BRAIN-O-VISION: BRAIN TUMOR DETECTION

Angelin Claret S.P.[1], Swati Datta[2], and Ish Kwatra[3]

[1] Department of Computational Intelligence, Faculty of Engineering and Technology
School of Computing, SRM Institute of Science and Technology,
Kattankulathur, Chengalpattu,
Tamil Nadu, India
Email id : angelins@srmist.edu.in

[2] Department of Computational Intelligence
School of Computing, SRM Institute of Science and Technology,
Kattankulathur, Chengalpattu,
Tamil Nadu, India
Email id : swati.datta2001@gmail.com

[3] Department of Computational Intelligence
School of Computing, SRM Institute of Science and Technology,
Kattankulathur, Chengalpattu,
Tamil Nadu, India
Email id : ishkwatra@gmail.com

Abstract. Timely intervention and better patient outcomes are dependent on early brain tumor identification. Even if they work well, conventional diagnostic techniques may have drawbacks including subjectivity and laborious analysis. As a result, sophisticated methods utilizing deep learning neural networks have surfaced as viable options for precise and automated brain tumor identification. This study, which employed MRI scans to identify brain tumors, was developed and evaluated and a comparitive analysis was drawn. The objective is to use 4 methods namely, MobileNetV2, EfficientNet, ResNet50 and VGG16 for the comparitive analysis and select the one which gives highest accuracy. We address the need for more advanced diagnostic techniques by automatically extracting pertinent characteristics from MRI scans and making accurate predictions using deep learning and Grad-Cam segmentation. Our approach entails preprocessing MRI data, convolutional neural network (CNN) architecture design, and model training and assessment with a carefully selected dataset. Our methodology is successful, as seen by the accuracies such as MobileNetV2 at 86%, EfficientNet at 84%, ResNet50 at 80%, VGG16 at 88%. The Grad-Cam segmentation performed at the final stage provides a clearer image in identifying the presence of tumor. All things considered, this study advances the area of medical image analysis and emphasizes how critical it is to use MRI and deep learning to combat brain cancers.

Keywords: Brain tumor, deep learning algorithms, MRI scans, image processing, convolutional neural networks, tensorflow.

1 Introduction

Brain tumors are a serious health issue that impact a lot of people all around the world. Between 85% and 90% of all primary central nervous system (CNS) tumors are of this kind; 308,102 cases are anticipated to be diagnosed with them annually worldwide. Given that the kind and grade of brain tumors can significantly affect survival rates, early diagnosis is essential for both successful treatment and better patient outcomes. However, because brain tumors can present with a variety of symptoms and require early discovery in order to allow for appropriate management, identifying them can be difficult.

Conventional approaches to brain tumor diagnosis, such as depending on radiologists to manually interpret MRI results, have a number of shortcomings. These include taking a lot of time, being prone to human mistake, and being interpreted biasedly. This highlights the requirement for advanced, automated techniques to improve the precision and efficiency of brain tumor diagnosis, especially when the lesions are small or located in intricate anatomical areas. In this context, integrating deep learning into medical picture analysis shows promise since it can provide extremely accurate predictions and automatically extract relevant characteristics from large datasets.

We have used deep learning techniques—especially those that use neural networks—have demonstrated in a variety of rehabilitative imaging tasks, such recognizing and classifying brain tumors. the role that deep learning plays in enhancing the efficacy of current symptomatic approaches and promoting the development of more reliable and flexible setups for brain tumor location. The purpose of our research is to create and assess a method that uses deep learning for identifying brain malignancies via magnetic resonance imaging (MRI). The four algorithms choosen finds out the smallest parts in the picture of brain and segments that part which consists of any tumor or not. Grad-Cam segmentation highlights very accurately those specific parts of the brain and helps to find brain tumors, including improved tumor morphology visualization, injury location, and differentiation between healthy and dangerous tissues.

2 Related Works

The literature review section provides a thorough analysis of previous studies relevant to the subject of brain tumor identification using deep learning methods in combination with MRI. In order to expand knowledge of the subject, this section attempts to shed light on the several study designs and approaches used in this industry. It includes a review of research that use traditional techniques, such as radiologists manually interpreting MRI data to detect brain tumors, and it points out both the advantages and disadvantages of these approaches. The limitations of these methods are emphasized, highlighting the need for more automated and accurate methods. The study also includes research that use MRI to identify brain tumors using deep learning methods, namely neural networks.

The designs and methodology used in these investigations, including the kinds of neural networks used (convolutional and recurrent neural networks, for example), as well as any particular adjustments or improvements made for the purpose of brain tumor identification, are described in detail. First we need to draw attention to the performance measures—such as area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and accuracy—that have been reported in these investigations. Next give a summary of the datasets used in earlier research on MRI and deep learning-based brain tumor identification. Then give an overview of these dataset's features, such as the quantity of MRI images, the kinds of tumors they contain, and any corresponding ground truth labels.

We need to talk about the difficulties and restrictions these datasets present, such as the lack of variety, class imbalance, and variable tumor features. Finally determine the common issues and restrictions that deep learning-based methods for MRI-based brain tumor identification have been shown to have in the literature. There are problems including overfitting, generalizing to unknown data, the interpretability of model predictions, class imbalance and the requirement for strong validation techniques. There are recent advancements and patterns in the detection of brain cancers using MRI and deep learning, such as the use of transfer learning, the integration of multi-modal imaging, and the creation of federated learning strategies. Many new avenues for study and innovation, such as the use of attention mechanisms for feature extraction and the usage of generative adversarial networks for data augmentation have come to picture. The accuracies obtained in past works seem to be low. Current transfer learning techniques, such as RESNET-100, VGGNET, Google-Net, AlexNet, etc., are used to identify brain tumors which are complex algorithms and hence find difficulty in providing more accuracies. Table I provides a summary of the many deep-learning strategies that the researchers have previously employed.

Table 1. Several deep-learning techniques used by the researchers in the past

Reference	Methodology	Algorithms	Accuracy
Nyoman Abiwinanda et al. [1].	Convolutional Neural Network	Deep CNN	84.20%

Yun Jiang et al. [2]	CNN-based multiscale threshold pattern approaches	CNN technique	86.30%
Dongnan Liu et al. [3]	Processing of multi-dimensional picture data	Deep CNN	86.50%
Yakub Bhanothu et. al. [4]	CNN detection and classification	CNN technique	77.6%

With the latest advancements in technology, tumor analysis is now possible with 3D scanning. Classification and identification of brain tumors using 3D image processing. A selection of 3D-based techniques is provided in Table II.

Table 2. Various 3D deep-learning techniques used by the researchers in the past

Reference	Methodology	Algorithms	Accuracy
Tuhin, Md. Akram Hossan et al. [6]	3D MRI, MRSI, and CT images	CNN together with three dimensions NBC	85.005%
Yong Xia and Yan Hu [7]	DCNN	Three-dimensional deep neural network	81.4%

3 Proposed Methods

The origin, size, and makeup of the dataset used in this study are all explained in detail. It consists of anatomic coverage and various resolutions of magnetic resonance imaging (MRI) images, including T1-weighted, T2-weighted, and FLAIR imaging modalities. The collection includes brain tumors of various histological grades and classifications. The dataset was divided into training (Fig. 1), and validation sets to guarantee an impartial assessment. The MRI data underwent preprocessing procedures, such as data augmentation, rescaling, image resizing, grey scale conversion and guassian blurring before to being fed into the deep learning model. Techniques for data augmentation, such random flips, zoom and rotations, were employed to enhance the training dataset's diversity. The architecture, including type (e.g., convolutional neural networks), particular layers (e.g., convolutional, pooling, fully connected), and activation functions, of the deep learning neural network that is employed to identify brain tumors is talked about. The model was adjusted architecturally for brain tumor identification by implementing regularization approaches and skip connections. An optimization method (like Adam), a learning rate schedule, and a loss function (like binary cross-entropy) were all used in the training process. In addition, information on early stopping criteria, epochs, and batch size was supplied in order to avoid overfitting during training. Describe the assessment measures that are used to gauge how well the deep learning model detects brain tumors performs. The area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and accuracy are among the primary metrics used. Describe any secondary metrics or qualitative evaluations (e.g., precision, recall, F1 score, visual examination of predicted tumor masks) that are utilized to offer further information about the performance of the model.

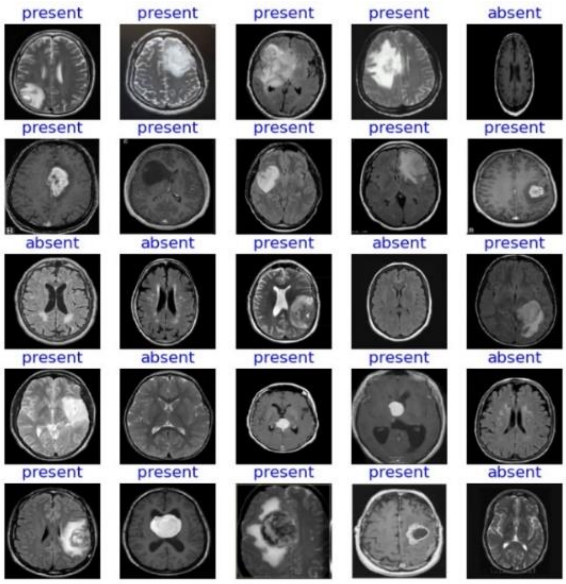

Fig. 1. Different kinds of brain tumors data set images used for the training of the model.

First we draw attention to the preprocessing part and check if there is any data imbalance. The preprocessing techniques are discussed before. Next we implement the models one by one. The four models used is MobileNetV2, EfficientNet, ResNet50 and VGG16. Then we compare performance analysis— such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC) —that have been reported in these investigations. A summary of the model used is also given. The model used is Sequential with dense and ReLu activation function. Finally we used Grad-Cam Segmentation for highlighting the tumor parts and set of examples taken to verify whether the model is working or not. Describe the software libraries and frameworks—such as TensorFlow, Matplotlib, or Keras—that were utilized to create the deep learning model. The 4 architechtures used here is MobileNetV2, EfficientNet, ResNet50 and VGG16. Give details on the GPU(s) or CPU(s) that were utilized in the training and inference hardware setup. Provide any other implementation information, such as code repositories, software versions, or hyperparameter values, that is necessary for replicating or expanding your study. The architecture diagrams of the 4 models: MobileNetV2, EfficientNet, ResNet50, and VGG16, respectively are as follows (Fig 2-5).

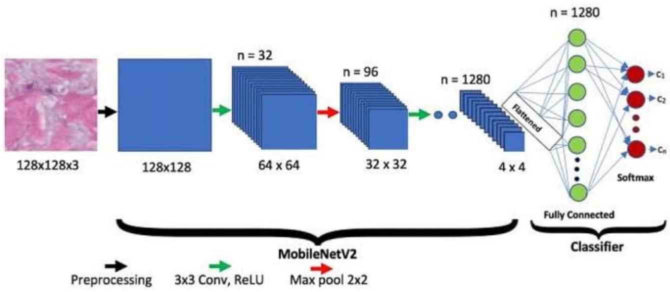

Fig. 2. MobileNetV2

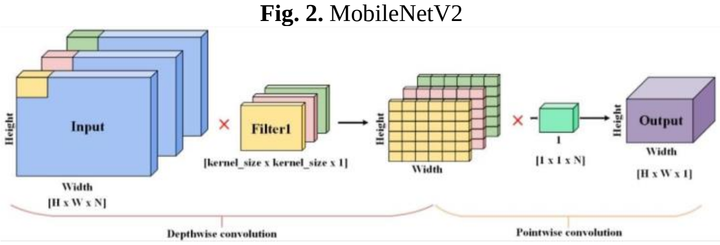

Fig. 3. EfficientNet

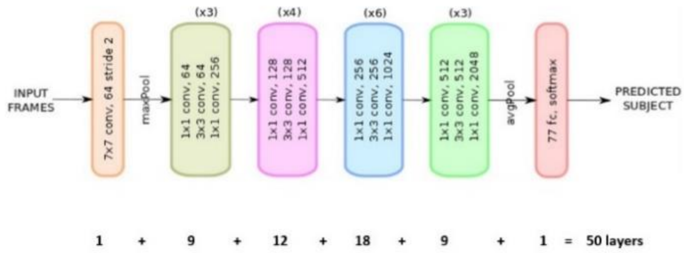

Fig. 4. RestNet50

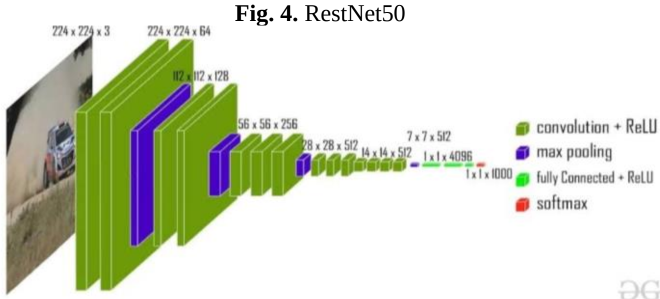

Fig. 5. VGG16

4 Experiments

The software libraries or frameworks used, such as TensorFlow or Keras, are specified along with specifications of the computer infrastructure, including the setup of GPU(s), CPU(s), and RAM. The setups or parameters specific to the experimental setup, such as the optimization approach, epoch count, batch size, and learning rate. the procedure that separated the dataset into training and validation sets so that the model could be evaluated. The percentages of data allotted to each group is training is 80% and validation is 20% for better model evaluation, eliminate overfitting and to provide sufficient data to both the sets. The training process's outcomes, including the training loss and any pertinent metrics (such accuracy and validation loss) were observed during training is depicted in Fig.6-9. To demonstrate the convergence and stability of the training process, we have provided graphs or visualizations that show the training curves over epochs. Utilized the proper assessment criteria, assess the trained deep learning model's performance on the test dataset. In order to assess each model and determine which has superior accuracy, we have also included an explanation of the primary evaluation metrics, which includes the area under the receiver operating characteristic curve (AUC), specificity, sensitivity, and accuracy. A numerical synopsis of the model's ability to identify brain tumors is given, along with any comparisons to industry standards or cutting-edge techniques. Hence, we found that VGG16 provided the maximum accuracy of 88.16% when compared. Next we used Grad-Cam segmentation and took few samples as input to check the working of it.

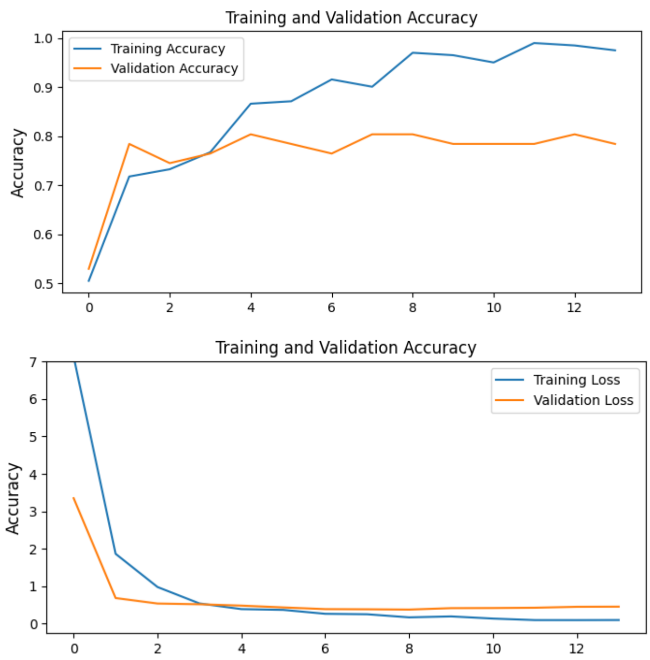

Fig 6. Accuracy of training and validation of MobileNetV2

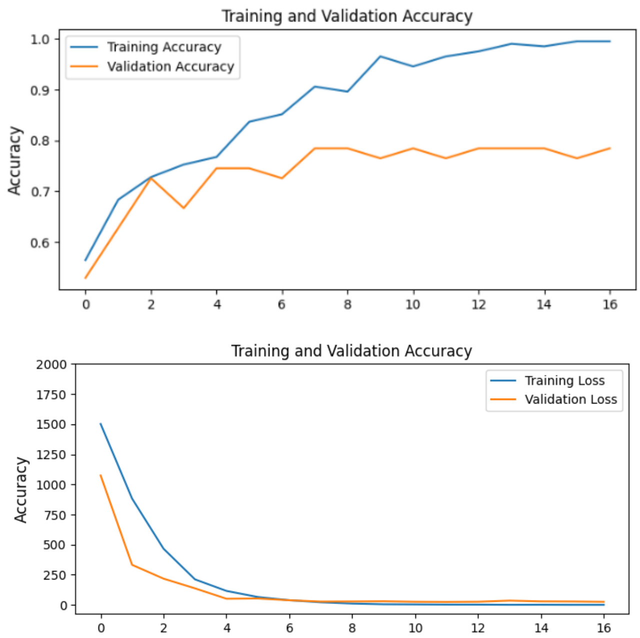

Fig 7. Accuracy of training and validation of EfficientNet

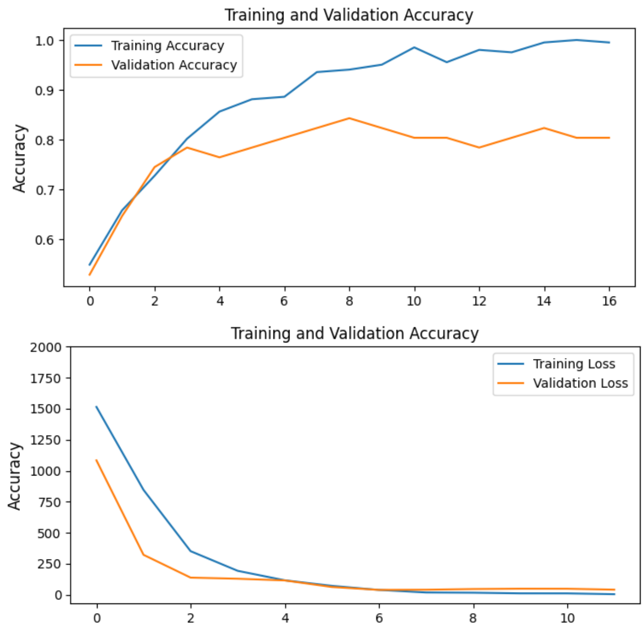

Fig 8. Accuracy of training and validation of ResNet50

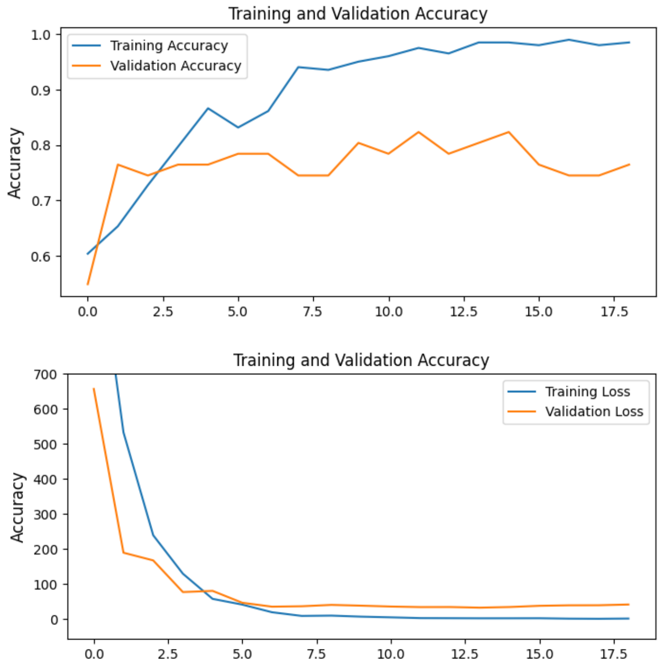

Fig 9. Accuracy of training and validation of VGG16

Incorporated qualitative evaluations of the model's performance, such as examining projected tumor masks superimposed on MRI pictures visually. The confusion matrix for the 4 architechtures are given below (Fig 10-13).

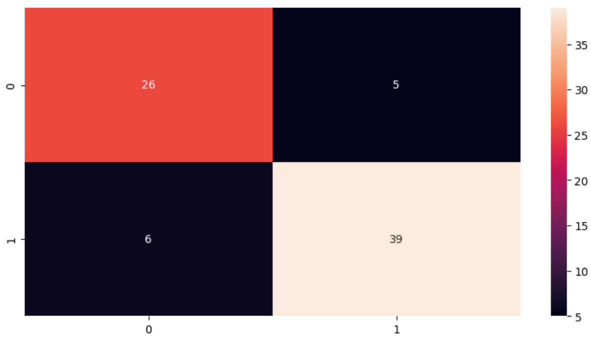

Fig. 10. Confusion Matrix of MobileNetV2

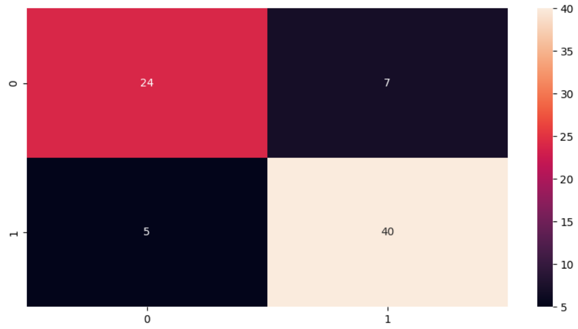

Fig. 11. Confusion Matrix of EfficientNet

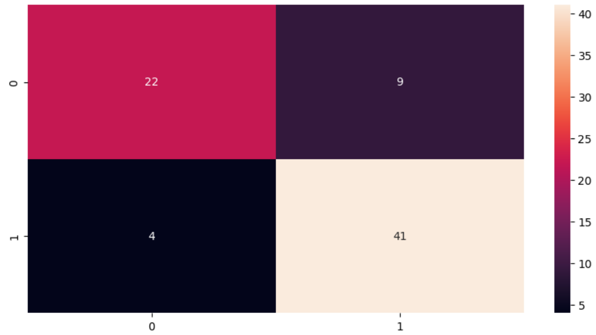

Fig. 12. Confusion Matrix of ResNet50

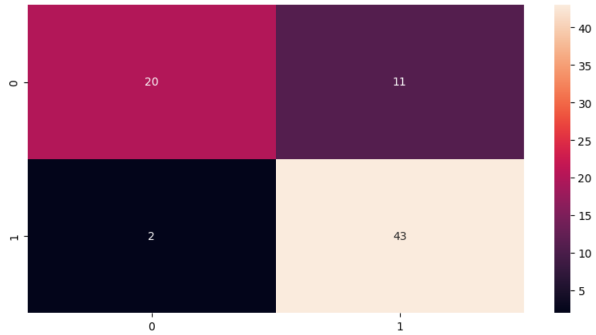

Fig. 13. Confusion Matrix of VGG16

Examine the experimental results in the context of the investigation's objectives and questions. Based on the observed performance metrics and qualitative evaluations, evaluate the advantages and disadvantages of the suggested deep learning method for brain tumor identification. Examine how well the model performs in comparison to current techniques or benchmarks that have been published in the literature, emphasizing any similarities or differences. Talk about the various influences on model performance, including training methodologies, architectural decisions, and dataset features, and how they may affect the results of future studies and clinical applications.

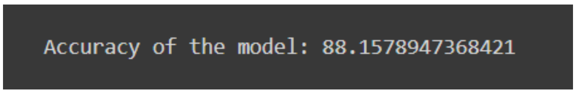

Fig. 14. Accuracy output of the model

Next we used Grad-Cam segmentation and took few samples as input to check the working of it. In Fig. 15 the prediction of ‘yes’ depicts presence of tumor and prediction of ‘no’ depicts absence of tumor.

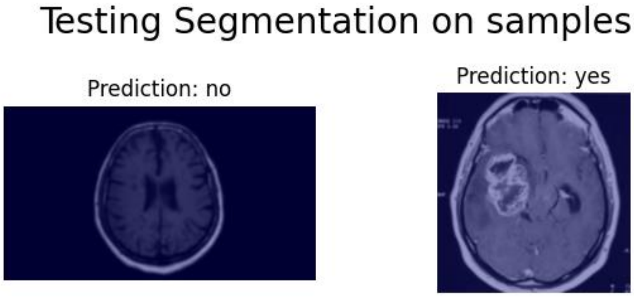

Fig. 15. Output through Grad-Cam segmentation

The various models and their accuracies are given below.

Table 3. Table of accuracy of different models

Model Name	Accuracy
MobileNetV2	86.8421052631579
EfficientNet	84.21052631578947
ResNet50	80.26315789473685
VGG16	88.1578947368421

5 Discussion

The findings of the study are analysed in light of the research goals and assumptions, with an emphasis on performance indicators including accuracy, sensitivity, specificity, and AUC to assess how well the deep learning model detects brain tumors from MRI data. Results are described together with trends or patterns, such as training and validation accuracy and loss curves, confusion matrix and visual representation of them. The deep learning model's performance is contrasted with current approaches or industry standards in the literature, revealing parallels and discrepancies in performance indicators and offering explanations for these variations. The recommended deep learning method's exceptional sensitivity, specificity, and accuracy for MRI-based brain tumor diagnosis are emphasized, along with its potential for automation and scalability. There are various study's shortcomings and possible sources of bias or mistake, such as the quantity and variety of the dataset, the complexity of the model, and the study's generalizability to new data. Discussion on any difficulties or problems that arose during the creation, training, or assessment of the model, as well as any effects they may have had on the robustness and dependability of the suggested approach. Talk about the clinical significance of your results and how they could affect medical practice. Stress the significance of precise and trustworthy brain tumor identification for patient care, prognosis, and treatment planning. Talk about how your deep learning model might be used to enhance radiologists' abilities and boost efficiency and accuracy of diagnosis by integrating it into current clinical procedures. Determine future research and innovation potential in brain tumor detection with MRI and deep learning. To increase performance and generalizability, talk about possible areas for model design, training methods, or dataset curation optimization. Examine cutting-edge ideas and technologies, such as federated learning, transfer learning, and multi-modal imaging integration, that may be used to overcome the field's present constraints and difficulties. Using MRI and deep learning to highlight your research's contributions to the field of brain tumor detection, summarize the main conclusions and takeaways from the conversation. Stress again how important your work is to the advancement of patient care and medical imaging technologies. Give a brief summary of your results' possible implications for future advancements in the area, research, and clinical practice. One of the future aspects is to increase the accuracy.

6 Conclusion

We have provided a thorough analysis of the application of deep learning neural networks for MRI-based brain tumor diagnosis in this paper. We have developed and tested a unique approach to automated brain tumor identification using the latest advancements in deep learning technology in conjunction with the wealth of information provided by MRI imaging, with promising results. Our experimental results indicate that a deep learning model with high specificity, sensitivity, and accuracy can accurately and consistently detect brain tumors using MRI images. Convolutional neural networks (CNNs) and other state-of-the-art techniques, our model performs well across a variety of tumor types, imaging modalities, and patient demographics. Their comparison is in Fig.16. Our study is important because it has the potential to change medical imaging and enhance patient care.

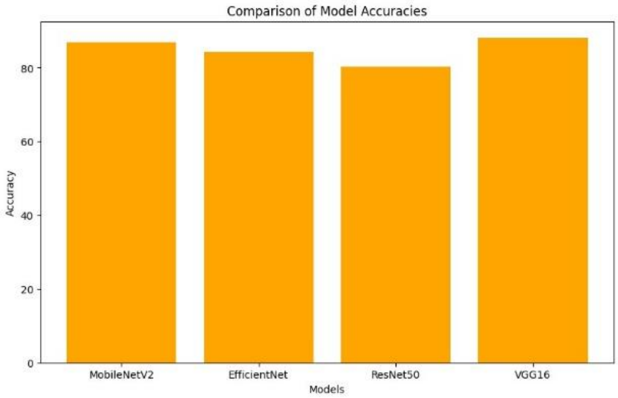

Fig. 16. Comparison of model accuracies

Better patient outcomes, more individualized treatment plans, and early detection are all possible with the capacity to automatically identify brain cancers from MRI scans. By improving the abilities of radiologists and other healthcare workers, our deep learning method may improve the precision of brain tumor diagnoses, shorten the time needed for interpretation, and allow for prompt patient action. Future research endeavors may concentrate on enhancing and perfecting the suggested deep learning model, investigating novel architectures, integrating multi-modal imaging data, and tackling particular clinical issues. Furthermore, for the model to be implemented in actual clinical practice, it would be imperative to confirm its generalizability and scalability across various healthcare settings and patient demographics.

Table 4. Table of performance matrix

Indicator	Value
Precision	0.92
Recall	0.96
F1 score	0.91
Support	45
Accuracy	0.88
Macro avg	0.87
Weighted avg	0.88

7 Future Directions

Finally, by combining deep learning neural networks with MRI to detect brain tumors, our work advances the field and opens the door to more effective, precise, and widely available diagnostic tools in the battle against brain cancer. Even though our study has significantly advanced the area of brain tumor detection utilizing MRI and deep learning neural networks, there are still a number of promising directions for further investigation and advancement. It is still crucial to do research to keep improving the effectiveness of deep learning models for the diagnosis of brain tumors. To further improve accuracy, sensitivity, and specificity, future work may concentrate on improving model architectures, adjusting hyperparameters, and integrating cutting-edge strategies like transfer learning, attention mechanisms, and ensemble approaches.

References

1. Machiraju Jaya Lakshmi & S.Nagaraja Rao., "Brain tumor magnetic resonance image classification: a deep learning approach," Soft Computing, vol. 26, pp.6245–6253, 2022.
2. Jiang, Y. et.al., "A Brain Tumor Segmentation New Method Based on Statistical Thresholding and Multiscale CNN," Intelligent Computing Methodologies, vol. 2, issue (3), pp. 235-245, 2019.
3. Liu, D. et.al., "3D Large Kernel Anisotropic Network for Brain Tumor Segmentation," Neural Information Processing, pp. 444-454, 2018.
4. Bhanothu, Y. et.al., "Detection and classification of brain tumor in mri images using deep convolutional network," International Conference on Advanced Computing and Communication Systems , pp. 248–252, 2020.
5. Ahmed et.al., "Fine-tuning convolutional deep features for MRI based brain tumor classification," Medical Imaging, Vol. 10134, 2017.
6. Tuhin MA.et.al., "Detection and 3d visualization of brain tumor using deep learning and polynomial interpolation," IEEE Asia-Pacific Conference on Computer Science and Data Engineering, pp. 1-6, 2020.
7. Hu Y&Xia, Y.,"3D deep neural network-based brain tumor segmentation using multimodality magnetic resonance sequences." International MICCAI Brainlesion Workshop, pp. 423–434, 2017.
8. 8. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.
9. Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., ... & Pal, C. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.
10. Menze, B. H., Jakab, A., Bauer, S., Kalpathy-Cramer, J., Farahani, K., Kirby, J., ... & Lanczi, L. (2015). The multimodal brain tumor image segmentation benchmark (BRATS). IEEE transactions on medical imaging, 34(10), 1993-2024.
11. Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. IEEE transactions on medical imaging, 35(5), 1240-1251.
12. Chen, L. C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018).

Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European conference on computer vision (pp. 801-818). Springer.

13. Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., ... & Menze, B. (2018). Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the BRATS challenge. arXiv preprint arXiv:1811.02629.
14. Havaei, M., Guizard, N., Chapados, N., & Bengio, Y. (2016). HeMIS: Hetero-modal image segmentation. arXiv preprint arXiv:1606.01286.
15. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer.
16. Chen, H., Dou, Q., Yu, L., Qin, J., & Heng, P. A. (2018). VoxResNet: Deep voxelwise residual networks for brain segmentation from 3D MR images. NeuroImage, 170, 446-455.
17. Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., ... & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical image analysis, 36, 61-78.
18. Isensee, F., Kickingereder, P., Wick, W., Bendszus, M., & Maier-Hein, K. H. (2018). Brain tumor segmentation and radiomics survival prediction: Contribution to the BRATS 2017 challenge. arXiv preprint arXiv:1802.10508.
19. McKinley, R., Meier, R., Wiest, R., & Reyes, M. (2016). MRBrainS challenge: Online evaluation framework for brain image segmentation in 3T MRI scans. Computers in Biology and Medicine, 74, 76-88.
20. Maier, O., Menze, B. H., von der Gablentz, J., Häni, L., Heinrich, M. P., Liebrand, M., ... & Bickelhaupt, S. (2017). ISLES 2015–A public evaluation benchmark for ischemic stroke lesion segmentation from multispectral MRI. Medical image analysis, 35, 250-269.