RESEARCH PAPER

MRI-based Brain Tumor Classification using Deep Learning Techniques

Kanaka Lakshmi K[1], Valli Rani P.[2], Sabitha CH[3], Divya Y.[4], Lakshmi Prasana M.[5], Dr. Ch Nooka Raju[6]

[1,2,3,4,5] Ramachandra College of Engineering, Eluru, Andhra Pradesh - 534007

[6] Department of Radiology, Centurion University of Technology and Management, Vizianagaram, Andhra Pradesh

Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

The magnetic resonance imaging (MRI) can be considered as a diagnostic tool used to detect the presence of neoplastic processes. Early diagnosis is very important because brain tumors can be fatal in case of a delay in the treatment. The former system of manual validation of the picture is subject to the skill of the person performing it, and hence, it requires greater accuracy. The idea behind our proposal is the convolutional neural networks (CNN) that apply the deep learning methods to develop a model that classifies common types of tumors. The purpose of this model is to make the process of diagnostics performed by neurologists and radiologists more accurate and efficient. The dataset comprises of 3264 real-time images of various individuals, including MRI images of three common categorized brain neoplasms: meningioma, glioma, and pituitary adenoma. After being trained on a large set of annotated images, the proposed model can be used to classify the MRI images presented into one of the three above categories.

Keywords: Convolutional neural networks (CNN), Magnetic resonance imaging (MRI), Deep learning, diagnostic, Dataset, Disease (brain tumor), medical imaging, cancer.

How to cite this article: Kanaka Lakshmi K, Valli Rani P, Sabitha CH, Divya Y, Lakshmi Prasana M, Nooka Raju C. MRI-based Brain Tumor Classification using Deep Learning Techniques. Int J Drug Deliv Technol. 2026;16(35s):359-374. DOI: 10.25258/ijddt.16.35s.41

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

Back to the Journal

1. Introduction

All the body cells reproduce themselves in a systematic process to ensure that the body is healthy and functioning properly. The cells which fail to control their growth replicate irregularly and in excess [5]. A tumor is a cluster of tissue which is a surplus of cells. Cerebral tumors can occur in different morphologies and sizes, appear in different locations, and have different intensities on the imageries-malignancies of the location within the brain. Nevertheless, the early detection of the brain tumor is important, and it can be done in a number of ways, such as biopsies, magnetic resonance imaging (MRI) [8]. MRI is mainly used in diagnosing brain tumors. central nervous system, such as brain tumors are ranked as the tenth major cause of mortality [6].

According to estimates made by the World Health Organization (WHO), about 4 million people in the world are infected with brain tumors, and in the recent past, the neoplasms have caused 1.2 million deaths. The cells in the human brain develop in an inappropriately high rate thus leading to the tumor in Brian. The differences are founded on age and gender [7]. The process involved in the identification of brain tumors is very difficult and complicated due to the shape and size of the tumor, the type of tumor and the fact that the tumor is detected through the MRI by measuring the difference between the white and black intensity. The photos of the tumor depict a solid white-colored tumor on the white block or pattern. Also, there is a part within the brain which possesses a similar intensity as the tumor cells. The photographs show a white block or pattern with a high level of brightness which represents the tumor [9]. Also, are within the brain have similar intensity as that of tumor cells. Incorrect diagnosis can occur in the classification of an MRI as benign or malignant that makes it necessary to use surgical methods and biopsies to provide additional explanation [10]. It is, therefore, important to identify the tumor among the other parts of the brain.

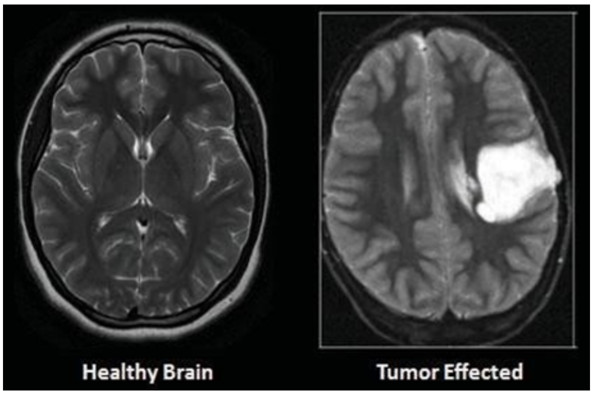

Fig. 1. Brain Tumor

The improvement in machine learning, particularly in the deep learning field, has led to the ability to identify and classify patterns in medical imaging [11]. The possibility of retrieving and mining information contained in data as opposed to depending on experts or scientific journals to learn is one of the achievements made in this area [12]. Machine learning is becoming an important tool to be used in various medical applications in a variety of fields [13]. These have been applied in predicting and detecting diseases, analyzing molecular and cellular structures, segmenting tissues, and classifying images. The current trends in image processing are convolutional neural networks (CNNs) due to their multi-layer structure and superiordiagnostic accuracy, primarily when the input picture count is huge [14]. Autoencoders refer to an unsupervised learning algorithm where neural networks are trained to learn how to encode data [15]. Deep learning (DL) and machine learning (ML)algorithms have been effectively employed to identify tumors, such as lung tumors, as well as identify cardiovascular stenosis [16]. Moreover, this paper highlights the development of a robust classification scheme of cerebral neoplasms through the use of state-of-the-art algorithms, including Adam optimization, two-dimensional Convolutional Neural Networks (CNN) [17], and CNN autoencoders. The project will help healthcare professionals make informed decisions by increasing the accuracy and reliability of brain tumor classification using the power of DL and conventional ML [18]. The paper is organized in a logical way; Section II briefly reviews the available literature, and Section III outlines the suggested framework including the Internet of Things (IoT) principles. The developments in software and hardware and the findings displayed in the section IV, and lastly the conclusions are positioned. They have been demonstrated to have a high level of diagnostic accuracy in terms of performance assessments.

2. Study Design

Gisella et al. [1], suggested a CNN model with a head that used ResNet50 architecture and a seven-layer convolutional network. During the test, this model was accurate and precise by 92 and 94 percent respectively. The project is aimed at applying deep learning algorithms to MRI scan to reach the exact diagnosis and treatment of brain tumors in patients. This study limitation does not provide any information on the specific categories of brain neoplasms that were included in the data that could be relevant to the external validity of the model to different tumor classifications. the possible biases or limitations of the data collection process, including these lection criteria on patients or the quality of the manual anomaly segmentation masks. Fails to investigate the interpretability of the deep learning model, which is significant to the learning of the features or patterns that lead to classification of brain tumors. Manish K. Aryaetal. In this study, a neural network called sanEfficient NetB7 is used to identify the presence of brain cancers using MRI scans with high accuracy. Levenberg-Marquardt algorithm is an extremely efficient method of non linear curve fitting. The majority of the limitations of the model are related to the fact that the training and testing datasets should be more diverse and this might restrict the applicability of the findings. The article fails to give the information concerning the extent of the used dataset, which might have an impact on the credibility of the results. The computational resources needed to execute the proposed methods are not mentioned in the paper which may become a limitation to practical applications. Afshar P, Mohammadiet.al.[3] DL algorithms are suggested to classify brain tumors according to an open data set, to differentiate between benign and malignant brain tumors. Thesuggestedframeworkachievesanimpressiveaccu racyof96.65. The categorization of brain tumors was done using Magnetic Resonance Imaging (MRI) data. The MR image dataset of brain tumor was sorted into malignant and benign slices to be analyzed. The weaknesses are that the study used a relatively small dataset to train and test the deep learning models, which could restrict the extrapolation of the findings. The paper lacks specifics on the pre-processing and augmentation methods employed, and this can lead to a decrease in the reproducibility of the study.

Sérgio Pereiraetal. [4], To detect the brain cancer, the researchers employed the pre-trained deep CNN models on the transfer learning methodology to learn characteristics on the brain MRI data. The paper is dedicated to the creation of the machine learning model to identify and classify brain tumors automatically with the help of CT or MRI scan. It is aimed at facilitating clinical diagnosis and availing medical practitioners with reliable means of diagnosing tumors to enable them offer the appropriate medicine to a patient. The study makes use of deep CNN architecture, namely theVGG16 architecture, which was trained using transfer learning to learn the features of the brain MRI data. The study limitations are not related to the dataset on which the machine learning model is trained and evaluated and this could affect the generalizability of the results. The lack of the comparison with the other existing models or ways of identifying brain cancer does not allow us to compare the efficiency of the proposed model and other techniques. The research is about brain tumors detection with the CT or MRI scans but it does not say the difficulties or limitations involved in other imaging modalities or techniques that can be applied in clinics.

3. Proposed Design

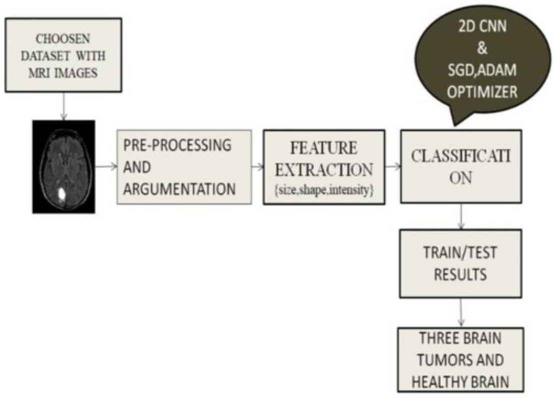

Fig. 2. Work flow diagram

A total of 3264 T1-weighted and contrast-enhanced magnetic resonance imaging (MRI) scans were used in this investigation. The data was divided into four groups of different images (glioma (926 images), meningioma (937 images), pituitary gland neoplasm (901 images), and normal brain (500 images). The pictures were obtained in sagittal, axial and coronal orientation. Convertinginputimageof1024*1024into150*150.UsinganImageEnhancementandImageSegmentation.

At the training stage, the model gradually works with batches of training examples, finds the loss corresponding to each batch and then modifies the parameters by using the Stochastic Gradient Descent (SGD). This process is repeated a certain number of times or until the required convergence criteria are achieved. When the training and the assessment of the model are completed, the efficacy of the model is estimated with regards to the performance on the test dataset, including the unseen instances that were not used in the course of the training process or evaluation. The model is used to make predictions on the testing set and performance measures are measured to test the ability of the model to generalize and determine how well it works to identify brain tumors in new and unseen MRI images.

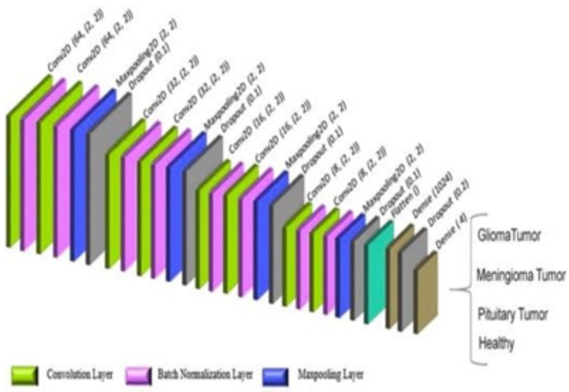

Fig. 3. Classification

Totallayers;16layers batch size. Input takes an image input size of 150 by150. The convolutional layer employs 2 by 2 filter and astride size of 1 and is preceded by relu unit which is rectified linear unit activation function fully connected layers where the first and second layers have channels and the third layers have channels,1perclass. Another technique of down sampling that is frequently applied in CNNs is called maxpooling and is used to shrink the spatial size of an input volume.

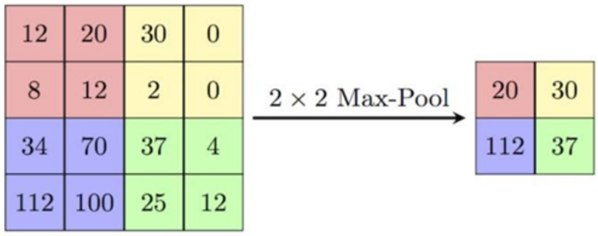

Fig. 4. Max pooling

Neurons between two distinct layers are linked together with a dense layer. It contains weights, biases and neurons. As a rule, these levels are placed in front of the output layer and are the final few layers of a convolutional neural network (CNN) architecture.

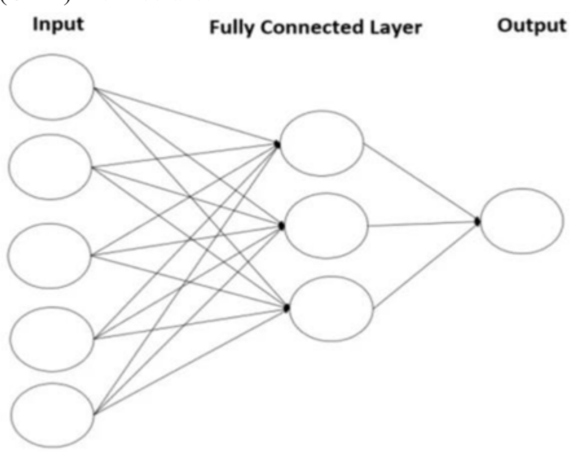

Fig. 5. Fully Connected Layer

The Dropout Layer is a regularization technique applied in CNN (as well as other deep learning models) to address the issue of overfitting. Over fitting is a situation where a model does extremely well on training data but does not perform well when using new unknown data.

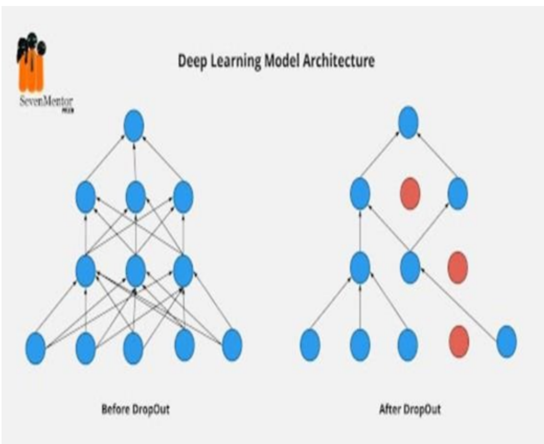

Fig. 6. Dropout Layer

The convolutional and pooling layers in CNN designs are usually followed with the flattened layer.

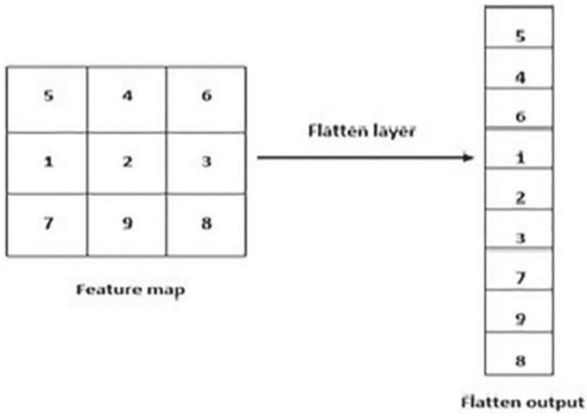

Fig. 7. Flatten Layer

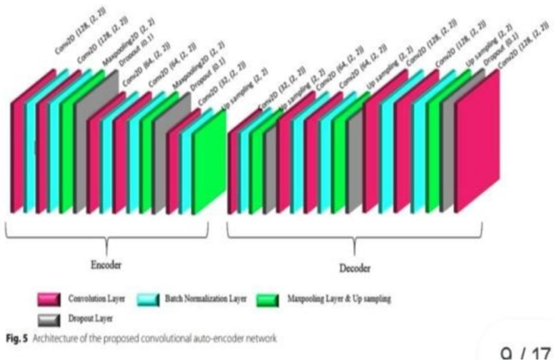

Fig. 8. Flatten Layer

The data set was trained and categorized by an auto-encoder network rather than produces input photos. In this study, network architecture was devised that had two main components. The former section involved convolutional auto-encoder architecture to train data, and the second section involved convolutional network assigned to classification assignments. This network uses the final output encoder layer as a result of the first part. In detection of brain tumor, the use of SGD assists in training CNN to adequately learn the underlying patterns and features found in MRI images of brain tumors. SGD can be used to reduce the loss function by using an iterative optimization to segment and detect tumors in previously unseen MRI scans.

3. Results and Discussion

Stochastic Gradient Descent (SGD) is a commonly used optimization tool in machine learning and deep learning, which is due to its simplicity and effectiveness.

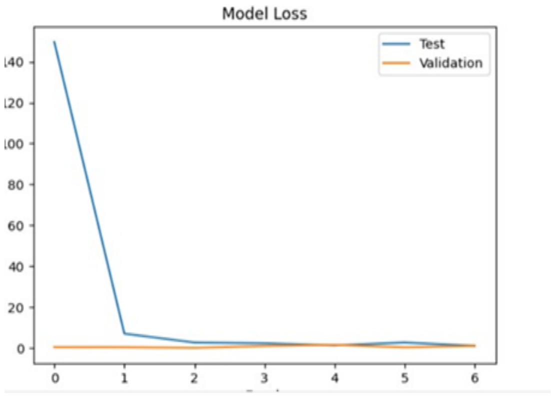

Fig. 9. Flatten Layer

The graph shows how the model loss changes over epochs with a brain tumor classification task with the blue line indicating test data loss and the orange line indicating validation data loss. The test and validation loss are fairly low at this 10 th epoch, at 1.0499 and 2.157, respectively, which signifies the increased accuracy of prediction in terms of brain tumor classification. The reduction in the loss is an indication of the improved capacity of the model to distinguish between the types of tumors with increasing the level of training.

Fig. 10. Flatten Layer

The image presents the outcome of a brain tumor classification project where an MRI scan is presented as well as a prediction output. The model anticipates that the brain tumor is present with a confidence of 96.1% with a specific classification of a glioma tumor. This is the last result of the project, which reflects the inference of the model at the end of 10 epochs.

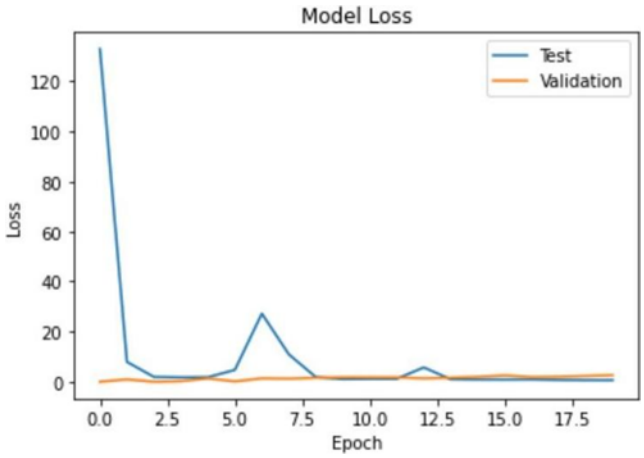

Fig. 11. Flatten Layer

The picture demonstrates the outcome of a brain tumor classification project, during which an MRI scan is presented, and the prediction output is shown. The model is able to give a brain tumor the 96.1 percent confidence that the model predicts the presence of the brain tumor, in particular, as a glioma tumor. This is the last result of the project and it shows the inference of the model at the end of 10 training epochs.

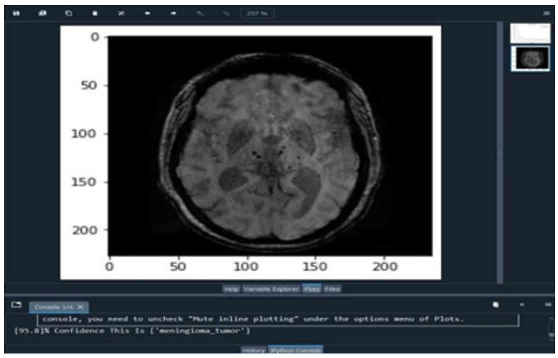

Fig. 12. Flatten Layer

The picture demonstrates the output of brain tumor classification project, where an MRI scan is shown together with the prediction output. The model confirms the existence of a brain tumor with a 95.8 percent level of confidence and the type of tumor is a meningioma tumor. This is the last output of the project, which is a reflection of the inference of the model once 15 epochs are completed.

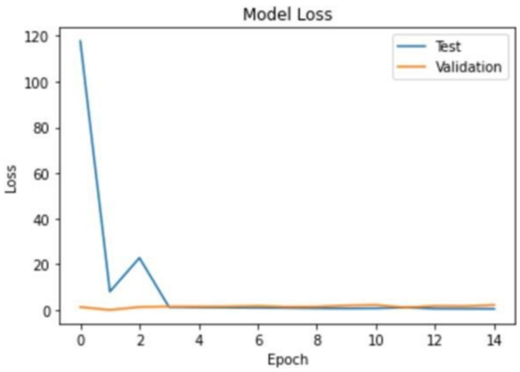

Fig. 13. Flatten Layer

The picture shows the output of a brain tumor classification project where a MRI scan is shown along with the expected output. The model estimates the existence of a brain tumor with a likelihood of 95.8 per cent and the type of tumor is a meningioma tumor. This is the end result of the project and the inference of the model once 15 training epochs are made.

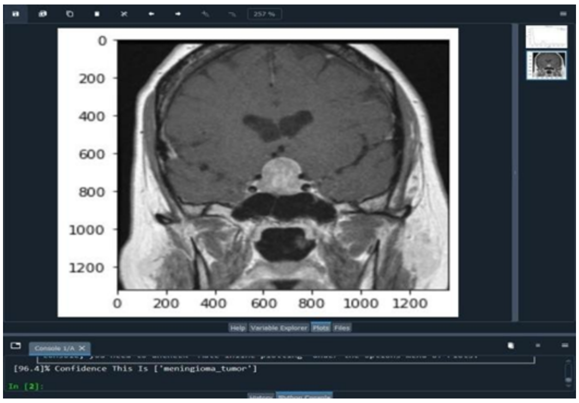

Fig. 14. Flatten Layer

The picture demonstrates the output of the brain tumor classification project, where an MRI scan is presented in the image and the prediction is shown. The model assumes that there is a brain tumor with a 96.4 percent accuracy that it is a tumor - meningioma one. This is a summation of the final findings of the project and it shows the inference made by the model at the end of 20 epochs. In the graph, the progression of the model loss over the epochs in a brain tumor classification task is shown, where the blue and orange lines show the test and validation data loss, respectively. Both the test and validation loss are relatively low at the 50 th epoch, which is at 0.1199 and 8.3049 respectively, indicating better accuracy in the categorization of brain tumors. The declining pattern of the loss is indicative of the improved differentiation capability of the model as they progress in training the tumor types.

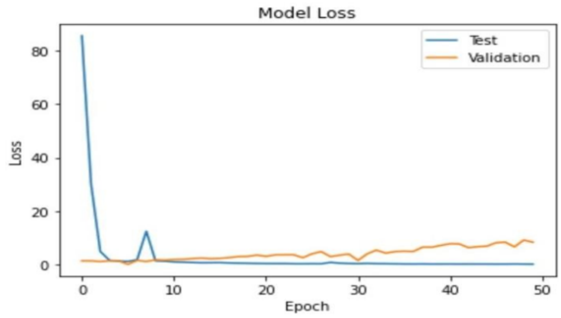

Fig. 15. Flatten Layer

The picture presents the outcome of a brain tumour classification project and an MRI scan is presented with the output of prediction. The model estimates the existence of a brain tumour with 95.81 percent accuracy and it is a pituitary tumor. This is the final result of the project, which indicates the inference of the model at the 50th epoch.

Fig. 16. Flatten Layer

The graph shows the loss dynamics of the model on a per-epoch basis in a brain tumor classification problem, where the blue line shows the test data loss and the orange line indicates the validation data loss. By the 100 th epoch, both the test and the validation losses are quite low, approximately 0.1132 and 7.3525 respectively, hence there is better accuracy in classifying brain tumors. The decline in loss indicates the increased differentiation capacity of the model towards accurate classification of tumor types with increasing training.

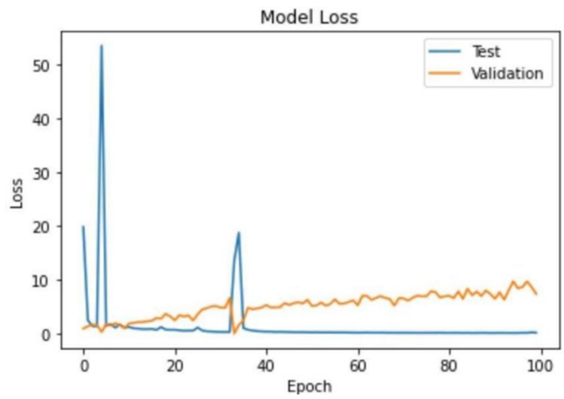

Fig. 17. Flatten Layer

Fig. 18. Flatten Layer

The picture represents the output of the brain tumour classification project, where an MRI scan is presented next to the prediction output. The model can predict the existence of a brain tumour with 96.4% confidence, in this case, it represents a glioma tumor. This is the final end result of the project and it shows the inference of the model upon the completion of 100 epochs.

Table No. 1 Comparison table of proposed models

ECHOPS	TESTACCURACY	STEP-LOSS
10	96.1	1.0499
15	95.8	0.7277
20	96.4	0.6957
50	95.4	0.1199
100	96.4	0.1132

4. Conclusion

Machine learning and artificial intelligence have wide application in the healthcare industry. Currently, there is an endeavor to design and develop deep networks that would detect illnesses by analyzing medical images. We have suggested to do this through the use of computational-based methods in brain tumor classification. Using CNNs, which are effective at detecting the complex patterns and features of complex data like MRI images, the rate of adaptive learning and momentum optimization through the Adam optimizer, we have developed a strong model that can effectively classify various types of brain tumors. By using CNNs, medical images can be analyzed automatically and quickly, which helps to relieve healthcare professionals and potentially make a diagnosis and treatment decision faster. The CNN model suggested presented an accuracy of 96.4 and 96.1 at the evaluation stage, which proves its usefulness in the brain tumor detection task. These values are also increased by applying different parameters in the creation of the neural network.

5. Conflict of interest

No

6. References

[1] Gisella Luisa Elena Maquen-Niño and Gilberto Carrión-Barco, "Brain Tumour Classification Deep Learning Model Using Neural Networks," International Journal of Online Engineering, vol. 19, no. 09, pp. 81–92, Jul. 2023.

[2] Manish K. Arya and Rajeev Agrawal, "Brain Tumour Classification Using Deep CNN-Based Transfer Learning Approach," International Journal of Biology and Biomedical Engineering, vol. 17, pp. 1–7, Mar. 2023.

[3] P. Afshar, A. Mohammadi, and K. N. Plataniotis, "Brain Tumor Type Classification via Capsule Networks," in Proceedings of the 25th IEEE International Conference on Image Processing (ICIP), 2018, pp. 3129–3133.

[4] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240–1251, Mar. 2016.

[5] D. M. Greeshma, S. Chalasani, S. T. Sriya, S. B. Ratnam, and S. Sana, "Azolla Crop Growing Through IoT by Using ARM Cortex-M0," in Proceedings of the 3rd International Conference on Artificial Intelligence and Signal Processing (AISP), Vijayawada, India, 2023, pp. 1–5. doi:10.1109/AISP57993.2023.1013503.

[6] G. Litjens, T. Kooi, B. Ehteshami Bejnordi, A. A. A. Setio, et al., "A Survey on Deep Learning in Medical Image Analysis," Medical Image Analysis, vol. 42, pp. 60–88, 2017.

[7] M. M. Badža and M. Č. Barjaktarović, "Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network," Applied Sciences, vol. 10, no. 6, pp. 1–9, 2020.

[8] M. K. Abd-Ellah, A. I. Awad, A. A. M.

Khalaf, and H. F. A. Hamed, “Two-Phase Multi-Model Automatic Brain Tumour Diagnosis System from Magnetic Resonance Images Using Convolutional Neural Networks,” EURASIP Journal on Image and Video Processing, vol. 2018, no. 1, pp. 97–104, 2018.

[9] Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, “A Deep Learning-Based Framework for Automatic Brain Tumors \
Classification Using Transfer Learning,” Circuits, Systems, and Signal Processing, vol. 39, no. 2, pp. 757–775, 2020.

[10] Gumaei, M. M. Hassan, M. R. Hassan, A. Alelaiwi, and G. Fortino, “A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification,” IEEE Access, 2019.