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# Brain Tumor Detection Using SPECT and PET Imaging

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**Abstract**: *Brain tumors present significant diagnostic challenges due to their heterogeneous nature and complex biological behavior. Nuclear medicine imaging techniques, specifically Single Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET), have become integral in the evaluation of brain tumors. These modalities provide functional and molecular imaging capabilities that complement traditional anatomical imaging methods like MRI and CT. In this Project we proposed a Brain Tumor Detection model that utilizes SPECT and PET imaging data combined with Deep Learning techniques. The process involves data preprocessing, feature extraction, and training classification model to distinguish between tumor and non-tumor brain scans. The system was evaluated using standard performance metrices such as accuracy, precision, recall and F1-score.The result demonstrates that functional imaging of an scans and results the Brain Tumor Scans in Probabilities of various stages in the Brain Tumor Detection Model with the accuracy of 98%.*

**Keywords**: Convolutional Neural Network, SPECT & PET Medical Imaging, Brain Tumor, Deep Learning

## I. INTRODUCTION

This Article study presents a fusion-based deep learning model that combines PET and SPECT images to enhance brain tumor classification and localization using a CNN[1]. In his ArticleBrain tumor detection model used a fine-tuned YOLOv7 model to detect brain tumors in MRI scans, achieving 99.5% accuracy in identifying gliomas, meningioma, and pituitary tumors[2].This Article proved thatDetecting brain tumors in their early stages is crucial in PET and SPECT imaging[3]. In this Article in modern days manual detection of brain tumours in MRI images is time consuming, inaccurate and tedious due to the large number of images and similarity between normal and tumor cells[4].In This Article proposes timely diagnosis of brain tumor using MRI and its potential[5].In this Article investigate the transfer learning method with the highest performance in the classification process of transfer learning methods on brain images [6].In this Study Brain tumours are abnormal masses that can be benign or malignant, affecting human life and requiring various treatments. This study proposes Brain MR Net, a deep learning model that uses attention modules [7]. In this Study A Neuroimaging is essential for accurate diagnosis and monitoring of brain tumors[8].Deep learning, a type of artificial intelligence, has gained significant attention for its potential to solve complex problems [9].In this article Myocardial single-photon emission computed tomography (SPECT) is widely used to diagnose myocardial ischemia, but its accuracy is affected by photon absorption artefacts. To overcome this, researchers proposed a deep-learning model that translates SPECT images to positron emission tomography (PET) imaging [10].In this study introduces an explainable deep learning framework for brain tumour detection using MRI images, combining ResNet50 with Grad-CAM for transparency.[11]Brain tumoursare serious conditions caused by uncontrolled and abnormal cell division. Magnetic resonance imaging (MRI) is one of the methods frequently used to detect brain tumours owing to its excellent resolution.[12]In this article developed a CNN and transfer learning-based model to detect brain tumours from MRI scans, achieving high accuracy in identifying gliomas, meningiomas, and pituitary tumours.[13]. In This paper proposes a novel end-to-end brain tumor segmentation method using an improved U-Net architecture with up skip connections and inception modules, achieving accurate segmentation results[14].In this

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Article The world Health organisation(WHO)classifies brain tumours as benign vs malignant, and then further categories malignant tumours into 4 grades based on histologic aggressiveness[15].

**Algorithm Proposed: -**

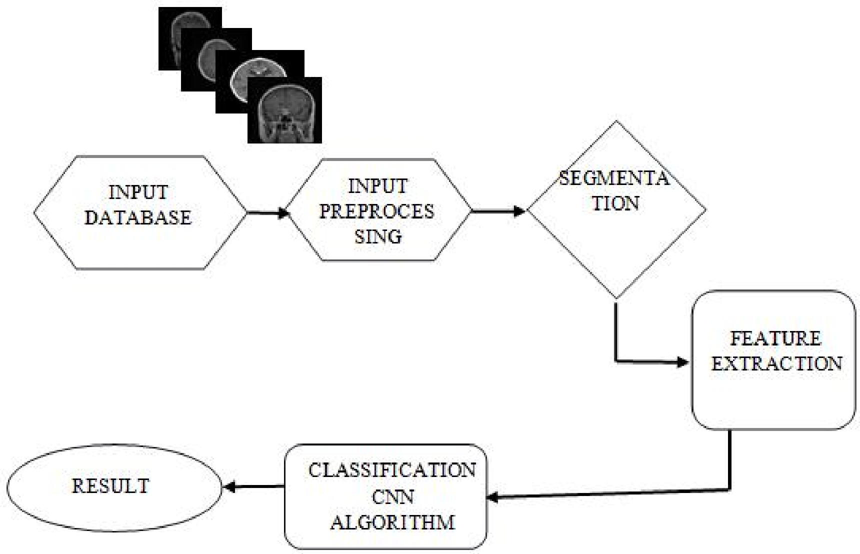


**Fig.1 Convolutional Neural Network**

**Architecture:**

- Sequential model with distinct layers.
- Conv2D Layers: Utilized 32 filters of 3x3 kernels with ReLU activation.
- A 2×2 max pooling operation was employed to down sample the feature maps and reduce spatial resolution.
- Flattened Layer: Transformation of output into a 1D array.
- ReLU Activation: Introduced non-linearity for better generalization on complex data.
- Output Layer: Comprised of 4 neurons with softmax activation for multi-class classification.

**Model Compilation:**

- Optimizer: Adam optimizer employed.
- Loss Function: sparse categorical crossentropy chosen based on existing literature.

**Modules Developed**

**Module 1:Dataset Collection**

- The Dataset size: “The Dataset consist of 7000 images”
- Dataset source: “The Dataset was obtained from Figshare custom dataset”

**Module 2:Data Preprocessing**

- Collect and prepare SPECT and PET images for analysis
- Data preprocessing are crucial steps before training your model to ensure the images are in a suitable format for deep learning.
- Input
- Output

**Normalization:** Normalize the pixel values to the range [0, 255] for image visualization or [0, 1] for model input.Resize to 224x224 pixels.

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**INPUT:**

**1. Resizing the Images**

We resize every image to a fixed size, like 256×256 pixels or 224×224 pixels.

**2. Normalizing Pixel Values**

We divide every pixel value by 255. For example, 200 becomes 200/255 ≈ 0.78.

**3. Enhancement (Improve Clarity)**

Adjust brightness and contrast

**4. Adjust brightness and contrast**

Use sharpening filters (like Laplacian or Unsharp Mask) to bring out fine details.

**5. Saving the Pre-processed Dataset**

**6. Final Output**

- After preprocessing, you'll have 7000 images that are:
- All the same size
- Have balanced brightness/contrast

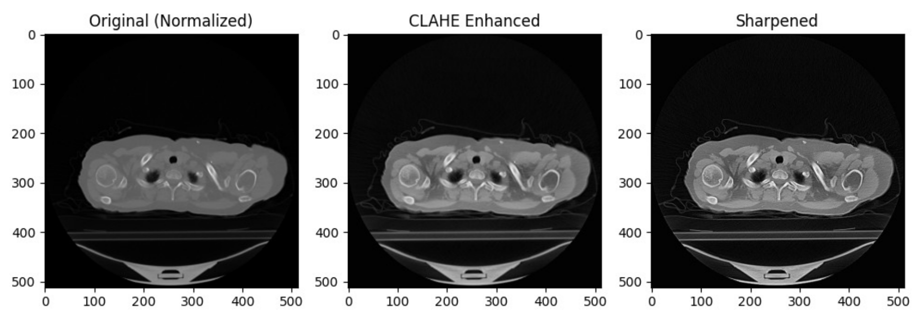


**Fig: 2.a**

**Python Libraries for Medical Imaging:**

**NumPy**: NumPy is used to extract features from medical images, such as texture features or shape features.

**TensorFlow & Keras**:TensorFlow and its sub-modules (keras, preprocessing, applications) for building and training theResNet50 model.

**Matplotlib**: Matplotlib used to display SPECT and PET images,allowing Clinicians to evaluate the accuracy of the Segmentation

**Module 3**: **Feature Extraction & Classification in Convolutional Neural Network Model Trained.**

"The model consists of a convolutional neural network (CNN) with three Conv2D layers, each followed by a MaxPooling2D layer. The Conv2D layers extract features from the input images using filters with a kernel size of 3x3. The MaxPooling2D layers downsample the feature maps, reducing the spatial dimensions and retaining important features. The feature maps are then flattened and fed into two dense layers, which output a probability distribution over the classes. The model uses dropout regularization with a dropout rate of 0.5 to prevent overfitting. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss function."

**1. Conv2D Layer:**

**- Layer Type:** Convolutional Neural Network (CNN) layer

- **Function:** Extracts features from images by applying filters that scan the image in both horizontal and vertical directions.

- **Parameters:**

**- Filters:** 32, 64, and 128 filters are used in the three Conv2D layers, respectively.

- **Kernel Size:** The kernel size is 3x3, which means the filter scans 3x3 pixel blocks.

**- Activation Function:** ReLU (Rectified Linear Unit) is used as the activation function.

**- Output:** Feature maps that represent the presence of specific features in the input image.

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**2. MaxPooling2D Layer:**

**- Layer Type: Downsampling layer**

**- Function:** Reduces the spatial dimensions of the feature maps by taking the maximum value across each window.

- **Parameters:**

- **Pool Size:** The pool size is 2x2, which means the layer takes the maximum value across 2x2 pixel blocks.

**- Output:** Down sampled feature maps that reduce the spatial dimensions and retain important features.

**3. Flatten Layer:**

**- Layer Type:** Flattening layer

**- Function:** Flattens the feature maps into a one-dimensional array, which is fed into the dense layers.

**- Output:** A one-dimensional array of features.

**4. Dense Layer:**

**- Layer Type:** Fully connected neural network layer

**- Function**: Processes the flattened feature array and outputs a probability distribution over the classes.

**- Parameters**:

**- Units:** The number of units in the dense layer is 128, which means the layer has 128 neurons.

- **Activation Function:** ReLU is used as the activation function in the first dense layer, and softmax is used in the second dense layer.

- **Output:** A probability distribution over the classes.

**5. Dropout Layer:**

**- Layer Type:** Regularization layer

**- Function:** Randomly sets a fraction of the neurons to zero during training, which helps prevent overfitting.

- **Parameters:**

- **Dropout Rate**: The dropout rate is 0.5, which means 50% of the neurons are randomly set to zero.

**Output:**

```
ot pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first l
ayer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Epoch 1/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 97s 528ms/step - accuracy: 0.6074 - loss: 0.8852 - val_accuracy: 0.7887 - val_loss: 0.5078
Epoch 2/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 83s 464ms/step - accuracy: 0.8320 - loss: 0.4366 - val_accuracy: 0.8833 - val_loss: 0.3055
Epoch 3/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 83s 463ms/step - accuracy: 0.8910 - loss: 0.2876 - val_accuracy: 0.8978 - val_loss: 0.2732
Epoch 4/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 84s 470ms/step - accuracy: 0.9188 - loss: 0.2335 - val_accuracy: 0.9054 - val_loss: 0.2497
Epoch 5/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 85s 473ms/step - accuracy: 0.9338 - loss: 0.1795 - val_accuracy: 0.9214 - val_loss: 0.2111
Epoch 6/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 84s 470ms/step - accuracy: 0.9467 - loss: 0.1408 - val_accuracy: 0.9428 - val_loss: 0.1583
Epoch 7/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 84s 469ms/step - accuracy: 0.9629 - loss: 0.1030 - val_accuracy: 0.9565 - val_loss: 0.1649
Epoch 8/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 83s 465ms/step - accuracy: 0.9667 - loss: 0.0921 - val_accuracy: 0.9542 - val_loss: 0.1447
Epoch 9/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 83s 465ms/step - accuracy: 0.9675 - loss: 0.0883 - val_accuracy: 0.9458 - val_loss: 0.1667
Epoch 10/10
179/179 ━━━━━━━━━━━━━━━━━━━━ 84s 466ms/step - accuracy: 0.9781 - loss: 0.0575 - val_accuracy: 0.9619 - val_loss: 0.1617
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considere
d legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_mod
el.keras')`.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 458ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 183ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 186ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 191ms/step
```

Fig: 2.b

```
Confusion Matrix:
[[276  24   0   0]
 [ 12 282   9   3]
 [  0   0 405   0]
 [  0   4   0 296]]
Classification Report:
              precision    recall  f1-score   support

      glioma       0.96      0.92      0.94       300
  meningioma       0.91      0.92      0.92       306
     notumor       0.98      1.00      0.99       405
   pituitary       0.99      0.99      0.99       300

    accuracy                           0.96      1311
   macro avg       0.96      0.96      0.96      1311
weighted avg       0.96      0.96      0.96      1311
```

Fig:2.c

**Module 4. Evaluation (User Interface):**
In this Module implements a web-based application for brain tumor classification using a deep learning model. The application is built using Flask, a popular web framework for Python.

**Methodology:**
The application uses the following components:

**1. Trained Model: A** deep learning model is trained on a dataset of brain tumor images and saved in the Keras format (. keras). The model is loaded using the keras.models. Loadmodel function.

**2. Flask App:** A Flask app is initialized to handle HTTP requests and responses. The app is configured to upload images to a specified folder.

**3. Image Upload:** The app allows users to upload images, which are stored in the upload folder.

**4. Prediction:** Once an image is uploaded, the app uses the trained model to make a prediction on the type of brain tumor present in the image.

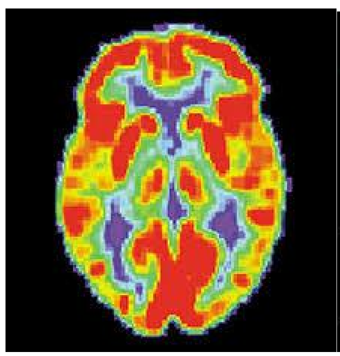
**Implementation:**
The implementation involves the following steps:

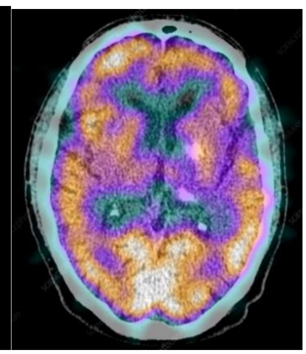
**1. Loading the Model:** The trained model is loaded using the keras. Models. load model function.

**2. Configuring the App**: The Flask app is configured to handle image uploads and store them in the specified folder.

**3. Making Predictions:** Once an image is uploaded, the app uses the trained model to make a prediction on the type of brain tumour present in the image.

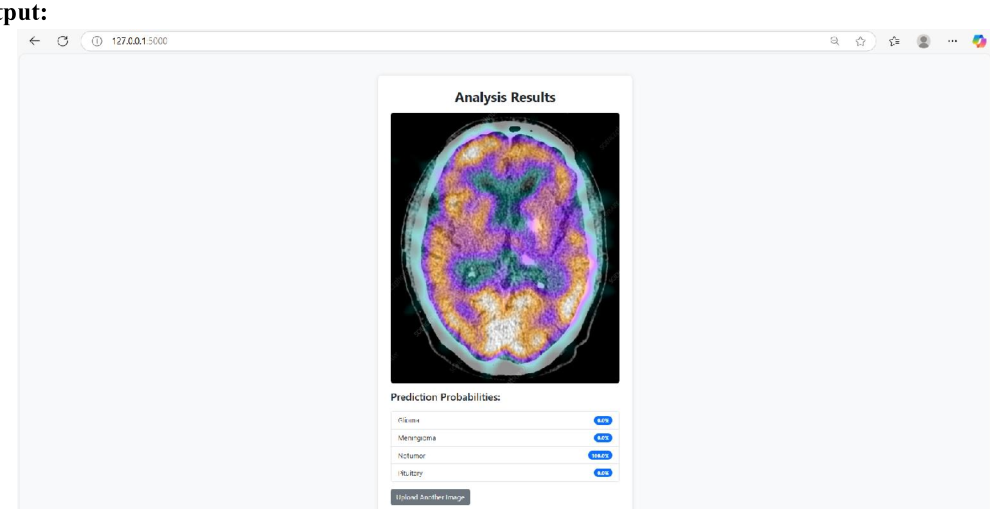
**Input Snapshot:**





**PET image** **SPECT image**

**Final Output:**



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