© JUL 2024 | IRE Journals | Volume 8 Issue 1 | ISSN: 2456-8880

Brain Tumor Detection System Using Deep Learning

JOSEPH JEREMIAH ADEKUNLE[1], ADEBANWO HASSAN, ADEBOLA[2], PRINCESS BEATRICE SUNDAY-JIMMY[3], ONYEKACHI INNOCENT IKE-OKPE[4], ABIODUN WISDOM OSHIREKU[5]

[1]*Department of Computer Science, National Open University of Nigeria.*

[2]*Department of Electrical and Electronic Engineering, Federal University of Petroleum Resources Effurun.*

[3]*Division of Oncology, Helix Biogen Institute*

[4]*Department of Health Outcomes and Biomedical Informatics, University of Florida.*

[5]*Department of Chemistry and Biochemistry, Brigham Young University.*

Abstract- Brain tumors significantly threaten human health, necessitating accurate and timely diagnosis to improve patient outcomes. Traditional diagnostic methods, such as manual analysis of MRI scans, are time-consuming, labor-intensive, and prone to human error. These limitations highlight the urgent need for more advanced, efficient, and reliable detection techniques. This article explores the implementation of deep learning, specifically convolutional neural networks (CNNs), in the detection of brain tumors. Deep learning models, which automate feature extraction and handle high-dimensional data, offer substantial improvements over traditional methods. We discuss the various layers of CNNs, and RNNs and their roles in processing and classifying medical images. By utilizing large datasets and transfer learning, these models can learn complex patterns and generalize well to new data, enhancing diagnostic accuracy and speed. The integration of deep learning in clinical settings can mitigate the challenges of traditional methods, such as high costs and the invasiveness of biopsies, leading to better patient care. Furthermore, the article emphasizes the importance of investing in data infrastructure, training healthcare professionals, and fostering research collaborations to advance the field. Regulatory and ethical considerations are also crucial to ensure the responsible and transparent use of AI in healthcare. In conclusion, the adoption of deep learning for brain tumor detection promises a significant leap forward in diagnostic capabilities, ultimately improving patient outcomes and setting a higher standard for medical care.

Indexed Terms- Brain Tumor, Magnetic Resonance Imaging (MRI), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning Algorithms, Convolutional Neural Network (CNN.

I. INTRODUCTION

Brain tumors are a critical health concern worldwide, characterized by abnormal cell growth within the brain or central spinal canal. These tumors can be either benign (non-cancerous) or malignant (cancerous), with the latter posing significant health risks due to their aggressive nature and potential to spread rapidly (American Brain Tumor Association, 2024) [1]. Brain tumors can lead to severe neurological impairments and are associated with high morbidity and mortality rates (Ostrom et al., 2021) [2]. Early detection of brain tumors is crucial for improving patient outcomes. Timely identification of tumors allows for early intervention, which can significantly enhance the effectiveness of treatment options such as surgery, radiation therapy, and chemotherapy. Early detection is associated with better prognosis, reduced treatment-related complications, and improved quality of life for patients (Smith et al., 2019) [3].

1.2 Problem Statement

Traditional brain tumor detection methods, primarily involving manual analysis of magnetic resonance imaging (MRI) scans, present several challenges. Radiologists and medical professionals must meticulously examine numerous MRI slices, which is a time-consuming and labor-intensive process. This manual approach is prone to human error, leading to potential misdiagnoses or delayed diagnoses, which can adversely affect patient outcomes (Paulson et al., 2018) [4]. There is a pressing need for more accurate and efficient detection techniques to overcome these limitations. Advanced methods that can automate and enhance the detection process are essential to support medical professionals in making precise and timely diagnoses. Deep learning, a subset of artificial intelligence (AI), has emerged as a promising solution, offering significant improvements in the accuracy and speed of brain tumor detection (Bhattacharyya et al., 2021) [5].

1.3 Overview of Traditional Diagnostic Methods for Brain Tumors

Traditional diagnostic methods for brain tumors encompass a range of imaging techniques, biopsies, neurological examinations, and electroencephalography (EEG), each with distinct advantages and limitations.

A. Imaging Techniques: This comprises Magnetic resonance images, computed tomography scans, and Positron emission tomography. Magnetic Resonance Imaging (MRI), is the most frequently used imaging technique for brain tumor diagnosis, utilizing strong magnetic fields and radio waves to produce detailed images of the brain. It is particularly effective in detecting soft tissue abnormalities. However, MRI scans are time-consuming, expensive, and unsuitable for patients with metal implants (Smith et al., 2019) [2]. Computed Tomography (CT) which is called the CT scan employs X-rays to generate cross-sectional images of the brain. They are favored in emergencies for their speed and ability to detect bleeding or bone abnormalities. Despite their quick and widespread availability, CT scans offer lower resolution for soft tissues and involve radiation exposure (Paulson et al., 2018) [3]. The Positron Emission Tomography (PET) Scans involve injecting a radioactive tracer to monitor metabolic activity in the brain, helping to differentiate between tumor types and detect recurrences. These scans, while informative, are expensive, limited in availability, and involve exposure to radioactive materials (Bhattacharyya et al., 2021) [4].

B. Biopsy: A biopsy, where a sample of tumor tissue is extracted for histopathological examination, is considered definitive for diagnosing brain tumors. There are two primary types: stereotactic needle biopsy and open surgical biopsy. While biopsies provide essential information on tumor type and grade, they are invasive procedures with associated risks such as infection and bleeding, and may not always be feasible depending on the tumor's location (Ostrom et al., 2021) [5].

C. Neurological Examination: Neurological examinations assess brain function, including cognitive abilities, motor skills, and sensory responses, to identify potential abnormalities. These non-invasive tests can provide initial indicators of brain issues but are less specific and often require follow-up with imaging or biopsy for a conclusive diagnosis (Smith et al., 2019) [2].

D. Electroencephalography (EEG): EEG measures the brain's electrical activity to detect abnormalities such as seizures, which can be associated with brain tumors. It is a non-invasive tool useful for monitoring brain function but is limited in its ability to detect structural abnormalities, often necessitating additional imaging techniques (Paulson et al., 2018) [3].

1.4 Challenges in Traditional Diagnostic Methods

Traditional diagnostic methods for brain tumors face several significant challenges that impact their effectiveness and efficiency. The manual analysis of imaging data, such as MRI and CT scans, requires considerable time and expertise, leading to potential delays in diagnosis and increased risk of oversight (Bhattacharyya et al., 2021) [4]. Additionally, human interpretation introduces variability and the risk of misdiagnosis due to factors like radiologist fatigue and differing levels of expertise (Smith et al., 2019) [2]. Advanced imaging techniques like MRI and PET scans, while effective, are expensive and not always accessible, particularly in low-resource settings. This limitation hinders their widespread use and timely diagnosis (Paulson et al., 2018) [3]. Moreover, biopsies, though definitive, are invasive and carry risks such as infection or bleeding. They are not always feasible, especially for tumors in critical or hard-to-reach areas of the brain (Ostrom et al., 2021) [5]. These challenges underscore the need for more advanced, efficient, and accurate diagnostic techniques. Innovations provided by deep learning and AI-driven approaches have the potential to significantly improve brain tumor detection, offering faster, more reliable, and less invasive diagnostic options, and ultimately enhancing patient outcomes.

- Machine Learning and Deep learning

Machine learning, a subset of artificial intelligence (AI), empowers computers to learn from data and improve performance without explicit programming [6]. Machine learning algorithms can extract valuable insights from complex datasets by analyzing patterns and making data-driven predictions or decisions. ML focuses on developing computer programs that can access and use data in learning by itself. Machine learning uses three learning methods known as algorithms. They are supervised, unsupervised, and semi-supervised learning [7].

Deep learning, a subset of machine learning, has emerged as a powerful tool for automated image analysis and pattern recognition [8]. Unlike traditional machine learning methods, which may require manual feature engineering, deep learning algorithms automatically extract hierarchical features from raw data, enabling them to perform superior tasks such as image recognition. Deep learning significantly enhances the capabilities of data scientists tasked with gathering, analyzing, and deciphering vast datasets. Its adoption expedites and simplifies these intricate processes, amplifying efficiency and efficacy in data-driven decision-making.

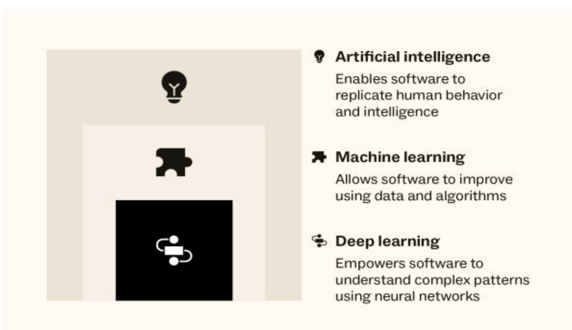


Fig.1.2: Overview of AI, ML, and DL

II. RELATED WORK

The literature on brain tumor recognition using deep learning is burgeoning, reflecting the growing interest and investment in this area of research. Numerous studies have explored different deep learning architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants, for analyzing MRI data and detecting brain tumors. These studies have demonstrated remarkable performance, showcasing the potential of deep learning to enhance the efficiency and accuracy of brain tumor diagnosis

In this literature review, we aim to provide a comprehensive overview of the current state-of-the-art brain tumor recognition systems using deep learning. Moreover, hybrid approaches that integrate deep learning with traditional machine learning methods have emerged, aiming to harness the complementary strengths of both paradigms. As the field continues to evolve, ongoing research endeavors seek to refine existing techniques, explore novel methodologies, and address remaining challenges to further enhance the efficacy of brain tumor recognition systems. We will delve into the methodologies employed, discuss the challenges faced, and explore potential avenues for future research and development. By synthesizing existing knowledge and identifying key research gaps, this review seeks to contribute to the advancement of brain tumor diagnosis and ultimately improve patient care.

2.1 Concept of Deep Learning

Deep learning specifically refers to neural networks with multiple hidden layers, known as deep networks. These deep networks can model very complex patterns and relationships in data, making them suitable for tasks such as image and speech recognition, natural language processing, and game playing. These networks consist of layers of interconnected nodes (neurons) where each connection has an associated weight. A basic neural network includes an input layer for receiving data, one or more hidden layers for processing data, and an output layer for producing results. The learning process involves feeding data through the network and transforming it through a series of linear and non-linear operations. The output is compared to the expected result, and the error is used to adjust the weights through backpropagation, an iterative process that continues until the network's predictions are sufficiently accurate (LeCun, Bengio, & Hinton, 2015) [9]. By automating feature extraction and learning hierarchical representations directly from raw data, deep learning excels in handling high-dimensional and unstructured data, outperforming traditional machine learning methods in these complex scenarios (Goodfellow, Bengio, & Courville, 2016) [11].

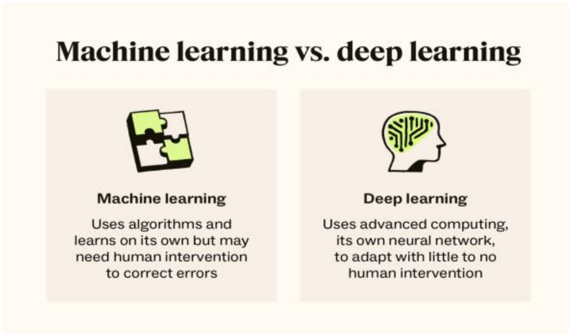


Fig.2.1: Machine Learning vs Deep Learning

2.2 Neural Networks

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates. In this sense, neural networks refer to systems of neurons, either organic or artificial. Neural networks are computational models inspired by the structure and functioning of biological neural networks in the human brain. They have become a fundamental component of artificial intelligence and machine learning, enabling computers to learn from data and perform complex tasks with remarkable accuracy and efficiency. Neural networks consist of interconnected nodes, or neurons, organized into layers. Information is processed through the network by propagating signals, or activations, from input neurons through hidden layers to output neurons. Each connection between neurons is associated with a weight, which determines the strength of the connection and influences the output of the network. The most common type of neural network is the feedforward neural network, where signals propagate in one direction, from input to output layers. These networks are widely used for tasks such as classification, regression, and pattern recognition. models.

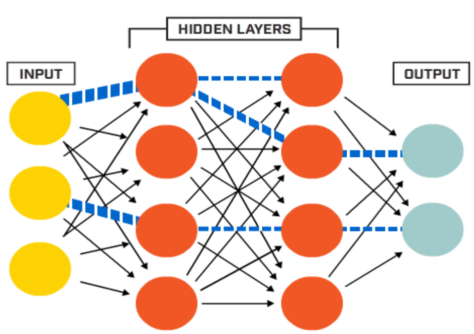


Fig.2.2: A Neural Network

An Artificial Neural Network is a computing system inspired by a biological neural network that constitutes the animal brain. Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. These are what help a Neural Network gain complexity in any problem. Increasing layers (with units) can increase the non-linearity of the output of a Neural Network. Each layer contains several Units/Neurons. The amount in most cases is entirely up to the creator. However, having too many layers for a simple task can unnecessarily increase its complexity and in most cases decrease its accuracy. The opposite also holds.

The Neural Network is constructed from 3 types of layers:

- Input layer: This is the initial data for the neural network.
- Hidden layers: It is an intermediate layer between the input and output layer and a place where all the computation is done.
- Output layer: The outer layer produces the result for given inputs.

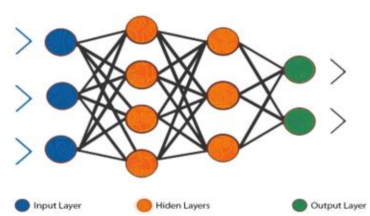


Fig.2.3: A Simple Artificial Neural Network Explaining the layers

There are 3 blue circles in the image above. They represent the input layer and usually are noted as vector *X*. There are 4 yellow and then 3 yellow circles again that represent the hidden layers. These circles represent the "activation" nodes and usually are noted as *W* or *θ*. The green circles are the output layer or the predicted value (or values in case of multiple output classes/types).

Each node is connected with each node from the next layer and each connection (black arrow) has a particular weight. Weight can be seen as an impact that

that node has on the node from the next layer. So, if we take a look at one node it would look like this

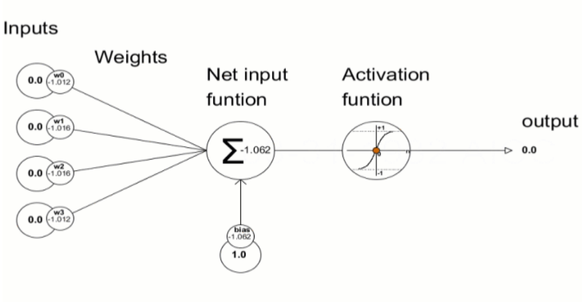


Fig.2.4: A Single Neuron in Action

a. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) are a specialized type of feedforward neural network designed for processing grid-like data, such as images, and have achieved state-of-the-art performance in computer vision tasks [12]. The CNN model for brain tumor recognition comprises several key layers: Convolution 2D, MAX Pooling 2D, Dropout, Flatten, Dense, and Activation. In the Convolution 2D layer, features are extracted from the input image, outputting data in matrix form. The MAX Pooling 2D layer then takes the largest element from the rectified feature map. Dropout randomly ignores selected neurons during training to prevent overfitting. The Flatten layer converts the data into a list format to feed into the fully connected layer. The Dense layer performs a linear operation where each input is connected to every output by weight, followed by a nonlinear activation function. The Activation layer uses the Sigmoid function to predict probabilities between 0 and 1. For model compilation, binary cross-entropy is used since there are two classes, 0 and 1. The Adam optimizer, which stands for Adaptive Moment Estimation, is employed due to its computational efficiency and low memory requirements. This optimizer is suitable for non-convex optimization problems and is straightforward to implement.

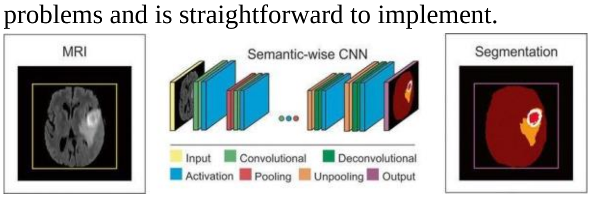


Fig.2.5 CNN model for brain tumor recognition [44]

III. PROPOSED METHODOLOGY

3.1 Introduction

This outlines the structure of the system problem, assesses existing algorithms, identifies data sources, and outlines methods of data collection. It details the specific techniques utilized to achieve the project's objectives, considering its aim and particular implementation specifications. Additionally, it provides a concise rationale for the chosen techniques in implementing the image segmentation system and acknowledges the algorithms employed in the process.

3.2 Overview of the Exiting Work

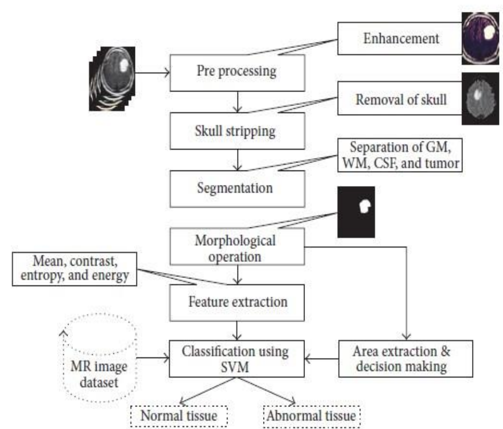


Fig.3.1 Existing workflow of brain tumor recognition system.

- In the first stage, there is a computer-based procedure to detect tumor blocks and classify the type of tumor using the Artificial Neural Network Algorithm for MRI images of different patients.
- The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations, and feature extraction are used for brain tumor recognition in the MRI images for the cancer-affected patients.
- This work has introduced one automatic brain tumor recognition method to increase the accuracy and decrease the diagnosis time.
- Image Preprocessing: As input for this system is MRI, scanned image and contain noise. Therefore, our first aim is to remove noise from the input image. As explained in the system flow, we are

using a high-pass filter for noise removal and preprocessing.

- Segmentation: Region growing is the simple region-based image segmentation technique. It is also classified as a pixel-based image segmentation technique since it involves the selection of initial seed points.
- Morphological operation: The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion are basic operations of morphology. Dilation is adding pixels to the boundary region of the object, while erosion is removing the pixels from the boundary region of the object.
- Feature Extraction: The feature extraction is used for edge recognition of the images. It is the process of collecting higher-level information about an image such as shape, texture, color, and contrast.
- Connected component labeling: After recognizing connected components of an image, every set of connected pixels having the same gray-level values is assigned the same unique region label.
- Tumor Identification: In this phase, we have having dataset of previously collected brain MRIs from which we are extracting features. The knowledge base is created for comparison.

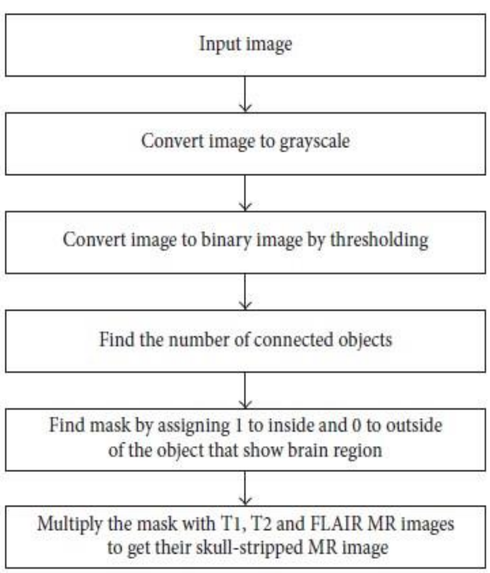


Fig. 3.2. Steps used in skull stripping algorithm.

- In the first step, we can take an image as input. In the image we used tumors in the image and only fat and water tissues in the images.
- In the second step convert the image to grayscale
  - Signal-to-noise
  - Complexity of the code
  - Learning image processing
  - Difficulty of visualization
  - Color is complex
- Then we convert the image to a binary image by thresholding.
  Thresholding is the simplest method of image segmentation and the most common way to convert a grayscale image to a binary image.
  In thresholding, we select the threshold value and then the gray level value below the selected threshold value is classified as 0. and equal and greater than the threshold value is classified as 1.
- Find the number of connected objects
- Find a mask by assigning 1 to the inside and 0 to the outside of the object that shows the brain region.

3.3 Proposed Workflow

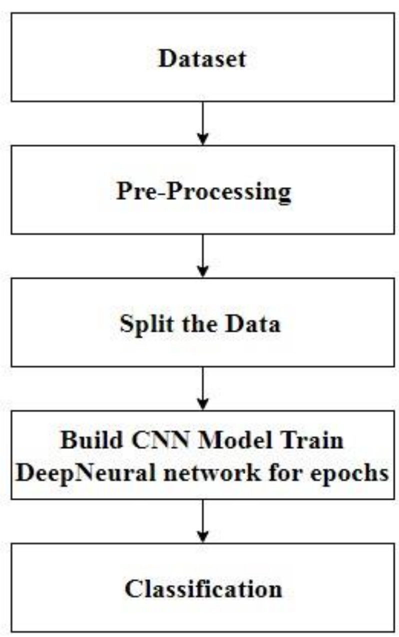


Fig. 3.3 Proposed workflow of brain tumor recognition system.

IV. DATASET DESCRIPTION AND IMPLEMENTATION

4.1 Introduction
Our Proposed methodology consists of collecting the dataset, identifying the tools and language to be used, preprocessing the data, data augmentation, building the model architecture, compiling the model, training and validating the model.

4.2 Dataset
The data set in this study consists of a collection of 10,000 MRI brain tumor images. The numbers of images in this dataset are classified as follows: 5000 images that were diagnosed with brain tumors and 5000 images that were diagnosed to be free of brain tumors. The brain tumor images were collected from the Kaggle depository website. We divided the data set as follows:

Brain Tumor	Training Samples	Validation Samples	Testing Samples
Yes	3500	1000	500
No	3500	1000	500
Total	7000	2000	1000

Table 1: Dataset division for training, validation, and testing

4.3 Language and tool used
We have used Python language, which is a high-level language with an easy user interface, and is a free and open-source language that allows the use of many libraries, including library keras, shutil, fnmatch, and os. The research team used several tools, the most important of which is Google Colab to write Python codes, a research tool for teaching and searching for a learning machine, it an easy to use and does not require any preparation for use, Google Colab is characterized by its speed in performance because it has very fast processors of type (GPU).

4.4 Image format
The dataset was collected from a set of Brain MRI Images for Brain Tumor Detection (JPG) format, to fit well with the model used to give the desired results.

4.5 Preprocessing
The first thing in the data preprocessing was to resize the Brain MRI Images as the images were of various sizes, the images

were resized to 200 by 200 Pixels, this image size collides with a balance between providing a high enough resolution for Brain Tumor Detection by the model and efficient training. All images were normalized to ImageNet standards. Then the image collection was categorized into two types, uploaded to a Google Drive account, and verified to be properly and accurately uploaded using Python code in the Google Colab environment.

4.6 Data augmentation
Generating more data usually means that the model will be more robust and prevent overfitting. Having a large dataset is crucial for the performance of the deep learning model. However, we improved the performance of the model by augmenting the images that we already have without collecting new images. Deep learning frameworks usually have built-in libraries for data augmentation utilities; we utilized five augmentation strategies to generate new training sets, (Rotation, width shift, height shift, horizontal flip, and vertical flip). Rotation augmentations are done by rotating the image right or left on an axis between 1° and 359°. The safety of rotation augmentations is heavily determined by the rotation degree parameter. Shifting and flipping images are a very useful transformation to encapsulate more details about objects of interest.

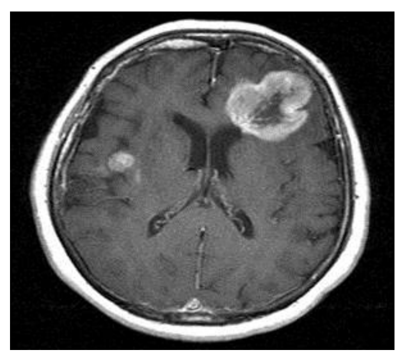


Figure 2: Original Brain MRI Image

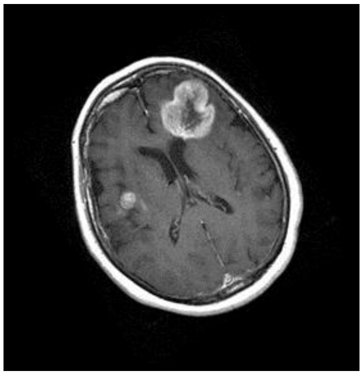
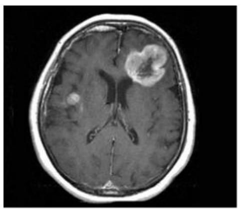


Figure 3: Brain MRI Image is rotated by 30 degrees



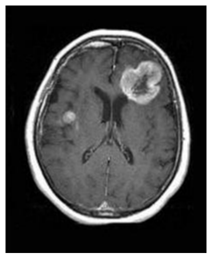


Figure 4: Brain MRI Image after width shift Figure 5: Brain MRI Image after height shift

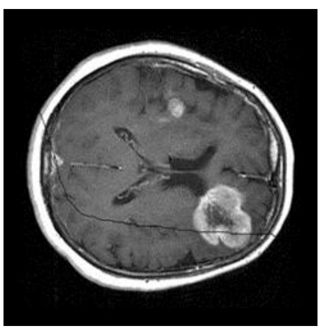


Figure 6: Brain MRI Image flipped horizontally

Figure 7: Brain MRI Image flipped vertically

4.7 Network Architecture

The dataset was trained for brain tumors using a model created from scratch and four pre-trained models for deep learning: VGG16, ResNet50, MobileNet, and InceptionV3.

4.8 Training and Validating the Models

We created a model from scratch with 12 convolutional layers followed by a fully connected hidden layer (as shown in Figure 9). The output layer uses softmax activation as it has to output the probability for each of the classes; to optimize the network Adam optimization was used. The model is ready to train, during the training, the model will iterate over batches of the training set, each of size batch size. For each batch, gradients will be computed and updates will be made to the weights of the network automatically. One iteration over all of the training sets is referred to as an epoch. Training is usually run until the loss converges to a constant. We added a checkpoint to the model to save the best validation accuracy. This is useful because the network might start overfitting after a certain number of epochs. This feature is implemented via the callback feature of Keras. A callback is a set of functions that are applied at given stages of the training procedure like the end of an epoch of training. Keras provides a built-in function for both learning rate scheduling and model check-pointing. We trained and validated our model and we got a training accuracy of 100% and a validation accuracy of 98.28% (as shown in Figure 10).

```
from keras import layers from keras import models
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
input_shape=(200, 200, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3),
activation='relu')) model.add(layers.MaxPooling2D((2,
2)))
model.add(layers.Conv2D(256, (3, 3),
activation='relu')) model.add(layers.MaxPooling2D((2,
2)))
model.add(layers.Conv2D(512, (3, 3),
activation='relu')) model.add(layers.MaxPooling2D((2,
2))) model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(2, activation='softmax'))
```

Figure 8: Model architecture

- 8s - loss: 0.0011 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0581 - val_acc: 0.9814 - val_fscore: 0.9814 Epoch 9/25
- 8s - loss: 9.0364e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0625 - val_acc: 0.9800 - val_fscore: 0.9800 Epoch 10/25
- 7s - loss: 7.7813e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0600 - val_acc: 0.9800 - val_fscore: 0.9800 Epoch 11/25
- 7s - loss: 6.8078e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0616 - val_acc: 0.9800 - val_fscore: 0.9800 Epoch 12/25
- 7s - loss: 5.9211e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0610 - val_acc: 0.9785 - val_fscore: 0.9785 Epoch 13/25
- 8s - loss: 5.2512e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0606 - val_acc: 0.9800 - val_fscore: 0.9800 Epoch 14/25
- 7s - loss: 4.6487e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0651 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 15/25
- 8s - loss: 4.1231e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0641 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 16/25
- 7s - loss: 3.6619e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0634 - val_acc: 0.9771 - val_fscore: 0.9771 Epoch 17/25
- 8s - loss: 3.2246e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0658 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 18/25
- 8s - loss: 2.8787e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0638 - val_acc: 0.9785 - val_fscore: 0.9785 Epoch 19/25
- 7s - loss: 2.5607e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0664 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 20/25
- 7s - loss: 2.3318e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0666 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 21/25
- 8s - loss: 2.0452e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0659 - val_acc: 0.9771 - val_fscore: 0.9771 Epoch 22/25
- 7s - loss: 1.8486e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0659 - val_acc: 0.9771 - val_fscore: 0.9771 Epoch 23/25
- 7s - loss: 1.6561e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0684 - val_acc: 0.9742 - val_fscore: 0.9742 Epoch 24/25
- 7s - loss: 1.4831e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0685 - val_acc: 0.9757 - val_fscore: 0.9757 Epoch 25/25
- 7s - loss: 1.4831e-04 - acc: 1.0000 - fscore: 1.0000 - val_loss: 0.0552 - val_acc: 0.9828 - val_fscore: 0.9828

Figure 9: Training and validation accuracy of the model

To visualize the training and validation of the model, we used "Matplotlib" to draw plots of the accuracy and loss of the training and validation. Figure 11 shows the learning curve of the network during training and validation. It is seen that the validation accuracy and training accuracy were increasing and it reached 100 % training accuracy and 99.28% validation accuracy. Figure 12 shows the loss curve of the network during training and validation. It is seen that the validation loss and training loss was decreasing with the number of iterations, that's great; it proved that the model works well.

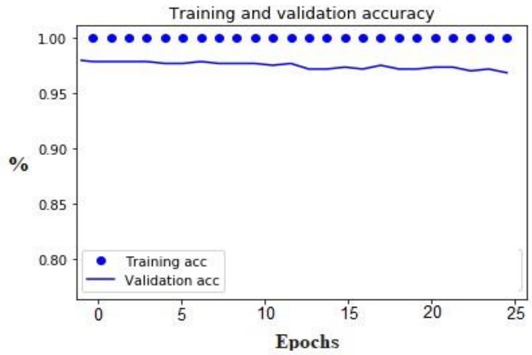


Figure 10: Training and validation accuracy curve of our model

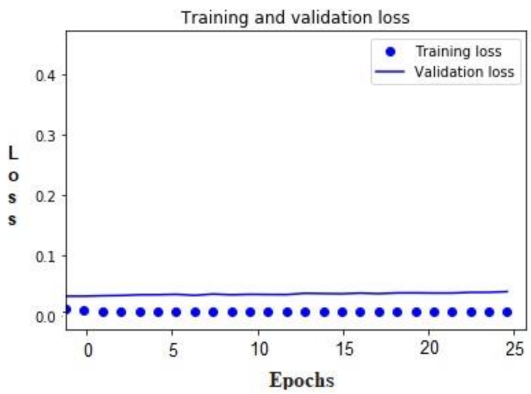


Figure 11: Training and validation loss curve of our model

CONCLUSION

In summary, the integration of deep learning in brain tumor detection presents a transformative approach that addresses many challenges associated with traditional diagnostic methods. The advanced capabilities of deep learning, particularly in automating feature extraction and handling high-dimensional data, offer significant improvements in accuracy, efficiency, and diagnostic speed. This technology has shown promise in overcoming limitations such as time-consuming manual analysis, human error, high costs, and the invasiveness of biopsies, ultimately enhancing patient outcomes through earlier and more precise detection.

RECOMMENDATIONS

1. Adoption in Clinical Settings: Healthcare institutions should consider adopting deep learning-based diagnostic tools to augment traditional methods. This can help radiologists and clinicians make faster and more accurate diagnoses, thereby improving patient care.
2. Investment in Data Infrastructure: To fully leverage the potential of deep learning, it is crucial to invest in data infrastructure that supports the collection, storage, and processing of large medical datasets. Robust data management systems will ensure the availability of high-quality data for training and validating deep learning models.
3. Training and Education: Medical professionals should be trained in the use of AI and deep learning technologies. Educational programs and continuous professional development can bridge the knowledge gap, enabling clinicians to effectively utilize these advanced tools in their practice.
4. Research and Collaboration: Continued research and collaboration between medical institutions, technology companies, and academic researchers are essential to advancing the field. This includes exploring novel deep learning architectures, improving model interpretability, and ensuring the ethical use of AI in healthcare.
5. Regulatory and Ethical Considerations: As deep learning models become more integrated into clinical practice, it is important to establish clear regulatory frameworks and ethical guidelines. Ensuring patient privacy, data security, and transparency in AI decision-making processes will build trust and promote the responsible use of these technologies.

By embracing deep learning for brain tumor detection, the healthcare community can achieve significant advancements in diagnostic accuracy and efficiency, ultimately leading to better patient outcomes and a higher standard of care.

REFERENCES

[1] American Brain Tumor Association. (2024). Facts and Statistics. Retrieved from abta.org

[2] Ostrom, Q. T., Cioffi, G., Gittleman, H., Patil, N., Waite, K., Kruchko, C., & Barnholtz-Sloan, J. S. (2021). CBTRUS Statistical Report: Primary Brain and Other Central Nervous System Tumors

Diagnosed in the United States in 2014–2018. Neuro-Oncology, 23(Supplement_2), iii1-iii105. DOI: 10.1093/neuonc/noab200.

[3] Smith, R. A., Andrews, K. S., Brooks, D., Fedewa, S. A., Manassaram-Baptiste, D., Saslow, D., ... & Wender, R. C. (2019). Cancer screening in the United States, 2019: A review of current American Cancer Society guidelines and current issues in cancer screening. CA: A Cancer Journal for Clinicians, 69(3), 184-210. DOI: 10.3322/caac.21557.

[4] Paulson, E. S., Erickson, B., Schultz, C., & Allen Li, X. (2018). Comprehensive MRI assessment for radiation therapy planning. Radiotherapy and Oncology, 127(2), 224-234. DOI: 10.1016/j.radonc.2018.01.011.

[5] Bhattacharyya, A., Sarma, M., & Kalra, M. K. (2021). Artificial intelligence in radiology: Applications, challenges, and future trends. Clinical Radiology, 76(7), 474-482. DOI: 10.1016/j.crad.2021.03.002.

[6] Ostrom, Q. T., Cioffi, G., Gittleman, H., Patil, N., Waite, K., Kruchko, C., & Barnholtz-Sloan, J. S. (2021). CBTRUS Statistical Report: Primary Brain and Other Central Nervous System Tumors Diagnosed in the United States in 2014–2018. Neuro-Oncology, 23(Supplement_2), iii1-iii105. DOI: 10.1093/neuonc/noab200.

[7] Russell, S. J., & Norvig, P. (2022). Artificial Intelligence: A Modern Approach (5th ed.). Pearson.

[8] Kaul, S. Enslin, and S. A. Gross. "History of artificial intelligence in medicine." Gastrointestinal endoscopy 92, no. 4 (2020): 807-812.

[9] Shen, D., Wu, G., & Suk, H. I. (2017). Deep Learning in Medical Image Analysis. Annual Review of Biomedical Engineering, 19, 221-248.

[10] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. DOI: 10.1038/nature14539.

[11] Bengio, Y. (2012). Practical recommendations for gradient-based training of deep architectures. Neural Networks: Tricks of the Trade, 437-478.

[12] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[13] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in neural information processing systems, 25, 1097-1105.

[14] Graves, A., Mohamed, A. R., & Hinton, G. (2013). Speech recognition with deep recurrent neural networks. In IEEE International Conference on Acoustics, Speech and Signal Processing (pp. 6645-6649).

[15] Bottou, L. (2010). Large-scale machine learning with stochastic gradient descent. In Proceedings of COMPSTAT'2010 (pp. 177-186). Physica-Verlag HD.

[16] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks, 61, 85-117.