E-ISSN: 2708-4485
P-ISSN: 2708-4477
IJEDN 2024; 5(1): 48-52

www.electronicnetjournal.com
Received: 14-01-2024
Accepted: 21-02-2024

KV Karthikeya
Senior Associate Software Engineer, AT&T, Sattva Knowledge City, Hyderabad, Telangana, India

Devi Venkatesh Gowtham
Aarnavi Research Technology, 21A/1, Ammasai Street, K.K. Pudur Sai Baba Colony, Coimbatore, Tamil Nadu, India

Sweta S Munnoli
Java Full Stack Developer internship, Kodnest, BTM Layout, Bengaluru, Tamil Nadu, India

Corresponding Author:
Devi Venkatesh Gowtham
Aarnavi Research Technology, 21A/1, Ammasai Street, K.K. Pudur Sai Baba Colony, Coimbatore, Tamil Nadu, India

A novel Ai-powered method for the early MRI-based detection of brain tumors

KV Karthikeya, Devi Venkatesh Gowtham and Sweta S Munnoli

DOI: https://doi.org/10.22271/27084477.2024.v5.i1a.56

Abstract
The timely and correct detection of brain tumors is essential to the improvement of therapy results as well as the quality of life of patients. This research was conducted with the intention of developing a convolutional neural network (CNN) image classifier that is capable of detecting brain tumors in magnetic resonance imaging (MRI) data. Brain tumours are a significant contributor to mortality and morbidity on a worldwide scale, with about 300,000 new cases being diagnosed each year indicating their prevalence. Because of its excellent spatial resolution and contrast in soft tissues, magnetic resonance imaging (MRI) is an extremely important tool for locating abnormalities in the brain. Nevertheless, the correct interpretation of MRI data continues to be a challenge because of the effects of human variability and variations in the appearance of tumors. These issues were addressed by this study via the use of convolutional neural networks (CNNs), which have shown amazing efficacy in the field of medical picture interpretation recently. A wide variety of CNN architectures were evaluated and used in order to enhance the identification of brain tumors. The top model outperformed prior studies by achieving a sensitivity level of 99.2%, a binary accuracy of 98.2%, and an accuracy of 97.5%. All of these accuracy levels were achieved by the top model. Deep learning techniques have the potential to significantly enhance the accuracy and reliability of diagnoses in healthcare settings, as shown by these results, which emphasize the promise of these techniques for clinical use.

Keywords: Brain tumors, MRI, convolutional neural networks, deep learning, image classification, medical imaging

Introduction

Brain cancers must be detected as soon as possible. Only definitive brain surgery can conduct the biopsy necessary to classify brain cancers. Brain tumors can be better identified and classified with the use of computational intelligence-oriented techniques [1]. It is crucial to accurately and quickly diagnose brain tumors if we want to improve patient outcomes through therapy. When it comes to identifying brain cancers, magnetic resonance imaging (MRI) is crucial because of the detailed anatomical information it provides. Instead, it would be extremely laborious and error-prone to manually segment and identify brain tumors from MRI images [2]. An unchecked proliferation of synapses, which occurs in brain cancer if not detected early, is known as a brain tumor. The survival of patients and the efficacy of their treatments depend on the prompt detection of brain tumors. There is a wide range in the characteristics, sizes, forms, and therapies for brain tumors. Because of this, human brain tumor detection is laborious, intricate, and prone to mistakes [3]. Brain tumors are the most common cause of brain cancer, which affects people all over the world. Brain cancer has a substantially lower incidence and prevalence rate compared to other cancers (e.g., breast, lung, skin, etc.). False tumor type identification and diagnostic delays contribute to the high fatality rates associated with brain malignancies, particularly in adults [4]. It is a very laborious task to manually detect and classify brain cancers using MRIs. The automation of these procedures is a critical need. Because of the high quality images they provide of inside organs, tissues, and malignancies, magnetic resonance imaging (MRI) has found extensive usage in medical imaging. The ability to detect brain cancers early on can greatly improve treatment outcomes [5].

Related Work

For early stage brain tumor detection utilizing MRI images, the study suggests a classical automatic segmentation technique [6]. The algorithm was tailored to MRI brain segmentation, while parameters were modified for the purpose. It depends on a multilevel thresholding method on a harmony search algorithm (HSO). Different colors are assigned to each section of the histogram, which is divided into segments by numerous thresholds that are dependent on the entropy and variance functions. Using morphological operations and then a connected component evaluation following segmentation, we can reduce the small arias that are thought to be noise and find brain tumors. Several performance metrics, including the Jaccard index, dice coefficient, and accuracy, are used to evaluate the effectiveness of brain tumor detection systems. Professionals in the field compare the results to those obtained manually. Using the Brain Images dataset, which was dubbed the "BraTS 2017 challenge," additional comparisons were made with various CNN and DLA methods. Two deep learning algorithms and multiple machine learning techniques were suggested in [7] for the purpose of using MRI brain images to accurately diagnose three different kinds of tumors-gliomas, meningiomas, and pituitary gland tumors-and to distinguish between tumor-free brains and healthy ones. This would allow doctors to detect tumors at an early stage with a high degree of precision. The research team examined a dataset of 3,264 MRI brain pictures that included both healthy brains and images of gliomas, meningiomas, pituitary gland tumors, and more. It all started with MRI brain scans that were processed and enhanced using algorithms. The next step was to create a convolutional auto-encoder network and a 2D CNN that were pre-trained using our given hyperparameters. Next, a 2D CNN has multiple convolutional layers, each of which uses a 2*2 kernel function. There are a total of sixteen layers in this network: eight convolutional and four pooling. Batch-normalization layers were added after each convolutional layer. The goal of this review paper is to look at the latest advancements in CNN approaches for segmenting and identifying brain tumors in MRI images. We explore the many CNN designs utilized for MRI analysis of brain tumors, identify the most significant challenges associated with this task, and assess the effectiveness metrics of these structures. This article aims to provide a comprehensive review of current state-of-the-art in convolutional neural network (CNN) based brain tumor evaluation of magnetic resonance imaging (MRI) data, highlighting the method's strengths and weaknesses. This article presents BrainCDNet, a new deep learning architecture, in [9]. A model like this one was created by merging pooling layers and addressing overfitting problems with 'He Normal' initialization, batch norm, and global average pooling (GAP) for layer weights. To start, we use a nimble filter to sharpen the input photos while preserving their edges and tiny features. Then, for feature extraction and classification, we used the proposed BrainCDNet. This study conducts all of its studies using two types of MRI databases: binary (healthy vs. pathological) as well as multiclass (glioma vs. meningioma vs. pituitary). Findings and analysis According to the data, the given model outperformed the state-of-the-art methods on both datasets, with a binary accuracy of 99.45% and a multiclass accuracy of 96.78%. A combination of supervised machine learning classifiers such as k-Nearest Neighbor (KNN), Support Vector Machine (SVM), using Linear Discriminant Analysis (LDA) and pre-trained deep learning convolutional neural network (CNN) patterns was introduced in [2, 3, 4, 10]. We made use of a magnetic resonance imaging (MRI) scan that included four different types of brain tumors: meningioma, pituitary, glioma, and no tumor at all. Using three different convolutional neural networks (CNNs)-GoogleNet, Shuffle-Net, and NasNet-Mobile-we were able to infer the features retrieved from the photos. Based on the trial results, Shuffle N *et al*. with SVM had the best results across all four metrics: Accuracy (98.40%), Precision (97%), Recall (96.75%), and Fl-Score (96.75%). Lastly, we measured our outcomes against many recently published state-of-the-art studies, and our suggested approach demonstrated superior performance.

Proposed work

In order to train and evaluate the classification system, this section gives an outline of the publicly accessible dataset that was preprocessed. It goes on to detail the assessment measures utilized and the classifiers that were constructed. These activities were accomplished using the methods indicated in Figure 1.

Overall Architecture of Brain Tumor Detection

Brain tumors may vary greatly in shape, size, and location, making image analysis of these tumors problematic. To identify out-of-the-ordinary occurrences in data that cannot be physically examined, researchers have put forward a number of distinct approaches, each with its own pros and cons. In order to objectively evaluate the performance of state-of-the-art processes, a benchmark dataset that can measure their effectiveness must be available. The amount of slices, pixel spacing, contrast, and sharpness of pictures of brain tumors might differ among systems. In this paper, we lay out the technical specifics of the suggested system that can identify brain cancers in images with remarkable speed and accuracy. Figure 1 displays the steps for processing, improving, training, and evaluating images of brain tumors. Prior research has examined some of the possible approaches to identifying and characterizing brain tumors. The sad truth is that these techniques have only been tested in a small number of research, and even then the results have been inconsistent. The major goal of the proposed approach is to provide reliable MRI tumor identification in the brain. The YOLOv7 model was chosen for this study due to its track record of successfully identifying brain cancers (Figure 1).

Dataset Collection

We used an MRI dataset that is publicly accessible on kaggle.com to guarantee that our results are legitimate. Since magnetic resonance imaging (MRI) scans are considered the diagnostic gold standard for brain malignancies, they are a part of this collection. The four subgroups that comprised our dataset of brain cancers were meningioma (2582 images), glioma (2548 photos), pituitary (2658 images), and no tumor (2500 images). The width and vertical dimensions of all the images were adjusted to 512 pixels. The majority of the dataset, 8232 MRI pictures, were utilized for training purposes in our study, while a smaller subset, 2056 MRI images, were reserved for testing purposes. As an example, Figure 1 displays brain tumor photographs from several categories. Table 1 displays the total number of images in several perspectives, including axial, coronal, and sagittal, for each of the three brain cancer types: glioma, pituitary, and meningioma. Remember that medical pictures, in comparison to standard images, are more complex and need for a higher degree of expertise to interpret correctly. A medical expert checked the labels on the brain tumor dataset to make sure they were accurate and consistent. The knowledge of this doctor was vital since it laid down standards for the tagging of the dataset. Nevertheless, it is dangerous to rely only on image analysis since not all brain tumors show distinctive imaging results. Cancers of the brain must therefore be diagnosed by pathology investigation. In order to provide a wealth of information for training models, our dataset included medical expert-annotated descriptions of aberrant language. For more accurate model building, more training data is better. In cases where there is a lack of data, data augmentation techniques may be used to boost the variety of the training samples. By creating additional versions of the current data, data augmentation may increase a model's generalizability. Finally, by using large amounts of tagged data that were selected by medical professionals, our algorithm was able to improve its prediction potential. By adding more diverse data to the training samples, data augmentation methods may further enhance the accuracy and reliability of the prediction models.

Data Preprocessing and Augmentation

Before being employed in classification issues, the brain tumor photographs went through a number of preparation steps that tried to standardize the dataset. The following is an outline of the preparatory work: To create a monochrome edition of the photos, the RGB shots were grayscaled. The data were made simpler, which reduced the computational effort. Every image now has a resolution of 640×640 thanks to the resizing process. Because of this stage, we know that all of the photographs will be consistent in size throughout the processing that follows. By employing a Gaussian blur filter, we were able to lower the picture noise and increase the output quality. This filtering technique reduces the sharpness of the picture without removing any of the crucial elements. Using a high-pass filter, the images were sharpened and complex characteristics were retrieved. You can better pick out important picture features with this filter applied since it sharpens the attention on edges and little details. To alter the shape and size of an image's features, the morphological procedures of dilatation and erosion were used. The amount of white spots (tumors) was reduced and gaps were highlighted by erosion, while dilatation was employed to fill gaps and increase white patches. The existence of black patches allowed for the identification of contours in three directions: vertically, horizontally, and from right to left. Finding the borders of objects and removing undesired black areas from photographs were both made easier with this method. The finished images were then ready to be sent into neural network simulations thanks to this processing. Tumor types shown in each image are glioma (Label 1), pituitary (Label 2), and meningioma (Label 3). To train and evaluate neural network models, we used preprocessed pictures together with their labels.

Table 1: Data augmentation on the brain tumor dataset.

Brain Tumor Dataset	Training Images			Testing Images	Total
	Original Images	Rotated Images	Flipped Images	Original Images	
Glioma	2039	4078	6117	509	12,743
Pituitary	2066	4132	6198	592	12,988
Meningioma	2127	4254	6381	455	13,217
No tumor	2000	4000	6000	500	12,500
Total	8232	16,464	24,696	2056	51,448

RESNET 50 Model

We improve the quality of early MRI images using the contrast stretching technology. Afterwards, data augmentation techniques like rotation and mirroring are used to generate a large dataset for the (CNN) architecture. The model's ability to generalize is strengthened, and the risk of overfitting is reduced. Next, we query a target dataset that focuses on brain tumors using a pre-trained CNN structure that was learned on the ImageNet dataset [6]. A key goal here is to extract unique visual features from MRI scans. Finally, we perform a crucial step in improving tumor identification by carefully classifying the automated characteristics. For a high-level overview of the data acquisition and classification architecture used to get the aforementioned findings, see Fig. 1. To begin, we import the Data MRI Images Database, which contains a variety of MRI scan types used for model training and testing. When one MRI scan enters the system, it is called the Input Image. Data preprocessing as well as augmentation is the next phase, and it involves shrinking photos and correcting contrast to improve the data collection. In order to reduce the likelihood of overtraining, data preparation methods such picture rotation, mirroring, as well as flipping are used. Next, once the photos have been pre-processed, the CNN-Based Feature Extraction phase uses a deep convolutional neural network to extract unique and valuable features. The Classified Result, which uses the produced characteristics to indicate whether or not the MRI includes a tumor, is the last output. It ensures that the model's preprocessing as well as feature extraction, augmentation utilities, and categorization procedures are adequate, therefore preventing inaccurate tumor detection.

Results & Discussion

The proposed dilated PDCNN model's implementation software is executed in MATLAB. There is 8 GB of random access memory (RAM), a Windows 10 software, and an Intel Core i5 CPU (3.2 GHz) on this computer.

Evaluation Metrics

After all of the testing and training is done, the model's performance in object identification should be evaluated using established criteria. A number of assessment metrics were used by the researchers. These included recall (RE), accuracy (AC), specificity (SP), sensitivity (SE), and confusion matrix (CM). The True Positives (TP), True Negatives (TN), False Positives (FP), while False Negatives (FN) are the metrics that are computed by running the model on a dataset consisting of 613 MRIs. In this context, TP stands for tumor occurrences that the model properly recognized and tagged as tumors, and FP for non-tumor instances that the model mistakenly categorized as tumors. If a tumor goes undetected throughout diagnostic testing, it is known as an unrecognized tumor (FN). "TN" means that the results were indeed negative, as predicted. When dealing with imbalanced datasets, the F1-score is more helpful since it measures the harmonic mean of FNs and FPs. The accuracy, precision, specificity, sensitivity, and F1-score of each model are determined using Equations [7-11] [34, 50] to assess their overall performance:

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$\mathrm{RE\ and\ SE} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}},$$

$$\mathrm{SP} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$\mathrm{AC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$\mathrm{F1-score} = \frac{2(\mathrm{TP})}{2(\mathrm{TP}) + \mathrm{FP} + \mathrm{FN}}$$

The PR, RE, as well as F1-score are crucial metrics for evaluating the effectiveness of a model in the healthcare industry. These metrics show how accurate the predictions are in relation to the overall number of detections, how effectively the probable positive events are recorded, and how balanced the metrics of recall and accuracy are. In deep learning, like in conventional ML, these metrics are fundamental for evaluating the robustness and accuracy of a model.

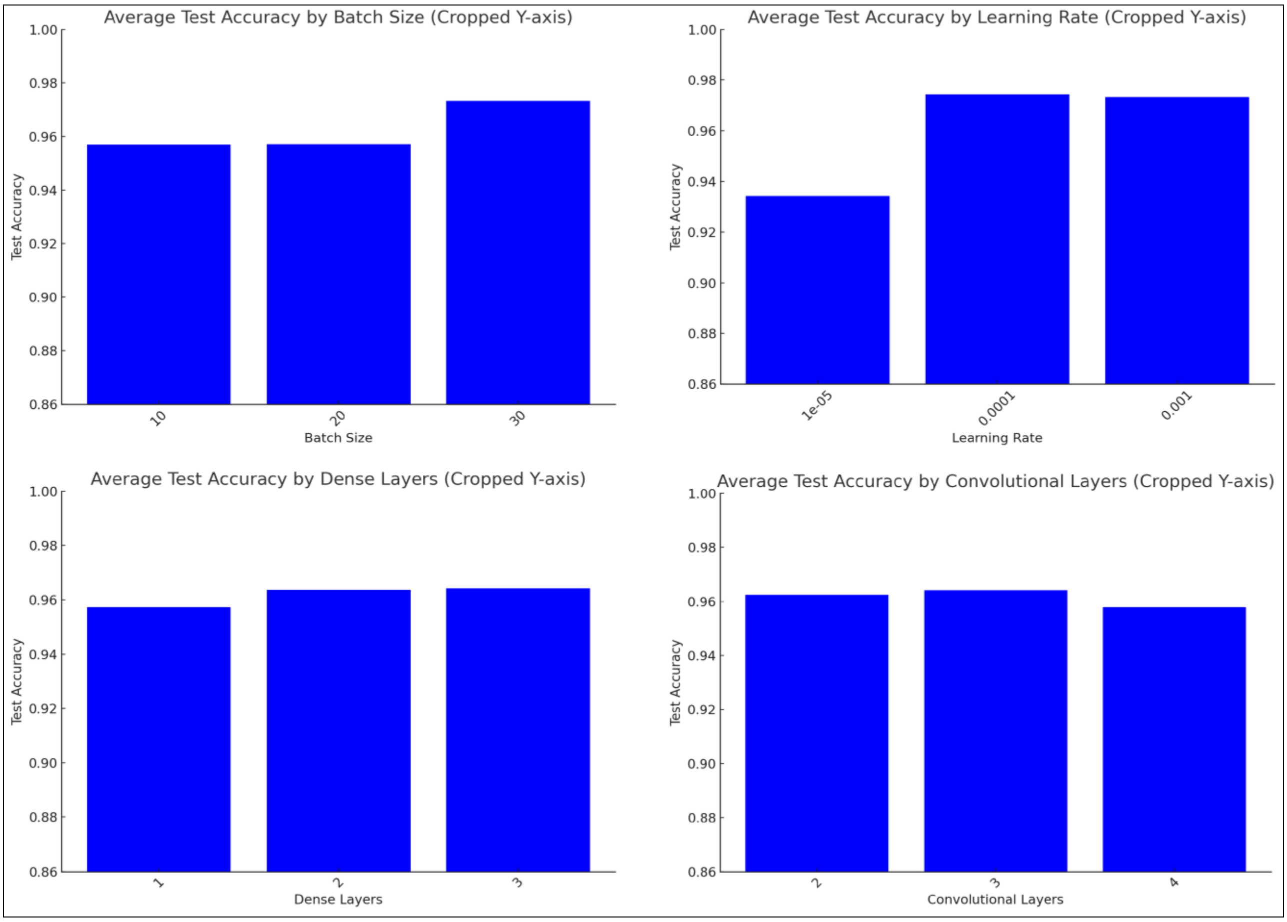

Fig 1: Validation results averaged across several hyperparameter settings

Table 2: Performance comparison of different methods based on precision, recall, and accuracy

Methods	Precision	Recall	Accuracy
Proposed	0.99510	0.99156	0.98214
CNN	0.97983	0.98380	0.97991
TL-CNN	0.98393	0.98000	0.97991
DNN	0.97983	0.97983	0.97767
CNN-with LSTM	0.97580	0.98373	0.97767

Conclusion

The timely and correct detection of brain tumors is essential to the improvement of therapy results as well as the quality of life of patients. This research was conducted with the intention of developing a convolutional neural network (CNN) image classifier that is capable of detecting brain tumors in magnetic resonance imaging (MRI) data. Brain tumours are a significant contributor to mortality and morbidity on a worldwide scale, with about 300,000 new cases being diagnosed each year indicating their prevalence. Because of its excellent spatial resolution and contrast in soft tissues, magnetic resonance imaging (MRI) is an extremely important tool for locating abnormalities in the brain. Nevertheless, the correct interpretation of MRI data continues to be a challenge because of the effects of human variability and variations in the appearance of tumors. These issues were addressed by this study via the use of convolutional neural networks (CNNs), which have shown amazing efficacy in the field of medical picture interpretation recently. A wide variety of CNN architectures were evaluated and used in order to enhance the identification of brain tumors. The top model outperformed prior studies by achieving a sensitivity level of 99.2%, a binary accuracy of 98.2%, and an accuracy of 97.5%. All of these accuracy levels were achieved by the top model. Deep learning techniques have the potential to significantly enhance the accuracy and reliability of diagnoses in healthcare settings, as shown by these results, which emphasize the promise of these techniques for clinical use.

References

1. Khan MF, Khatri P, Lenka S, Anuhya D, Sanyal A. Detection of brain tumor from the MRI images using deep hybrid boosted based on ensemble techniques. In: 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC); 2022. p. 1464-1467.
2. Yenugula M. Examining partitioned caches performance in heterogeneous multi-core processors.
3. Yenugula M. Monitoring performance computing environments and autoscaling using AI.
4. Yenugula M. A systematic literature study on energy-efficient duty cycle MAC protocol for IoT network. In: AIP Conference Proceedings. 2024 Sep, 3131(1).
5. Manukonda KR. A deep reinforcement learning strategy for MEC enabled virtual reality in telecommunication networks. Int. J Computing Eng.; c2024.
6. Roy Gupta B. Deep learning-based detection of pituitary, glioma, and meningioma tumors from brain MRIs. Int. J Multidisciplinary Res.; c2024.
7. Khan FZ, Ayoub S, Gulzar Y, Majid M, Reegu FA, Mir MS, *et al*. MRI-based effective ensemble frameworks for predicting human brain tumor. J Imaging, 2023, 9.
8. Manukonda KR. Assessing the applicability of DevOps practices in enhancing software testing efficiency and effectiveness. J Math Comput. Appl.; c2022.
9. Aleid A, Alhussaini K, Alanazi RS, Altwaimi M, Altwijri O, Saad AS, *et al*. Artificial intelligence approach for early detection of brain tumors using MRI images. Appl. Sci.; c2023.
10. Saeedi S, Rezayi S, Keshavarz H, Niakan Kalhori SR. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decis Mak, 2023, 23.
11. Swamy H. Software quality analysis in edge computing for distributed DevOps using ResNet model. Int. J Sci. Eng. Technol.; c2021.
12. Swamy H. Leveraging AI for enhanced application service monitoring. Int. J Comput. Eng. Technol. 2024;15:92-106. DOI: 10.5281/zenodo.13131932.
13. Swamy H. Smart spending: Harnessing AI to optimize cloud cost management.
DOI: 10.5281/zenodo.13132258.
14. Yenugula M, Goswami SS, Kaliappan S, Saravanakumar R, Alasiry A, Marzougui M, *et al*. Analyzing the critical parameters for implementing sustainable AI cloud system in an IT industry using AHP-ISM-MICMAC integrated hybrid MCDM model. Mathematics. 2023;11(15):3367.