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Smart Diagnosis System Neural Tumor Classification

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ABSTRACT: This paper addresses the smart diagnosis system neural tumor classification of the human brain is the major controller of the humanoid system. The abnormal growth and division of cells in the brain lead to a brain tumor, and the further growth of brain tumors leads to brain cancer. In the area of human health, Computer Vision plays a significant role, which reduces the human judgement that gives accurate results. CT scans, X-Ray, and MRI scans are the common imaging methods among magnetic resonance imaging (MRI) that are the most reliable and secure. MRI detects every minute objects. Our paper aims to focus on the use of different techniques for the discovery of brain cancer using brain MRI. In this study, we performed preprocessing using the bilateral filter (BF)for removal of the noises that are present in an MR image. This was followed by the binary thresholding and Convolution Neural Network techniques for reliable detection of the tumor region. Training, testing, and validation datasets are used. Based on our machine, we will predict whether the subject has a brain tumor or not. The resultant outcomes will be examined through various performance examined metrics that include accuracy, sensitivity, and specificity. It is desired that the proposed work would exhibit a more exceptional performance over its counterparts.

KEYWORDS: Brain tumor, Magnetic resonance imaging, Adaptive Bilateral Filter, Convolution Neural Network.

I. INTRODUCTION

- Medical imaging is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities.
- The medical imaging processing refers to handling images by using the computer. This processing includes many types of techniques and operations such as image gaining, storage, presentation, and communication. This process pursues the disorder identification and management. This process creates a data bank of the regular structure and function of the organs to make it easy to recognize the anomalies. This process includes both organic and radiological imaging which used electromagnetic energies(X-rays and gamma), solo grapy, magnetic, scopes, and thermal and isotope imaging. There are many other technologies used to record information about the location and function of the body. Those techniques have many limitations compared to those modulates which produce images. The brain tumor is one of all the foremost common and, therefore, the

deadliest brain disease that have affected and ruined several lives in the world. Cancer is a disease in the brain in which cancer cells ascends in brain tissues. Conferring to a new study on cancer, more than one lakh people are diagnosed with brain tumors every year around the globe. Regardless of stable efforts to overcome the complications of brain tumors Magnetic resonance (MR) imaging and computed tomography (CT)scans of brain ate two most general tests to check the existence of a tumor and recognize its position for progressive treatment decisions.

II. RELATED WORK:

• Brain tumor detection has been a critical area of research in medical imaging due to its direct impact on patient survival rates. Recent years have seen significant progress with the application of machine learning (ML)and deep learning(DL) techniques to automate and enhance the accuracy of tumor identification and classification.

1.TRADITIONAL MACHINE LEARNING APPROACHES

- Early efforts in brain tumor detection relied on hand crafted feature extraction combined with classical ML algorithms
- Support Vector Machines (SVMS)
- Have been widely used due to their ability to handle high-dimensional data. Cha plot et al. (2006) utilized Discrete Wavelet Transform (DWT) for feature extraction and classified tumors using an SVM, showing promising accuracy on MRI scans.
- Random Forests (RF) and K-Nearest Neighbors(K-NN)
- Have also been employed for tumor classification Tiwari et al. (2014) used texture and shape features for classification with RF, achieving robust performance on clinical datasets.

2. DEEP LEARNING-BASED TECHNIQUES

- The emergence of DL has revolutionized medical image analysis, especially with Convolutional Neural Networks (CNNS)
- CNN- based models have demonstrated superior performance in automatic feature extraction from MRI images. Pereira et al. (2016) proposed a deep CNN model for brain tumor segmentation using small kernels, which significantly improved accuracy and reduced overfitting.
- 3D CNNS, as introduced by Kamnitsas et al (2017) in their Deep Medic architecture, utilize volumetric MRI data and capture spatial features more effectively than 2D CNNS.

3.TRANSFER LEARNING AND PRETRAINED

Networks:

- Transfer learning allows models trained on large-scale data sets (e.g., Image Net) to be adapted for medical imaging tasks with limited data:
- Models like VGG16, ResNet50, and InceptionV3 have been fine-tuned for brain tumor classification tasks with considerable success.

4.EMERGING TRENDS

- Attention mechanisms and transformer-based models are being explored to enhance performance on complex imaging tasks.
- Self-supervised learning and semi-supervised methods are gaining attention due to limited labeled medical data.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

• A typical system architecture for brain tumor detection involves preprocessing MRI images,extracting relevant features to identify tumors.

SYSTEM ARCHITECTURE

1.DATA ACQUISITION: The process begins with acquiring brain MRI scans,often from datasets like the Brain Tumor Segmentation (BRATS) challenge dataset .

2.PREPROCESSING: This stage involves cleaning and preparing the images for analysis .common techniques include noise reduction (using filters like median or Wiener filters),skull stripping and image enhancement to improve contrast.

3.FEATURE EXTRACTION: This step focuses on extracting meaningful information from the preprocessed images.Deep learning models like CNNs automatically learn relevant features,while handcrafted features can be extracted using techniques like Wavelet transforms.

4.MODEL TRAINING: Amachine learning model ,often a CNN is trained using the extracted features and corresponding labels.(eg.tumor or no tumor)

5.CLASSIFICATION: The trained model is then used to classify new,unseen MRI images,predicting whether they contain a brain tumor and potentially its type.

METHODOLOGY:

1.DATASPLITTING: The data set is typically divided into training,validation ,testing sets to evaluate the models performance.

2.MODEL SELECTION: CNN are popular choice for brain tumor detection due to their ability to automatically learn hierarchical features from images.

3.REAL -TIME APPLICATION: The system can be integrated with medical imaging equipment to provide near real-time tumor detection and classification ,aiding in clinical decision -making.

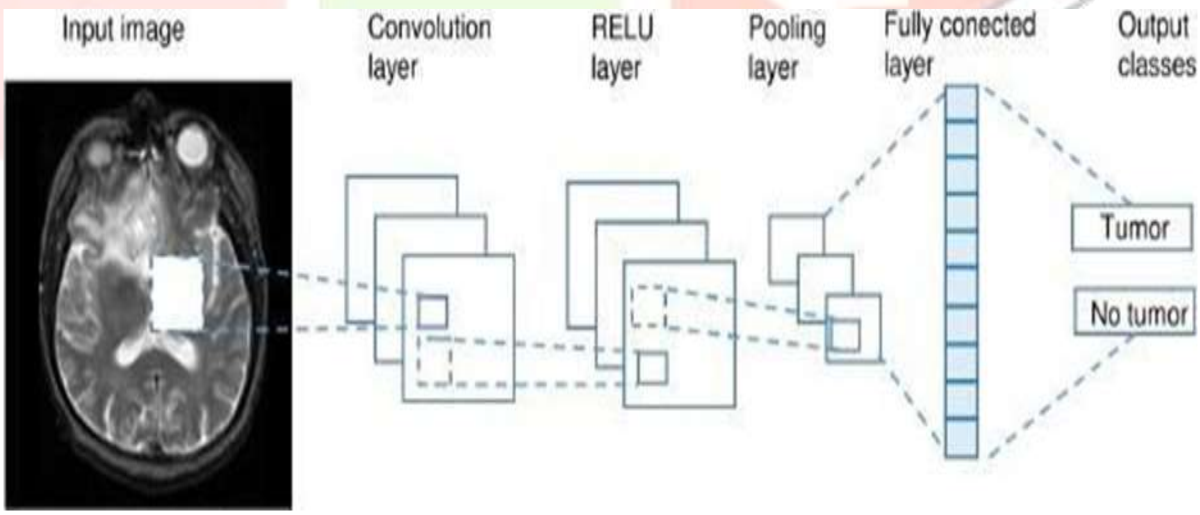

Fig.3.1. Proposed System

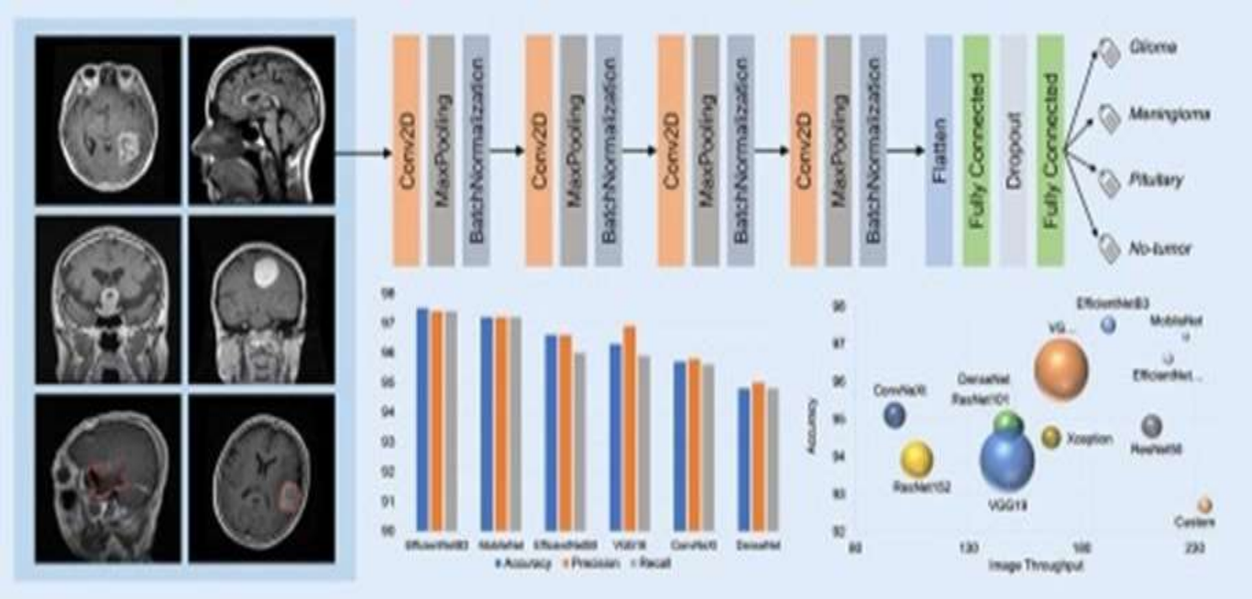

Fig.3.2. Convolutional Neural Network (CNN)

IV. IMPLEMENTATION AND TECHNOLOGIES USED

- System implementation is the process of executing the proposed design and converting it into a working solution. In the context of brain tumor detection, the implementation involves developing a deep learning-based model that can accurately process MRI images, detect tumor regions, and classify tumor types. The system is developed to automate the diagnostic process and assist medical professionals in identifying brain abnormalities more efficiently.
- The implementation phase includes steps such as loading and preprocessing the MRI dataset, designing the deep learning architecture, training the model, validating its accuracy, and deploying the model for real-time predictions. The main goal is to create a user-friendly, accurate, and reliable system that can assist in early diagnosis and improve patient outcomes
- **Python:** The primary programming language used due to its simplicity and powerful libraries for data science and machine learning.
- **TensorFlow / Keras:** Deep learning frameworks used to build, train, and evaluate Convolutional Neural Networks (CNNs) for tumor classification.
- **OpenCV:** Used for image processing tasks like reading, resizing, and enhancing MRI images.
- **NumPy and Pandas:** For handling and manipulating image data and associated labels in structured form.
- **Matplotlib / Seaborn:** For visualizing the performance of the model (e.g., accuracy graphs, confusion matrix).
- **Google Colab /JupyterPython:** The primary programming language used due to its simplicity and powerful libraries for data science and machine learning.
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- **Google Colab / Jupyter Notebook:** Platforms used for coding, model training, and experimentation due to their ease of use and GPU support.

- **Pre-trained Models (VGG16, ResNet, etc.):** Used for transfer learning to improve accuracy and reduce training time with limited data.
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- **Google Colab / Jupyter Notebook:** Platforms used for coding, model training, and experimentation due to their ease of use and GPU support.
- **Pre-trained Models (VGG16, ResNet, etc.):** Used for transfer learning to improve accuracy and reduce training time with limited data.

V. CODE FOR BRAIN TUMOR USING DEEP LEARNING

```
import numpy as np import pandas as pd import matplotlib.pyplot as plt from sklearn.model_selection import
train_test_split from sklearn.metrics import accuracy_score ### Prepare/collect data
In[2]:
import os path = os.listdir('brain_tumor/Training/') classes = {'no_tumor':0, 'pituitary_tumor':1}
In[5]: import cv2 X=[] Y=[]
for cls in classes: pth = 'brain_tumor/Training/'+cls for j in os.listdir(pth): img = cv2.imread(pth+'/'+j, 0) img
= cv2.resize(img, (200,200)) X.append(img) Y.append(classes[cls]) In[6]: In[7]:
print(np.unique(Y))
In[8]:
print(pd.Series(Y).value_counts())
# In[9]:
X.shape, X_updated.shape
### Visualize data
In[10]:
plt.imshow(X[0], cmap='gray')
### Prepare data In[9]:
### Split Data In[13]:
xtrain, xtest, ytrain, ytest = train_test_split(X_updated, Y, random_state=10,test_size=.20)
# In[14]:
print(xtrain.shape, xtest.shape)
### Feature Scaling
```

In[15]:

print(xtrain.max(), xtrain.min()) print(xtest.max(), xtest.min()) xtrain = xtrain/255 xtest = xtest/255

print(xtrain.max(), xtrain.min()) print(xtest.max(), xtest.min())

Feature Selection: PCA

In[19]:

from sklearn.decomposition import PCA

In[20]:

print(xtrain.shape, xtest.shape) pca = PCA(.98) pca_train = pca.fit_transform(xtrain) pca_test = pca.transform(xtest) pca_train = xtrain pca_test = xtest

In[ ]:

print(pca_train.shape, pca_test.shape)

#print(pca.n_components_)

#print(pca.n_features_)

Train Model

In[24]:

from sklearn.linear_model import LogisticRegression from sklearn.svm import SVC

In[25]:

import warnings warnings.filterwarnings('ignore') lg = LogisticRegression(C=0.1) lg.fit(xtrain, ytrain) In[26]:

sv = SVC()

sv.fit(xtrain, ytrain)

Evaluation

In[29]: print('logistic score') print("Training Score:", lg.score(xtrain, ytrain)) print("Testing Score:", lg.score(xtest, ytest)) In[30]:

print('svm score')

print("Training Score:", sv.score(xtrain, ytrain)) print("Testing Score:", sv.score(xtest, ytest)) from sklearn.neighbors import KNeighborsClassifier neigh = KNeighborsClassifier(n_neighbors=3) neigh.fit(xtrain, ytrain) print('knn score') print("Training Score:", neigh.score(xtrain, ytrain)) print("Testing Score:", neigh.score(xtest, ytest)) from sklearn.ensemble import RandomForestClassifier clf = RandomForestClassifier(max_depth=2, random_state=0)

clf.fit(xtrain, ytrain) print('knn score') print("Training Score:", clf.score(xtrain, ytrain)) print("Testing Score:", clf.score(xtest, ytest))

Prediction

In[32]:

pred = sv.predict(xtest)

In[39]:

misclassified=np.where(ytest!=pred) print(misclassified)

In[41]: print("Total Misclassified Samples: ",len(misclassified[0])) print(pred[36],ytest[36])

TEST MODEL

In[42]:

dec = {0:'No Tumor', 1:'Positive Tumor'}

In[43]: plt.figure(figsize=(12,8)) p = os.listdir('brain_tumor/Testing/') c=1 for i in

os.listdir('brain_tumor/Testing/no_tumor/')[:9]: plt.subplot(3,3,c) img =

cv2.imread('brain_tumor/Testing/no_tumor/'+i,0) img1 = cv2.resize(img, (200,200))

img1 = img1.reshape(1,-1)/255 p = sv.predict(img1) plt.title(dec[p[0]]) plt.imshow(img, cmap='gray') plt.axis('off')

c+=1 In[44]:

plt.figure(figsize=(12,8))

p = os.listdir('brain_tumor/Testing/') c=1

for i in os.listdir('brain_tumor/Testing/pituitary_tumor/')[:16]: plt.subplot(4,4,c) img =

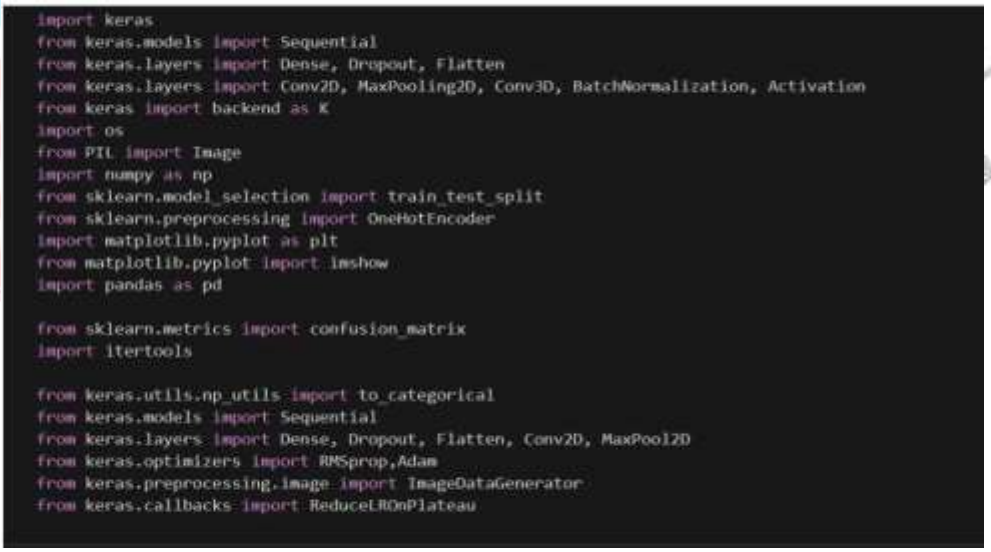
cv2.imread('brain_tumor/Testing/pituitary_tumor/'+i,0) img1 = cv2.resize(img, (200,200)) img1 =

img1.reshape(1,-1)/255 p = sv.predict(img1) plt.title(dec[p[0]]) plt.imshow(img, cmap='gray')

plt.axis('off')

c+=1

TEST RESULTS: All the test cases mentioned above passed successfully. No defects encountered.



```
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D, Conv3D, BatchNormalization, Activation
from keras import backend as K
import os
from PIL import Image
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
import pandas as pd

from sklearn.metrics import confusion_matrix
import itertools

from keras.utils.np_utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
from keras.optimizers import RMSprop,Adam
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ReduceLROnPlateau
```

Fig.5.1. Import Libraries

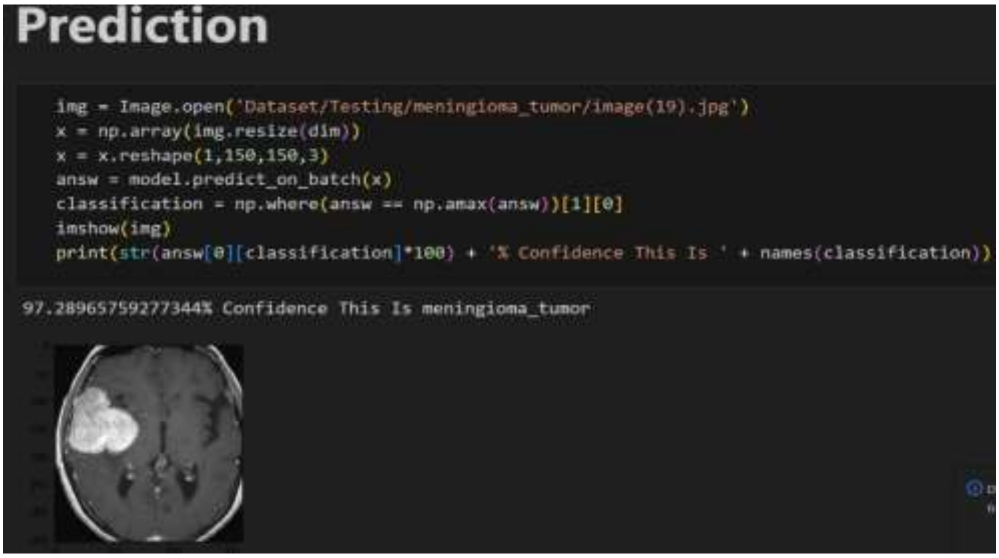


Fig.5.2. MRI Brain Tumor Classification Prediction with Confidence Score

VI. CONCLUSION

In this project, we successfully developed an automated brain tumour detection and segmentation system using Convolutional Neural Networks (CNN). CNN is known to be one of the most effective deep learning techniques for image classification and segmentation, especially in medical imaging. Our system was designed to analyze MRI scans and accurately identify tumour regions, achieving an accuracy of 84%. The process began with preprocessing the MRI images, where we converted them into grayscale to simplify the data while preserving important features. Noise was effectively reduced using adaptive bilateral filtering, which helped retain the edge details and enhance the overall image quality. We then applied thresholding methods to convert the images into binary format, making feature extraction by the CNN more effective.

After preprocessing, the images were passed into the CNN model, which was trained to detect and segment tumour areas. The model produced fast, consistent, and reliable results, which helped reduce the time required for diagnosis and minimized the need for manual segmentation by radiologists. One of the biggest strengths of this system lies in its automation and consistency. Unlike manual analysis, which can vary from expert to expert, our CNN-based system delivers uniform results, ensuring greater diagnostic accuracy. The system also proved to be computationally efficient, cost-effective, and suitable for deployment even in resource-limited environments. Its scalability allows it to be used across various clinical settings, improving the accessibility of quality diagnostics.

Moreover, the system supports early tumour detection, which plays a vital role in improving treatment outcomes for patients. By reducing dependency on manual processes, it enables radiologists to manage more cases efficiently. While the results were promising, there is still scope for improvement. Future enhancements may include the use of more advanced architectures like U-Net, ResNet, or hybrid deep learning models for better performance. Techniques like transfer learning and fine-tuning can also be applied to deal with limited datasets, and training on more diverse data can increase robustness. The integration of this system into realtime diagnostic platforms, such as mobile applications or cloud-based tools, has the potential to support remote or underserved areas.

In conclusion, this project demonstrates the effectiveness of deep learning, especially CNNs, in the field of medical diagnostics. It highlights how artificial intelligence can significantly enhance the speed, accuracy, and accessibility of brain tumour detection. With further development and wider adoption, such intelligent systems can become an essential part of modern healthcare, supporting doctors in making faster and more accurate decisions, ultimately leading to better outcomes for patients worldwide.

VII. FUTURE ENHANCEMENT

The current implementation of the proposed brain tumor detection system using Convolutional Neural Networks (CNN) has shown promising results with an accuracy of 84%. However, there are several opportunities for enhancement and expansion in future research. One major observation during experimentation is the dependency on large, high-quality training datasets. In the medical imaging domain, collecting and annotating large volumes of MRI data is often a challenging and time-consuming task. Therefore, there is a pressing need to develop robust models that can operate effectively even with limited or imbalanced datasets. To overcome this challenge, future work can focus on **data augmentation techniques** such as rotation, flipping, zooming, and contrast adjustments to synthetically expand training data. Moreover, **transfer learning** can be adopted where pre-trained models on large image datasets can be fine-tuned on medical datasets to improve performance with fewer data samples.

Additionally, the system can be enhanced by incorporating **weakly supervised learning** and **semi-supervised learning algorithms**, which can learn effectively from a small number of labeled images and a large amount of unlabeled data. These approaches can significantly reduce the need for extensive manual annotation.

Another important future direction is the integration of **self-learning or reinforcement learning algorithms**, which enable the system to improve its performance over time by learning from feedback or outcomes. This could make the model adaptive to new and unseen medical cases, making it more reliable in real-world diagnostic environments. Furthermore, incorporating advanced deep learning architectures like **U-Net, DenseNet, ResNet**, or **attention-based models** can enhance the segmentation accuracy and enable more precise identification of tumor boundaries. Hybrid models that combine CNNs with Recurrent Neural Networks (RNNs) or Transformer-based networks may also be explored for improved spatial and contextual understanding.

Cross-platform compatibility is another area for future improvement. Developing lightweight versions of the model suitable for deployment on **mobile devices** or **edge computing platforms** can enable remote diagnostics, particularly in rural or resource-limited settings. Cloud integration with real-time processing capabilities can also facilitate large-scale implementation in hospitals and diagnostic labs.

Another scope of enhancement lies in **multi-modal medical image processing**, where combining MRI, CT, and PET scans could give a more comprehensive understanding of the tumor. This can lead to better diagnosis, classification, and treatment planning.

In conclusion, while the proposed system provides a strong foundation, future enhancements can focus on model generalization, reduction of computational complexity, improved training methodologies, real-time implementation, and integration with existing clinical workflows. These improvements will not only boost accuracy and efficiency but also make brain tumor detection more accessible and scalable globally.

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