

Brain Tumor Detection using CNN

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Abstract— Tumors of the brain are malignant growths that can arise within the brain itself or in the surrounding tissues. Individuals affected by brain tumors often face significant challenges in terms of their overall health and quality of life. The prompt identification and precise diagnosis of brain tumors are crucial for formulating an effective treatment plan. Over the years, convolutional neural networks (CNNs) have emerged as a promising approach in the field of medical imaging and artificial intelligence (AI). These advancements have led to the development of automated techniques for diagnosing brain tumors. In this study, we propose a CNN-based method for identifying brain cancers using MRI images. The proposed CNN architecture consists of multiple layers of convolutional processing, followed by maximum pooling, batch normalization, and dropout processing. To ensure the accuracy of the model, it is trained using a large dataset that includes various types of brain MRI scans, including both normal and tumor images. Our team conducted an investigation of this proposed procedure using a dataset comprising brain MRI pictures obtained from different locations.

Index Terms— MRI, CNN, Data augmentation, Resnetv50model.

I. INTRODUCTION

Furthermore, the localization of brain tumors is essential for surgical planning and intervention. Accurate identification of the tumor's location helps surgeons determine the best approach for removal, minimizing damage to healthy brain tissue and reducing the risk of complications. Deep learning techniques, such as CNNs, have demonstrated their ability to precisely localize brain tumors in medical images, aiding surgeons in their decision-making process. In addition to localization, characterizing brain tumors is crucial for determining their type, grade, and aggressiveness. This information is vital for developing personalized treatment plans and predicting patient prognosis. CNNs can analyze various imaging modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET), to extract features that differentiate between different tumor types and grades. By accurately characterizing brain tumors, CNNs enable clinicians to make informed decisions regarding treatment options, such as surgery, radiation therapy, or chemotherapy. The use of CNNs in brain tumor analysis has also facilitated the integration of multi-modal imaging data. By combining information from different imaging modalities, such as MRI and PET, CNNs can provide a more comprehensive and accurate assessment of brain tumors. This integration allows for a more holistic understanding of the tumor's characteristics, aiding in treatment planning and monitoring the tumor's response to therapy. Moreover, the automation of brain

tumor analysis using CNNs has significantly improved efficiency and reduced the burden on radiologists. Traditionally, radiologists manually analyze medical images, which can be time-consuming and prone to human error. CNNs can process large datasets quickly and accurately, providing consistent and reliable results. This automation frees up radiologists' time, allowing them to focus on more complex cases and providing better patient care. Overall, the localization and characterization of brain tumors using CNNs have revolutionized medical image analysis. The integration of deep learning techniques in this field has led to faster and more accurate identification of brain tumors, improved surgical planning, personalized treatment strategies, and enhanced patient outcomes. As advancements in medical imaging and AI continue, the role of CNNs in brain tumor analysis is expected to further expand, contributing to advancements in diagnosis, treatment, and research in the field of neuro-oncology.

II. LITERATURE SURVEY

A survey on Brain Tumor Detection Using Image Processing Techniques published on the year 2017 Author by Luxit Kapoor, Sanjeev Thakur Journal Name IEEE 7th International Conference on Cloud Computing, Data Science & Engineering Summary This study summarizes the different Medical Image Processing methods that contribute to the process of diagnosing brain cancers using MRI scans. These techniques may be found in the Medical Image Processing category. The findings of the research were utilized to compile this paper, which provides an exhaustive rundown of the many approaches that may be taken. In addition, a shortened description of each approach may be found further down this page. In addition, the "segmentation" step is the one that is regarded as being the most important stage out of all the many phases that are involved in the process of discovering cancers. This phase ensures that the criteria are met in an accurate manner at all times.

A. Review of Brain Tumor Detection from MRI Images publication on the year: 2016 Author: Deepa, Akansha Singh Journal Name IEEE International Conference on Computing for Sustainable Global Development. Summary Recent scientific progress in the identification and segmentation of brain tumors is described in this article. In this article, a range of approaches to identifying brain tumors via the use of MRI data are discussed. These approaches have been used by a variety of researchers. According to the results of this investigation, one of the areas of research that sees the most activity is the automated detection and segmentation of brain tumors using MRI images.

B. Review of CNN Model Kernel Extreme Learning Machines (KELM) was used to classify brain tumors while CNN was used to extract information from brain pictures. The results that Pashaei and colleagues [1] got showed an accuracy percentage of 93.68%. According to Phaye et al. [2] in order to categorize the various forms of brain cancer, many capsule networks were employed. The conventional convolution layer in the Caps Net was replaced in this design with a densely coupled convolution layer, which brought about an improvement in accuracy from 90.07% to 95.03%. Classifying brain tumors using DL, Avsar and Salcin [3] created a quicker region-based CNN (quicker R-CNN) with a 91.66% success rate.

A. Existing Solution

First, a computer-based method using an Artificial Neural Network Algorithm is used to identify tumor blocks and categorize tumor types in MRI images collected from several patients. The second step involves applying several image processing methods to MRI scans of cancer patients in an effort to spot any brain tumors. These techniques include feature extraction, morphological procedures, picture segmentation, and histogram equalization in Fig.1. The images of cancer patients who have been afflicted by the illness are analyzed using these techniques. The goal of this study was to create an automated system for the recognition of brain tumors. The main goals of the study were twofold: first, they wanted to enhance the diagnostic accuracy of the procedure, and second, they wanted to speed up the process as much as possible.

Image Preprocessing: This system accepts input in the form of MRI pictures as well as scanned images, and both types of images include noise. As a direct consequence of this, the very first thing that we need to do is clean up the input image by removing all the noise. The system flow dictates that we do noise cancellation and initial processing using a high pass filter. This was explained in more detail before. Segmentation: The basic approach of segmenting photos based on areas has been given the name "region growing".

The procedure starts with selecting seed points, making it a pixel-based approach to picture segmentation. The morphological method extracts boundary regions from brain scans, particularly effective on binary images. It rearranges the order of pixel values without changing their mathematical values. Dilatation adds pixels to enlarge an object, while erosion subtracts pixels to reduce it. Feature extraction enables edge detection in photographs. Picture segmentation extracts metadata like contours, textures, colors, and contrast levels. Connected component labeling groups pixels with the same grayscale values and assigns them a label. In the tumor identification stage,

brain MRIs from a previous phase are used to extract features. Comparison is crucial in building a knowledge base.

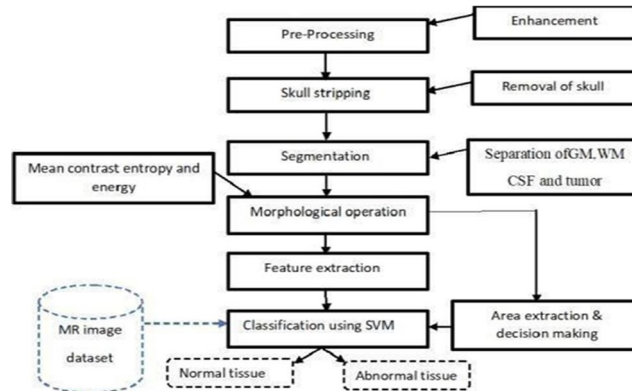


Figure 1. Solution Of Brain Tumor Detection

B. Proposed Solution

The proposed methodology for brain tumor detection can be divided into five distinct components. The first component is the data set, which consists of a collection of MRI images. These images serve as the input for the detection system. The second component is the preprocessing step, where the images are prepared for further analysis. This may involve tasks such as noise reduction, image enhancement, and normalization. The third component is the initialization step, where the initial parameters of the deep neural network model are set. This includes setting the number of layers, the number of neurons in each layer, and the activation functions to be used. The fourth component is the construction of the CNN model after partitioning the data. The data set is divided into training and testing data, with eighty percent of the images allocated to the training data and the remaining twenty percent assigned to the testing data. The CNN model is then constructed using the training data. The fifth component is the training of the deep neural network for a specified number of epochs. During this phase, the CNN model is trained using the training data. The model learns to recognize patterns and features in the images that are indicative of the presence or absence of a brain tumor. To enhance the variety of options, a selection of MRI images from the dataset can be utilized as input images. This allows for a more diverse range of images to be used in the training and testing phases. These findings align with the conclusions presented in N. Chakraborty's paper titled "Brain MRI images for Brain tumor Detection Kaggle" [4-7]. Prior to saving the image, it is necessary to resize the label and encode it. This ensures that the label is in a suitable format for further analysis and classification. During the data splitting phase, eighty percent of the images were allocated to the Training Data, while the remaining twenty percent were assigned to the Testing Data. This division allows for the model to be trained on a large portion of the data while still having a separate set of images to evaluate its performance. To guide the process, a deep neural network should be constructed and trained using the CNN paradigm. This involves setting up the layers and neurons of the network, as well as defining the loss function and optimization algorithm. Subsequently, a verdict of either "yes" or "no" was assigned to the image based on the presence or absence of a tumor. A positive tumor resulted in a "yes" verdict, whereas a negative tumor led to a "no" verdict.

C. Proposed Methodology Using CNN

The CNN developed for cancer detection consists of six layers, including hidden layers, and has shown remarkable results in tumor detection. The recommended strategy involves using a convolutional layer to convert MRI images into a one-dimensional form, making it easier for the network to process and analyze the data. A convolutional kernel with 32 filters of size 2×2 is applied to extract relevant features from the images. An activation function is applied to introduce non-linearity into the network. To prevent overfitting, a Max Pooling layer is employed to reduce the spatial dimensions of the data while retaining important features. The dimensions for this layer are set to $64 \times 64 \times 32$, and the pool size is set to (2, 2). The Max Pooling layer helps in reducing computational complexity, preventing overfitting, and capturing salient features of the MRI images for accurate tumor detection. Overall, this CNN with its six layers, convolutional layer, activation function, and Max Pooling layer has shown significant results in tumor detection, aiding in early diagnosis in Figure 2. This approach is necessary due to the splitting of input photographs in both spatial dimensions the layer arrangement of the model is designed to extract features from the input data in a hierarchical manner. The first layer applies a set of filters to the input image,

which highlights certain patterns and edges. The subsequent layers build on these features and extract more complex patterns and shapes. The batch normalization layers help to normalize the output of the convolution layers, which improves the stability and speed of the training process. The max pooling layers reduce the spatial dimensions of the feature maps, which helps to reduce the computational complexity of the model. The dropout layers randomly drop out some of the neurons during training, which helps to prevent over fitting and improve the generalization performance of the model. The choice of the number of filters in each convolution layer is based on empirical observations and experimentation. The first two layers have fewer filters as they are responsible for extracting low-level features, while the subsequent layers have more filters as they need to capture more complex patterns. The model is trained on a relatively small dataset of 213 images, which is a challenging task as deep learning models typically require large amounts of data to achieve high accuracy. However, the model achieves an impressive accuracy of 99% on the test set, which indicates that it has learned to generalize well to new data. Overall, the layer arrangement and hyper parameters of the model have been carefully chosen to achieve high accuracy while minimizing over fitting and computational complexity.

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	416
conv2d_1 (Conv2D)	(None, 128, 128, 32)	4128
batch_normalization (Batch Normalization)	(None, 128, 128, 32)	128
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
dropout (Dropout)	(None, 64, 64, 32)	0
conv2d_2 (Conv2D)	(None, 64, 64, 64)	8256
conv2d_3 (Conv2D)	(None, 64, 64, 64)	16448
batch_normalization_1 (Batch Normalization)	(None, 64, 64, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 64)	0
dropout_1 (Dropout)	(None, 32, 32, 64)	0
flatten (Flatten)	(None, 65536)	0
dense (Dense)	(None, 512)	33554944
dropout_2 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 2)	1026
Total params: 33,585,602		
Trainable params: 33,585,410		
Non-trainable params: 192		

Figure 2. Implementation of CNN model

D. Model Losses And Accuracy

The provided visual representation illustrates the losses and validation losses, with the x-axis denoting the number of epochs and the y-axis representing the loss. Specifically, the training loss is depicted as a yellow line, while the validation loss is represented by a green line. The graph in Figure 3 effectively demonstrates that the training loss consistently diminishes over the course of time, whereas the validation loss initially decreases but subsequently exhibits an upward trend. This observed pattern is frequently encountered in the field of machine learning, signifying that the model is beginning to excessively fit the training data.

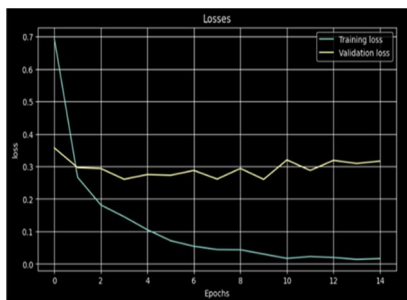


Figure 3. Model Losses

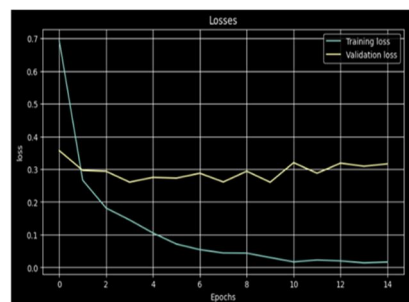


Figure 4. Model Accuracy

The graph in Figure 4 also highlights the importance of monitoring both the training and validation accuracy of a machine learning model. While the training accuracy may continue to improve, it is crucial to ensure that the model is not simply memorizing the training data and failing to generalize to new data. This is where validation accuracy comes into play, as it provides insight into how well the model is performing on unseen data. Furthermore, the plateau in the validation accuracy suggests that the model may have reached its optimal

performance on the validation set. This can be an indication that further improvements to the model may require additional data or a different approach altogether. Overall, the line graph provides valuable information on the performance of a machine learning model and emphasizes the importance of monitoring both the training and validation accuracy throughout the training process.

E. Classification Report

The confusion matrix is a tool that allows for the calculation of various metrics, such as accuracy, precision, recall, and F1 score. Accuracy represents the proportion of correctly predicted examples, while precision indicates the proportion of predicted positives that are truly positive. Recall denotes the proportion of true positives that were predicted correctly. On the other hand, the F1 score is a harmonic means of precision and recall. The confusion matrix in the provided image shows the following values for these metrics: Accuracy - 96.87%, Precision - 92%, Recall - 100%, and F1 score - 96% in Figure 5. These metrics collectively indicate that the model performs exceptionally well in the classification task at hand. In summary, the confusion matrix demonstrates that the model is well-suited for this specific classification task, as it exhibits a high level of accuracy in identifying the positive class.

```
1/1 [=====] - 9s 9s/step
Confusion matrix:
[[11  1]
 [ 0 20]]
Accuracy Score: 0.96875
Classification report:
```

	precision	recall	f1-score	support
0	0.92	1.00	0.96	11
1	1.00	0.95	0.98	21
accuracy			0.97	32
macro avg	0.96	0.98	0.97	32
weighted avg	0.97	0.97	0.97	32

Figure 5. Classification Report

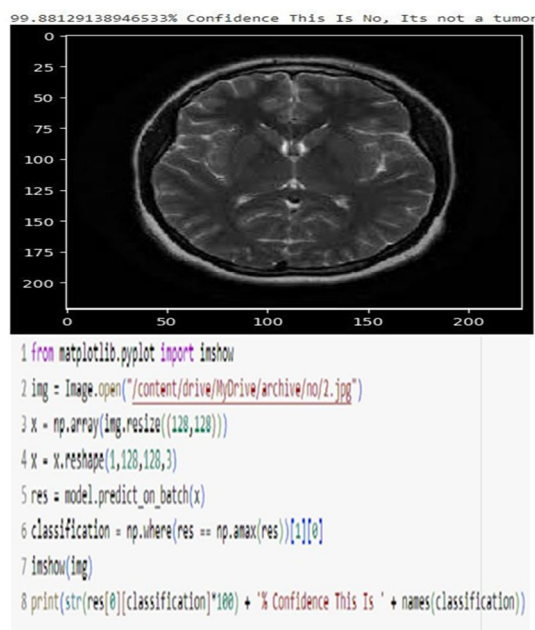


Figure 6. Output of Brain Tumor

The process of using MRI scans to detect brain tumors involves several steps. After the scan is complete, the image is stored in My Drive. The image is then accessed using a command to open the file for further processing as shown in Figure 6. The next step is to resize and reshape the image to fit the input requirements of the CNN model. Various image processing techniques are used for this. The processed image is then fed into the CNN model for training. During training, the model learns to identify features that indicate the presence or absence of a brain

tumor. Once trained, the model can analyze new MRI scans and make predictions based on the features it has learned. Overall, this process requires specialized knowledge and expertise, but with the help of advanced machine learning algorithms, accurate diagnoses can be made and appropriate treatment can be provided.

III. CONCLUSIONS

The use of Convolutional Neural Networks (CNN) in our project was instrumental in achieving exceptional results. By employing CNN, we were able to achieve an impressive accuracy rate of 96.87% in Fig.5. This accuracy was obtained by utilizing a split ratio of 80:20 for a dataset consisting of 215 photographs. This means that only 20% of the photos were allocated for testing, while the remaining 80% were dedicated to training the CNN model. Looking ahead, our future objective is to incorporate three-dimensional imaging of the brain into our project. This will allow us to achieve a more precise segmentation of brain tumors. However, this advancement comes with its own set of challenges. Dealing with a larger dataset, which will be required for three-dimensional imaging, will pose greater difficulties. To overcome these challenges, we plan to compile a comprehensive collection of data that emphasizes the abstract aspects pertaining to our nation. By adopting this strategic approach, we aim to expedite the completion of our work and operate with enhanced efficiency. The larger dataset will provide us with a more robust foundation for training our CNN model, enabling us to achieve even more accurate results in the segmentation of brain tumors. Ultimately, our goal is to contribute to the advancement of medical imaging technology and improve the diagnosis and treatment of brain tumors.

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