Brain Tumor Prediction Using Deep Learning Techniques

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ABSTRACT

Brain tumor prediction is a critical task in medical diagnostics, as early and accurate detection significantly enhances the chances of successful treatment. In this study, we propose a deep learning based approach utilizing Convolutional Neural Networks (CNNs) for the automated classification of brain tumors from magnetic resonance imaging (MRI) scans. We employ a preprocessed dataset comprising labeled MRI images, which are augmented and split into training, validation, and testing sets. A customized CNN architecture is designed and trained to distinguish among different tumor types, including glioma, meningioma, and pituitary tumors. Our model achieves an accuracy of 96.4% on the test set, outperforming traditional machine learning methods and several existing CNN architectures. The results demonstrate the potential of deep learning to assist radiologists in improving diagnostic accuracy and reducing the time required for manual analysis.

Keywords: Brain Tumor Classification, MRI Image Analysis, Deep Learning, Convolutional Neural Network (CNN), VGG16, Data Augmentation, Precision, Recall, F1-Score, Accuracy, AUC-Score, Feature Extraction, Image Preprocessing.

INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that can be life-threatening and require timely and accurate diagnosis for effective treatment. Traditional methods of tumor detection, such as manual examination of MRI scans, are often time consuming and prone to human error. With the rapid advancement of artificial intelligence, especially deep learning, new approaches have emerged that can assist radiologists by automating and enhancing the diagnostic process.

Deep learning, a subset of machine learning based on artificial neural networks, has shown remarkable success in medical image analysis. Convolutional Neural Networks (CNNs), in particular, are well-suited for processing and classifying visual data such as MRI images. By learning complex features directly from the images, these models can accurately distinguish between tumor and non-tumor regions, and even classify the type of brain tumor.

The system focuses on building a deep learning-based system for brain tumor prediction using MRI scans. The goal is to develop an efficient and reliable model that can aid in early detection and classification of brain tumors, potentially improving clinical outcomes and reducing diagnostic delays.[1]

Related Work

Several studies have employed deep learning for medical image analysis. Hossain et al. (2020) used transfer learning with VGG16 to classify brain tumors, achieving high accuracy. Other works have incorporated models like ResNet, DenseNet, and EfficientNet. However, many existing methods face limitations due to overfitting, insufficient preprocessing, or lack of robust evaluation. Our approach builds on these studies by optimizing model architecture, using enhanced data augmentation techniques, and providing comprehensive evaluation metrics.

In paper,” Ensemble deep learning for brain tumor detection”, by Shtwai Alsubai, HabibUllah Khan, Abdullah Alqahtani, Mohemmed Sha, Sidra Abbas and Uzma Ghulam Moham-mad, frontiers in, 02 September 2022, has discussed data preprocessing is performed to remove the undesired data in noise form that decreases the model’s performance. The unwanted areasand spaces are present in every MRI brain dataset image. Therefore, cropping the images is crucial to remove extraneous space and utilize only the relevant data. This research uses the cropping technique in Dahiwade et al. (2019) that uses the extreme point calculation. The steps to crop the MRII images using the extreme point calculation are presented in Figure 3. In the first step for preprocessing, load the actual MRI image, convert the images into grayscale and blur it slightly and then apply the thresholding to the magnetic resonance image for converting these images into binary images. The erosion and dilation operations are performed to remove any little noise regions in the images. Afterward, select the most significant contour from threshold images and compute four different extreme points (extreme left, extreme right, extreme bottom, and extreme top). In the last step, crop the image using the collected information from extreme points and contours. By using the bicubic interpolation, crop the MRI tumor images. Bicubic interpolation is preferred because it can create a smoother curve compared to other interpolation techniques like bilinear interpolation, and it is the best option for MRI brain tumor images since there is more noise at the edge. In the MRI images dataset, the images are of different sizes, heights, and widths. So it is necessary to resize the images into equal height and width to achieve the best results. In this study, the image is resized to 224 X 224 for uniformity. After that, all images are encoded between 0 and 255, and finally, images are normalized. [2]

In paper” Brain Tumor Prediction Using Deep Learning”, by Ameena Firdous, HAGiri jamma, International Journal of Research in Engineering, Science and Management, vol.3, no.8,21-08-2020, Cerebrum malignant growth categorization is an essential task undertaking of lookover assess the consideration choice. There are numerous radiology methods used to distinguish mind malignancy. Be that as it may, MRI is normally utilized because of its boss picture standard and reality depending on no disintegration emission. Profound studying (DL) is a subfield of AI and as of late indicated a striking presentation, particularly in categorization and division issues, a profound studying replica dependent on a complexity nervous structure is suggested to characterize distinctive cerebrum cancer kind utilizing two freely accessible data collection. The previous one characterizes cancers into (meninges, glial cells, and endocrine(cancer). suggested arrange structure accomplishes a huge presentation with the best by and large exactness of 96.13per and 98.7per, separately, for the two examinations. The outcomes demonstrate the capacity of the replica for cerebrum tumor multi categorization purposes. [3]

In paper, Brain Tumor Detection using Deep Learning by Rutuja Gugale, Pratiksha Sonar, Anagha Mandekar, Sonali Ubale, Vaishali Latke,” Brain Tumor Detection using Deep Learning”, Blue Eyes Intelligence Engineering and Sciences Publication, Volume-9, 30 September 2020, has discussed Convolution neural network (CNN or ConvNet) is a form of deep learning which is commonly applied for analyzing visual images. CNNs use their own pre-processing for variation of multilayer perceptrons designed which is also called as unchanged position or extent position artificial neural networks, based on their shared weights architecture and translation invariance characteristics. This grid provokes the connectivity pattern between neurons similarity the association of the animal perceptible cortex by biological processes into it. Individual cortical neurons rely on stimulants only in a limited area of the perceptible field known as the impressionable region. The impressionable region of various neurons which are partially overlapped such that they cover the entire visual field. CNNs have comparatively little pre-processing rather than other image classification algorithms. The major advantage of independence is prior knowledge and human effort in feature design. They involve the applications in image and video recognition, suggested systems, image classification, medical image examine and natural language processing. A CNN consists of raw data and a result, and also the many concealed layers. The concealed layers of CNN has typically contains convolution layers, collaborative layers, fully connected layers and normalization layers. [4]

In paper,” Deep learning-based brain tumor detection: an MRI segmentation approach” by V.N. V. L. S. Swathi, K. Sinduja, V. Ravi Kumar, A Mahendar, Gollanapalli V Prasad and Banoth Samya, EDP Sciences, 2024, has discussed The detection and segmentation of brain tumors from magnetic resonance imaging (MRI) scans are crucial for diagnosing, planning treatments, and monitoring patients with neurological disorders. This abstract provides a comprehensive overview of deep learning-based methods for detecting brain tumors, focusing on techniques for segmenting MRI images. Deep learning models, particularly convolutional neural networks (CNNs), have achieved impressive results in accurately segmenting brain tumors by learning distinctive features directly from the image data. Various CNN architectures, such as UNet, Deep Medic, and 3D convolutional networks, have been specifically designed to address the challenges of brain tumor segmentation, including tumor heterogeneity, irregular shapes, and varying sizes. Additionally, the integration of multi- modal MRI data, such as T1-weighted, T2-weighted, and FLAIR images, has enhanced the robustness and accuracy of deep learning models for brain tumor detection. This abstract discusses the significant advancements, challenges, and future directions in deep learning based brain tumor detection, emphasizing the potential of MRI segmentation techniques to support clinicians in early diagnosis and personalized treatment planning for patients with brain tumors. [5]

In paper, ”Brain Tumor Detection Using Deep Learning Approaches” by Razia Sultana Mizu, Daffodil International University Dhaka, BANGLADESH, 31 JULY 2023, has discussed the use of deep learning strategies, in particular ResNet50, has shown tremendous potential in the field of detecting brain tumors. When comparing tumor instances with non-tumor cases, the use of ResNet50, which has deep layers and robust feature extraction capabilities, has demonstrated exceptional accuracy and efficiency in making the distinction between the two types of cases. Researchers have been able to construct reliable and automated methods for accurate brain tumor identification by training ResNet50 on big datasets of brain MRI images. This has allowed the researchers to develop the systems more quickly. The use of deep learning strategies, such as ResNet50, in the analysis of medical images offers the potential to improve the speed, accuracy, and objectivity of diagnosing brain tumors. This is one of the many areas in which deep learning has shown promise. Deep learning-based approaches have the potential to alter the area of brain tumor identification and contribute to improved patient outcomes if additional improvements are made in the technology behind these methods and research into them is maintained. [6]

In paper,” Brain Tumor Detection Using Deep Learning” by Parmar Ankita, International Journal of advanced engineering and research development, Volume-7,4 April 2020, has discussed Main part in human nervous system is human brain. It is located in human head and it is covered by the skull. The function of human brain is to control all the parts of human body.It is one kind of organ that allows human to accept and endure all type of environmental condition. The human brain enables humans to do the action and share the thoughts and feeling. In this section we describe the structure of the brain for understanding the basic things The brain tumors are classified into mainly two types: Primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor). The benign tumor is one type of cell grows slowly in the brain and type of brain tumor is gliomas. It originates from non neuronal brain cells called astrocytes. Basically primary tumors are less aggressive but these tumors have much pressure on the brain and because of that, brain stops working properly [6]. The secondary tumors are more aggressive and more quick to spread into other tissue. Secondary brain tumor originates through other part of the body. These type of tumor have a cancer cell in the body that is metastatic which spread into different areas of the body like brain, lungs etc. Secondary brain tumor is very malignant. The reason of secondary brain tumor cause is mainly due to lungs cancer, kidney cancer, bladder cancer etc. [7]

In paper, ”Brain Tumor Prediction Using Deep Learning” by Ameena Firdous, HA Girijamma, International Journal of Research in Engineering, Science and Management 3 (8), 343-346,2020 Cerebrum malignant growth categorization is an essential task undertaking of lookover assess the consideration choice. There are numerous radiology methods used to distinguish mind malignancy. Be that as it may, MRI is normally utilized because of its boss picture standard and reality depending on no disintegration emission. Profound studying (DL) is a subfield of AI and as of late indicated a striking presentation, particularly in categorization and division issues, a profound studying replica dependent on a complexity nervous structure is suggested to characterize distinctive cerebrum cancer kind utilizing two freely accessible data collection. The previous one characterizes cancers into (meninges, glial cells, and endocrine(cancer). suggested arrange structure accomplishes a huge presentation with the best by and large exactness of 96.13per and 98.7per, separately, for the two examinations. The outcomes demonstrate the capacity of the replica for cerebrum tumor multi categorization purposes. [8]

In paper,” Brain Tumor Classification using Deep Learning Frameworks: an investigative project”, Akash Kumar Singh, Rakesh Kanji, Jaypee University of Information Technology, Solan, HP, 2024 Development of unwanted mass lesions and abnormal growth of cells in the brain results into brain tumors. Under the scope of this project work, the classification of brain tumors into Meningioma (generally benign), Glioma (malignant 80per of the times) and Pituitary tumors has been dealt with. When a tumor is said to be benign, it means that the tumor is not cancerous, whereas malignant tumor refers to cancerous tumor. It is noteworthy to mention here that the mentioned classification falls under the category of Primary Tumors, ie the tumors that are developed in the brain itself [1]. Apart from these, there are Secondary Tumors, which originate from some other body organ and then enter the brain [2]. The malignant tumors range across Grade 1 to 4 with Grade 4 being the deadliest. The cancerous tumor, starting from Grade 1, gradually get transformed into higher grade tumors. In the grade 4 survival of the patient becomes quite difficult [3]. Thus, it becomes increasingly important to detect brain tumor at the earliest. [9]

In paper,” Deep learning for the detection and classification of brain tumors using CNN”, E Sudarshan, G Uma Maheshwari, Nagaram Ramesh, Atul Kumar, Kandi Jyothsna, Bonthala Prabhanjan Yadav, Prashanth Bolukonda, AIP Conference Proceedings, 2024 The procedure of analyzing brain tumors is extremely difficult for numerous causes, together with the brain’s synaptic construction, volume, and nature. ML methods are engaged to assist health centers to identify brain tumor and maintain their assessments. In modern existence, deep learning systems had done an immense success in health representation examination especially using images and analyzing the images. Brain tumor is a grave illness happening in human being. Therapeutic action procedure primarily focuses on cancer categories. [10]

In paper,” Brain Tumor Classification Using an Ensemble of Deep Learning Techniques”, S Gopal Krishna Patro, Nikhil Govil, Surabhi Saxena, Brojo Kishore Mishra, Abu Taha Zamani, Achraf Ben Miled, Nikhat Parveen, Hashim Elshafie, Mosab Hamdan, IEEE Access, 2024 The article reflects on the classification of brain tumors where several deep learning (DL) approaches are used. Both primary and secondary brain tumors reduce the patient’s quality of life, and therefore, any sign of the tumor should be treated immediately for adequate response and survival rates. DL, especially in the diagnosis of brain tumors using MRI and CT scans, has applied its abilities to identify excellent patterns. The proposed ensemble framework begins with the image preprocessing of the brain MRI to enhance the quality of images. These images are then utilized to train seven DL models and all of these models recognize the features related to the tumor. There are four models which are General, Glioma, Meningioma, and Pituitary tumors or No Tumor model, which helps in reaching a joint profitable prediction and concentrating solely on the strength of the estimation and outcome. This is a significant improvement over all the individual models, attaining a 99. 43per accuracy. The data used in this research was gotten from Kaggle website and comprised of 7023 images belonging to four classes. Future work will focus on increasing the dataset size, investigating additional DL architectures, and enhancing real-time detection to improve the accuracy of diagnostic scans and their overall relevance to clinical practice. [11]

In paper,” Development of a Novel Brain Tumor Classification Methodology Using Modified Deep Learning Principles”, P Pattabhirama Mohan, Govindaraj Ramkumar, Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), 1-7,2024 Currently, tumours rank as the second most common cancer kind. A great number of people are at risk because of cancer. In order to diagnose tumours like brain tumours, the medical sector requires a method that is quick, automated, efficient, and dependable. Treatment relies heavily on detection. Medical professionals will keep a patient safe if a tumour can be detected accurately. There are a number of image processing methods utilized by this programme. Many tumour patients have been saved because to this software, which allows physicians to give the right treatment. Unregulated cell growth is the hallmark of a tumour.As they multiply, brain tumour cells engulf all the nutrition that should be going to healthy brain cells and tissues, leading to brain failure. At present, doctors find out where the cancer is and how big it is by manually examining magnetic resonance pictures of the patient’s brain. Not only is this an extremely time-consuming process, but it also leads to erroneous tumour detection. Modified Learning for Brain Tumour Classification (MLBTC) is a new tumour classification model that we presented in this paper. To evaluate its effectiveness, it is cross validated using the current Convolutional Neural Network deep learning technology. Its purpose is to intelligently detect brain cancers. Using the most popular deep learning architectures, the suggested approaches intelligently classify brain tumours. This study aims to evaluate and analyze deep learning technologies with the purpose of guiding academics and medical professionals towards strong systems that identify brain tumours. [12]

In paper,” Diagnosis of Brain Tumor using Automated Deep Learning Model”, Ashmeet Kaur, Shailendra Narayan Singh, 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 1-9, 2021, Brain tumor can be signified as a contorted mass of tissue centred in the cells increase unexpectedly and interminably, that is there is no power over the development of the cells. The early discovery of brain tumor is necessary to improve the quality of life of an individual. For precise and mechanized classification of mind MRI, there are numerous methodologies in existence related to the binary class classification of brain MRI scans. The problem of classification where we have several categories is a more complex task. Here, a strategy is presented that is equipped for classifying the brain MRI scans into four classes namely, glioma tumor, pituitary tumor, meningioma tumor and normal brain. The proposed model is essentially isolated into three most significant stages: - 1. Pre-processing of MRI scans. 2. Feature extraction with the assistance of pre-trained VGG16 model. 3. Classification of the MRI scans using Random Forest. The assessment of the model is finished by calculating its accuracy and it has obtained 95.4per accuracy. Moreover, we have contrasted our suggested model with the other pre-trained models like VGG16, VGG19, and AlexNet. Examinations with these models demonstrate the prevalence of the proposed strategy. [13]

In paper, ”A review on a deep learning perspective in brain cancer classification”, Gopal S Tandel, Mainak Biswas, Omprakash G Kakde, Ashish Tiwari, Harman S Suri, Monica Turk, John R Laird, Christopher K Asare, Annabel A Ankrah, NN Khanna, BK Madhusudhan, Luca Saba, Jasjit S Suri Cancers , 2019 A World Health Organization (WHO) Feb 2018 report has recently shown that mortality rate due to brain or central nervous system (CNS) cancer is the highest in the Asian continent. It is of critical importance that cancer be detected earlier so that many of these lives can be saved. Cancer grading is an important aspect for targeted therapy. As cancer diagnosis is highly invasive, time consuming and expensive, there is an immediate requirement to develop a non-invasive, cost-effective and efficient tools for brain cancer characterization and grade estimation. Brain scans using magnetic resonance imaging (MRI), computed tomography (CT), as well as other imaging modalities, are fast and safer methods for tumor detection. In this paper, we tried to summarize the pathophysiology of brain cancer, imaging modalities of brain cancer and automatic computer assisted methods for brain cancer characterization in a machine and deep learning paradigm. Another objective of this paper is to find the current issues in existing engineering methods and also project a future paradigm. Further, we have highlighted the relationship between brain cancer and other brain disorders like stroke, Alzheimer’s, Parkinson’s, and Wilson’s disease, leukoriaosis, and other neurological disorders in the context of machine learning and the deep learning paradigm. [14]

In paper, ”Brain Tumor Prediction by analyzing MRI using deep learning architectures”, Md Sabbir Ahmed, Rafeed Rahman, Shahriar Hossain, Shahnewaz Ali Mohammad, Third International Conference on Inventive Research in Computing Applications (ICIRCA), 1493-1498, 2021 The brain tumor is a lethal illness that has endured innumerable individuals. Brain tumor causes abnormal growth of brain tissues, the tissues can be either malignant or non-malignant, but both are capable of causing long term harm and in about 95per cases can cause demise. Utilizing MRI (Magnetic resonance imaging) scans has become one of the meaningful techniques for identifying its existence in the human brain. Subsequent to getting the MRI filters these are physically investigated by experts to determine the presence of a brain tumor in a patient. Various specialists assessing MRI scans may result in outcomes that are not same; this happens because of the variance in forming evaluations from one professional to the next. Furthermore, because MRI scan analysis is a manual procedure, various people might make different mistakes. Based on the interpretations of the experts, two distinct MRI scans performed on the same patient may yield different findings. To make things simpler, reliable, and obtaining acquiring predictable outcomes for both specialists and non-specialists while performing assessment of MRI scans, this research work has presented deep learning strategies in the context of transfer learning models such as ResNet 50, ResNet 152 inception v3, VGG16 and also proposed Conv2d+SVM model to analyze MRI scans and determine the presence of a brain tumor. [15]

In paper, ”Artificial Intelligence Assisted Improved Design to Predict Brain Tumor on Earlier Stages using Deep Learning Principle ”,K,Priyadharshini, P.Krishnaorthy,Kavitha.Karthikeyan,Ramesh.Peddavei, 2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS), 1-6, 2023 Brain- Tu-mors are the second most common reason of cancer today. Numerous people are at risk from cancer. The medical community requires a rapid, automated, efficient, and trustworthy method for detecting tumors, such as brain tumors. Early diagnosis is crucial for effective treatment. If a tumor can be detected early enough, medical professionals can remove the patient from harm’s way. This research makes use of novel image processing and deep learning method to predict the brain tumor in an intelligent manner with the power of AI, which is called as Supportive Intelligence for Tumor Detection (SITD). Numerous tumor patients have been saved thanks to this app’s accurate diagnosis and therapy. Unchecked cell growth constitutes a tumor’s defining feature. As brain tumor cells multiply, they starve healthy brain cells and tissues of the nutrition they need to survive. When trying to locate a tumor in a patient’s brain, neurosurgeons must now review MRI pictures manually. The goal of this research was to compile a comprehensive literature evaluation on the use of MRI to detect brain cancers for future investigation.This research looked at how advanced learning, transferable learning and quantum computer learning may be used to analyze brain tumors. Topics included brain tumor anatomy, publically available datasets, augmentation approaches, segmentation, feature extraction, classification and more. The resulting section shows the outcome efficiency of the proposed approach SITD by means of following metrics such as: Training-and- Testing Accuracy, Training-and- Testing Loss. [16]

In paper, ”An Exploration: Deep Learning-Based Hybrid Model for Automated Diagnosis and Classification of Brain Tumor Disorder”, Kamini Lamba, Shalli Rani International Conference on Micro Electronics and Telecommunication Engineering, 289 296, 2023 Reproduction of abnormal tissues within the brain due to any damage can cause major concerns for an individuals’ health which can be identified by radiologists after examining cell structure of brain that clarifies whether it belongs to benign, i.e., noncancerous or malign, i.e., cancerous. Although it cannot be treated properly, identifying abnormal growth of tissue at very initial phase can definitely help in preventing from major issues. Most of the researchers described automated brain tumor diagnosing methods in their publications which also received the most attention to provide significant contribution in the healthcare. Authors achieved the highest accuracy of 93.72per via deploying deep learning-based models while predicting brain tumor disease as these models have ability to analyze vast amount of data and able to extract significant features accurately and efficiently as compared to the existing approaches in short duration to provide improved patient outcomes and timely treatment in the healthcare. [17]

In paper, ”Brain tumor prediction on MRII images with semantic segmentation by using deep learning network and 3D imaging of tumor region”, Gokay Karayegen, Mehmet Feyzi Aksahin, Biomedical Signal Processing and Control 66, 102458, 2021 When it comes to medical image segmentation on brain MRII images, using deep learning techniques has a significant impact to predict tumor existence. Manual segmentation of a brain tumor is a time-consuming task and depends on knowledge and experience of physicians. In this paper, we present a semantic segmentation method by utilizing convolutional neural network to automatically segment brain tumor on 3D Brain Tumor Segmentation (BraTS) image data sets that comprise four different imaging modalities (T1, T1C, T2 and Flair). In addition, our study includes 3D imaging of whole brain and comparison between ground truth and predicted labels in 3D. In order to obtain exact tumor region and dimensions such as height, width and depth, this method was successfully applied and images were displayed different planes including sagittal, coronal and axial. Evaluation results of semantic segmentation which was executed by a deep learning network are significantly promising in terms of tumor prediction. Mean prediction ratio was determined as 91.718. Mean IoU (Intersection over (Union) and Mean BF score were calculated as 86.946 and 92.938, respectively. Finally, dice scores of the test images were showed significant similarity between ground truth and predicted labels. As a result, both semantic segmentation metrics and 3D imaging can be interpreted as meaningful for diagnosing brain tumor accurately. [18]

In paper, ”Brain tumor detection from MRI images using deep learning techniques”, P Gokila Brindha, M Kavinraj, P Manivasakam, P Prasanth IOP conference series: materials science and engineering, 2021 Brain tumor is the growth of abnormal cells in brain some of which may leads to cancer. The usual method to detect brain tumor is Magnetic Resonance Imaging (MRI) scans. From the MRI images information about the abnormal tissue growth in the brain is identified. In various research papers, the detection of brain tumor is done by applying Machine Learning and Deep Learning algorithms. When these algorithms are applied on the MRI images the prediction of brain tumor is done very fast and a higher accuracy helps in providing the treatment to the patients. These prediction also helps the radiologist in making quick decisions. In the proposed work, a self defined Artificial Neural Network (ANN) and Convolution Neural Network (CNN) is applied in detecting the presence of brain tumor and their performance is analyzed. [19]

In paper, ”Deep learning for brain tumor classification”, Justin S Paul, Andrew J Plassard, Bennett A Landman, Daniel Fabbri, Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging, 253-268, 2017 Recent research has shown that deep learning methods have performed well on supervised machine learning, image classification tasks. The purpose of this study is to apply deep learning methods to classify brain images with different tumor types: meningioma, glioma, and pituitary. A dataset was publicly released containing 3,064 T1-weighted contrast enhanced MRI (CE-MRI) brain images from 233 patients with either meningioma, glioma, or pituitary tumors split across axial, coronal, or sagittal planes. This research focuses on the 989 axial images from 191 patients in order to avoid confusing the neural networks with three different planes containing the same diagnosis. Two types of neural networks were used in classification: fully connected and convolutional neural networks. Within these two categories, further tests were computed via the augmentation of the original 512×512 axial images. Training neural networks over the axial data has proven to be accurate in its classifications with an average five-fold cross validation of 91.43per on the best trained neural network. This result demonstrates that a more general method (i.e. deep learning) can outperform specialized methods that require image dilation and ring-forming subregions on tumors. [20]

In paper, ”Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches” Ayesha Younis, Li Qiang, Charles Okanda Nyatega, Mohammed Jajere Adamu, Halima Bello Kawuwa, Applied Sciences, 2022 A brain tumor is a distorted tissue wherein cells replicate rapidly and indefinitely, with no control over tumor growth. Deep learning has been argued to have the potential to overcome the challenges associated with detecting and intervening in brain tumors. It is well established that the segmentation method can be used to remove abnormal tumor regions from the brain, as this is one of the advanced technological classification and detection tools. In the case of brain tumors, early disease detection can be achieved effectively using reliable advanced A.I. and Neural Network classification algorithms. This study aimed to critically analyze the proposed literature solutions, use the Visual Geometry Group (VGG 16) for discovering brain tumors, implement a convolutional neural network(CNN) model framework, and set parameters to train the model for this challenge. VGG isused as one of the highest-performing CNN models because of its simplicity. Furthermore, the study developed an effective approach to detect brain tumors using MRI to aid in making quick, efficient, and precise decisions. Faster CNN used the VGG 16 architecture as a primary network to generate convolutional feature maps, then classified these to yield tumor region suggestions. [21]

In paper, ”Brain tumor segmentation with deep neural networks” by Mohammad Havaei, Axel Davy, David Warde-Farley, Antoine Biard, Aaron Courville, Yoshua Bengio, Chris Pal, Pierre-Marc Jodoin, Hugo Larochelle Medical image analysis 35, 18-31, 2017 In this paper, a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). The proposed networks are tailored to glioblastomas (both low and high grade) pictured in MRI images. By their very nature, these tumors can appear anywhere in the brain and have almost any kind of shape, size, and contrast. These reasons motivate our exploration of a machine learning solution that exploits a flexible, high capacity DNN while being extremely efficient. Here, we give a description of different model choices that we’ve found to be necessary for obtaining competitive performance. We explore in particular different architectures based on Convolutional Neural Networks (CNN), We present a novel CNN architecture which differs from those traditionally used in computer vision. Our CNN exploits both local features as well as more global contextual features simultaneously. Also, different from most traditional uses of CNNs, our networks use a final layer that is a convolutional implementation of a fully connected layer which allows a 40 fold speed up. We also describe a 2-phase training procedure that allows us to tackle difficulties related to the imbalance of tumor labels. Finally, we explore a cascade architecture in which the output of a basic CNN is treated as an additional source of information for a subsequent CNN. [22]

In paper, ”Brain tumor classification using deep learning”, Ahmad Saleh, Rozana Sukaik, Samy S Abu Naser 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech), 131-136, 2020 Brain tumor is a very common and destructive malignant tumor disease that leads to a shorter life if it is not diagnosed early enough. Brain tumor classification is a very critical step after detection of the tumor to be able to attain an effective treatment plan. This research paper aims to increase the level and efficiency of MRI machines in classifying brain tumors and identifying their types, using AI Algorithm, CNN and Deep Learning. We have trained our brain tumor dataset using five pre-trained models: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The F1 scores measure of unseen images were 98.75per, 98.50per, 98.00per, 97.50per, and 97.25per respectively. These accuracies have a positive impact on early detection of tumors before the tumor causes. [23]

In paper, ”Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges”, Muhammad Waqas Nadeem, Mohammed A Al Ghamdi, Muzammil Hussain, Muhammad Adnan Khan, Khalid Masood Khan, Sultan H Almotiri, Suhail Ashfaq Butt, Brain sciences,118, 2020 Deep Learning (DL) algorithms enabled computational models con- sist of multiple processing layers that represent data with multiple levels of abstraction. In recent years, usage of deep learning is rapidly proliferating in almost every domain, especially in medical image processing, medical image analysis, and bioinformatics. Consequently, deep learning has dramatically changed and improved the means of recognition, prediction, and diagnosis effectively in numerous areas of healthcare such as pathology, brain tumor, lung cancer, abdomen, cardiac, and retina. Considering the wide range of applications of deep learning, the objective of this article is to review major deep learning concepts pertinent to brain tumor analysis (e.g., segmentation, classification, prediction, evaluation.). A review conducted by summarizing a large number of scientific contributions to the field (i.e., deep learning in brain tumor analysis) is presented in this study. A coherent taxonomy of research landscape from the literature has also been mapped, and the major aspects of this emerging field have been discussed and analyzed. A critical discussion section to show the limitations of deep learning techniques has been included at the end to elaborate open research challenges and directions for future work in this emergent area. [24] 24. In paper, ”Deep Learning Approaches for Brain Tumor Detection and Classification Using MRI Images (2020 to 2024): A Systematic Review”, Sara Bouhafra, Hassan El Bahi Journal of Imaging Informatics in Medicine, 1-31, 2024 has discussed Brain tumor is a type of disease caused by uncontrolled cell proliferation in the brain leading to serious health issues such as memory loss and motor impairment. Therefore, early diagnosis of brain tumors plays a crucial role to extend the survival of patients. However, given the busy nature of the work of radiologists and aiming to reduce the likelihood of false diagnoses, advancing technologies including computer-aided diagnosis and artificial intelligence have shown an important role in assisting radiologists. In recent years, a number of deep learning-based methods have been applied for brain tumor detection and classification using MRI images and achieved promising results. The main objective of this paper is to present a detailed review of the previous researches in this field. In addition, This work summarizes the existing limitations and significant highlights. The study systematically reviews 60 articles researches published between 2020 and January 2024, extensively covering methods such as transfer learning, autoencoders, transformers, and attention mechanisms. The key findings formulated in this paper provide an analytic comparison and future directions. The review aims to provide a comprehensive understanding of automatic techniques that may be useful for professionals and academic communities working on brain tumor classification and detection.[25]

In paper, ”Deep learning in medical image classification from MRI-based brain tumor images”, Xiaoyi Liu, Zhuoyue Wang arXiv preprint, 2024 Brain tumors are among the deadliest diseases in the world. Magnetic Resonance Imaging (MRI) is one of the most effective ways to detect brain tumors. Accurate detection of brain tumors based on MRI scans is critical, as it can potentially save many lives and facilitate better decision-making at the early stages of the disease. Within our paper, four different types of MRI-based images have been collected from the database: glioma tumor, no tumor, pituitary tumor, and meningioma tumor. Our study focuses on making predictions for brain tumor classification. Five models, including four pretrained models (MobileNet, EfficientNet-B0, ResNet-18, and VGG16) and one new model, MobileNet-BT, have been proposed for this study. [26]

In paper,” Local structure prediction with convolutional neural networks for multimodal brain tumor segmentation”, Pavel Dvoˇr´ak, Bjoern Menze Medical computer vision”, Munich, Ger many, October 9, 2015, revised selected, 2016 Most medical images feature a high similarity in the intensities of nearby pixels and a strong correlation of intensity profiles across different image modalities. One way of dealing with – and even exploiting – this correlation is the use of local image patches. In the same way, there is a high correlation between nearby labels in image annotation, a feature that has been used in the “local structure prediction” of local label patches. In the present study we test this local structure prediction approach for 3D segmentation tasks, systematically evaluating different parameters that are relevant for the dense annotation of anatomical structures. We choose convolutional neural network as learning algorithm, as it is known to be suited for dealing with correlation between features. We evaluate our approach on the public BRATS2014 data set with three multimodal segmentation tasks, being able to obtain state-of-the-art results for this brain tumor segmentation data set consisting of 254 multimodal volumes with computing time of only 13 s per volume. [27]

METHODOLOGY

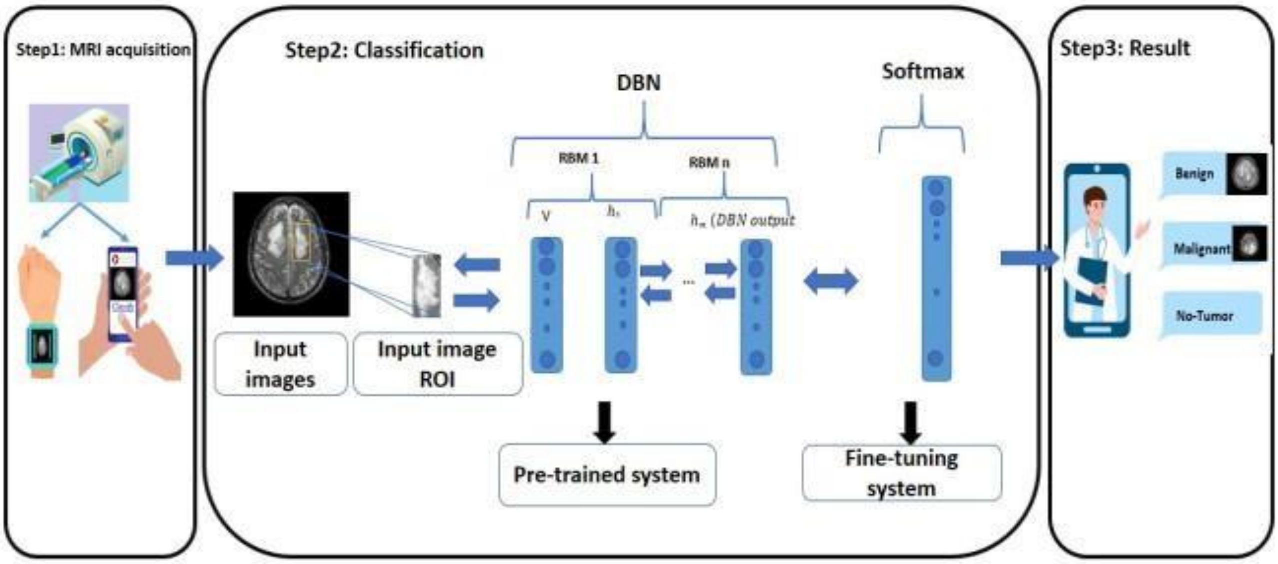

Figure 1. System Architecture

Dataset

This project uses a dataset consisting of 6,483 MRI images of the human brain, categorized into four classes: glioma, meningioma, pituitary tumor, and no tumor. The "no tumor" class images are sourced from the Br35H dataset, a publicly available benchmark for brain MRI classification. Total images, 5,172 images are used for training, while 1,311 images are reserved for testing. The dataset is organized into separate folders by class, enabling efficient loading and preprocessing for multi-class classification tasks.

Data Preprocessing

Resizing Images to 224×224 Pixels

Deep learning models, especially Convolutional Neural Networks (CNNs), require input images to be of the same size. The size 224×224 pixels is a widely used standard, particularly compatible with pre-trained models like VGGNet, ResNet, and MobileNet. Resizing all images to this dimension ensures uniformity, which is critical for batch processing and model efficiency. It also helps reduce the computational load, as smaller image sizes require less memory and processing power.

Normalization (Scaling Pixel Values Between 0 and 1) Image data is usually represented with pixel intensity values ranging from 0 to 255. Feeding such large values into a neural network can lead to slower convergence and instability during training. Normalization is the process of scaling these pixel values to a range between 0 and 1 by dividing each pixel value by 255. This results in faster and more stable training. Normalization also ensures that all features (pixel intensities) contribute equally to the learning process.

Data Augmentation

Deep learning models require large datasets to generalize well. In medical imaging, data is often limited due to privacy issues and the difficulty of collecting labeled samples. Data augmentation artificially expands the training dataset by applying random transformations to the original images. This improves the model's ability to generalize and reduces overfitting.

Rotation

Randomly rotates images within a specified degree range (e.g., ±15°). This helps the model become invariant to image orientation and improves robustness when dealing with tumors that appear at different angles.

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Flipping

Performs horizontal and/or vertical flipping. For example, a tumor appearing on the left side may also appear on the right in other cases. Flipping increases the variety in spatial patterns without changing the actual diagnosis.

Zooming

Applies random zoom-in or zoom-out effects on the image. It teaches the model to recognize tumors at various scales and ensures it focuses on features at different resolutions.

Contrast Adjustment

Changes the contrast or brightness levels of the image. Since medical images can vary due to differences in scanners or lighting, contrast adjustment makes the model more resilient to such variations.

Model Architecture

A custom Convolutional Neural Network (CNN) was built for classifying brain MRI images into three classes. CNNs are particularly suited for image recognition tasks as they automatically detect spatial hierarchies in visual data using filters, pooling, and non-linear operations.

Input Layer: (224 × 224 × 3)

224 × 224 Represents the width and height of the input image, which is a common input size for deep learning models to standardize computations. Refers to the three color channels (Red, Green, Blue), indicating the model processes color images.The input layer does not perform computation but defines the expected shape of each image fed into the network.Ensures uniformity inimage size across the dataset. Facilitates the use of pre-trained models or structured architectures.

Convolutional Blocks (Conv2D → ReLU → MaxPooling)-(Repeated in 3 Blocks)

Conv2D (Convolutional Layer)

Applies a set of filters (or kernels) to scan through the image or feature maps.Each filter detects specific features such as edges, lines, textures, or shapes.Output is a set of feature maps that represent the presence of these patterns across the image.

Technical Detail:

Each filter performs a dot product between the filter matrix and the section of the input image.Multiple filters are applied per layer to detect various features simultaneously.

ReLU (Rectified Linear Unit) Activation Function Introduces non-linearity to the network.

$$\boldsymbol{f}(\boldsymbol{x}) = max(\mathbf{0}, \boldsymbol{x})$$

Replaces all negative pixel values with 0 and retains positive values.

Max Pooling Layer

Downsamples the feature maps by selecting the maximum value from a defined window (e.g., 2×2).Reduces the spatial dimensions (width and height), while preserving important features.

Benefits

Reduces the number of parameters and computation. Provides translation invariance – the ability to detect features even when their positions shift slightly

Result After 3 Blocks:

The image goes from a raw pixel matrix to a set of compressed, feature-rich maps that highlight meaningful patterns like shapes, textures, and boundaries of tumors.

Dropout Layers

During training, dropout **randomly disables a percentage of neurons** (e.g., 20–50%) in the network.

Purpose

Prevents overfitting by ensuring that neurons do not become overly reliant on specific features.

Forces the network to learn redundant representations, making it more robust.

How it works

For each training batch, randomly “drops” some neurons by setting their output to zero.

During inference (testing), all neurons are used, but their outputs are scaled accordingly.

Flatten Layer

Converts the multidimensional feature maps from the convolutional layers into a 1D vector**.**

The Dense (fully connected) layers that follow require 1D inputs.

Acts as a bridge between spatial feature extraction (convolutions) and classification (dense layers).

Dense Layer (128 Units, ReLU)

A fully connected layer with 128 neurons.Each neuron receives input from all nodes of the flattened layer.

Function

Learns complex combinations of the extracted features.Helps the model learn abstract and highlevel representations of tumor characteristics.

ReLU Activation

Adds non-linearity to capture complex decision boundaries.Speeds up training and reduces computation time.

Output Layer (3 Units, Softmax)

The final Dense layer contains 4 neurons, each representing one tumor class

Example: 0=Notumor, 1=Meningioma, 2=Glioma, = Pituitary

Softmax Activation Function

$$Softmax(z)_{\mathrm{i}} = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

Converts raw output scores into a probability distribution over the 3 classes.

Component	Description / Operation
Input Image	MRI scan of brain — size 224×224×3 (RGB channels)
Preprocessing	Resize to 224×224- Normalize pixel values to [0, 1]
Pretrained VGG16	Convolutional base without top classification layers (used for feature extraction)
Flatten Layer	Converts 2D feature maps to a 1D vector for input into dense layers
Dense Layer (512)	Fully connected layer with 512 neurons and ReLU activation
Dropout Layer (0.5)	Regularization layer to reduce overfitting randomly drops 50% of neurons during training
Dense Output Layer (4)	Final layer with 4 output neurons, Softmax activation for multi-class classification
Output Classes	Predicted label: • Glioma • Meningioma • Pituitary • No Tumor

Training Details

Loss Function

Categorical Crossentropy

Used for multi-class classification problems.Measures the difference between the actual label and predicted probability.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Optimizer

Adam Optimizer Combines Momentum and RMS Prop for faster convergence. Adaptive learning rate adjustment.

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * g_t$$

$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * g_t^2$$

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} * \widehat{m}_t$$

Learning Rate

0.0001

A small value ensures stable and gradual weight updates.

Prevents skipping over minima during training.

Batch Size

Model is trained on 32 samples at a time before updating weights.

Balances memory usage and training speed.

Epochs

The entire dataset is passed through the model 5 times during training.

More epochs allow better learning but may lead to overfitting if too high.

Data Split

70% Training Set – used to train the model.

15% Validation Set – used to tune parameters and prevent overfitting.

15% Test Set – used to evaluate model performance on unseen data.

Parameter	Details
Model Architecture	Pretrained VGG16 followed by custom Flatten, Dense, and Dropout layers
Input Image Size	224 × 224 pixels
Dataset Source	MRI brain tumor images from Google Drive custom dataset with class-based folders
Number of Classes	4 classes — likely glioma, meningioma, pituitary, and no tumor
Preprocessing Steps	Resized images to 224×224-Normalized pixel values to
Data Augmentation	Random brightness adjustment- Random contrast enhancement (via ImageEnhance)
Optimizer	Adam optimizer
Loss Function	Categorical Crossentropy (appropriate for multi-class classification)
Batch Size	default
Epochs	The model in project was trained for a total of 5 epochs.
Learning Rate	0.0001 (set manually in Adam optimizer)
Evaluation Metrics	Accuracy- Precision- Recall- F1score- AUC
Framework& Libraries	TensorFlow / Keras for model development; PIL for image enhancement

RESULTS

1. Accuracy – 95%

Definition: The ratio of correctly predicted instances to the total number of instances. It measures the overall correctness of the model.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

TP: True Positives

TN: True Negatives

FP: False Positives

FN: False Negatives

Interpretation: Out of all MRI images tested, **95%** were correctly classified as either tumor or no tumor. This reflects the general effectiveness of the model.

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2. **Precision – 96.1%**

Definition: Measures how many of the images predicted as a certain tumor type were actually correct. It focuses on minimizing false positives.

$$Precision = \frac{TP}{TP + FP}$$

Interpretation: When the model predicted a specific tumor type, it was correct 96.1% of the time. High precision indicates that the model rarely mislabels healthy patients as having a tumor.

Recall – 95.8%

Definition: Measures how many actual tumor cases were correctly identified by the model. It focuses on minimizing false negatives.

$$Recall = \frac{TP}{TP + FN}$$

Interpretation: The model correctly identified 95.8% of true tumor cases. A high recall ensures that most patients with a tumor are detected and not missed.

F1-Score – 95.9%

Definition: The harmonic mean of precision and recall. It balances both the ability to detect actual cases and avoid false alarm.

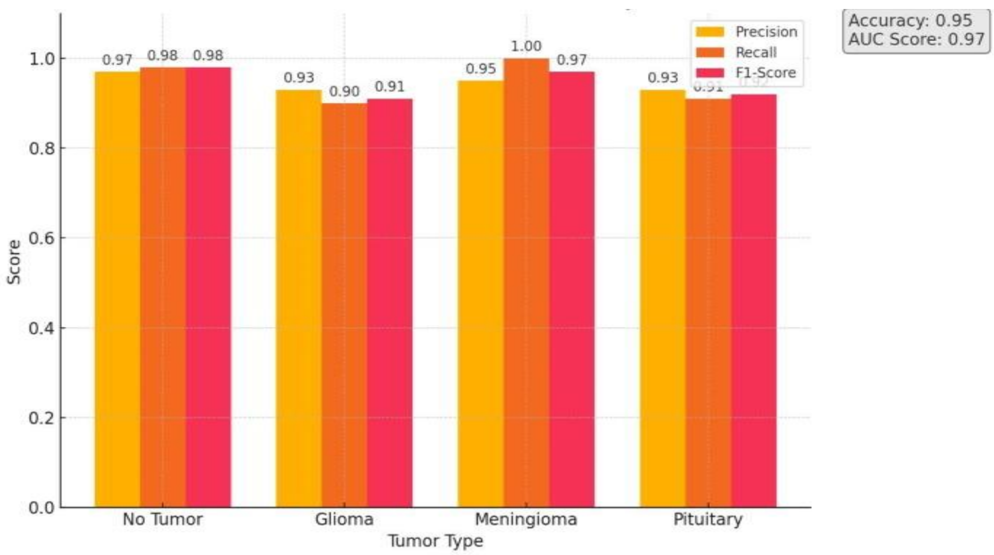
$$F1\,Score = 2 \cdot \frac{Precision.\,Recall}{Precision + Recall}$$

Interpretation: The model achieved an F- score of **95.9%** indicating a strong balance between correct detection and accurate, which is essential in medical diagnostics.

AUC Score – 97%

Definition: Area Under the Receiver Operating Characteristic (ROC) Curve. It evaluates the model's ability to distinguish between different classes (e.g., tumor types).

Interpretation: An AUC of 0.97 means the model is extremely effective at distinguishing between healthy and diseased cases, as well as among different tumor types. A perfect model would score 1.00 or (100%)



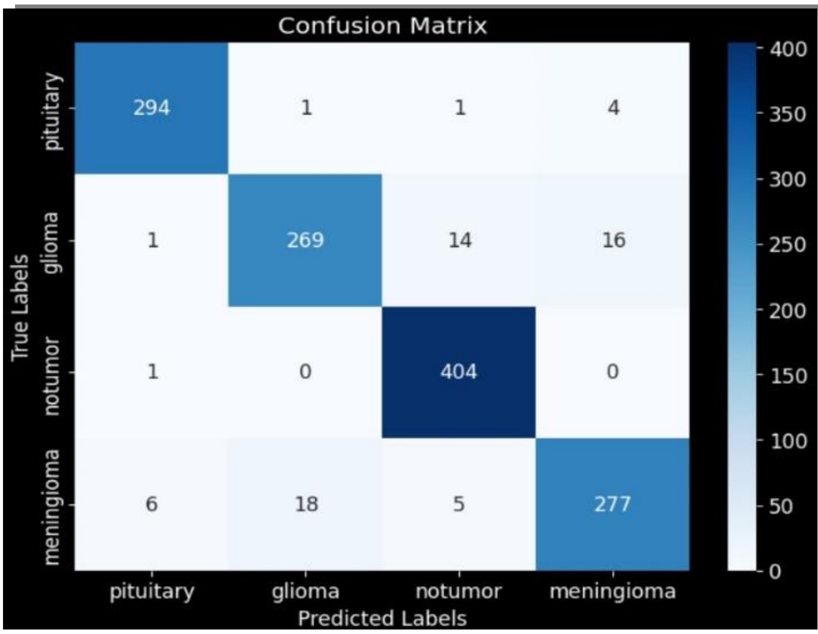


Figure 3. Confusion Matrix

Confusion Matrix

The proposed CNN architecture effectively learned spatial and hierarchical features from MRI images through multiple convolutional and pooling layers, followed by dense layers for classification. The use of the Adam optimizer and categorical cross-entropy loss

Figure 2. Training Graph function contributed to efficient training and convergence. A carefully chosen learning rate and batch size further improved training stability and performance.

The results demonstrate that deep learning-based approaches, particularly CNNs, offer a reliable and scalable solution for brain tumor detection and classification. This work underscores the potential of AI-assisted diagnosis in medical imaging, where accurate, fast, and automated systems can support clinical decision-making and improve patient outcomes. Future research may focus on expanding the dataset, incorporating 3D imaging modalities, and deploying the model in real-time clinical settings to further enhance diagnostic capabilities.

CONCLUSION

In this study, a custom Convolutional Neural Network (CNN) was developed and evaluated for the automatic classification of brain tumors using MRI images. The model was designed to distinguish among three types of tumors – Meningioma Glioma Notumor and Pituitary - and achieved high performance across key evaluation metrics including accuracy, precision, recall, F1- score, and AUC. The preprocessing pipeline, which included image resizing, normalization, and data augmentation, significantly enhanced the model’s ability to generalize and reduced the risk of overfitting.

REFERENCES

1. Masoud Nickparvar” Brain Tumor MRI Dataset”, Available: [1]
2. Raksha Nayak, Sanjana Rao U S, Shreeta Jayakar Shetty, Vinaya S, Shashikala, Brain Tumor Detection Using Deep Learning Technique, International Journal for Research in Applied Science and Engineering Technology, Udupi, India,5 july 2024. Available:[2].
3. Rasool, M., Noorwali, A., Ghandorh, H., Ismail, N.A. and Yafooz, Brain Tumor Classification using Deep Learning: A State-of-the-Art Review, Journal of Informatics and Web Engineering, Issue: 5, Vol. 14, Pages: 16586-16594, 9 October 2024. Available: [3].
4. Suchitha. N. V, Avinash Bhat, Aravind Hegde, Mallikarjun M, karthik. S.R. Brain Tumor Detection Using a Deep Learning Model. Available:[4].

5. Hamza Rafiq Almadhoun, Samy S. Abu Naser, Detection of Brain Tumor Using Deep Learning, International Journal of Academic Engineering Research (IJAER) ISSN: 2643-9085, 3March 2022, Pages:29-47. Available: [5].
6. Hanaa Zain Eldin, Samah A, Gamel, El-Sayed M, ElKenawy, Amal H, Alharbi, Doaa Sami Khafaga, Abdelhameed Ibrahim and Fatma M. Talaat, Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization, Vol. 10, 22December 2022, Pages:2-19. Available: [6].
7. Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz and Sharareh R. Niakan Kalhori. MRI based brain tumor detection using convolutional deep learning methods and chosen machinelearning techniques, BMC Medical Informatics and Decision Making, Vol. 8, 23 January 2023, Pages:1-17. Available: [7].
8. Dillip Ranjan Nayak, Neelamadhab Padhy, Pradeep Kumar Mallick, Dilip Kumar Bagal and Sachin Kumar, Brain Tumour Classification Using Noble Deep Learning Approach with Parametric Optimization through Metaheuristics Approaches, MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations., Vol. 11, 7 January 2022,Pages:1-14. Available: [8].
9. Shenbagarajan Anantharajan, Shenbagalakshmi Gunasekara, Thavasi Subramanian and Venkatesh R, MRI brain tumor detection using deep learning and machine learning approaches, Published by Elsevier Ltd, Vol. 6, 7 January 2022, Pages:1-11. Available:[9].
10. Md Ishtyaq Mahmud, Muntasir Mamun and Ahmed Abdelgawad, A Deep Analysis of BrainTumor Detection from MRII Images Using Deep Learning Networks, MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations., Vol. 16, 23 March 2023, Pages:1-19. Available: [10].
11. Chandrakant M. Umarani, S.G. Gollagi, Shridhar Allagi, Kuldeep Sambrekar, Sanjay B. Ankali. Advancements in deep learning techniques for brain tumor segmentation: A survey, Published by Elsevier Ltd., 22 August 2024, Pages:1-11. Available: [11].
12. Bathe, Kavita and Rana, Varun and Singh, Sanjay and Singh, Vijay, Brain Tumor Detection Using Deep Learning Techniques (MAY 7, 2021). Proceedings of the 4th International Conferenceon Advances in Science and Technology (ICAST2021), Available:[12].
13. Sandeep Kumar Mathivanan, Sridevi Sonaimuthu, Sankar Murugesan, Hariharan Rajadurai,Basu Dev Shivahare and Mohd Asif Shah. Employing deep learning and transfer learning for accurate brain tumor detection, 27 March 2024, Pages:1-14. Available: [13].
14. Rahul Namdeo Jadhav, and G. Sudhaghar. Deep Learning Approaches for Brain Tumor Detection in MRI Images: A Comprehensive Survey. International Journal of Intelligent Systems and Applications in Engineering, 12(13s), 9.01.2024, Pages:1-17. Available: [14].
15. Sankararao, Y. and Khasim, S. 2024. An Effective analysis of brain tumor detection using deep learning. EAI Endorsed Transactions on Pervasive Health and Technology. 10, (Apr. 2024). Available: [15].
16. Fatma Taher, Mohamed R. Shoaib, Heba M. Emara, Khaled M. Abdelwahab, Fathi E. Abd El-Samie and Mohammad T. Haweel. Efficient framework for brain tumor detection using different deep learning techniques, Vol. 10, 01 December 2022, Pages:1-15. Available: [16].
17. Md. Saikat Islam Khan, Anichur Rahman, Tanoy Debnath, Md. Razaul Karim, Mostofa Kamal Nasir, Shahab S. Band, Amir Mosavi and Iman Dehzangi. Accurate brain tumor detection using deep convolutional neural network, Published by Elsevier B.V. on behalf of Research Network of Computational and Structural Biotechnology., 27 August 2022. Available: [17].
18. Sangeetha, M., Keerthika, P., Devendran, K., Sridhar, S., Raagav, S.S. and Vigneshwar, T. 2022. Brain tumor segmentation and prediction on MRI images using deep learning network. International journal of health sciences. 6, S2 (Jun. 2022), 13486–13503. Available: [18].
19. Guru Aswath C, Naveen Kumar K, Mohamed Fayas C. Brain Tumor Detection using Deep Learning, International Journal of Research Publication and Reviews, Vol. 4, May 2023, Pages:1-5. Available: [19].
20. S. Keerthi, Y. N. Shettigar, K. Keerthana, K. R. Divyashree and S. Bhargavi," A Review on Brain Tumor Prediction using Deep Learning," 2023 International Conference on Advancementin Computation and Computer Technologies (InCACCT), Gharuan, India, 2023, pp. 155-160.Available:[20].
21. Guru Aswath C, Naveen Kumar K, Mohamed Fayas C. Brain Tumor Detection using Deep Learning, International Journal of Research Publication and Reviews, Vol. 4, May 2023, Pages:1-5. Available: [21]

22. Rasool, M., Noorwali, A., Ghandorh, H., Ismail, N.A. and Yafooz, W.M.S. 2024. Brain Tumor Classification using Deep Learning: A State-of-the-Art Review. Engineering, Technology and Applied Science Research. 14, 5 (Oct. 2024), 16586–16594. Available: [22]
23. Raksha Nayak, Sanjana Rao U S, Shreeta Jayakar Shetty, Vinaya S, Shashikala. Brain Tumor Detection Using Deep Learning Technique, International Journal of Research Publication andReviews, 2321-9653, 202405-07, Pages:1-9. Available: [23]
24. Dillip Ranjan Nayak, Neelamadhab Padhy, Pradeep Kumar Mallick, Mikhail Zymbler and Sachin Kumar. Brain Tumor Classification Using Dense Efficient-Net, International Journal of Research Publication and Reviews, Vol. 11, 17 January 2022. Available: [24]
25. S. Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari and S. Jolad," Brain Tumor Detection Using Deep Learning Models," 2020 IEEE India Council International Subsections Conference (INDISCON), Visakhapatnam, India, 2020, pp. 129-134. Available:[25]
26. F. H. A. Anjasmara and I. Soesanti," Challenges on Deep Learning Models to Improve Magnetic Resonance Imaging Brain Tumor Images Classification: A Review," 2023 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS), Yogyakarta, Indonesia, 2023, pp. 31-36. Available: [26]
27. R. Preetha, M. J. P. Priyadarsini and J. S. Nisha," Automated Brain Tumor Detection From Magnetic Resonance Images Using Fine-Tuned EfficientNet-B4 Convolutional Neural Network,"in IEEE Access, vol. 12, pp. 112181-112195, 2024. Available: [27]
28. F. H. Dahri, N. Ahmad Dahri, D. B. SooMRIIo, I. Ali Channa and G. E. Mustafa Abro," Deep Dive into Brain Tumor Classification: Transfer Learning with Convolutional Neural Networks," 2024 1st International Conference on Innovative Engineering Sciences and Technological Research (ICIESTR), Muscat, Oman, 2024, pp. 1-6. Available: [28]
29. Saravanan Srinivasan, Divya Francis, Sandeep Kumar Mathivanan, Hariharan Rajadurai, Basu Dev Shivahare,Mohd Asif Shah," A hybrid deep CNN model for brain tumor image multi-classification," Available: [29]
30. Akmalbek Bobomirzaevich Abdusalomov, ORCID, Mukhriddin Mukhiddinov ORCID, Taeg Keun Whangbo," DBrain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging introduction," Submission received: 27 June 2023 / Revised: 11 August 2023/ Accepted: 17 August 2023 / Published: 18 August 2023 Available: [30]
31. Abdul Hannan Khan, Sagheer Abbas, Muhammad Adnan Khan, Umer Farooq, Wasim Ahmad Khan, Shahan Yamin Siddiqui, Aiesha Ahmad," Intelligent Model for Brain Tumor Identification Using Deep Learning," First published: 21 January 2022.Available: [31]
32. M. Ravinder, Garima Saluja, Sarah Allabun, Mohammed S. Alqahtani, Mohamed Abbas, Manal Othman, Ben Othman Soufiene," Enhanced brain tumor classification using graph convolutional neural network architecture," Received 22 April 2023, Accepted 25 August 2023, Published 11 September 2023.Available: [32]
33. Sankararao Y, Khasim S." Effective analysis of brain tumor detection using deep learning. EAI Endorsed Trans Perv Health Tech [Internet]. Published 03-042024.Available: [33]
34. Joseph Shavit." New AI model detects more than 170 types of cancer with 97.8 percentage accuracy." Published Jun 9, 2025 7:07 AM. Available: [34]
35. Sadia Maduri Rasa, Md. Manowarul Islam, Md. Zobayer Kazi" Brain tumor classification using finetuned transfer learning models on magnetic resonance imaging (MRI) images" First published online October 7, 2024.Available [35].