model (CNN+KNN) to categorize brain tumors by using MRI images. CNN extracts features and feeds them into KNN (K-Nearest Neighbor), which has 96.25 percent accuracy.

Sarhan, A. M. [15] has proposed a new CAD technique for MR imaging categorization of brain tumors by applying the DWT's strong energy compactness property. This device brings out features from brain MR imaging (DWT). This feature is feeded into CNN for classification which gives an accuracy of 99.3%. Rathi, & et al. [18] have suggested segmentation, feature extraction, and classification are the three modules that make up the proposed technique. MKPC (Multiple-Kernel-based-Probabilistic-Clustering) is used to segment the data, and major features are selected using LDA (Linear Discriminant Analysis) and fed into a FFBN (Feed-Forward Back Propagation Network). The precision of this technique is 0.88, 0.80, and 0.83.

III. Proposed Method

Windows 10 with Intel Core i5 7th Gen along with Google Colab is used in the study. Brain Tumor Classification (BTC-MRI) dataset having four classes, from Kaggle is used. Its size is 87 MB and has two dictionaries as testing and training contains four classes as Glioma-Tumor, Meningioma-Tumor, Pituitary-Tumor, and No-Tumor. Fig.1. represents a few images from the BTC-MRI dataset.

In order to handle the time complexity, training is completed, testing is performed with 2870 and 80 images respectively and randomly. A CSV file is maintained with two columns describing the image name and disease type. Fig. 2 illustrates the fusion of CNN and RFC along with the proposed model and approach. TM (Threshold Method), RBS (Region Based Segmentation), CBS (Clustering Based Segmentation Method), and WB (Watershed-Bad Method) has been applied and noticed that Simple Gaussian Filter Method is more effective.

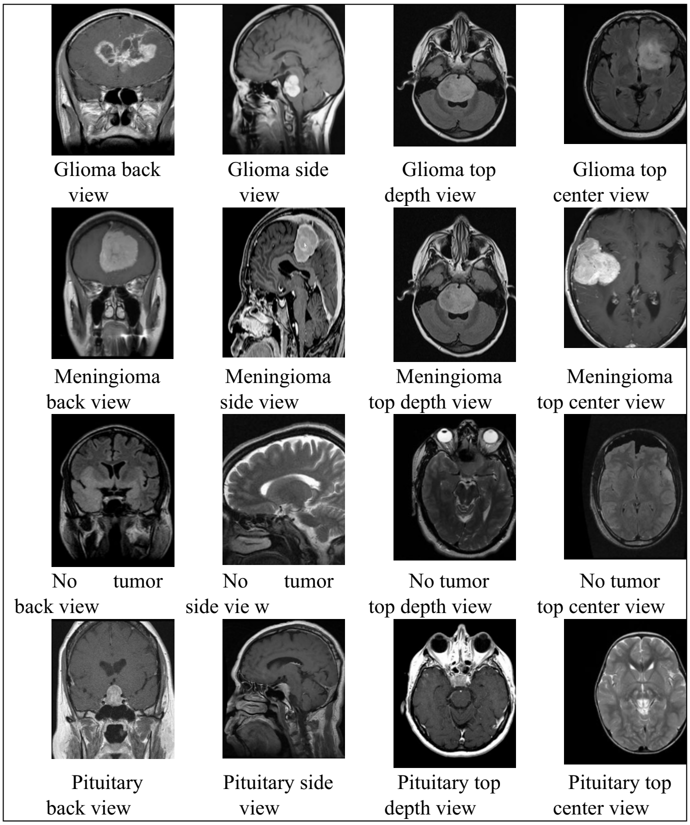


Fig 1. Training dataset and Testing dataset sample MRI images illustrating tumor and no tumor with different views

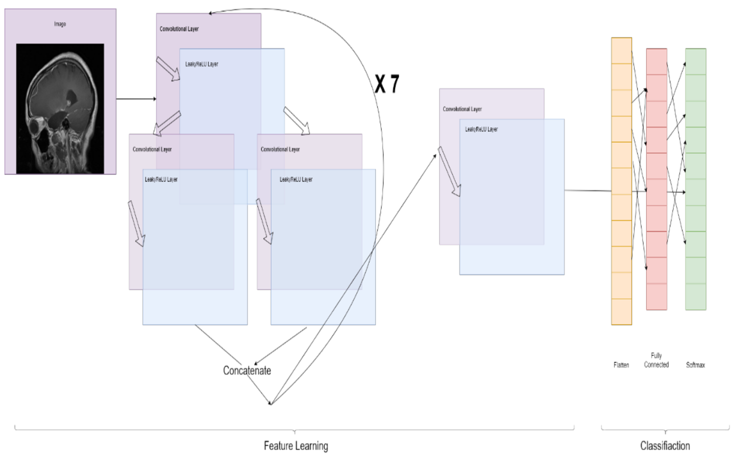


Fig 2. The architecture of the hybrid model

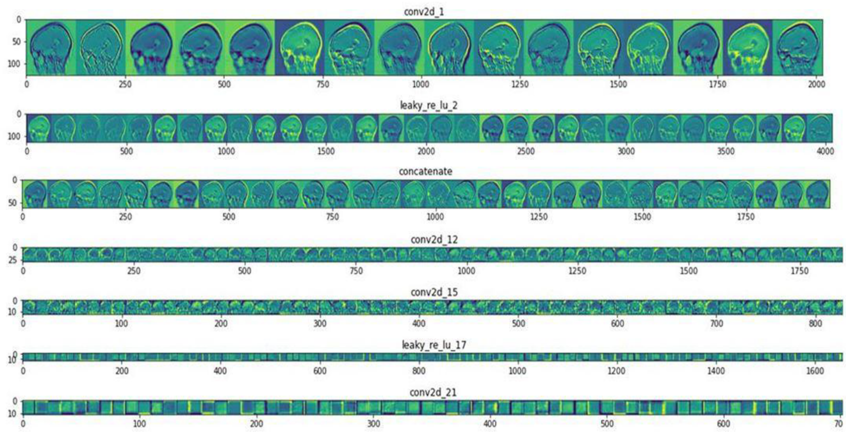


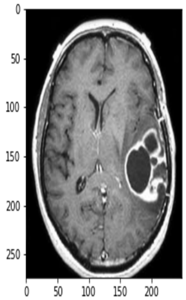
Fig 3. Sample images of feature extraction process of CNN with defined architecture.

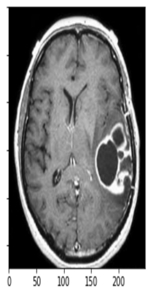
Functional API is used in this architecture which is helpful for sharing features, input and output layers to other models. 256X256X3 dimension with zero-centred-normalization is used. There are four categories in this classification problem as Glioma, Meningioma, Pituitary, and No Tumor, Finally, the completely connected layer is a four-class categorization task with specifications such as the BLRF (Bias Learn Rate Factor) and WLRF (Weight Learn Rate Factor).

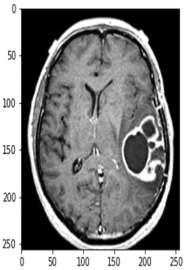
Fig 4. Sample image

Fig 5. Sample image resize 256X256X3

Fig 6. Processed image with resize 256X256X3







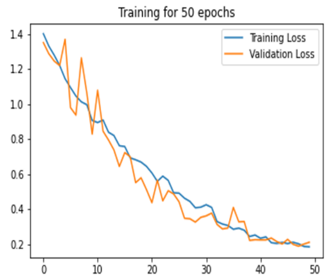


Fig 7. Training accuracy and Validation accuracy at 50 epochs

Fig 8. Training loss and Validation loss at 50 epochs

IV. Result and Discussion

The CNN model's architecture is listed in CNN model framework and illustrated in Fig 1. An activation mechanism is used to bring out high-level features from a completely connected layer. CNN extracts non-handcrafted features from each image. Testing dataset images are pre-processed, converted into an array, and store in a 2D array is prediction purposes. Feature extracted model then evaluate that gives an accuracy for this study as 92.51%.

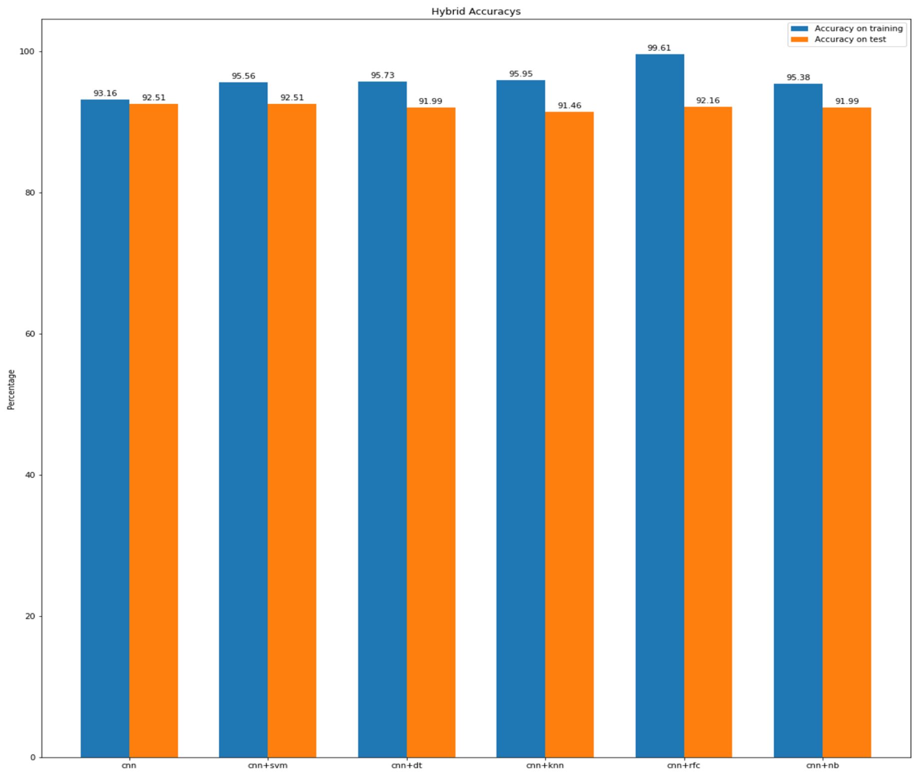


Fig 9. Overall accuracy of Training and Test validation for each hybrid

Each classification model is implemented separately such as SVM, KNN, RFC, DT and NB. Each classifier algorithm is implemented and fits with our CNN feature-based model predicted output with respect to proposed method which results 92.51% accuracy.

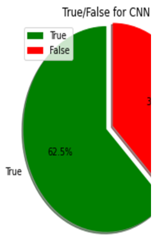


Fig 10.(a) CNN True/False result

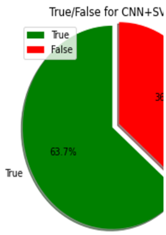


Fig 10.(b) CNN+SVM True/False result

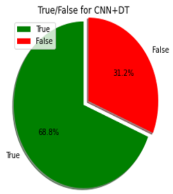


Fig 10.(c) CNN+DT True/False result

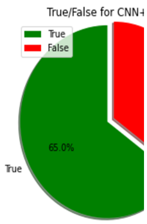


Fig 10.(d) CNN+KNN True/False result

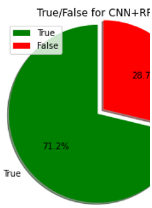


Fig 10.(e) CNN+RFC True/False result

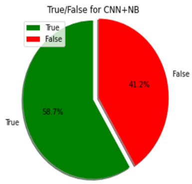


Fig 10.(f) CNN+NB True/False result

Fig 10. Truth classification by each hybrid on the Testing

V. Conclusion and Future Work

A combination of the CNN+RFC framework is considered for the MR imaging of brain tumor, The framework is trained using the Kaggle brain tumor dataset. The non-handcrafted features are extracted and used for various Classifiers such as SVM, CNN, KNN, RFC, NB, and DT to predict the output class. Performance measures as accuracy is used to assess the advantage and viability of the proposed combined CNN+RFC framework. The dataset is complex and the present study provides better solution in terms of several benefits. This combination of the CNN+RFC framework appears to be an optimistic framework for MR imaging for brain tumor categorization as it save time and complexity as compared with other methods. The proposed combined CNN+RFC framework is the efficient and influential image identification and categorization classifiers.

Reference

1. Kharat, K. D., Kulkarni, P. P., & Nagori, M. B. (2012). "Brain tumor classification using neural network based methods," *International Journal of Computer Science and Informatics*, *1*(4).
2. Zulpe, N., & Pawar, V. (2012)." GLCM textural features for brain tumor classification." *International Journal of Computer Science Issues (IJCSI)*, *9*(3), 354.
3. Sachdeva, J., Kumar, V., Gupta, I., Khandelwal, N., & Ahuja, C. K. (2013), "Segmentation, feature extraction, and multiclass brain tumor classification," *Journal of digital imaging*, *26*(6), 1141-1150.
4. Suganthe, R. C., Revathi, G., Monisha, S., & Pavithran, R. (2020), "Deep Learning Based Brain Tumor Classification Using Magnetic Resonance Imaging," *Journal of Critical Reviews*, *7*(9), 347-350.
5. Ari, A., & Hanbay, D. (2018), "Deep learning based brain tumor classification and detection system," *Turkish Journal of Electrical Engineering & Computer Sciences*, *26*(5), 2275-2286.
6. Arasi, P. R. E., & Suganthi, M. (2019), "A clinical support system for brain tumor classification using soft computing techniques," *Journal of medical systems*, *43*(5), 1-11.
7. Gaikwad, S. B., & Joshi, M. S. (2015), "Brain tumor classification using principal component analysis and probabilistic neural network," *International Journal of Computer Applications*, *120*(3).
8. Simonetti, A. W., Melssen, W. J., Edelenyi, F. S. D., van Asten, J. J., Heerschap, A., & Buydens, L. M. (2005), "Combination of feature-reduced MR spectroscopic and MR imaging data for improved brain tumor classification," *NMR in Biomedicine: An International Journal Devoted to the Development and Application of Magnetic Resonance In vivo*, *18*(1), 34-43.
9. Biller, A., Badde, S., Nagel, A., Neumann, J. O., Wick, W., Hertenstein, A., ...& Kleesiek, J. (2016), "Improved brain tumor classification by sodium MR imaging: prediction of IDH mutation status and tumor progression," *American Journal of Neuroradiology*, *37*(1), 66-73.
10. Roy, S., Sadhu, S., Bandyopadhyay, S. K., Bhattacharyya, D., & Kim, T. H. (2016),"Brain tumor classification using adaptive neuro-fuzzy inference system from MRI," *International Journal of Bio-Science and Bio-Technology*, *8*(3), 203-218.
11. Sapra, P., Singh, R., & Khurana, S. (2013), "Brain tumor detection using neural network," *International Journal of Science and Modern Engineering (IJISME) ISSN*, 2319-6386.
12. Madhusudhanareddy, P., & Prabha, I. S. (2013), "Novel approach in brain tumor classification using artificial neural networks," *International Journal of Engineering Research and Applications*, *3*(4).
13. Gauvain, K. M., McKinstry, R. C., Mukherjee, P., Perry, A., Neil, J. J., Kaufman, B. A., & Hayashi, R. J. (2001), "Evaluating pediatric brain tumor cellularity with diffusion-tensor imaging," *American Journal of Roentgenology*, *177*(2), 449-454.
14. Rajesh Sharma, R., & Marikkannu, P. (2015), "Hybrid RGSA and support vector machine framework for three-dimensional magnetic resonance brain tumor classification," *The Scientific World Journal*, *2015*.
15. Sarhan, A. M. (2020), "Brain tumor classification in magnetic resonance images using deep learning and wavelet transform," *Journal of Biomedical Science and Engineering*, *13*(06), 102.

16. Padma, A., & Sukanesh, R. (2011), "Automatic classification and segmentation of brain tumor in CT images using optimal dominant gray level run length texture features," *International Journal of Advanced Computer Science and Applications*, *2*(10).
17. Luts, J., Poullet, J. B., Garcia-Gomez, J. M., Heerschap, A., Robles, M., Suykens, J. A., & Huffel, S. V. (2008), "Effect of feature extraction for brain tumor classification based on short echo time 1H MR spectra," *Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine*, *60*(2), 288-298.
18. Rathi, V. G. P., & Palani, S. (2015), "Brain tumor detection and classification using deep learning classifier on MRI images," *Research Journal of Applied Sciences, Engineering and Technology*, *10*(2), 177-187.
19. Zacharaki, E. I., Wang, S., Chawla, S., Soo Yoo, D., Wolf, R., Melhem, E. R., & Davatzikos, C. (2009), "Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme," *Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine*, *62*(6), 1609-1618.
20. Pathak, A. N., & Sunkaria, R. K. (2014), "Multiclass brain tumor classification using SVM," *International Journal of Computer Applications*, *97*(23).
21. Srinivas, B., & Rao, G. S. (2019), "A Hybrid CNN-KNN model for MRI brain tumor Classification," *International Journal of Advanced Science and Technology (IJAST)*, *127*, 20-25.
22. Havaei, M., Larochelle, H., Poulin, P., & Jodoin, P. M. (2016), "Within-brain classification for brain tumor segmentation," *International journal of computer assisted radiology and surgery*, *11*(5), 777-788.
23. Jayachandran, A., & Dhanasekaran, R. (2017), "Multi class brain tumor classification of MRI images using hybrid structure descriptor and fuzzy logic based RBF kernel SVM," *Iranian Journal of Fuzzy Systems*, *14*(3), 41-54.
24. Kothari, A., & Indira, B. (2015), "A study on classification and detection of brain tumor techniques," *International Journal of Computer Engineering and Technology*, *6*(11), 30-35.
25. Narmatha, C., Eljack, S. M., Tuka, A. A. R. M., Manimurugan, S., & Mustafa, M. (2020), "A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images," *Journal of Ambient Intelligence and Humanized Computing*, 1-9.
26. Sajjad, M., Khan, S., Muhammad, K., Wu, W., Ullah, A., & Baik, S. W. (2019), "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," Journal of computational science, 30, 174-182.
27. Deepak, S., & Ameer, P. M. (2019), "Brain tumor classification using deep CNN features via transfer learning," Computers in biology and medicine, 111, 103345.
28. García-Gómez, J. M., Tortajada, S., Vidal, C., Julià-Sapé, M., Luts, J., Moreno-Torres, À & Robles, M. (2008), "The effect of combining two echo times in automatic brain tumor classification by MRS," NMR in Biomedicine: An International Journal Devoted to the Development and Application of Magnetic Resonance In vivo, 21(10), 1112-1125.
29. Mzoughi, H., Njeh, I., Wali, A., Slima, M. B., BenHamida, A., Mhiri, C., & Mahfoudhe, K. B. (2020), "Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification," Journal of Digital Imaging, 33, 903-915.
30. Chinnu, A. (2015), "MRI brain tumor classification using SVM and histogram based image segmentation," International Journal of Computer Science and Information Technologies, 6(2), 1505-1508.
31. Sumitra, N., & Saxena, R. K. (2013), "Brain tumor classification using back propagation neural network," International Journal of Image, Graphics and Signal Processing, 5(2), 45.
32. Ritschel, K., Pechlivanis, I., &Winter, S. (2015), "Brain tumor classification on intraoperative contrast-enhanced ultrasound," International journal of computer assisted radiology and surgery, 10(5), 531-540.
33. Dahab, D. A., Ghoniemy, S. S., & Selim, G. M. (2012), "Automated brain tumor detection and identification using image processing and probabilistic neural network

techniques," International journal of image processing and visual communication, 1(2), 1-8.
34. Sawakare, S., & Chaudhari, D. (2014), "Classification of brain tumor using discrete wavelet transform, principal component analysis and probabilistic neural network," International journal for research in emerging science and technology, 1(6), 13-19.
35. Sachdeva, J., Kumar, V., Gupta, I., Khandelwal, N., & Ahuja, C. K. (2012), "A dual neural network ensemble approach for multiclass brain tumor classification," International journal for numerical methods in biomedical engineering, 28(11), 1107-1120.
36. Yadav, R. and Choudhary, S. K. (2022) "*A framework to detect skin disease using deep learning technique*," International Journal of Health Sciences, Vol. 6, Issue S5, pp. 7260-7270.