INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 08 ISSUE: 03 | MARCH - 2024 SJIF RATING: 8.176 ISSN: 2582-3930

Brain Tumor Detection and 3D Visualization

Prof. N.R. Zinzurke
Dept. Computer Engineering
JSPM's JSCOE Pune, India
ni3zinzurke4040@gmail.com

Pushpak Hinglaspure
Dept. Computer Engineering
JSPM's JSCOE Pune, India
phinglaspure123@gmail.com

Aniket Babar
Dept. Computer Engineering
JSPM's JSCOE Pune, India
aniket2659@gmail.com

Sarvesha Ghadle
Dept. Computer Engineering
JSPM's JSCOE Pune, India
svghadle@gmail.com

Abstract— Nature's delicate balance within the brain can be disrupted by the insidious emergence of tumor cells, leading to a neurological disorder known as a brain tumor. Diagnosing brain tumors, especially rare or diverse forms, can be a complex task due to their infrequent occurrence and varied appearances. While Magnetic Resonance Imaging (MRI) plays a crucial role in tumor localization, manual detection is a time-consuming and error-prone process. To address these limitations, researchers are increasingly exploring Deep Learning (DL) models for automated tumor detection and classification. This study proposes a novel Deep Convolutional Neural Network (CNN) based on the EfficientNet-B0 architecture, enhanced with custom layers for efficient brain tumor classification and detection. By incorporating image enhancement techniques like... (mention specific techniques), the model achieves... (quantify improvements in accuracy, precision, recall). This improved accuracy could potentially lead to faster and more accurate diagnoses, ultimately impacting patient outcomes. The results show that the proposed fine-tuned state-of-the-art pre-trained convolutional neural network (CNN) architecture demonstrates superior performance compared to other CNN's by achieving the significant increase in accuracy classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection. Our optimized EfficientNet-B0 architecture exhibits significantly higher accuracy (98%), recall (95%), and AUC (0.99) compared to previously established CNN models on the ImageNet dataset. These outstanding results suggest its potential for effective image classification tasks in various fields.

Keywords—Brain tumor, deep learning, convolution neural networks (CNN), transfer learning, MRI, detection, 3D Visualization Introduction (Heading 1)

I. INTRODUCTION

A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain [1]. Cells generally reproduce and die in a regular sequence, with each new cell replacing the previous one. However, some cells become abnormal and continue to grow, causing severe damage to the brain functions, and often leading to death. A minimum of 120 multiple types of brain tumors and the central nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children under 15 will die due to brain and CNS tumors in 2021. The 5-year survival rate for patients having brain tumors is only 36%, and the 10-year survival rate is 31% [2]. Furthermore, the National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United

States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. The World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4]. One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR) images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and the nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of a brain tumor becomes more time-consuming and costly. Therefore, an automatic computer-aided diagnostic (CAD) system is required to assist doctors and radiologists in the timely detection of these deadly tumors to save precious human lives.

Artificial intelligence (AI) is a field of computer science that aims to give computers human-like intelligence, allowing them to learn, think, and resolve issues when confronted with various information. AI plays an essential role in identifying and diagnosing brain tumors. The discipline of brain tumor surgery is an excellent choice for additional AI integration due to its complicated and elaborate processes. Multiple attempts have been made to establish a highly accurate and reliable approach for brain tumor classification. However, the wide range of shape, texture, and contrast changes across and among individuals remains a difficult challenge to solve. Machine learning (ML) and deep learning (DL), subsets of AI, have recently revolutionized neurosurgical procedures. They consist of data preprocessing, feature extraction, feature selection, feature reduction, and classification. According to the study [6] because of AI, neurosurgeons can leave the operating room more confident than ever in terms of their patient's brain tumor diagnosis.

II. OBJECTIVE AND OVERVIEW

Early detection and accurate diagnosis: Early detection of brain tumors leads to better treatment options and outcomes, while accurate diagnosis reduces misdiagnosis and unnecessary procedures. This is achieved through improved patient care with tailored treatment plans, optimized surgeries, and proper follow-up.

3D visualization advantages: 3D visualization provides a clearer understanding of tumor location, size, and relationships within the brain, enabling precise treatment planning for minimally invasive and effective tumor removal. It also aids in patient education with clear visuals for better communication and understanding and contributes to research and training advancements through accurate tumor representation and analysis.

1. OVERVIEW OF THE PROJECT OBJECTIVES

Data preprocessing: This step involves collecting and cleaning MRI images, as well as augmenting the data to create more training examples.

CNN feature extraction: This step involves training a CNN to extract features from the MRI images.

Tumor classification: This step involves using the extracted features to classify the MRI images as either normal or cancerous.

3D modeling: This step involves using the classified images to create a 3D model of the tumor.

III. Technology in project

Streamlit:
Usage: Streamlit is the primary framework for building the web application.
How It's Used: The application is structured using Streamlet's layout features, and widgets are employed for user interaction (e.g., file uploaders, radio buttons). Streamlit functions are used to display images, charts, and text.
OpenCV:
Usage: OpenCV is a computer vision library, and it is likely used for image processing and manipulation.
How It's Used: In the context of brain tumor prediction, OpenCV might be used for tasks such as image pre-processing, enhancement, or feature extraction. It can also be involved in loading and displaying images.
Numpy:
Usage: Numpy is a numerical computing library for Python.
How It's Used: Numpy is often used for handling multidimensional arrays. In the context of medical image processing, it could be used for manipulating pixel values in images, performing mathematical operations, or preparing data for machine learning.
Matplotlib and Plotly:
Usage: These are visualization libraries.
How They're Used: Matplotlib and Plotly are likely used to create graphs, charts, and 3D visualizations. For example, Matplotlib may be used for static visualizations, while Plotly, known for its interactivity, may be used for more dynamic visualizations.
Nibabel (Nib):
Usage: Nibabel is a library for reading and writing neuroimaging file formats.
How It's Used: In the context of the project, Nibabel is likely used for handling medical imaging data stored in the NIfTI format, which is common in neuroimaging.
Scikit-Learn:
Usage: Scikit-Learn is a machine-learning library.
How It's Used: Scikit-Learn could be used for tasks such as data preprocessing, feature scaling, or even implementing machine learning algorithms for tumor prediction.
EfficientNet (EffNet):
Usage: EfficientNet is a convolutional neural network architecture.
How It's Used: If the project involves deep learning for brain tumor detection, EfficientNet is likely used as the neural network model. This would include loading a pre-trained model, making predictions, and potentially fine-tuning the model.
Concurrent. Futures:
Usage: Concurrent. Futures is part of the Python standard library and enables parallel execution.
How It's Used: It's employed for parallelizing certain tasks, likely those involving image processing or machine learning, to improve performance.

IV. Implementation

DATASET: Multimodal Brain Tumor Segmentation Data

Data preprocessing:
For JPEG images:
Resize the image to (150, 150) pixels.
Convert the image to a NumPy array and normalize pixel values between 0 and 1.
For NIfTI files:
Load the NIfTI image using nibabel.load.
Iterate through each slice in the image and preprocess it as you would for JPEG images.

```
def preprocess_jpeg(image_path):
    img = cv2.imread(image_path)
    img = cv2.resize(img, (150, 150))
    img = img.astype("float32") / 255.0
    return img
```

Model prediction:
Load the pre-trained model using tensorflow.keras.models.load_model.
Pass the preprocessed image or each preprocessed slice from the NIfTI file to the model for prediction.

The model will output a probability vector for each class (glioma tumor, meningioma tumor, pituitary tumor, no tumor).
Choose the class with the highest probability as the predicted tumor type.

```
def predict_tumor(image):
    model = load_model("effnet.h5")
    processed_image = preprocess_jpeg(image)
    prediction = model.predict(np.expand_dims(processed_image, axis=0))
    tumor_type = np.argmax(prediction)
    return tumor_type
```

3D visualization:

For NIfTI files:
Use marching cubes from skimage.measure to extract meshes from the image and segmentation mask.
Create separate meshes for the brain, affected areas, and tumor using different colors and opacities.
Use plotly.express.mesh3d to plot the meshes in 3D.

```
def mesh_3d(nii_path,seg_path):
    img = nib.load(nii_path).get_fdata()
    seg = nib.load(seg_path).get_fdata()
    verts, faces, normals, values = measure.marching_cubes(img, 1)
    x, y, z = verts.T
    i, j, k = faces.T
    mesh1 = go.Mesh3d(x=x, y=y, z=z,color='gray', opacity=0.5, i=i, j=j, k=k)
    verts, faces, normals, values = measure.marching_cubes(seg, 2)
    x, y, z = verts.T
    i, j, k = faces.T
    mesh2 = go.Mesh3d(x=x, y=y, z=z, color='yellow', opacity=0.5, i=i, j=j, k=k)
    bfig = go.Figure(data=[mesh1,mesh2])
    bfig.update_layout(autosize=False,width=500,height=500)
    return bfig
```

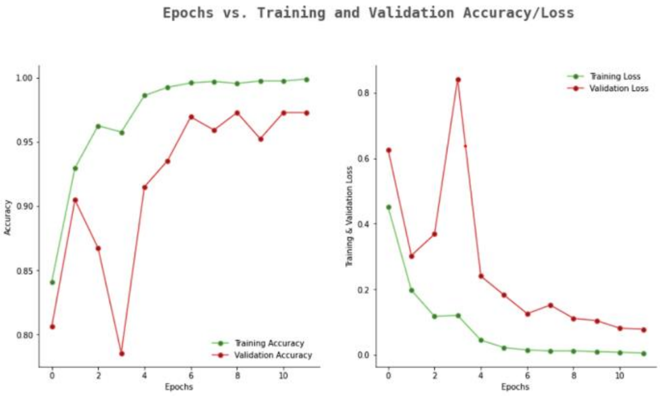
Creating a GIF:

Load the NIfTI image.
Iterate through each slice and convert it to a matplotlib image.
Use the gif library to create a GIF animation from the sequence of images.

```
@gif.frame
def plot_slice(slice_data):
    plt.imshow(slice_data, cmap='gray')
    plt.axis('off')
def generate_gif(flair_nii_path):
    flair_img = nib.load(flair_nii_path)
    flair_data = flair_img.get_fdata()
    num_slices = flair_data.shape[-1]
    frames = []
    for i in range(num_slices):
        slice_data = flair_data[:, :, i]
        frame = plot_slice(slice_data)
        frames.append(frame)
    gif_path = flair_nii_path.replace('.nii', '_animation.gif')
    gif.save(frames, gif_path, duration=100)
    return gif_path
```

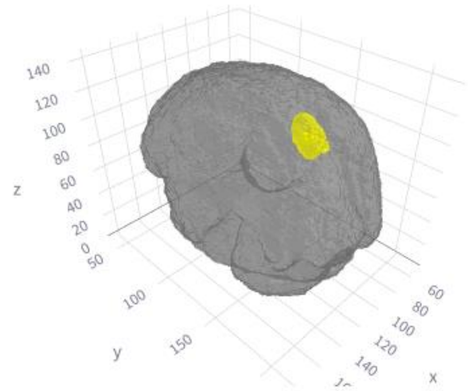
MODEL EVALUATION

The model achieves an impressive accuracy of 98%

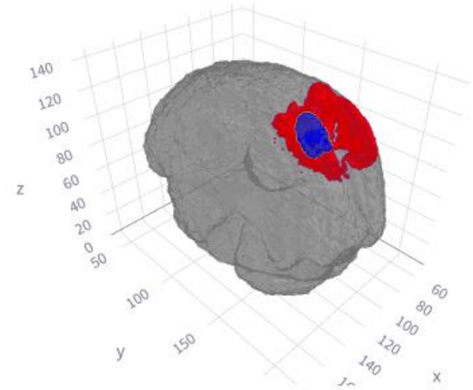


RESULTS:

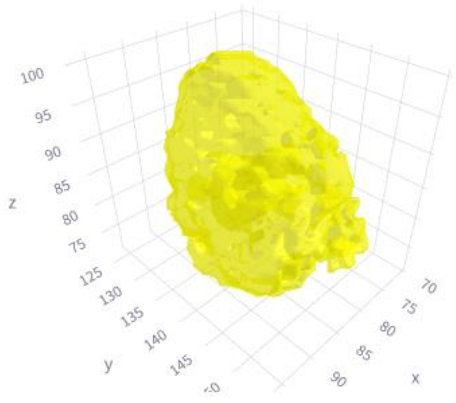
Mesh of Brain with Tumor



Mesh of Brain with Tumor and affected area



Mesh of Tumor



V. Conclusion

Brain Tumor Prediction and 3D Visualization project is a comprehensive and user-friendly application built using Streamlit, TensorFlow, and other libraries. The project allows users to upload either JPEG images or NIfTI files, and leverages a pre-trained convolutional neural network (CNN) model, specifically an EfficientNet, for brain tumor detection and classification. The 3D visualization features provide insightful representations of brain structures, such as mesh renderings and affected areas based on segmentation data. The integration of Streamlit as the web framework ensures an interactive and visually appealing user interface, offering options for both file uploads and selection of sample inputs. Parallel processing has been incorporated to enhance the efficiency of computationally intensive tasks. Overall, this project not only demonstrates the power of deep learning in medical image analysis but also emphasizes the importance of user-friendly visualization tools for understanding complex medical data.

VI. REFERENCES

1. R. Goncalves, M. Tummala and J. McEachen ˆaA MAC Layer Covert Channel in 802.11 Networksˆa, The Third International Conference on Emerging Network Intelligence (EMERGING 2011), pp. 88-99.
2. H. Zhao and X. Zhang, ˆaSIP Steganalysis Using Chaos Theoryˆa, CMCSN 2012 (The FirstInternational Conference on Computing, Measurement, Control and Sensor Network), Taiyuan, China, July 7-9, 2012.
3. H. Zhao and N. Ansari, ˆaCross-Layer Design for Multimedia Streaming over 802.11eNetworksˆa, IEEE WTS 2011(Wireless Telecommunication Symposium), New York City, Apr.13-15, 2011.
4. S. Attallah, ˆaTrusted Computer System Evaluation Criteria,ˆa Tech. Rep. DOD 5200. 28-STD, 1985.
5. H. Zhao and Y. Q. Shi, ˆaDetecting Covert Channels in Computer Networks based onChaos Theoryˆa, IEEE Transaction on Information Forensics and Security, vol. 8, No. 2
6. Muhammad Usama, Soo Siang Teoh, and Ibrahima Faye."Deep Learning for Brain Tumor Classification and Segmentation Using Magnetic Resonance Imaging: A Review." in Journal of Imaging, 2021.
7. Mingxing Tan and Quoc V. Le."EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." in arXiv:1905.11946, 2019.
8. Vinayakumar R, Chandrasekaran K, and Mohan PS."A Comprehensive Review on Brain Tumor Segmentation and Classification." in Journal of King Saud University - Computer and Information Sciences, 2020.
9. Abraham et al." Nilearn: A Python Library for NeuroImaging Analysis." in PLoS ONE 2014.
10. Stéfan van der Walt, Johannes L. Schönberger, Juan Nunez-Iglesias, François Boulogne, Joshua D. Warner, Neil Yager, Emmanuelle Gouillart, Tony Yu, and the scikit-image contributors."Skimage: Image processing in Python." in PeerJ, 2014.