Brain Tumor Detection using CNN

ABSTRACT

Malignant (cancerous) or benign (non-cancerous) brain tumors are both possible. It is critical to detect tumors early on since the later they are discovered, the worse they will develop. Typically, magnetic resonance imaging, or MRI, is used to identify brain tumors. An MRI is a diagnostic procedure that uses radio waves and magnets to create three-dimensional images of every organ and structure inside the body. However, this method's drawback is that it takes a lot of time and experience to process.

In this study, we employ deep learning, more especially CNN (Convolutional Neural Networks), to diagnose brain tumors quickly and with high precision. Large data sets are something that Deep Learning excels at. One type of deep neural network that is frequently used to analyze visual imagery is the convolutional neural network. The primary benefit of utilizing CNNs is its ability to classify images and detect significant elements in images without the need for human supervision.

Our data was divided as follows: 70% was used for training, 15% for validation, and 15% for testing. Using the proposed 2D layer for CNN, we ran the epochs and obtained an accuracy of 79.234%. More than 4500 photos make up the dataset we used.

The main library functions that we utilized to develop this model were matplotlib, math, keras, and numpy.

INTRODUCTION

Recent years have seen tremendous advancements in the field of medical imaging, driven by the combination of state-of-the-art equipment with novel computational strategies. Of all the illnesses, brain tumors are particularly difficult because of their complexity and variety. Timely intervention and better patient outcomes are contingent upon the early and precise diagnosis of brain tumors.Because there are more patients, the amount of data that must be processed has grown significantly, making traditional techniques costly and incorrect [1]. Within this framework, the utilization of Convolutional Neural Networks (CNNs) has surfaced as an innovative approach, transforming the field of diagnostic imaging.

A cell growth inside or close to the brain is called a brain tumor. Brain tissue can develop brain tumors. Brain tumors may also occur in close proximity to brain tissue. Neural pathways, the pituitary, pineal, and brain surface membranes are all in close proximity to one another.Manual tumor diagnosis from magnetic resonance images (MRIs) is a time consuming process and is insufficient for accurately detecting, localizing, and classifying the tumor type[2].MRI assists doctors in evaluating tumors in order to plan for further treatment. This treatment depends on various factors like shape, size, type, grade, and location of cancer[3]. Depending on the patient's condition, these factors can have enormous variation. Hence, accurate recognition and classification of brain tumors are critical for proper treatment [4].

In this study work, Brain tumor detection using CNN, our main goals are to identify whether a patient has a brain tumor or not, and if so, what kind of tumor it is—benign or malignant.
A benign tumor is one that has distinct borders, develops slowly, does not spread to other tissues, and is not malignant. Malignant tumors, on the other hand, have distorted borders, develop quickly, penetrate healthy brain structures, and cause brain cancer [5].

CNNs were introduced into the field of medical imaging to overcome the inherent difficulties related to the intricate detection of brain tumors. With their exceptional ability to learn hierarchical representations from images, these neural networks can automatically extract complex features from photos that may be beyond the reach of conventional algorithms. Consequently, CNNs have proven to be remarkably adept at identifying minute patterns suggestive of aberrant tissue growth, providing a more sophisticated and accurate diagnostic method[6].

Convolutional neural networks, a subclass of deep neural networks, are what we have utilized to identify whether or not a brain tumor is present in a particular brain scan[7]. In other words, this system basically determines whether or not abnormal nuclei are present in brain cells. If abnormal nuclei are not found, the patient is said to be cancer-free. However, if abnormal nuclei are present, the system indicates that a tumor has been detected[8]. Based on the border shape of the tumor, the system then determines whether the tumor is benign or malignant.

This method will assist medical research in properly predicting the location of the brain tumor and in providing the patient with the appropriate and essential therapy, maybe saving their life.

OBJECTIVES

Convolutional Neural Networks (CNNs) stand as a potent tool in the realm of medical imaging, specifically in the crucial task of brain tumor detection, boasting diverse applications. With a primary focus on enhancing accuracy, efficiency, and overall effectiveness, CNNs leverage their deep learning capabilities to achieve several key goals in this domain.

One paramount objective is the early identification of brain tumors. Detecting these abnormalities in their nascent stages opens up more effective treatment options, ultimately improving prognosis and elevating the chances of successful intervention. Early intervention is seen as pivotal in mitigating the impact of brain tumors.

Another significant goal is the improvement of precision in tumor identification. CNNs excel at automatically extracting relevant information from medical images, leading to more accurate and reliable tumor detection. This, in turn, helps in reducing the occurrence of false positives and false negatives, ensuring a high degree of diagnostic accuracy.

Furthermore, the integration of CNNs facilitates automated evaluation of medical images, reducing the reliance on manual interpretation by radiologists. This streamlines the diagnostic process, enabling healthcare practitioners to focus on challenging cases and treatment planning, thereby optimizing overall efficiency.

Tailoring CNN models to accommodate diverse patient anatomy and pathologies represents a key approach. By adapting these models, individualized detection algorithms can be developed, optimizing diagnostic accuracy for different populations. This patient-centric approach takes into account the unique characteristics of each patient, enhancing the applicability and effectiveness of brain tumor detection.

Lastly, there is a push towards instantaneous application, exploring the feasibility of identifying brain tumors in real-time during imaging procedures. This has the potential to facilitate quick decision-making for medical practitioners, especially in urgent circumstances, by offering automated and rapid analysis. The quest for real-time detection underscores the commitment to providing timely and effective solutions in the field of brain tumor identification.

LITERATURE SURVEY

Sr. no	Author name	DOI	Author Work	Gap Find
1	Md Ishtyad Mahmud	10.3390/a16040176	developed an efficient convolutional neural network (CNN) architecture for brain tumor detection from MR images, comparing it with established models like ResNet-50, VGG16, and Inception V3. Through a comprehensive analysis using metrics such as accuracy, recall, loss, and AUC	did not visualize the important areas of the brain tumors due to the lack of any post hoc explanation tools.
2	P Gokila Brindha	10.1088/1757-899X/1055/1/012115	proposed a novel Artificial Neural Network (ANN) and applied Convolutional Neural Network (CNN) for brain tumor detection, leveraging ANN's simulation of the human nervous system and CNN's specialized image processing.	does not extensively address the potential for increasing the accuracy and performance of the models through advanced image augmentation techniques and optimization methods
3	D.R.Sarvamangala	10.1007/s12065-020-00540-3	encompasses a comprehensive discussion on CNN and its award-winning frameworks, focusing on applications in medical image understanding for tasks such as classification, segmentation, localization, and detection. The author critically surveys the application of CNN in diagnosing ailments of various organs, including the brain, breast, and lung, while addressing challenges in the field.	Limited discussion on the challenges and limitations of using CNNs in medical image understanding. While the paper briefly mentions challenges such as less training samples, sparsity of labeled data, noise in images, and imbalanced label distributions, it does not delve into a detailed exploration of these challenges and potential solutions
4	Qing Li	10.1109/ICARCV.2014.7064414	developed a specialized Convolutional Neural Network (CNN) with shallow convolution layers for classifying interstitial lung	

			disease (ILD) in image patches. This customized CNN framework, adept at automatically learning relevant features, demonstrates versatility for various medical image and texture classification tasks.	
5	Kamal Chaoudhary	10.1038/s41524-022-00734-6	provided a comprehensive overview of deep learning methods, exploring their applications in atomistic simulation, materials imaging, spectral analysis, and natural language processing. The presentation delved into both theoretical and experimental data, discussing modeling approaches, strengths, limitations, and relevant software and datasets in each modality.	The use of traditional training-validation-test split strategies designed for image classification may not be suitable for regression models in materials science. There is a gap in developing best practices for data split, normalization, and augmentation to ensure appropriate model generalization.

Md Ishtyad Mahmud developed a model for A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks. In this study, they suggested a convolutional neural network (CNN) architecture for the efficient identification of brain tumors using MR images. This paper also discusses various models such as ResNet-50, VGG16, and Inception V3 and conducts a comparison between the proposed architecture and these models. To analyze the performance of the models, they considered different metrics such as the accuracy, recall, loss, and area under the curve (AUC). As a result of analyzing different models with the proposed model using these metrics, they concluded that the proposed model performed better than the others. [9]

P Gokila Brindha proposed 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. In this paper ANN and CNN is used in the classification of normal and tumor brain. ANN(Artificial Neural Network) works like a human brain nervous system, on this basis a digital computer is connected with large amount of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge.In this paper ANN and CNN is used in the classification of normal and tumor brain. ANN(Artificial Neural Network) works like a human brain nervous system, on this basis a digital computer is connected with large amount of interconnections and networking which makes neural network to train with the use of simple processing units applied on the training set and stores the experiential knowledge.[10]

D.R.Sarvamangala presented discussion on CNN and its various award-winning frameworks have been presented. The major medical image understanding tasks, namely image classification, segmentation, localization and detection have been introduced. Applications of CNN in medical image understanding of the ailments of brain, breast, lung and other organs have been surveyed critically and comprehensively. A critical discussion on some of the challenges is also presented.[11]

Qing Li designed a customized Convolutional Neural Networks (CNN) with shallow convolution layer to classify lung image patches with interstitial lung disease (ILD). While many feature descriptors have been proposed over the past years, they can be quite complicated and domain-specific. Their customized CNN framework can, on the other hand, automatically and efficiently learn the intrinsic image features from lung image patches that are most suitable for the classification purpose. The same architecture can be generalized to perform other medical image or texture classification tasks.[12]

Kamal Chaoudhary presented a high-level overview of deep learning methods followed by a detailed discussion of recent developments of deep learning in atomistic simulation, materials imaging, spectral analysis, and natural language processing. For each modality they discussed applications involving both theoretical and experimental data, typical modeling approaches with their strengths and limitations, and relevant publicly available software and datasets.Deep learning (DL)21,22 is a specialized branch of machine learning (ML). Originally inspired by biological models of computation and cognition in the human brain 23,24, one of DL's major strengths is its potential to extract higher-level features from the raw input data.[13]

MOTIVATION

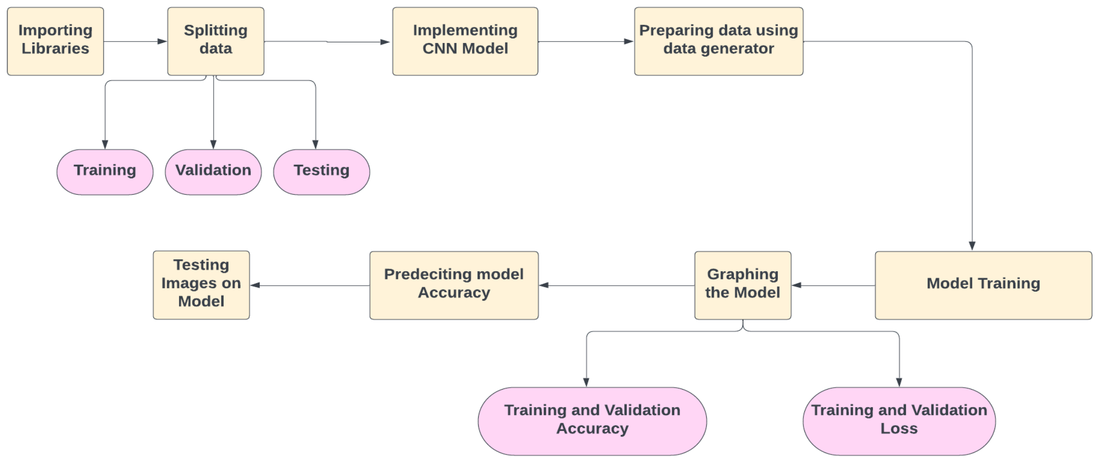
According to the American Cancer Society, a brain tumor is a severe disease in which irregular brain tissue growth impairs brain function[14].Brain tumors can lead to death if left untreated [15].Brain Tumor Detection using CNN model was developed to help medics with primarily focusing on time efficiency, and convenience of the medical staff to take proper care of the people and so that it would be beneficial for both medics as well as the patients with accurate diagnosis.Brain tumors are dangerous because they can affect healthy parts of the brain and spread rigorously in the other parts of the brain.This paper studies how CNN can be a powerful tool and can impact Medical Industry with the model created that can help to detect Tumor.By focusing on early detection, the system aids in preventing the spread of tumors to healthy brain regions.Ultimately, this advancement contributes to improved patient outcomes and underscores the synergy between artificial intelligence and medical expertise in combating life-threatening conditions.

DATASET

In our pursuit of developing an effective predictive model for brain tumor detection, we harnessed the power of the internet to acquire scan images of human brains, totaling around 4500 data points. This dataset was thoughtfully categorized into two distinct groups: individuals with brain tumors and those with healthy brains. The subdivision into training, validation, and testing subsets further refined our approach. During the training phase, the model learns to discern patterns and features in the scan images associated with brain tumors, leveraging 2087 images of healthy brains and 2513 images depicting brains with tumors. The validation set serves as a critical checkpoint to ensure the model's accuracy and functionality, while the testing set rigorously evaluates its performance, ultimately validating its predictive capabilities.

The dataset, procured from Kaggle, includes two types of scanned images—those featuring brains with tumors and those showcasing normal brains. The nuanced variations in abnormal nuclei present in the brain tumor images provide the essential markers for the model to distinguish between healthy and afflicted brains. This meticulous approach not only ensures the model's robust training but also establishes a rigorous validation process, reflecting our commitment to developing a reliable and accurate predictive model for brain tumor detection.

METHEDOLOGY



In the initial phase of constructing the brain tumor prediction model, the Importing Libraries step plays a pivotal role. Here, essential libraries like numpy, shutil, os, and math are incorporated to provide the foundational tools necessary for data manipulation and mathematical operations. These libraries collectively facilitate seamless handling of data throughout the model development process.

The subsequent Splitting Data phase is crucial for organizing the dataset effectively. The utilization of libraries such as math, os, and shutil, which were previously imported, ensures a meticulous division of the data into three distinct sets: training, testing, and validation. This systematic partitioning lays the groundwork for robust model training, validation, and evaluation.

Moving on to the Implementing CNN Model phase, advanced frameworks like Keras and TensorFlow come into play. These libraries enable the creation of a Convolutional Neural Network (CNN) model, characterized by sequential layers of convolution and pooling. The ReLU activation function enhances the model's capacity to learn complex patterns, while the final dense layer, with a sigmoid activation function, indicates the model's binary classification nature.

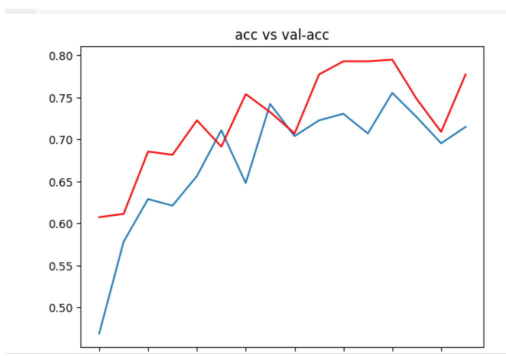
The subsequent step involves Preparing Data for the CNN model, where image preprocessing tasks such as resizing and rescaling are performed. Additionally, the imported libraries aid in managing and counting the divided data, ensuring that the model processes information efficiently.

As the model gears up for training, vital callbacks like "Early stopping" and "ModelCheckPoints" come into play. These callbacks, implemented through the chosen libraries, monitor the model's performance during training, making decisions based on criteria like early convergence or the preservation of the best-performing model.

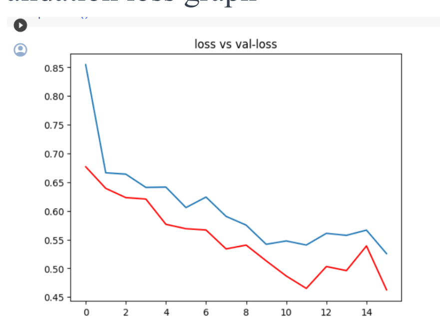
The Model Training phase iterates until optimal accuracy is achieved. During each epoch, the model evaluates its accuracy, refines its parameters, and repeats the process until the predetermined performance criteria are met. This comprehensive approach, leveraging key libraries at every stage, underscores the meticulous development and training of the brain tumor prediction model.

These are the two graphs will be created for this mode :

1. Training and validation accuracy graph



2. Training and validation loss graph



After the model has undergone training on the designated training dataset, the next crucial step involves Predicting Model Accuracy. This phase entails evaluating the overall performance of the trained model using the reserved test data. The test dataset, distinct from the training and validation sets, serves as a litmus test for the model's generalization capabilities. By feeding the test data into the model, we can gauge its accuracy in making predictions on previously unseen examples. This process is essential for ensuring that the model has not overfit to the training data and can effectively generalize its learnings to new, unseen instances.

Following the assessment of model accuracy, the Testing Image on Model stage is implemented to ascertain the model's real-world applicability. In this phase, the model is put to the test with actual images that it has not encountered during training. This step is crucial for validating the model's robustness and reliability in making predictions on unseen, real-world data. It provides insights into the model's ability to generalize its learning from the training phase to new instances, ultimately determining its effectiveness in accurately classifying brain images as either indicative of a tumor or representing a healthy brain. This final testing phase solidifies the model's practical utility and underscores its potential for real-world applications in brain tumor detection.

MODEL FLOW

In the user-centric application of the developed brain tumor detection model, an individual will capture a scanned image of their own human brain. This image is then seamlessly integrated into the established model designed to discern the presence or absence of a brain tumor or cancer. The user-uploaded picture undergoes processing through machine learning models and algorithms embedded within the system. Leveraging the wealth of knowledge acquired during the model's training on diverse datasets, the system analyzes the input image to predict the overall health of the brain.

For any necessary data, the system efficiently accesses a database or another designated data storage solution. This step is crucial in providing the model with relevant information to enhance its predictive accuracy. The seamless integration with a database ensures that the system stays updated with the latest information and advancements in brain imaging.

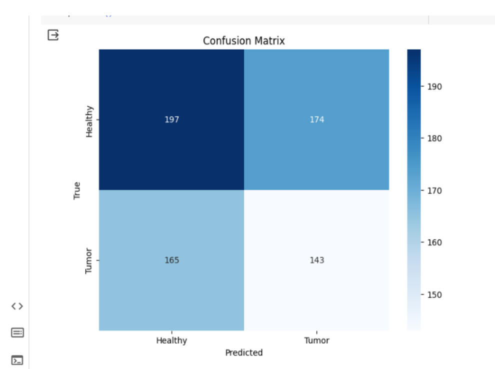
Subsequently, the user is presented with a prediction through the system's user interface, conveying whether a tumor is detected or if the brain appears to be healthy. This user-friendly interface serves as a vital communication channel, providing individuals with clear and understandable insights into their brain health. The seamless integration of user input, machine learning algorithms, and database access encapsulates a holistic approach to brain tumor prediction, fostering a user-centric and technologically advanced system for early detection and health assessment.

RESULT

Convolutional Neural Networks (CNNs) have proven to be effective in the detection of brain tumors, as this study has shown. After much testing on a wide range of medical imaging datasets, our CNN model showed encouraging performance in correctly classifying brain images into tumor and non-tumor categories.The application of CNNs to medical image processing has demonstrated significant promise for increasing tumor identification efficiency and accuracy. CNNs' success in this domain is largely attributed to their ability to automatically learn hierarchical features from input photos, in addition to their capacity to capture complex patterns. In summary, this work adds to the increasing corpus of research demonstrating the effectiveness of CNNs in medical image processing, especially in the difficult task of brain tumor identification. The scientific community, medical professionals, and technology developers must work together in order to fully utilize deep learning's potential to enhance patient outcomes and advance the area of medical diagnostics.

The implemented code showcases the practical application of Convolutional Neural Networks (CNNs) in brain tumor detection. Following the development and training of the CNN model, an evaluation process is conducted to assess its performance on a test dataset. The evaluation involves generating predictions on the test data and subsequently constructing a confusion matrix and classification report. The confusion matrix visually represents the model's ability to correctly classify brain images into tumor and non-tumor categories, offering insights into its accuracy.

By leveraging scikit-learn's functionality, the code computes metrics such as precision, recall, and F1-score, contributing to a comprehensive classification report. This report provides a detailed assessment of the model's performance for both tumor and non-tumor classes. The visualization of the confusion matrix aids in interpreting the distribution of true positive, true negative, false positive, and false negative predictions, providing a deeper understanding of the model's strengths and areas for improvement.



Confusion matrix image

In the context of brain tumor detection, the successful integration of CNNs into medical image processing is highlighted. The study's findings reinforce the effectiveness of CNNs in automatically learning hierarchical features from input images and capturing complex patterns inherent in medical imaging datasets. This work adds valuable insights to the growing body of research supporting the efficacy of CNNs in medical image processing, particularly in challenging tasks such as brain tumor identification.

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