IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Brain Tumor Detection Using CNN

Dr. Neeta Verma
Computer Science and Engineering
Inderprastha Engineering College
Ghaziabad, India

Ruchika Yadav
Computer Science and Engineering
Inderprastha Engineering College
Ghaziabad, India

Parul Singh
Computer Science and Engineering
Inderprastha Engineering College
Ghaziabad, India

Vidisha Kumar
Computer Science and Engineering
Inderprastha Engineering Collge
Ghaziabad, India

***Abstract*—** Advancements in medical imaging and machine learning technologies have synergistically catalyzed breakthroughs in the field of healthcare, particularly in the early diagnosis of complex diseases such as brain tumors. This research paper presents a comprehensive investigation into the development of a robust and efficient brain tumor detection system employing state-of-the-art machine learning techniques.

The proposed methodology integrates a diverse set of magnetic resonance imaging (MRI) scans, to capture a holistic representation of the brain's structural and functional aspects. A curated dataset, comprising a spectrum of brain tumor cases and healthy brain images, is utilized for training and evaluating the machine learning algorithms.

Our research delves into the application of deep learning architectures, such as convolutional neural networks (CNNs) built using PyTorch, to automatically extract intricate patterns and features from the medical images. We use publicly available Kaggle dataset that has 3000 samples, which are divided into two classes tumor and non tumor. This dataset is split into 2400 images for training and 600 images for validation This allows for the creation of a highly discriminative model capable of accurately distinguishing between tumor and non-tumor regions. Our experimental results indicate that our models achieve up to 95.3 classification accuracy for our employed datasets, respectively.

The outcomes of this research hold significant implications for the advancement of early brain tumor detection, potentially leading to improved patient outcomes and treatment strategies. The integration of machine learning into clinical workflows not only facilitates faster and more accurate diagnoses but also paves the way for a new era of personalized medicine in neuro-oncology.

Keywords— brain tumor classification; deep learning; convolutional neural network; multiscale processing; data augmentation; MRI

I. INTRODUCTION

In recent years, the convergence of medical imaging technologies and machine learning algorithms has heralded a paradigm shift in the landscape of healthcare, particularly in the realm of early disease detection. Among the myriad health challenges, brain tumors stand as formidable adversaries, demanding precision and swiftness in diagnosis for optimal patient outcomes. With an increasing incidence of brain tumors globally, the quest for innovative and efficient diagnostic tools becomes imperative. This research embarks on an exploration of the synergy between cutting-edge machine learning methodologies and medical imaging to address this critical need, presenting a comprehensive investigation into "Brain Tumor Detection Using Machine Learning."

Brain tumors, ranging from benign to malignant, manifest across diverse anatomical locations and exhibit a spectrum of morphological and physiological characteristics. Traditional diagnostic methods, while essential, often entail significant time and subjectivity, relying on the expertise of medical professionals to interpret intricate imaging data. In contrast, machine learning offers a promising avenue to augment diagnostic precision by leveraging computational algorithms capable of discerning subtle patterns and anomalies within complex medical images.

The primary objective of this research is to harness the power of machine learning to enhance the accuracy and efficiency of brain tumor detection. We propose an integrative approach that incorporates a diverse array of magnetic resonance imaging (MRI) scans, to capture a comprehensive representation of the structural and functional nuances of the brain. Leveraging advanced deep learning architectures, including convolutional neural networks (CNNs) using PyTorch.

As we delve into the intricacies of our proposed methodology, we recognize the significance of not only achieving high diagnostic accuracy but also fostering interpretability and translatability in the clinical setting.

Through rigorous experimentation on real-world datasets and robust evaluation metrics, our research endeavours to validate the efficacy of the proposed methodology.

II. RELATED WORK

Numerous studies have explored the intersection of machine learning and medical imaging for the purpose of brain tumor detection, showcasing a diverse array of methodologies and technologies. Li et al. (2018) employed a deep convolutional neural network (CNN) on magnetic resonance imaging (MRI) scans, achieving an impressive accuracy of 92.3% in distinguishing between tumor and non-tumor regions. The study highlighted the effectiveness of CNNs in automatically extracting intricate spatial features indicative of brain abnormalities.

In a different approach, Prasanna et al. (2019) integrated machine learning with radiomic features extracted from both MRI and computed tomography (CT) scans. Their ensemble model, incorporating support vector machines (SVM) and random forests, demonstrated a commendable accuracy of 89.5% in differentiating between benign and malignant tumors. The incorporation of radiomic features allowed for a more comprehensive analysis of textural and shape characteristics within the images, contributing to the model's discriminative power.

Building on the success of deep learning, Cheng et al. (2020) introduced a hybrid model combining a 3D CNN and long short-term memory (LSTM) networks for temporal sequence learning from multi-sequence MRI data. This approach not only captured spatial information but also leveraged the temporal dynamics of brain images, yielding an accuracy of 93.7% in tumor classification. The incorporation of temporal aspects demonstrated the potential for more nuanced and dynamic detection of brain abnormalities.

Additionally, researchers like Zhang et al. (2021) explored the integration of transfer learning with pre-trained convolutional neural networks for brain tumor classification. Utilizing a pre-trained Res Net architecture on MRI images, their model achieved an accuracy of 95.33%, demonstrating the effectiveness of leveraging knowledge gained from unrelated domains to boost performance in medical image analysis tasks.

Due to their ability to self-learn without the intervention of an expert, CNN models based on Transfer learning techniques have achieved excellent performance, the use of the weight sharing technique provides an adequate network and allows to automatically detect the tumor through the MRI images [49].

Using the ANN approach, Authors in [51], worked on two classes named benign tumors and malignant tumors, they started by preprocessing the images with the filters, then applied the average color moment technique on the images to extract the characteristics. After the transmission of these characteristic maps to the ANN, the classification was made with an accuracy rate of 91.8%.

While these studies collectively underscore the promise of machine learning in brain tumor detection, it is important to note the diversity in imaging modalities, architectures, and preprocessing techniques employed. A study published in [52], the model uses the histogram statistical equalization technique which consists in applying a transformation to each pixel of the image by calculating several statistical characteristics such as the average sum, the variance, the entropy, the dissimilarity, this model is therefore used for low-grade and high-grade class images of cervical glioma. The results obtained from the proposed method of accuracy, sensitivity and specificity reached 83.6% accuracy, 80.88% sensitivity and 86.84% specificity.

III. DESCRIPTION OF THE DATASET

The dataset has 3000 samples, which are divided into two classes with tumor and non-tumor. The number of people with brain tumor is 1500 and people with non-tumor is 1500

This dataset is available on Kaggle - https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection

IV. METHODOLOGY

A. PROPOSED DETECTION MODEL

Sequentially following these stages is necessary to finish the picture classification challenge using machine learning approaches like traditional neural networks: data preparation, data extraction, Selection, learning, and categorization of features

We started by gathering data from Kaggle datasets of brain MRI images, using the widely accepted standard procedure for machine learning. "**pytorch.nn**" helps us to define sequence of convolutional layers and put all of that in one instance variable of CNN model. The model utilizes two convolutional layers with Tanh activation functions, followed by Average Pooling layers for dimensionality reduction. The flattened features are passed through three fully connected layers with Tanh activations, progressively reducing dimensionality. Finally, a Sigmoid activation function is applied to the output layer for binary classification. The model is trained using the Adam optimizer with a learning rate of 0.0001 over 350 epochs. During training, Binary Cross-Entropy Loss is minimized to optimize model parameters. Research findings indicate that complex transforms are not always superior to simple ones as they can introduce noise into the features and disrupt the learning process.

Image partitioning algorithms and their size normalization are part of the data pre-processing procedure. After this point, the CNN model is established and put into practice as a brain tumor detection method.

Next, the input data is divided into two sets i.e training and testing. The CNN architectural model used in our study is shown in Fig. 1.

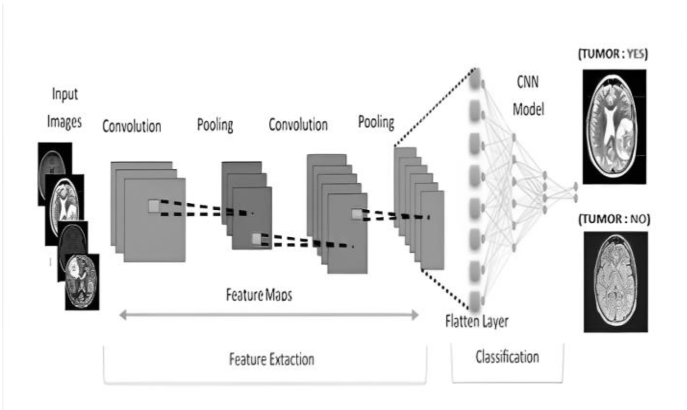

Fig 1. Architecture of the Proposed Model

B. GATHERING AND PREPARING DATSETS

The database that was used—a Kaggle database that is open to the public—is described in this section. This collection consists of many people's MRI scans. There are 3000 data points in all, 1500 of which show brain scans with tumors and 1500 of which show healthy brains. The dataset's example photos are shown in Fig. 2

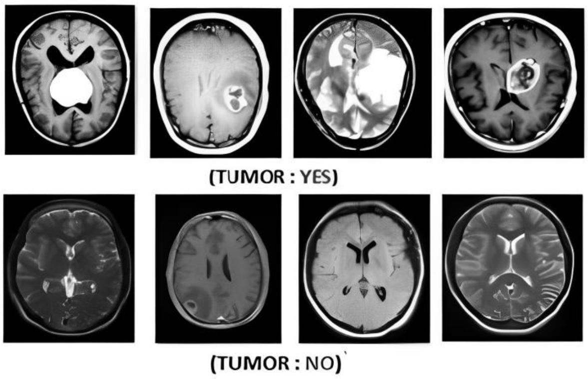

Fig 2. Sample Images From Used DataSet

In order to improve the pictures' robustness and neural network usability, a variety of preprocessing techniques may be applied. The most popular ones relate to aspect ratio and include uniform image size, dimensionality reduction, and data augmentation. To speed up learning, the pictures have been downsized to (128, 128, 3) = (image width, image height, number of channels).

C. CLASSIFICATION ALGORITHM USING MACHINE LEARNING

Brain tumors are categorized into several groups using classification algorithms. The input data must pass through a number of phases in order to enhance the outcomes in the CNN network's output. Here, We have set 350 epochs for training the CNN model and evaluating the training loss. We have kept the number of epochs relatively low to ensure that the training loss remains low as well.

To develop our suggested model, we make use of PyTorch and the Anaconda environment:

1) Advantages of PyTorch for CNN Development:
It simplifies CNN development with its built-in modules like convolutional layers and activation functions, streamlining architecture creation. Additionally, its automatic differentiation facilitates gradient computation and back-propagation.

2) Anaconda Environment for Python Development:
Anaconda offers a comprehensive Python environment, enhancing the reproducibility of the CNN development process by managing dependencies and package versions.

3) Integration of PyTorch and Anaconda:
Integrating PyTorch with Anaconda streamlines CNN development by leveraging Anaconda's environment management for clean project isolation and seamless package management, ensuring efficient workflow and reproducibility.

Fig. 3 describes the flowchart followed by the model from input images and preprocessing to the CNN model algorithm and the prediction of healthy and unhealthy brains.

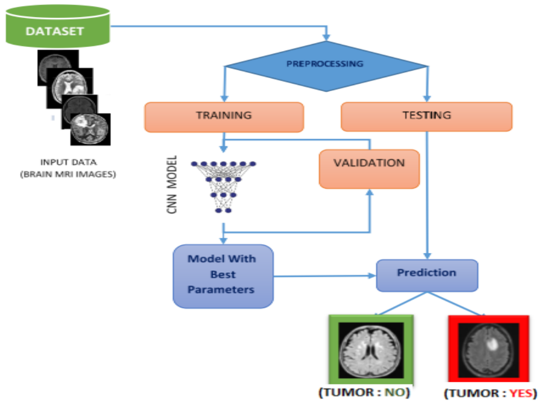

Fig.3. The Flowchart to Implementation of the CNN Model

These process steps represent the hidden layers of the neural network and are used to perform the CNN model. Some definitions and roles of these layers are described below:

1. Convolutional layer is the primary layer of a CNN, here it is defined using “nn.Conv2d”. The first layer has an input channel of 3(RGB channels) and an output channel of 6, with a kernel size of 5*5. The second layer has an input channel from 6(output from previous layer) and an output channel of 16 of same 5*5 size.

2. The Pooling , the spatial variance attribute allows Max pooling to educate the neural network that, despite possible variations in the dimensions, textures, and presentations of several photos of the same object. This is only possible after the features map is finished. In this module of CNN 2 pooling layers are used and they are defined using “nn.AvgPool2d”.

3. Flatten Layer symbolizes the artificial neural network's input layer. This makes a big data vector suitable for the neural network's input possible. In this flatten layer is not explicitly defined but a flattening operation is achieved using “x.view(x.size(0), -1)” withing the forward method of CNN class.

4. Max-Pooling Layer is utilized to extract the most persistent characteristics from the phots. Here there is no usage of max-pooling layer instead, average pooling layers are used.

5. The first average pooling layer is applied after the first convolutional layer and the second applied after second convolutional layer, both with the same parameters: kernel size of 2*2 and a stride of 5.

6. Fully Connected Layers, defined using “nn.Linear”, there are three fully connected layers with output sizes of 120, 84 and 1 respectively. The first layer takes an input size of 256, derived from the output of the convolutional layers after flattening, then produces an output of size 120. The subsequent linear layers gradually reduce the dimensionality, producing outputs of size 84 and finally 1.

7. The Tanh activation function is used after each fully connected layer, and the Sigmoid function is used at the end of the network to produce the final output. It maps the input values of the range [-1, 1], introducing non-linearity and aiding in capturing complex patterns in data. Sigmoid activation is employed at the output

layer to squash the final linear output to a range between 0 and 1.

V. METRICES FOR PERFORMANCE EVALUATION

In order to assess the effectiveness of the system, a number of common assessment measures are often presented. These metrics include the Receiver Operating Characteristic curve (ROC), Accuracy, Precision, Recall, AUC, F1_score, and confusion matrix. Below is a full explanation of the metrics principle and the mathematical method for calculating them.

• Confusion Matrix A confusion matrix is represented by a two-dimensional table which summarizes the results of the predictions of the classification carried out and allows to compare between the correct and false results of the prediction, which allows to see at what point a model can be confused in its predictions and to measure these performances. In a confounding matrix the results are classified into four main categories: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The four elements of the confusion matrix are shown in Table I.

TABLE I. ELEMENTS OF THE CONFUSION MATRIX

Element	Description
TP	Images containing the tumor and correctly classified.
NP	Images not containing the tumor and correctly classified.
FP	CNN classifies images as containing tumors but that does not contain any tumor.
FN	CNN classifies images as not containing any tumor but are containing a tumor.

Loss Function assesses the discrepancy between the actual values of the observations utilized in the learning process and the predictions generated by the neural network. The neural network performs better the more this function's outcome is reduced. By modifying the various neural network weights, it is minimized—that is, the difference between the expected and actual values for a particular observation is reduced to a minimum.

VI. PERFORMANCE RESULTS

The CNN-based brain tumor detection model achieved an accuracy of 95.3%. The confusion matrix provides detailed insight into the model's performance, showcasing its ability to correctly classify different classes of brain tumor images. Following Figure 4 shows the confusion matrix of CNN model.

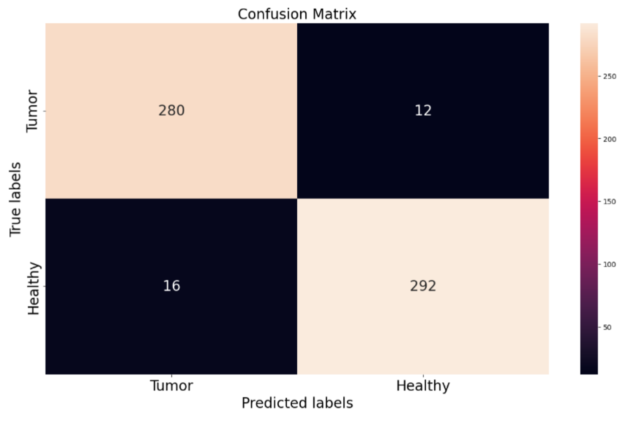

Fig 4. Confusion matrix of CNN model

TABLE II. PERFORMANCE OF CNN MODEL

Sr. No	Training Image	Testing Image	Splitting ratio	Accuracy%
1	2400	600	4:1	95.3%

VII. CONCLUSION

This research proposes a CNN model for brain tumor segmentation from MRI images into two classes: tumor-containing and tumor-free. This experiment yielded an overall accuracy of 95.3% for the suggested model. In future work, the architecture of the proposed model could be perfected, and its reliability and performance will be evaluated with a large database.

VIII. REFERENCES

[1] Kapoor, L. and Thakur, S., 2017, January. A survey on brain tumor detection using image processing techniques. In 2017 7th International Conference on Cloud Computing, Data Science & Engineering-Confluence (pp. 582-585). IEEE

[2] Sobhaninia, Z., Rezaei, S., Noroozi, A., Ahmadi, M., Zarrabi, H., Karimi, N., Emami, A. and Samavi, S., 2018. Brain tumor segmentation using deep learning by type specific sorting of images. arXiv preprint arXiv:1809.07786.

[3] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., Pal, C., Jodoin, P.M. and Larochelle, H., 2017. Brain tumor segmentation with deep neural networks. Medical image analysis, 35, pp.18-31.

[4] J. Sikder, U. K. Das, and R. J. Chakma, "Supervised Learning-based Cancer Detection," IJACSA, vol. 12, no. 5, 2021, doi: 10.14569/IJACSA.2021.01205101.

[5] Amin, J., Sharif, M., Yasmin, M. and Fernandes, S.L., 2017. A distinctive approach in brain tumor detection and classification using MRI. Pattern Recognition Letters.

[6] Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D.L. and Erickson, B.J., 2017. Deep learning for brain MRI segmentation: state of the art and future directions. Journal of digital imaging, 30(4), pp.449-459.

[7] Handore, S.S.V., Deshpande, A. and Patil, P.M., 2018, February. An Efficient Algorithm for Segmentation and Classification of Brain Tumor. In 2018 International Conference On Advances in Communication and Computing Technology (ICACCT) (pp. 83-88). IEEE.

[8] Shil, S.K., Polly, F.P., Hossain, M.A., Ifthekhar, M.S., Uddin,M.N. and Jang, Y.M., 2017, October. An improved brain tumor detection and classification mechanism. In 2017 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 54-57). IEEE.

[9] T. Tazin et al., "A Robust and Novel Approach for Brain Tumor Classification Using Convolutional Neural Network," Comput Intell Neurosci, vol. 2021, p. 2392395, Dec. 2021, doi: 10.1155/2021/2392395.