

Deep Learning-Based Detection and Classification of Brain Tumors Using MRI Images

Shubhra Chinchmalatpure^{1*}, Pratiksha Chafle²

Abstract

Brain tumor detection using magnetic resonance imaging (MRI) is a critical task in the early detection and treatment of brain tumors. Manual analysis of brain tumor detection using MRI is a tedious task that requires expertise in the field. Therefore, this study proposes a deep learning-based approach for brain tumor detection and classification using Convolutional Neural Networks (CNN). The proposed approach preprocesses the MRI image using normalization, resizing, and noise reduction. The proposed CNN learns discriminative features from the image without any manual intervention in feature engineering. The proposed CNN model is trained and tested on a publicly available benchmark dataset for MRI images. The performance of the model was assessed using accuracy, precision, recall, F1 score, and confusion matrix. Experimental results revealed that the proposed CNN model attained a classification accuracy of 94.6%. This shows that the proposed model performs better in brain tumor diagnosis compared to traditional machine learning algorithms like Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN).

Keywords: Brain tumor detection, magnetic resonance imaging (MRI), deep learning, convolutional neural networks (CNN), medical image analysis

INTRODUCTION

Brain tumors are one of the most critical neurological problems that may result in significant morbidity and mortality if not identified in their early stages. Therefore, it becomes essential to identify brain tumors in their early stages to plan treatment, surgery, and prognosis [1]. Among the neuroimaging modalities available to identify brain tumors, magnetic resonance imaging (MRI) has been found to be the most used technique for the diagnosis of brain tumors due to its non-invasive nature, providing better soft tissue contrast, and offering detailed information regarding the structures of the brain. However, the process of using MRI for diagnosis is still a challenging task and relies on the skills of radiologists. Furthermore, the increasing volume of medical image data has increased the workload for doctors and has the potential to introduce variability in the diagnosis process [2]. Therefore, computer-aided diagnosis systems for automatic detection and classification of brain tumors have been proposed.

Traditional methods for brain tumor detection and classification using computer-aided diagnosis systems included conventional image processing and machine learning techniques in which features are extracted, and classification is achieved using SVM and k-NN [3, 4]. Although promising results have been achieved by these methods, their performance has been constrained by the challenges associated with handcrafted feature engineering. In recent times, deep learning has also been identified as a promising paradigm in medical image analysis. In this case, Convolutional Neural Networks (CNNs) have been identified as a promising paradigm in medical image analysis due to their potential to learn feature representations directly

*Author for Correspondence

Shubhra Chinchmalatpure

E-mail: Shubhra.chinchmalatpure@raisoni.net

¹Research Scholar, Department of Computer Science, GH Rasoni University, Dhoda Bargaon, Madhya Pradesh, India

²Assistant Professor, Department of Computer Science, GH Rasoni University, Dhoda Bargaon, Madhya Pradesh, India

Received Date: May 07, 2026

Accepted Date: May 29, 2026

Published Date: July 20, 2026

Citation: Shubhra Chinchmalatpure, Pratiksha Chafle. Deep Learning-Based Detection and Classification of Brain Tumors Using MRI Images. International Journal of Brain Sciences. 2026; 3(2): 36–44p.

from raw image data. Based on this promising potential, this study proposes a deep learning-based framework for the automatic detection and classification of brain tumors using MRI images. The performance of the proposed model has been evaluated using performance metrics.

LITERATURE REVIEW

Automated approaches for brain tumor detection from MRI images have been extensively researched in the literature. Initially, the research was centered on traditional machine learning techniques and the application of handcrafted feature engineering techniques [5, 6]. Features – such as texture features like the Gray-Level Co-occurrence Matrix (GLCM) and wavelet features – were extracted from the MRI images and classified by machine learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Although the classification results were satisfactory, the classification was heavily dependent on the quality of the handcrafted features engineered from the MRI images [7–9]. With the advent of high computational power and the availability of more medical image datasets, deep learning has become the major trend in brain tumor analysis. Especially, Convolutional Neural Networks (CNNs) achieved higher performance in brain tumor analysis by learning discriminative features from brain MRI images [10–12]. Several studies were conducted using CNN-based methods for normal and tumor brain image classification [13]. To enhance the classification accuracy even better, researchers have also employed transfer learning methods for brain tumor classification and detection from MRI scans by utilizing pre-trained deep CNN architectures such as VGG16, ResNet50, and DenseNet121 [14]. Such transfer learning methods have been reported to achieve better convergence and classification accuracy, especially when limited medical imaging data are available [15]. Although deep learning models have shown good performance, one major challenge is the lack of interpretability, and deep learning models are no exception. Due to the “black-box” nature of deep learning models, clinicians may not be able to easily comprehend the reasoning behind the classification outcome obtained from the model. For this reason, Explainable Artificial Intelligence (XAI) techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM), have been incorporated to enable the visualization of key areas in MRI images that are being used to make predictions.

DATASET DESCRIPTION AND PREPROCESSING

Dataset Description

The efficacy of the developed deep learning model was tested using a publicly available brain tumor MRI image dataset. This dataset was collected from an open-source medical image repository. This dataset consists of MRI images of different classes: glioma, meningioma, pituitary tumor, and normal brain. This dataset contains 7023 brain MRI images of various classes from multiple patients, obtained under standard conditions. Images are available in grayscale form, depicting different views of the human brain. Each image was labeled by domain experts. This dataset is appropriate for supervised classification of brain tumor images. The dataset varies significantly in terms of tumor size, shape, location, and intensity, which makes it a realistic dataset. This dataset is challenging for testing the robustness of the proposed deep learning model. For efficient training and testing of the dataset, it was divided into three sets: training, validation, and testing. Out of all the images, 70% were used for training, whereas 15% were used for validation and another 15% for testing (Table 1).

Table 1. Distribution of MRI images across tumor classes in the dataset.

Tumor class	Number of images
Glioma	1621
Meningioma	1645
Pituitary Tumor	1757
Normal	2000
Total Images	7023

Preprocessing Steps

Prior to training the deep learning model, several preprocessing steps were performed on the MRI images to enhance the quality of the images and maintain uniformity in the dataset. Preprocessing is a

vital step in medical image analysis, as it is common for MRI images to exhibit inhomogeneity, noise, and resolution variations during scanning due to different scanning protocols.

Firstly, intensity normalization was conducted to eliminate inter-scan intensity variation. This process standardized the intensity distribution of pixels in all MRI images. This process is essential to ensure that the deep learning model does not concentrate on any unnecessary intensity variations. Secondly, all MRI images were resized to a specific resolution to ensure uniformity in the dimensions of the images. This uniformity in image dimensions is essential to allow the Convolutional Neural Network (CNN) to process the images in batches. To increase generalization and prevent overfitting, data augmentation was used to increase the diversity of the training set. These data augmentation techniques include rotation, flipping, and scaling, which increase the diversity of the training set, hence enhancing the robustness of the model to changes in the orientation of the tumor. Finally, the preprocessed MRI images are converted into a tensor format and used as input to the deep learning model for feature extraction and classification. This standard preprocessing procedure was used to increase the stability of training, hence enhancing the performance of the model.

PROPOSED METHODOLOGY

Proposed Framework

The proposed method intends to automatically detect and classify brain tumors from MRI images by employing a deep learning-based approach. The proposed framework for the classification process consists of four major steps: MRI data acquisition, preprocessing, feature extraction by employing a Convolutional Neural Network (CNN), and classification. The framework is aimed at learning discriminative spatial features from MRI images to classify brain tumors accurately (Figures 1 & 2).

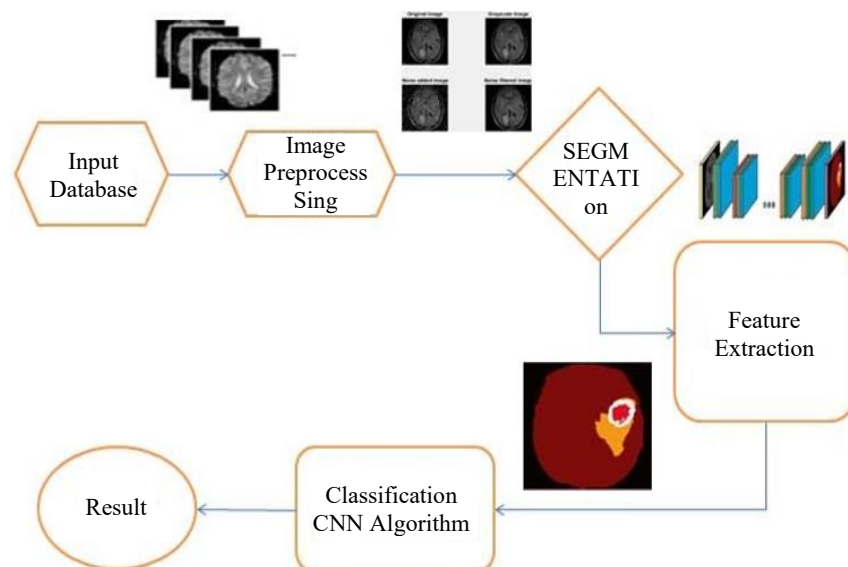


Figure 1. CNN-based framework for brain tumor detection and classification from MRI images.

Model Architecture

The fundamental idea of the proposed framework is based on a CNN structure for MRI image classification. CNN is a good approach for medical image classification due to its ability to learn local spatial hierarchies and represent features in images. The structure of the proposed CNN includes multiple convolutional layers with activation and pooling functions following each convolutional layer. The convolutional layers of the CNN aim to learn the image features from the MRI images, starting from low-level features such as edges and texture in the first layers and progressing to higher-level features such as tumor shape and structural features in the deeper layers [16]. The Rectified Linear Unit (ReLU) activation functions are used to introduce non-linearity in the model, thus aiding the model in

achieving better convergence rates. Max pooling layers are also incorporated into the model to reduce the spatial dimensions and hence the complexity of the model. The inclusion of pooling also aids in achieving translation invariance, where the tumor can occur at different locations in the images obtained from the MRI scans. Once the features are extracted, the feature maps are flattened and passed through several fully connected layers, where the features are integrated to arrive at a conclusion for the classification.

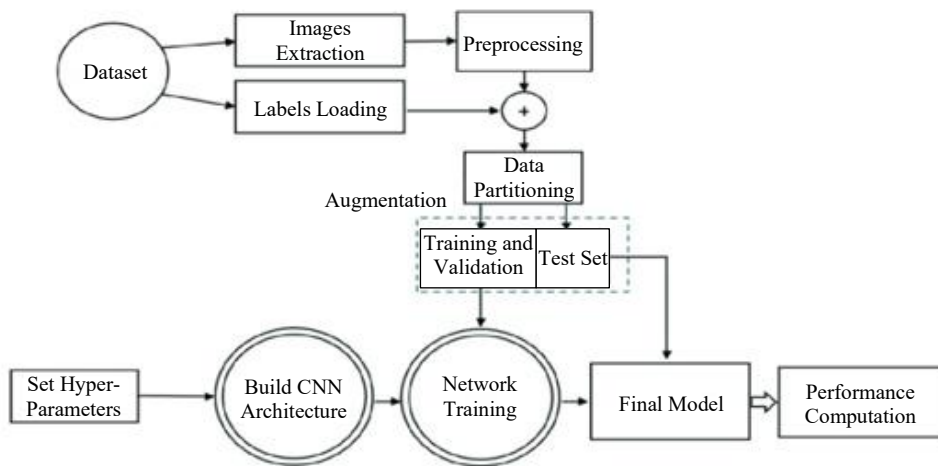


Figure 2. Block diagram of the proposed deep learning-based framework for brain tumor detection and classification using MRI images.

Training Strategy

The CNN model uses supervised learning to train on labeled MRI images. Categorical cross entropy loss is used to calculate the error between the predicted labels and the actual labels. Adaptive optimization is used to optimize the parameters of the CNN model. Regularization methods – such as dropout – are implemented in the fully connected layers to prevent overtraining. The performance of the CNN model is checked on a validation set. Early stopping is implemented to prevent overtraining once convergence is reached [17].

Classification Output

The result of the proposed model is a probability distribution over a set of predefined classes related to tumors. The class that has the maximum probability is considered as a predicted label. This framework of automated classification can be effectively used to identify the locations of brain tumors in MRI images.

Algorithm 1: Brain Tumor Detection and Classification Using Deep Learning

Input

- MRI image dataset $D = \{I_1, I_2, \dots, I_n\}$.
- Corresponding class labels $L = \{l_1, l_2, \dots, l_n\}$.

Output

Trained CNN model M .

Predicted tumor class for test MRI images.

1. Load MRI Dataset D and label L .
2. D preprocessing, $D, D \leftarrow \text{preprocess}(d)$ // normalization, resizing, noise removal.
3. Partition D in training, validation and testing sets.
4. Introduce the CNN Architecture // convolution, pooling, fully connected, softmax layers.
5. For each epoch do

6. Extract features using CNN layers
7. Calculate Classification Loss
8. Update network weights using backpropagation
9. Validate the Model Using the Validation Set
10. End For
11. Evaluate the trained model M on test dataset
12. Compute performance metrics
13. Output predicted brain tumor class labels (Figure 3).

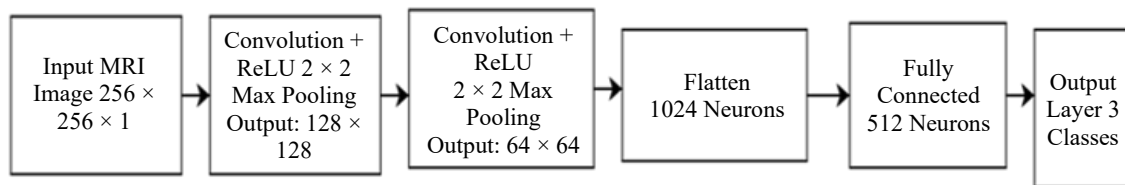


Figure 3. CNN architecture is used for brain tumor detection and classification from MRI images.

Although the MRI images are not visually represented in the manuscript, all experiments were performed directly on the digital MRI images using a CNN image processing pipeline. The MRI image was converted into a numerical image matrix and represented by a two-dimensional pixel intensity array. To achieve consistency among different MRI scans and image acquisition devices, the images were resized to a fixed resolution of 256×256 pixels and normalized by Z-score standardization. The preprocessed MRI images were then used to feed into the CNN model as input tensors of size $256 \times 256 \times 1$, where the single channel represents the gray scale intensity values. The CNN model was used to perform hierarchical feature extraction using a series of convolutional and pooling layers. The initial layers of the CNN model extracted low-level features, including edges and textures, while the deeper layers learned higher-level features, including tumor shape, boundary, and texture features. The deep features extracted from the CNN model were then used to perform a series of fully connected layers to produce the final tumor class label [18, 19].

EXPERIMENTAL SETUP

Dataset Partitioning

The data set was split into three disjoint sets: training, validation, and testing. The training set was employed for learning the parameters of the model, the validation set was employed for tuning the hyperparameters and monitoring the convergence of the model, and the test set was employed for the performance evaluation and assessment of the generalization capability of the suggested model [20]. A standard data split ratio was employed in the current study, where 70% were employed for training, 15% for validation, and 15% for testing. Data augmentation was employed for the training set.

Implementation Details and Hyperparameters

The proposed CNN model has been implemented using a deep learning framework. It has been trained using a workstation with GPU acceleration. The proposed CNN model has been trained using a supervised learning approach. Categorical cross-entropy has been used as the loss function. Efficient weight optimization has been achieved using the Adam optimizer. The hyperparameters have been chosen empirically to ensure the stable training of the model. The learning rate has been set to 0.001. Mini-batch training has been conducted with a batch size of 32. The model has been trained for 50 epochs. Early stopping has been conducted to avoid overfitting and to prevent the model from being trained unnecessarily [21, 22].

Dropout regularization has been conducted to avoid overfitting in the proposed CNN model.

Evaluation Metrics

The performance of the proposed framework for brain tumor detection and classification has been evaluated using classification metrics that are usually applied in medical image analysis tasks. The accuracy of the proposed system has been calculated as the ratio of the total number of instances correctly classified to the total number of instances in the dataset.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision was found by calculating the ratio of the number of correctly predicted positive instances to the total number of instances predicted as positive.

$$\text{Precision} = \frac{TP}{FP + TP} \quad (2)$$

Recall (Sensitivity) was computed as the number of correct predicted positive instances divided by the total number of actual positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

The F1-score was calculated based on the harmonic mean of precision and recall. Moreover, the performance of the developed brain tumor detection and classification system was evaluated based on a confusion matrix, which gives a graphical representation of the classification results (Table 2).

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Table 2. Performance comparison of machine learning and deep learning models for brain tumor classification.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	85.4	83.9	82.5	83.2
K-NN	88.1	86.7	85.2	85.9
CNN (Proposed)	94.6	94.1	93.8	93.9

Table 2 shows a performance comparison between conventional machine learning classifiers and the developed CNN-based classifier. As seen from Table 2, the developed CNN-based classifier outperformed conventional classifiers – such as SVM and k-NN classifiers – in terms of all performance metrics. This proves the capability of the CNN model in learning features from brain tumor images (Figure 4).

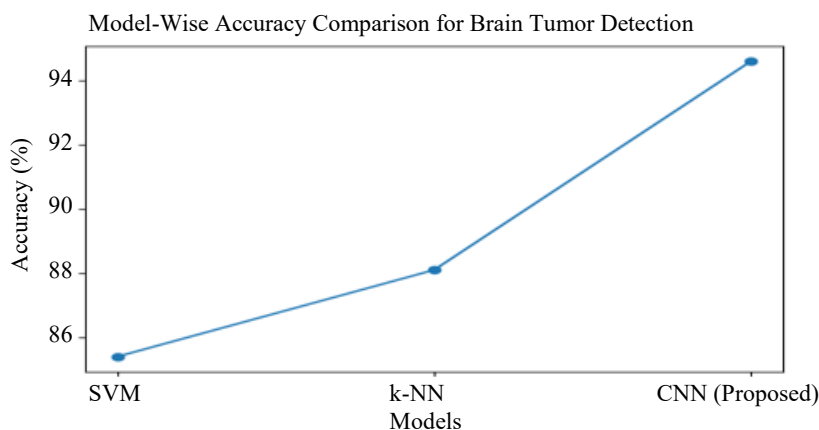


Figure 4. Model-wise accuracy comparison for brain tumor detection.

Figure 4 shows the model-wise accuracy comparison chart for brain tumor detection using various classification models. The results show that the proposed CNN model obtained the highest classification accuracy of 94.6 percent compared to traditional machine learning models such as SVM and k-NN. The accuracy obtained by the SVM model was 85.4 percent, and the accuracy obtained by the k-NN model was 88.1 percent [23, 24]. While the traditional models gave satisfactory results, their performance was restricted due to the reliance on traditional handcrafted feature extraction techniques. On the contrary, the CNN model learned features directly from the MRI images. This helped the model to learn complex features in the brain tumor images. The improved classification accuracy demonstrates the efficacy of feature learning using deep learning techniques over traditional machine learning techniques and confirms the reliability of the proposed CNN model [25–27].

Statistical Significance Analysis

To confirm the improvement in classification performance of the proposed CNN model, a statistical significance test was carried out by comparing the classification performance of the proposed CNN model with other traditional classification models of machine learning algorithms. This was done based on certain classification performance parameters, such as accuracy, precision, recall, and F1-score, which were calculated from the test data [28].

The improvement in classification performance parameters of the proposed CNN model shows that the improvement is significant and not due to any other factors or fluctuations in the performance parameters of the classification models. This is clear from the classification performance of the proposed CNN model and other traditional classification models such as SVM and k-NN [29, 30]. To further validate the reliability of the proposed model, several experiments have been conducted. In all the experiments, the classification metrics of the proposed CNN model have been found to be higher than those of the traditional machine learning classifiers.

RESULTS AND DISCUSSION

In this section, the experimental results of the suggested deep learning-based approach to brain tumor detection and classification will be discussed. The efficiency of the suggested CNN model will be evaluated compared to traditional machine learning classifiers.

Experimental Observations

The CNN model also demonstrated stable convergence during training. This indicated that the choice of architecture and parameters for the model was appropriate for the given classification task. The data augmentation process also contributed to the robustness of the model by helping the network classify the tumor's spatial changes. Moreover, the validation-based monitoring process helped to prevent overfitting and ensured that the model generalized well for unseen MRI images.

Further analysis of the confusion matrix revealed that most classification errors were between visually similar tumor classes. This demonstrated the complexity of the classification problem rather than any failure in the model. However, the CNN model had high overall performance and thus proved to be reliable for brain tumor detection and classification.

DISCUSSION

From a clinical point of view, the proposed framework holds significant promise as a decision support system for radiologists, as it may help reduce clinical work and limit observer variability in the detection and classification of brain tumors. The high recall rates obtained by the proposed CNN-based framework are also very significant from a clinical point of view, as it reduces the chances of missing tumor detection cases. Based on experimental results and analysis, it can be concluded that the proposed approach for brain tumor detection and classification outperforms traditional machine learning approaches.

CONCLUSION

This paper proposed a framework for the detection and classification of brain tumors by utilizing deep learning. The proposed framework was based on an end-to-end CNN model that could directly learn hierarchical spatial features from MRI scans. These are highly important for brain tumor classification.

The experimental results and comparison with traditional machine learning classifiers, such as SVM and k-NN, indicated that the proposed CNN model outperformed the traditional classifiers in terms of accuracy, precision, recall, and F1-score. The better performance of the proposed approach could be attributed to the ability of deep learning models to automatically learn complex and discriminative image features. The robustness and reliability of the proposed framework were also indicated by the consistent performance. From the practical point of view, the suggested framework has tremendous potential for clinical decision support systems. For instance, the suggested framework may be helpful to radiologists in automating brain tumor detection and classification, thereby improving the accuracy and speed of diagnosis. For example, the high recall rate obtained in the suggested framework is significant from the practical point of view because it reduces false negatives in brain tumor detection.

The findings obtained from the current study validate the effectiveness of CNN-based deep learning models for brain tumor detection and classification using MRI images. The suggested framework is reliable and efficient in improving accuracy in brain imaging.

Future Scope

The proposed framework based on deep learning has several extensions that can be made in the future to improve its clinical utility and robustness. This includes the use of various MRI modes – such as T1, T2, FLAIR, and contrast-enhanced images – to improve the classification performance by considering various tumor features.

Moreover, the use of tumor segmentation as a preprocessing step for classification can be explored to improve the accuracy of tumor region detection. The proposed framework can be tested on a larger dataset to improve its robustness and generalization ability.

REFERENCES

1. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. *Commun ACM*. 2017;60(6):84–90.
2. Mahaur B, Mishra KK, Singh N. Improved Residual Network based on norm-preservation for visual recognition. *Neural Networks*. 2023 Jan 1;157:305-22.
3. Litjens G, Kooi T, Bejnordi BE, Setio AA, Ciompi F, Ghafoorian M, Van Der Laak JA, Van Ginneken B, Sánchez CI. A survey on deep learning in medical image analysis. *Medical image analysis*. 2017 Dec 1;42:60-88.
4. Noh H, Hong S, Han B. Learning deconvolution network for semantic segmentation. In *Proceedings of the IEEE international conference on computer vision 2015* (pp. 1520-1528).
5. Weng W, Zhu X. INet: convolutional networks for biomedical image segmentation. *IEEE Access* 9: 16591–16603 [Internet]. 2021.
6. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H. Brain tumor segmentation with deep neural networks. *Medical image analysis*. 2017 Jan 1;35:18-31.
7. Isensee F, Jaeger PF, Kohl SAA, Petersen J, Maier-Hein KH. nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation. *Nat Methods*. 2021;18(2):203–11.
8. Bashir-Gonbadi F, Khotanlou H. Brain tumor classification using deep convolutional autoencoder-based neural network: Multi-task approach. *Multimed Tools Appl*. 2021;80(13):19909–29.
9. Cheng J, Huang W, Cao S, Yang R, Yang W, Yun Z, Wang Z, Feng Q. Enhanced performance of brain tumor classification via tumor region augmentation and partition. *PloS one*. 2015 Oct 8;10(10):e0140381.

10. Bauer S, Wiest R, Nolte LP, Reyes M. A survey of MRI-based medical image analysis for brain tumor studies. *Phys Med Biol*. 2013;58(13):129.
11. Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE Trans Med Imaging*. 2016;35(5):1240–51.
12. Mahaur B, Mishra KK, Singh N. Improved Residual Network based on norm-preservation for visual recognition. *Neural Networks*. 2023 Jan 1;157:305-22.
13. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Pal C, Jodoin PM, Larochelle H. Brain tumor segmentation with deep neural networks. *Medical image analysis*. 2017 Jan 1;35:18-31.
14. Springenberg JT, Dosovitskiy A, Brox T, Riedmiller M. Striving for simplicity: The all convolutional net. *arXiv preprint arXiv:1412.6806*. 2014 Dec 21.
15. Huang G, Liu Z, Pleiss G, Van Der Maaten L, Weinberger KQ. Convolutional networks with dense connectivity. *IEEE Trans Pattern Anal Mach Intell*. 2019;44(12):8704–16.
16. Zhou T, Ruan S, Canu S. A review: Deep learning for medical image segmentation using multi-modality fusion. *Array*. 2019 Sep 1;3:100004.
17. Khan NM, Abraham N, Hon M. Transfer learning with intelligent training data selection for prediction of Alzheimer's disease. *IEEE Access*. 2019 Jun 3;7:72726-35.
18. Sahlol AT, Yousri D, Ewees AA, Al-Qaness MA, Damasevicius R, Elaziz MA. COVID-19 image classification using deep features and fractional-order marine predators algorithm. *Sci Rep*. 2020;10(1):15364.
19. Abdusalomov AB, Mukhiddinov M, Whangbo TK. Brain tumor detection based on deep learning approaches and magnetic resonance imaging. *Cancers (Basel)*. 2023;15(16):4172.
20. Akkus Z, Galimzianova A, Hoogi A, Rubin DL, Erickson BJ. Deep learning for brain MRI segmentation: State of the art and future directions. *J Digit Imaging*. 2017;30(4):449–59.
21. Khan MA, Ashraf I, Alhaisoni M, Damaševičius R, Scherer R, Rehman A, et al. Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists. *Diagnostics (Basel)*. 2020;10(8):565.
22. Gammoudi I, Ghazi R, Mahjoub MA. 3D brain tumor segmentation using modified U-Net architecture. In *2023 International Conference on Cyberworlds (CW) 2023 Oct 3 (pp. 9-15)*. IEEE.
23. Ahmad M, Abdullah M, Moon H, Han D. Plant disease detection in imbalanced datasets using efficient convolutional neural networks with stepwise transfer learning. *Ieee Access*. 2021 Oct 13;9:140565-80.
24. Dosovitskiy A. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*. 2020.
25. Margulan N, Nurtay M, Kissina M, Mira K, Ardak T, Tau A, et al. Brain tumor classification using deep convolutional neural networks. *Компьютерная оптика*. 2025;49(2):253–62.
26. Rehman A, Naz S, Razzak MI, Akram F, Imran M. A deep learning-based framework for automatic brain tumors classification using transfer learning. *Circuits Syst Signal Process*. 2020;39(2):757–75.
27. Saeedi S, Rezayi S, Keshavarz H, Niakan Kalhori SR. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. *BMC Med Inform Decis Mak*. 2023;23(1):16.
28. Talo M, Baloglu UB, Yıldırım Ö, Acharya UR. Application of deep transfer learning for automated brain abnormality classification using MR images. *Cognitive Systems Research*. 2019 May 1;54:176-88.
29. Seetha J, Raja SS. Brain tumor classification using convolutional neural networks. *Biomed Pharmacol J*. 2018;11(3):1457.
30. Joshi S, Shah R, Chandola Y, Uniyal V. Classification of brain MRI images using end-to-end trained AlexNet & end-to-end pre-trained MobileNet. *Int J Res Publ Rev*. 2024;5(7):205–18.