Innovations

A Novel Approach for MRI Medical Image Classification and Tumor Detection Using Deep Learning Model

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Abstract: *Timely and accurate identification is crucial for effective treatment of brain tumor, which are a major health concern worldwide. Integrating cutting-edge machine learning methods with medical imaging technologies, this research demonstrates a state-of-the-art method for detecting brain tumors. To improve the accuracy and speed of tumor detection, the suggested technique uses deep learning algorithms and convolutional neural networks (CNNs). In this work a large dataset of brain pictures from different imaging modalities, such as computed tomography (CT) and magnetic resonance imaging (MRI), are used. After performing pre-processing, normalization operations on collected dataset, it is used to train a convolutional neural network (CNN) architecture, which trains the model to recognize brain tumor by their detailed patterns and properties.Using both internal and external validation datasets, the model is tested on a full suite of metrics, including accuracy, specificity, and sensitivity. Our methodology shows promise for early and accurate diagnosis, with results showing a significant improvement in detection accuracy (96.66%) compared to standard methods.*

Keywords:*Brain Tumor, Convolution Neural Network, Transfer-learning, Anisotropic diffusion filtering, and Brain Tumor Area Segmentation.*

1. Introduction

A significant contributor to contemporary human mortality is brain tumors, as evidenced by the 2020 global statistics of 308,102 new cases and an estimated 251,320 deaths. Projections for 2040 indicate a staggering increase to 29.5 million new cases and 16.4 million deaths worldwide. Despite constituting less than 2% of all human cancers, as reported by the World Health Organization, the severe morbidity and complications associated with brain tumors underscore their substantial impact on public health.The early detection of tumorous cellsin the brain throughMRI scan, helps in early diagnosis and also reduces the mortality rate [1]. The tumors are classified as malignant (cancerous) and benign (noncancerous) tumors. The benign tumors are the initial stage of extra cell generation instead of one, due to the malfunctioning of the cell generation system in the human body. When these generated extra cells gain some mass and start to flow from one place to any place inside the body through the bloodstream, called malignant. Standard MRI sequences differentiate tumor types based on visual characteristics, contrast, density, and metastatic rate [2]. The major symptoms of brain tumors are dizziness, headaches,vision problems, mental changes, balance loss, etc. There are a lot of various diagnosis methods like CT scan,MRI, tissue biopsy, etcfor tumor detection but having side effects like; motor deficit, and visual field effects, during analyzing the tumor stage and size for further tumor progression.Deep learning instructs computers to emulate human thought and behavior in tasks like image, sound, or text classification, often surpassing human performance. An example is the popular artificial neural network, composed of interconnected simulated neurons for efficient information processing. Deep learning involves a set of neural techniques that autonomously learn features from input data.Brain cancers inMRI datasets may be both classified and segmented using a deep neural network that Kulkarni and Sundari [3] developed. There are two parts to the model. The first part uses morphological operations and thresholding to segment brain tumors. The second part is for abnormal or normal tumor classification. The Discrete Wavelet Transform (DWT) is used to classify features extracted after segmentation by feeding them into the neural network. By comparing the findings with a transfer learning strategy, we can evaluate the correctness of the proposed model. Notable performance indicators include a recall of 1, an f-score of 96.77%, and a precision rate of 93.75%. By combining the ideas of adaptive fuzzy logic and the frog lean algorithm for error optimization, Deb and Roy [4] presented a hybrid deep learning model for accurate brain tumor identification. After bilateral filtering reduces noise, the model uses gray-level co-occurrence matrices (GLCM) for effective feature extraction. An AFDNN, which is based on adaptive fuzzy logic, is then used to classify brain tumors effectively using the extracted features. By combining morphological operations with size and area thresholding, tumor segmentation can be accomplished. Excellent performance indicators, such as sensitivity (99.9%), accuracy (96.6%), true negative rate (5.43%), false positive rate (0.43%), and precision (99.8%), are displayed by the suggested model. For the purpose of classifying MRI images as either benign or malignant tumors, Singh et al. [5] presented a model employing a modified convolution neural network (MCNN). Partitioning the dataset into training and testing sets follows preprocessing. To compensate for data scarcity during model training, data is augmented or shuffled. The suggested model is protected against overfitting by incorporating dropout layers into the CNN model's second and final convolution layers. This model has an f-1 score of 99.21%, an accuracy of 99.88% during training and validation, a precision of 99.55%, and a sensitivity of 98.99%. Ghadi and Salman [6] introduced a model for MRI-based tumor segmentation and classification. To improve the model's performance, the authors used a hybrid feature extractor that combined the probability density function (PDF) with two-dimensional continuous wavelet transformation (2D-CWT). A CNN classifier is used to accurately classify brain tumors after characteristics are extracted. With an f-1 score of 97.73% and an accuracy of 97.43%, the suggested model is quite impressive. To segregate brain tumors from MRI scans with different contrast levels, Cherguifet al.[7] used a fully connected deep neural network (U-Net). The suggested approach employs a downsampling and upsampling method to precisely localize and segment features from the input MRI picture. An expanding block, a contracting block, and a bottleneck block make up the entire body of the suggested model. Downsampling encompasses the contracting and bottleneck processes, whereas upsampling encompasses the rest. The suggested model outperforms state-of-the-art approaches with a dice similarity of 0.81.Raut at el.[8] used a dataset of MRI images of brain tumors to create an automated method for detecting and segmenting these tumors. With the use of a downsampling and upsampling autoencoder, the tumor can be detected. Each of the three convolution layers equipped with 8, 16, and 32 filters and measuring 3*3 would execute the downsampling and thresholding processes, and the author also suggested a max pooling layer and a relu pooling layer. The k-means clustering method is used to identify the size and location of brain tumors using segmentation. When compared to the current model, the suggested one performs far better.To detect and segment brain tumors automatically, Kumar et al. [9] suggested an active contour (AC) edgeless method. To further address issues with low precision and excessive complexity, the active contour approach is used to perform skull stripping during the preprocessing step. Among the reported multi-class cancers, meningioma(81%), glioma (56%), and pituitary tumors (71%), the proposed model has the highest accuracy.Information technology and the e-healthcare system have recently been introduced in the medical field, aiding clinical experts in giving patients better medical care.According to data compiled by cancer.net, 1,918,030 new instances of cancer are diagnosed each year in the world, with an annual death toll of roughly 609,360. A staggering 251,329 people lose their lives and 308,102 are diagnosed every year due to malignancies in the brain and central nervous system (CNS).There are a variety of techniques available for spotting anomalies in brain MRI scans, however these methods can always be better.Within this proposed architecture, a multi-class classification model is built using a deep learning approach (CNN& transfer learning). This layout has a minimal number of layers and most fined features suggested using pearson's chi-square algorithms, which results in a simpler model and faster calculation.

2. Proposed brain tumorclassification model

This research introduces a high-performing hybrid model for classifying brain tumor MRI images. Initially, pre-processed MRI images undergo classification using a hybrid chi-square Deep CNN. If a tumor is present, the model evaluates its exact location and size through an anisotropic diffusing and thresholding-based approach. The proposed MRI image classifier involves five stages, encompassing low-contrast MRI image acquisition and preprocessing, data division into training and testing sets, data augmentation, and shuffling operations on the training set, model training, and evaluation using the remaining test set [10]. A 70:30 ratio is applied for training and testing the model, respectively. The flow chart depicting the proposed brain tumor classification models is illustrated in Figure 1.

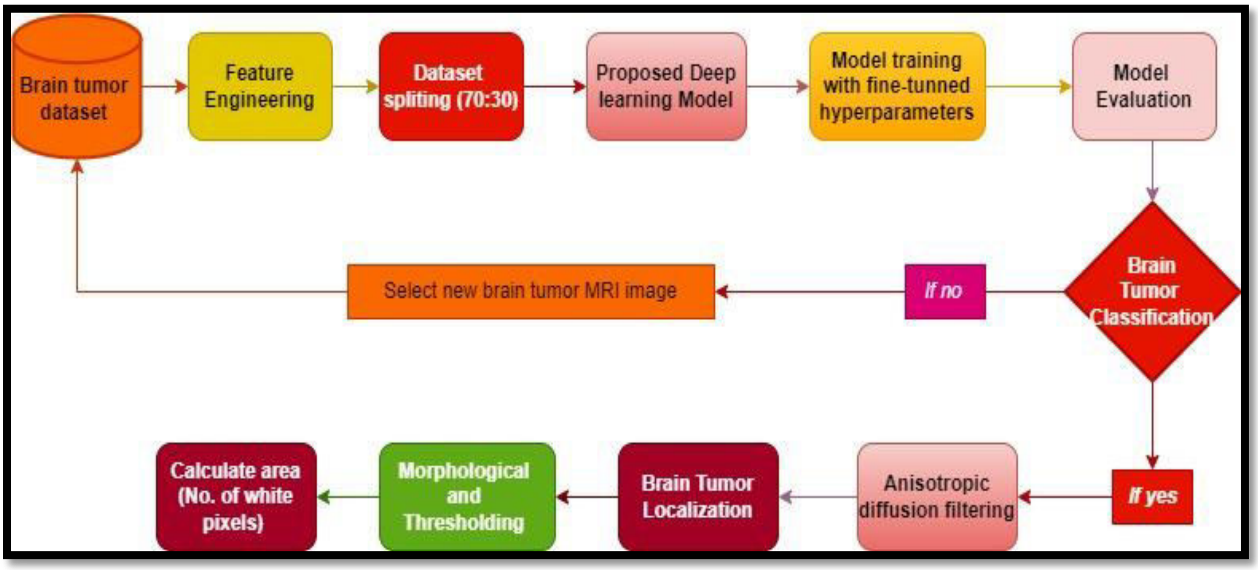


Figure 1:Suggested schematic for Hybrid DCNN based automated brain tumor classification and region detection

The operation of the proposed model is divided into three groups. In the first phase after input image acquisition, preprocessing, dataset leveling, and data splitting (70:30) are performed. Inthe second phase, proposed models are trained after performing data augmentation and shuffling operations to avoid data shortage [11]. In the third phase, the performance of the trained modelis evaluated based on model accuracy, precision,recall, and f-1 scores.

2.1 Dataset collection and Pre-processing

We gathered 3000 low-contrast MRI images, classified into three groups: benign (1500) and malignant (1500), from an online resource. Using OpenCV library and noise-removing filters, we preprocessed these images to simplify the model and enhance its efficiency in classifying tumor types with optimal computational time [12]. Figure 2 shows a sample of the preprocessed MRI brain tumor images collected.

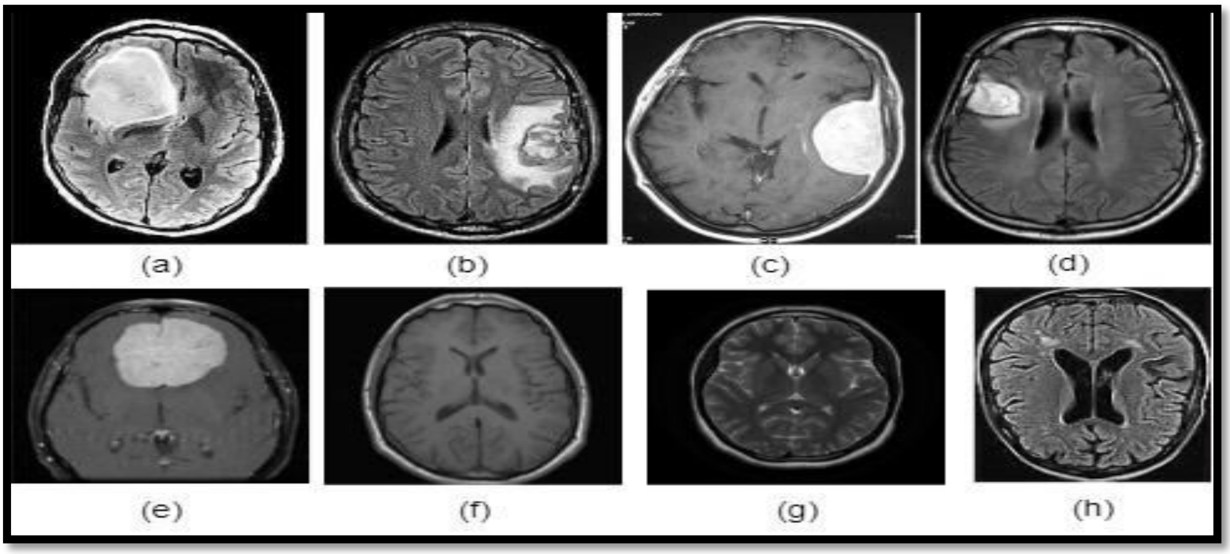


Figure 2: Sample of a collected& ore-processedbrain tumor MRI images

2.2 Convolution Neural Network

CNNhave become prevalent in medical imaging for analyzing and classifying images, with a focus on extracting the most significant features [13]. The artificial neural network (ANN) then utilizes these extracted features, obtained through the CNN network, to perform image classification. The CNN model employs a convolution layer with the relu function for feature extraction, where the dimensions of height, width, and depth play a crucial role in determining the extracted features. The architecture of the CNN model comprises four main layers: convolution, relu, pooling, and flattening, as illustrated in figure 3.

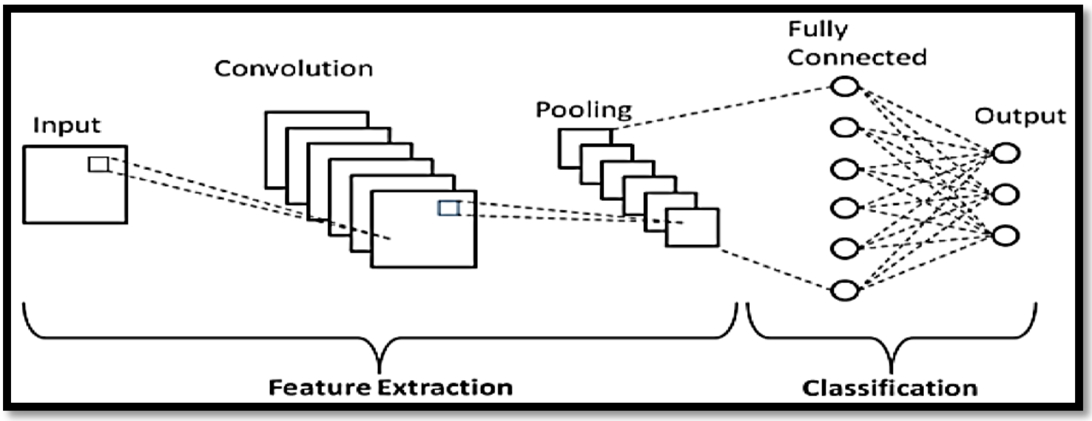


Figure 3: General block diagram of CNN model

As depicted in Figure 3, the CNN model is a fusion of a feature extraction component and a classification model. The CNN segment handles feature extraction, leveraging the convolution and relu layers to extract highly effective features, while the max-pooling layer is employed for dimensional reduction, contributing to a further reduction in model complexity. The intricate internal structure of the CNN model is elaborated upon below.

2.2.1 Convolution Layer

In CNN model, the primary parameters of the convolution layer are the stride, padding, and filter size. The value of stride determines the convoluted image size and the left-to-right filter shifting that occurs during a convolution operation[14]. The kernel of the filter moved one or two divisions to the right when stride is equal to 1 or 2. Padding is utilized to either expand the supplied binary image or keep it at its initial size. If the convolution procedure uses valid padding, the image size can be decreased without losing any important features; however, if the padding is not legitimate, the image size stays the same. The new size of the convoluted picture is is $[x'_r, x'_c, x'_d]$ if the input image's height, width, and depth are $[x_r, x_c, x_d]$. Results from (1), (2), and (3) are used to evaluate the x'_r, x'_c, x'_d as given below.

$$x'_r = \frac{x_r + 2*Padding - filtersize}{stride} + 1 \quad (1)$$

$$x'_c = \frac{x_c + 2*Padding - filtersize}{stride} + 1 \quad (2)$$

$$x'_d = \text{F} \quad (3)$$

With:

x_r, x_c, x_d: input image parameter(height, width, and depth)

x'_r, x'_c, x'_d: Convoluted image parameters

F: used filters = total number of input features

2.2.2 Relu Layer

The Rectified Linear Unit function (ReLU) introduces non-linearity to an input image, enabling the CNN model to extract an increasing number of features [15]. Operative on a thresholding concept, the relu function sets all lung x-ray image pixels with values below zero or in the negative grayscale range to zero, while the remaining pixels are shifted to 1. Following the relu operation, the image transforms into black and white, with a significant proportion of black pixels. The mathematical representation of the relu function is expressed by equation (4).

$$f(x) = \begin{Bmatrix} 0 & if x < 0 \\ 1 & if x \geq 0 \end{Bmatrix} \quad (4)$$

2.2.3 Pooling Layer

To minimize model complexity and computational time, the CNN model incorporates the pooling operation. This operation acts indirectly as a principle component analysis (PCA). The resulting size of the image after pooling depends on the pool size. Two types of pooling operations are utilized: Max-pooling and average pooling. For max pooling, the maximum value within the pool size is selected, while for average pooling, the average of all pool values based on the pool size is computed. Figure 4, illustrates max and average pooling operations applied to 4*4 input images with a pool size 2*2.

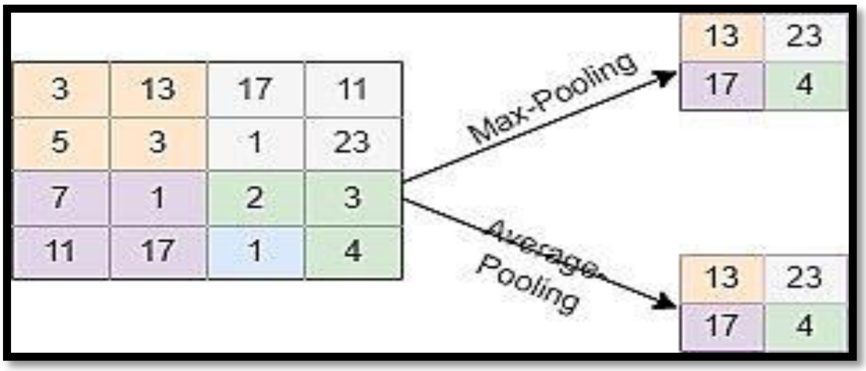


Figure 4: Max-pooling and average-pooling operations

2.3 Artificial Neural network

The ANN comprises interconnected nodes or artificial neurons with predefined weights [16]. The training of the model is facilitated by the backpropagation algorithm, where these weights are iteratively updated until the model achieves accurate predictions. Figure 5, illustrates the structure of a single neuron in the ANN classifier.

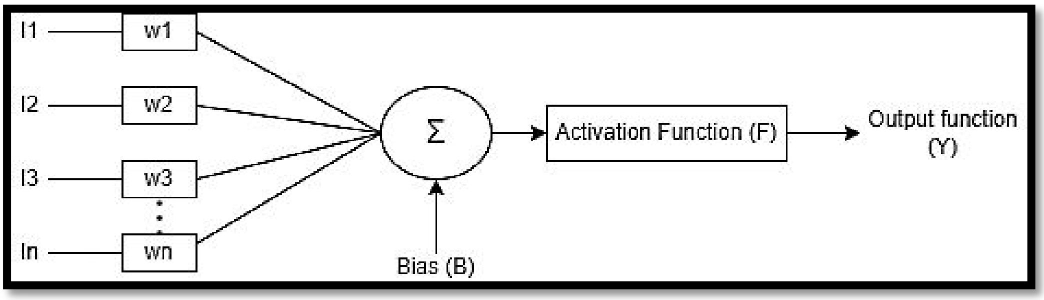


Figure 5: ANN classifier structure

$$\text{Output function} = \text{Activation function}[\Sigma(\text{Input variable} * \text{corresponding weights}) + \text{Bias}]$$

$$\text{Output function (Y)} = \text{F} * \left[\left((\text{I}_1 * \text{W}_1) + \cdots + (\text{I}_n * \text{W}_n)\right) + \text{B}\right] \quad (5)$$

Where;

$I_1, I_2, \ldots \ldots, I_n$ = number of input neurons (features)

$w_1, w_2, \ldots \ldots, w_n$ = weight assigned to each neuron

B= Biased (constant that control the output)

Y = Output of the neural network

F = Activation function

2.4 Transfer Learning Approach

When time and data are limited for model training, transfer learning approaches come into play. In transfer learning, the knowledge or weights of a pre-trained model are transferred to a new model, expediting the learning process and enhancing accuracy [17]. The transfer learning model exhibits favorable accuracy and computational time compared to building a model from scratch. Figure 10 illustrates the performance comparison between transfer learning and a model built from scratch

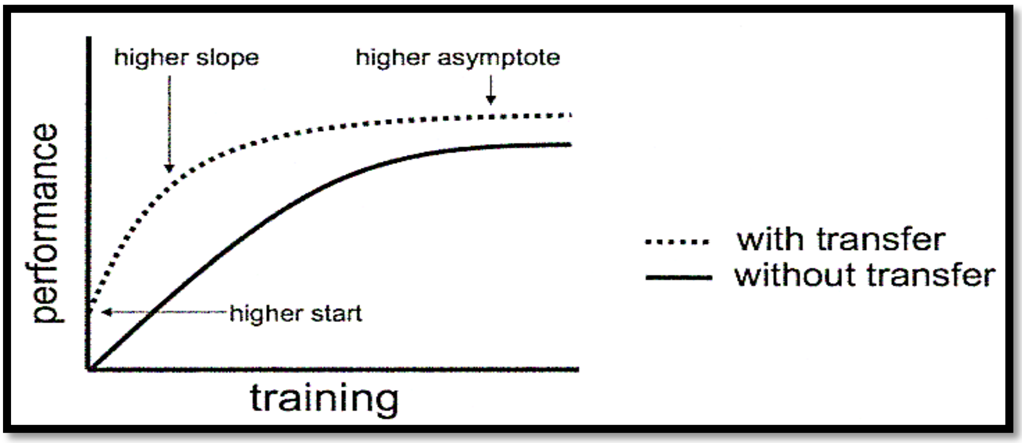


Figure 6: Performance of transfer learning vs model from scratch

Figure 6 shows that the performance in terms of training time, accuracy, and learning rate of a model with a transfer learning approach is much higher than a model built from scratch.

3. Experimental Results

The suggested binary class low contrast brain tumor MRI image classifier is implemented in google colab (python 3.8) using deep learningeapproaches. The proposed model is tested using a system that has4 GB RAM, and an 8th generation i7-2.5 GHz processor with 450 lung x-rays images of three classes.

3.1 Confusion Matrix

The anticipated confusion matrix is used to produce the model's specificity, recall, accuracy, precision, and F1 score metrics [18]. These indicators are used to evaluate how well the model is doing its job. The complete general confusion matrix for a three-class scenario is shown in Figure 7. Themathematical equations used to calculate the performance measure parameters for three class are described below.

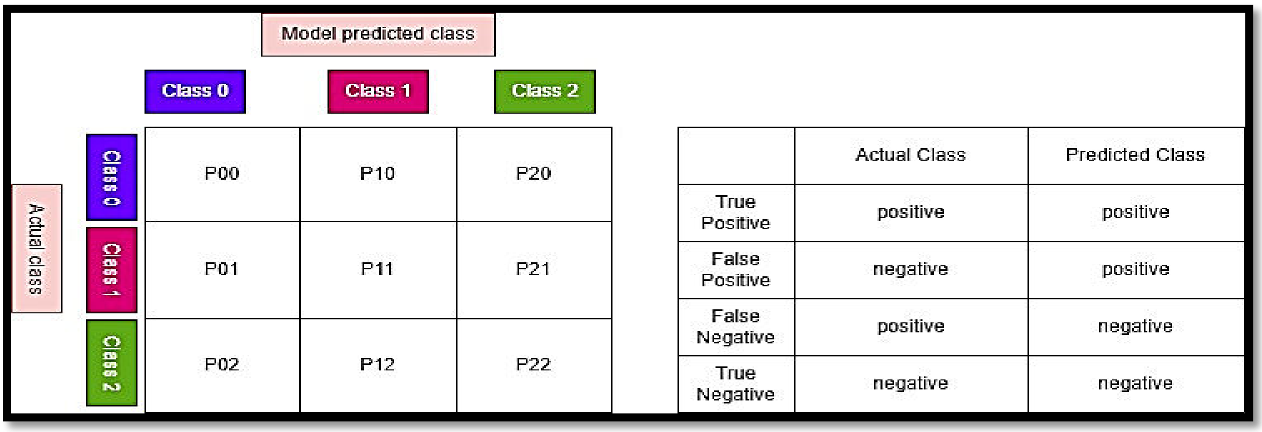


Figure 7:3-Class confusion Matrix

$$\text{Precission} = \frac{\text{True Positive}}{(\text{True Positive+False Positive})} = \frac{P_{00}}{P_{00}+P_{01}+P_{02}} \quad (13)$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True Positive+False Positive})} = \frac{P_{00}}{P_{00}+P_{10}+P_{20}} \quad (14)$$

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{(\text{Positive+Negative})} = \frac{P_{00}+P_{11}+P_{22}}{P_{00}+P_{01}+P_{02}+P_{10}+P_{11}+P_{12}+P_{20}+P_{21}+P_{22}} \quad (15)$$

$$\text{F}-1\text{ Score} = \frac{2*\text{Precision}*\text{Recall}}{(\text{Precision+Recall})} \quad (16)$$

3.2 Accuracy and predicted outcomes of proposed CNN model

After constructing the proposed CNN model, which comprises three convolution layers with feature extractor sizes of 32, 64, and 128, three max-pooling layers with a pool size of 22, four ReLU layers for introducing nonlinearity, and two fully connected layers after flattening, the model is trained using 1500 images. Data augmentation and shuffling operators, employed in conjunction with the training process, mitigate data scarcity concerns. The trained model is evaluated on a test set of 450 MRI images. The training and validation accuracies, tuned with hyperparameters (input image size=150150, batch size=32, steps per epoch=46, trainable parameters=9564227) for the proposed CNN model, along with the corresponding confusion matrix, are illustrated in Figure 8.

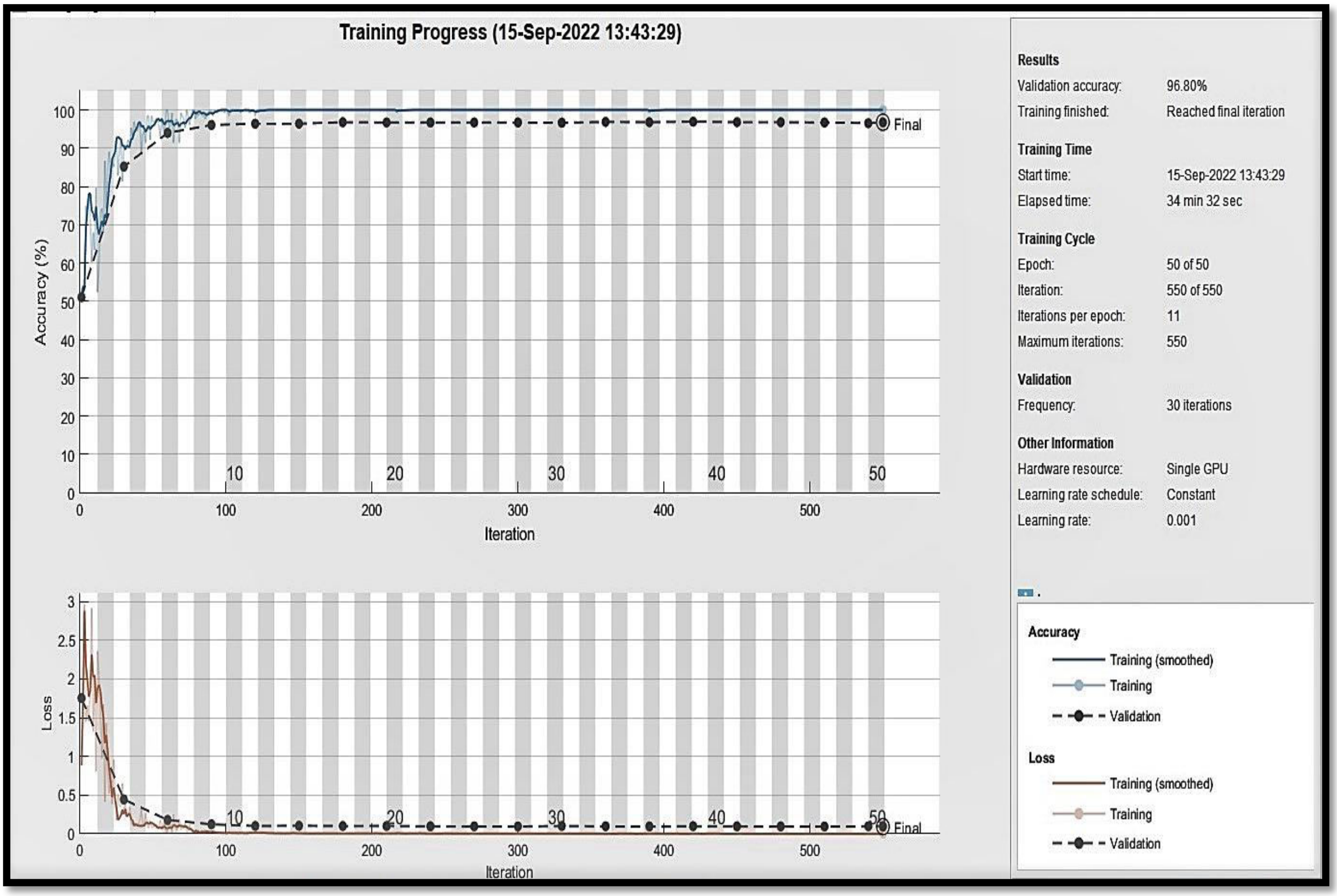


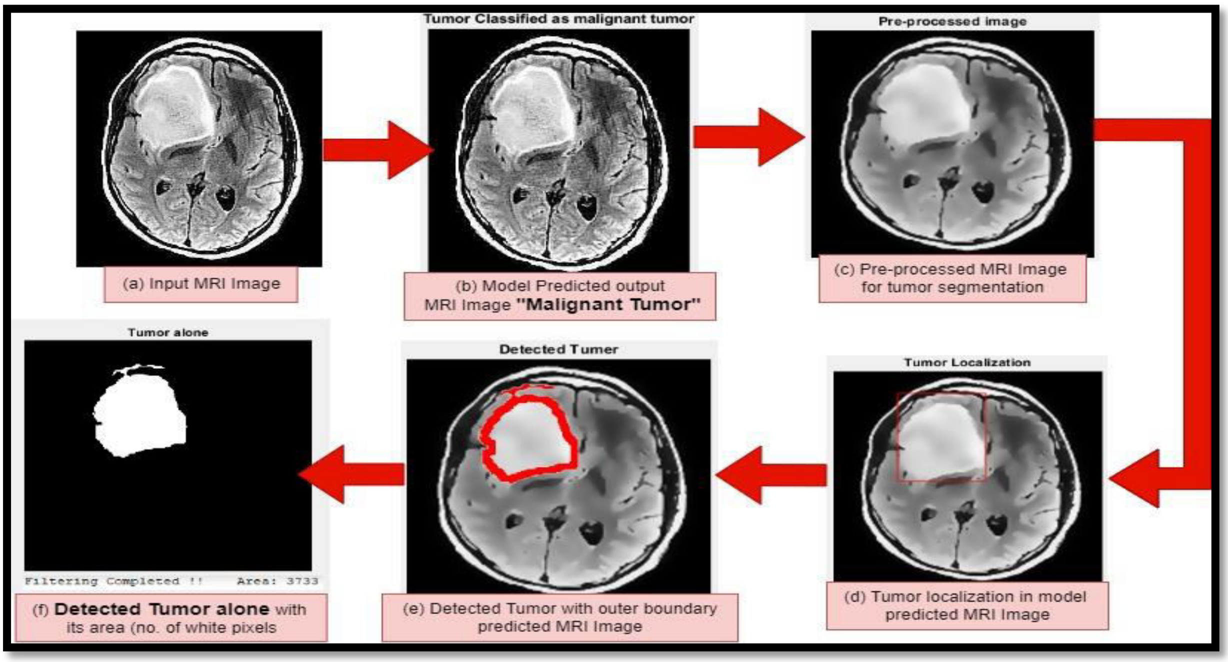
Figure 8: Training and validation accuracy Vs loss of Deep-CNN for MRI image classification

The accuracy score, training and validation plots of proposed deep CNN are shown in figure 8 and table 1.

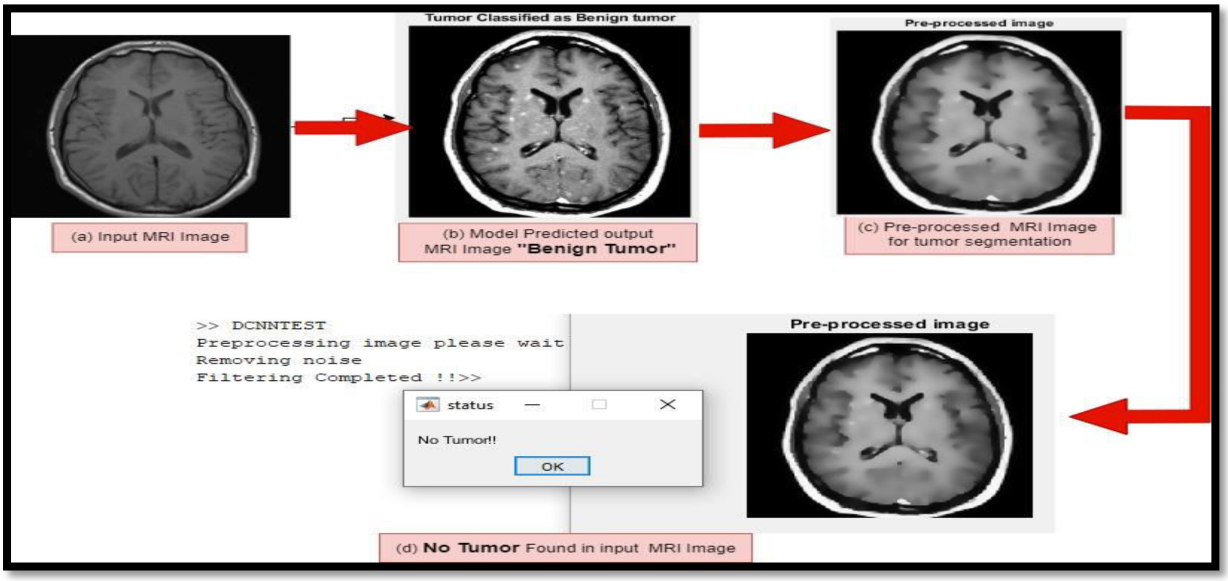
Table 1: Training and testing accuracy of the proposed model with different no. of epoch

Type of Tumor	True Positive	True Negative	False Positive	False Negative	Precision	Sensitivity	Specificity	Accuracy	F-score
Benign	438	432	18	12	0.9605	0.9555	0.9655	0.9666	0.9666
Malignant	432	438	12	18	0.9729	0.9588	0.9589	0.9666	0.9666

The proposed model predicted after performing preprocessing and anisotrohic diffusion filtering are shown below in figure 9 (a) and 9 (b).



9(a)



9 (b)

Figure 9 : (a) & (b) Deep CNN predicted malignant & benign tumor MRI images

Few samples of proposed hybrid deep CNNmodel predicted images are shown in figure 10.

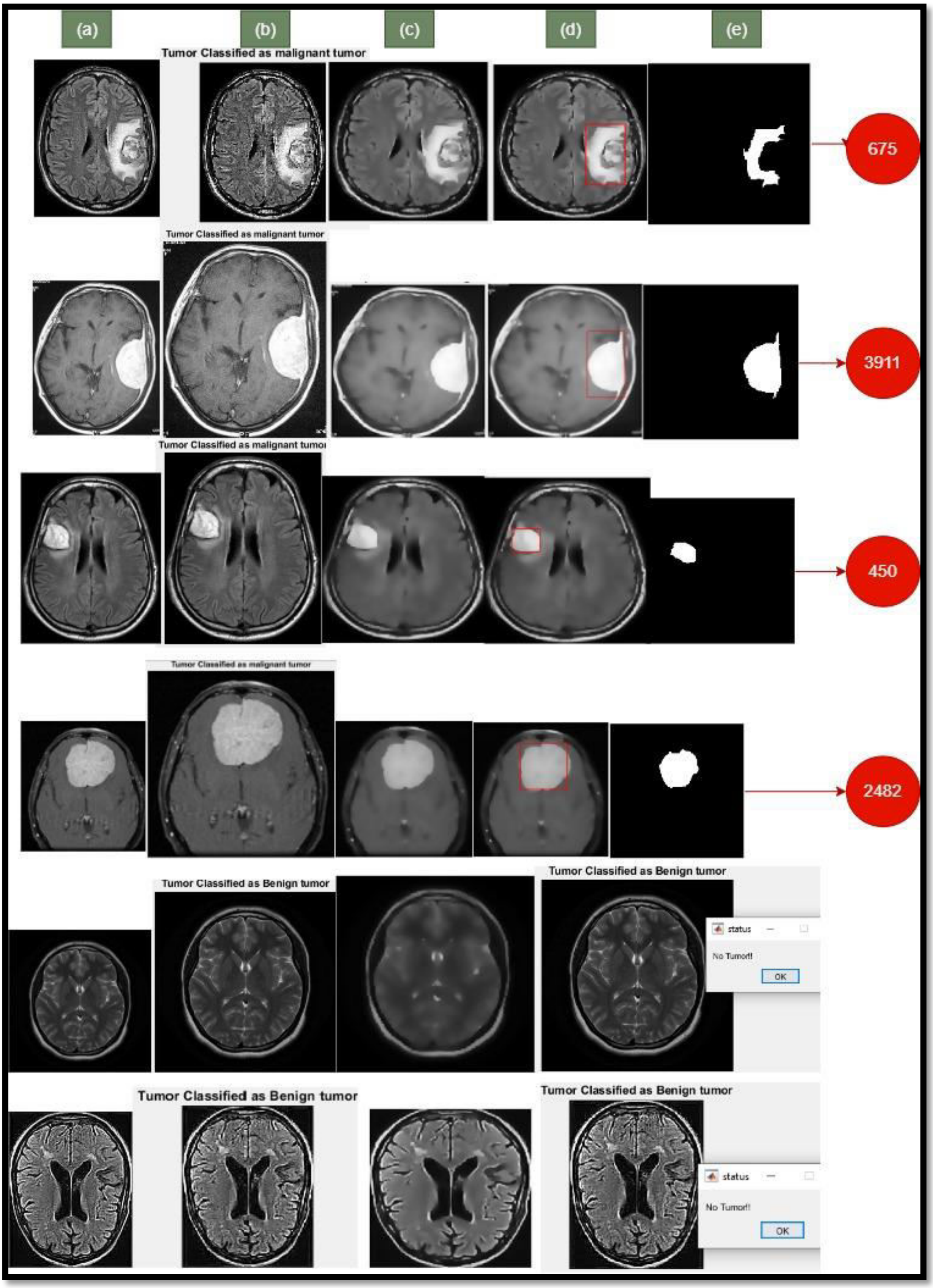


Figure 10: A samples of proposed hybrid deep CNNmodel predicted images

The accuracy and bar graphs of all proposed models, for binary class (benign and malignant) low contrast

MRI image classification are shown in table 2 and figure 11.

Table 2:Training and testing accuracy of the proposed model with different no. of epoch

Proposed approaches	Training Accuracy	Testing Accuracy
HOG Feature+ ECOC-SVM classifier(Epoch= 50)	89.78%	89.55%
VGG-16 (Epoch=50)	92.57%	91.51%
DenseNet 201((Epoch=50)	84.40%	72%
Proposed CNN Classifier ((Epoch=50)	**97.27%**	**96.75%**

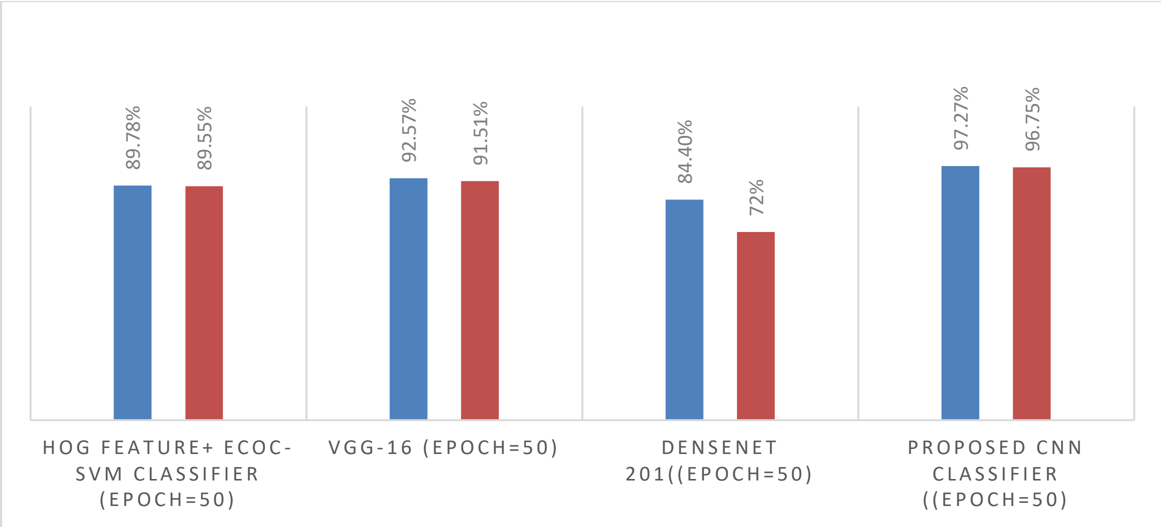


Figure 11: Bar graph of proposed model accuracy for different classifiers

The design of our proposed model is characterized by simplicity in terms of convolution layers, utilizing fewer trainable parameters (9564227) compared to VGG-16 and DenseNet201. Demonstrating superior accuracy on the same dataset, our proposed model outperforms existing models. Specifically, it excels in accurately classifying low-contrast brain tumor MRI images with an impressive 96.66% accuracy. This model is well-suited for the classification of binary class 2-dimensional brain tumor MRI images.

4. Conclusion and Future Work

Timely and accurate identification is crucial for effective treatment of brain tumor, which are a major health concern worldwide. Integrating cutting-edge machine learning methods with medical imaging technologies, this research demonstrates a state-of-the-art method for detecting brain tumors. To improve the accuracy and speed of tumor detection, the suggested technique uses deep learning algorithms and CNNs. In this work a large dataset of brain pictures from different imaging modalities, such as CT and magnetic, MRI, are used. After performing pre-processing, normalization operations on collected dataset, it is used to train a CNN architecture, which trains the model to recognize brain tumor by their detailed patterns and properties.Using both internal and external validation datasets, the model is tested on a full suite of metrics, including accuracy, specificity, and sensitivity. Our methodology shows promise for early and accurate diagnosis, with results showing a significant improvement in detection accuracy (96.66%) compared to standard methods like VGG-16 and DenseNet-201.In the future, the proposed algorithms for brain tumor MRI image classification is tested on a 3-dimensional dataset using some advanced deep learning approach.

References

[1] A. Miglani, H. Madan, S. Kumar, and S. Kumar, "A literature review on brain tumor detection and segmentation," Proc. - 5th Int. Conf. Intell. Comput. Control Syst. ICICCS 2021, pp. 1513–1519, 2021.

[2] H. Singh and R. Ratan, "Segmentation of Brain Tumor from MRI Images Using Modified Morphological Novel Approach," in Proc. of Second Int. Conf. on Smart Energy and Commun., Algorithms for Intelligent Systems. Springer, Singapore, pp. 73–84, 2021.

[3] S. M. Kulkarni and G. Sundari, "A framework for brain tumor segmentation and classification using deep learning algorithm," Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 8, pp. 374–382, 2020.

[4] D. Deb and S. Roy, "Brain tumor detection based on hybrid deep neural network in MRI by adaptive squirrel search optimization," Multimed. Tools Appl., vol. 80, no. 2, pp. 2621–2645, 2021.

[5] H. Singh, R. Ratan, J. V. Desai, and P. G. Kohli, "Benign and Malignant Tumor Classification from MRI Images using Modified Convolution Neural Network Approach," Turkish J. Comput. Math. Educ., vol. 12, no. 10, pp. 575–582, 2021.

[6] N. M. Ghadi and N. H. Salman, "Brain tumors classification based on segmentation techniques and wavelet transform," Int. J. Nonlinear Anal. Appl., vol. 13, no. 2, pp. 2247–2256, 2022.

[7] H. Cherguif, J. Riffi, A. M. Mahraz, A. Yahyaouy, and H. Tairi, "Brain tumor segmentation based on deep learning's feature representation," J. Imaging, vol. 7, no. 12, pp. 1–8, 2021.

[8] G. Raut, A. Raut, J. Bhagade, and S. Gavhane, "Deep Learning Approach for Brain Tumor Detection and Segmentation," 2020 IEEE Int. Conf. on Convergence to Digital World (ICCDW 2020), pp. 1-5, 2020.

[9] S. B. Kumar, R. Panda, and S. Agrawal, "Brain Magnetic Resonance Image Tumor Detection and Segmentation Using Edgeless Active Contour," 2020 11th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2020, pp. 1-7, 2020.

[10] M. Ali, S. O. Gilani, A. Waris, K. Zafar, and M. Jamil, "Brain Tumour Image Segmentation Using Deep Networks," IEEE Access, vol. 8, no. 1, pp. 153589–153598, 2020.

[11] L. H. Shehab, O. M. Fahmy, S. M. Gasser, and M. S. El-Mahallawy, "An efficient brain tumor image segmentation based on deep residual networks (ResNets)," J. King Saud Univ. - Eng. Sci., vol. 33, no. 6, pp. 404–412, 2021.

[12] R. Ranjbarzadeh, A. B. Kasgari, and S. J. Ghoushchi, "Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi - modalities brain images," Sci. Rep., vol. 11, no.1, pp. 1–17, 2021.

[13] W. Zhang, G. Yang, H. Huang, W. Yang, X. Xu, Y. Lui, and X. Lai, "ME-Net: Multi-encoder net framework for brain tumor segmentation," Int. J. Imaging Syst. Technol., vol. 31, no. 4, pp. 1834–1848, 2021.

[14] P. K. Chahal, S. Pandey, and S. Goel, "A survey on brain tumor detection techniques for MR images," Multimed. Tools Appl., vol. 79, no. 29, pp. 21771–21814, 2020.

[15] Z. Ullah, U. Farooq, S. Lee, and D. An, "A hybrid image enhancement based brain MRI images classification technique," Medical hypotheses, vol. 143, no. 1, pp. 109922-109940, 2020.

[16] K. K. Gupta, N. Dhanda, and U. Kumar, "A novel hybrid method for segmentation and analysis of brain MRI for tumor diagnosis," Adv. Sci. Technol. Eng. Syst., vol. 5, no. 3, pp. 16–27, 2020.

[17] K. K. Dewangan, D. K. Dewangan, S. P. Sahu, and R. Janghel, "Breast cancer diagnosis in an early stage using novel deep learning with hybrid optimization technique," Multimed. Tools Appl., vol. 81, no. 10, pp. 13935–13960, 2022.

[18] A. Baccouche, B. G. Zapirain, C. C. Olea, and A. S. Elmaghraby, "Connected-UNets: a deep learning architecture for breast mass segmentation," npj Breast Cancer, vol. 7, no. 1, pp. 1–12, 2021.