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EXPERT BRAIN TUMOR DETECTION AND CLASSIFICATION SYSTEM USING TWO LEVEL DIAGNOSIS

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.**Abstract:** Brain tumors are a significant health concern globally, with early and accurate detection being critical for effective treatment and improved patient outcomes. This paper presents an innovative approach for brain tumor detection and classification using a two-level diagnosis system. The proposed system combines advanced medical imaging techniques with artificial intelligence algorithms to enhance the accuracy and efficiency of brain tumor diagnosis. Furthermore, the proposed system incorporates an expert system that integrates medical knowledge and decision-making rules. The expert system refines the diagnosis results by considering additional clinical parameters, patient history, and expert opinions, ensuring a comprehensive and accurate diagnosis. This research contributes significantly to the field of medical imaging and artificial intelligence, offering a robust and reliable solution for brain tumor detection and classification. The proposed system has the potential to revolutionize clinical practices, leading to early diagnosis, personalized treatment plans, and ultimately, improved outcomes for patients with brain tumors.
Index Terms—Brain Tumor Detection, Tumor Classification, Medical Imaging, Deep Learning

I. Introduction

Brain tumors remain a significant public health concern, underscoring the need for advanced diagnostic methods to achieve early detection and precise classification. The timing of diagnosis is critical as it directly impacts treatment decisions and patient outcomes. While traditional diagnostic approaches are valuable, they often face challenges in accuracy and efficiency.

The integration of advanced medical imaging technologies with state-of-the-art artificial intelligence (AI) algorithms has opened avenues for more accurate and rapid brain tumor diagnosis. This research introduces an expert system for brain tumor detection and classification, utilizing a sophisticated twolevel diagnostic approach. The system leverages cutting-edge medical imaging, deep learning, and machine learning techniques to enhance diagnostic accuracy and reliability. By combining image processing, convolutional neural networks (CNNs), and expert systems, this approach aims to revolutionize neuroimaging diagnostics.

The subsequent sections of this paper will delve into the methodology, including image preprocessing techniques, the architecture of the CNN model, machine learning algorithms for tumor classification, and the integration of expert knowledge into the diagnostic process. Extensive evaluations on diverse datasets will be presented to demonstrate the system's effectiveness and reliability.Furthermore, we will discuss the implications of our findings, potential applications in the medical field, and avenues for future research, highlighting the transformative potential of this expert brain tumor detection and classification system.

II Problem Definition

The analysis of brain tumors through imaging poses significant challenges due to the diverse characteristics of these tumors, including variations in size, shape, and location. Various techniques have been suggested for detecting abnormalities in data that are not directly observable, each with distinct strengths and weaknesses. It is crucial to have a benchmark dataset that can objectively evaluate the effectiveness of cutting-edge procedures for assessing brain tumors. Additionally,

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different imaging devices can yield brain tumor images with varying sharpness, contrast, number of slices, and pixel spacing, further complicating the analysis process.

III .Literature Survey

[1] Lin, J., Lin, J., & Lu, C. (Year). "CKD-TransBTS: Clinical Knowledge-Driven Hybrid Transformer With Modality-Correlated Cross-Attention for Brain Tumor Segmentation." This paper introduces CKD-TransBTS, a brain tumor segmentation model that leverages clinical knowledge and imaging principles to improve accuracy in MRI-based brain tumor detection.

[2] Ottom, M. A., & Rahman, H. A. (Year). "Znet: Deep Learning Approach For 2D Mri Brain Tumor Segmentation." The Znet Model Uses Deep Learning Techniques, Including Skip Connections And Encoder-Decoder Models, Along With Data Augmentation, To Achieve High Accuracy In Segmenting Brain Tumors From Mri Images

[3] Noreen, N., & Palaniappan, S. (Year). "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor." This study proposes a deep learning model that combines feature extraction methods from pretrained models like Inception v3 and DenseNet201 to improve brain tumor diagnosis and classification.

[4] Ramprasad, M. V. S., & Rahman, M. Z. U. (Year). "SBTC-Net: Secured Brain Tumor Segmentation and Classification Using Black Widow With Genetic Optimization in IoMT." The SBTC-Net model focuses on securing brain tumor images using watermarking techniques and then applies segmentation and classification using transfer learning methods.

[5] Ramprasad, M. V. S., & Rahman, M. Z. U. (Year). "SBTC-Net: Secured Brain Tumor Segmentation and Classification Using Black Widow With Genetic Optimization in IoMT." This work emphasizes the importance of early detection of brain tumors and introduces SBTC-Net, a secure segmentation and classification system using transfer learning and watermarking in the Internet of Medical Things (IoMT) environment.

IV . Existing System

Machine learning models, especially Convolutional Neural Networks (CNNs), are trained using extensive datasets of labeled MRI scans that include both healthy and tumor-affected images. These models are trained to discern patterns and connections within the data, enabling them to classify new, unseen MRI scans as either containing a tumor or being tumor-free. CNNs, in particular, are highly effective for brain tumor detection as they excel at recognizing patterns in images. Their strength lies in their capability to automatically learn features from the data, eliminating the need for manual feature extraction, which is a considerable advantage in medical imaging analysis.

V. Drawbacks

Several existing systems are limited to performing segmentation only and face various technological challenges. Some of these systems only operate on cancerous images, lacking the capability for staging and exhibiting lower accuracy. Additionally, they often do not compute the area of the tumor until after preprocessing the image and segmenting it. These methods have primarily focused on segmentation in the detection of brain cancer, with limited success in a few studies and mixed outcomes overall. In contrast, the suggested method prioritizes accurate brain tumor detection in MRI scans.

❑ **Assumptions :**

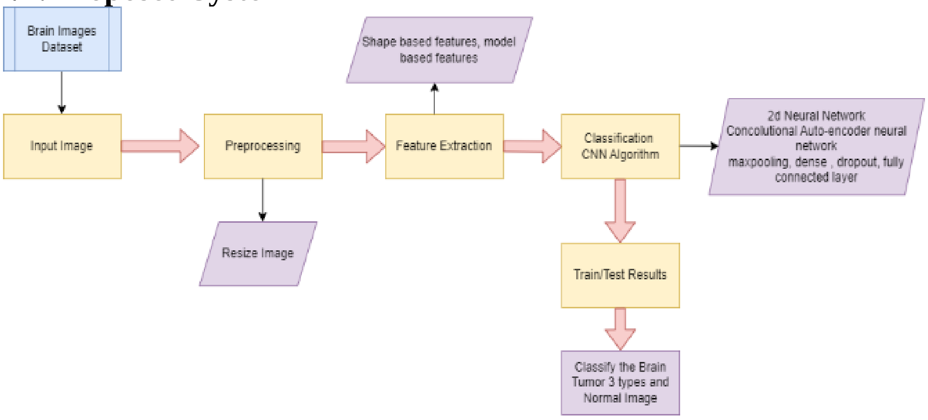
- The MRI dataset utilized for training purposes is meticulously labeled and encompasses a wide spectrum of brain tumor images as well as images depicting healthy brain tissue.
- The features derived from MRI images are pertinent and comprehensive enough to differentiate between tumor-affected areas and healthy brain tissue accurately..

❑ **Dependencies** :

• This method requires a large and varied MRI dataset that includes labeled images representing both tumor and non-tumor cases, which must be readily accessible.

• Access to hardware resources like GPUs or TPUs is essential for efficient training of deep learning models, as training on CPUs can be time-consuming.

VI. Proposed System



The initial step in brain tumor detection involves inputting the MRI image for processing. This image undergoes preprocessing and segmentation techniques. Preprocessing aims to enhance important image features for further analysis, while segmentation divides the digital image into segments that aid in subsequent processes. Feature extraction extracts all relevant features from the input images, which are then compared with the trained dataset. The output indicates the presence of a tumor, with possible categories being Glioma, Pituitary, Meningioma, or No tumor.

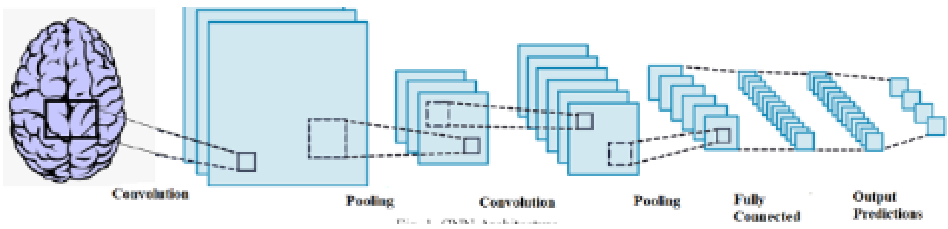
Dataset:

The dataset used consisted of 3264 T1-weighted contrast-enhanced MRI images, categorized into glioma (1321 images), meningioma (1339 images), pituitary gland tumor (1457 images), and healthy brain (1595 images).

Image Pre-processing:

The images were resized to 200x200 pixels as input for the networks and were augmented by conversion in two directions to increase the dataset's diversity.

3) 2D CNN



The convolutional network, also known as a neural network, is structured hierarchically with links between convolution layers, pooling layers, and fully connected layers. Notably, pooling layers are not necessary after every convolution layer. This network architecture comprises eight convolutional and four pooling layers. The final pooling layer, producing 2D output, is converted to a 1D layer through flattened layers for input to the fully connected layers. Padding is used to manage the output size of convolutional layers, ensuring consistent handling of input data edges.

To classify data into categories using softmax activation, a 1024-node fully connected layer and a 4-node fully connected layer were employed. Batch-normalization layers were incorporated to prevent overfitting, along with a dropout layer at a 0.1 rate following max-pooling and fully connected layers. The ReLU activation function was used in all layers except the final fully connected layer. The Adam optimizer was chosen for efficiency, with various learning rates tested (0.01, 0.001, 0.0001), with 0.001 identified as the optimal rate based on minimum learning error.

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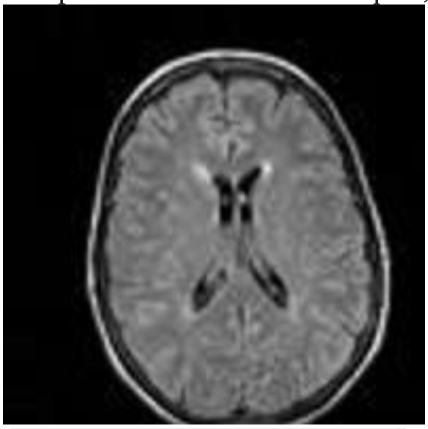
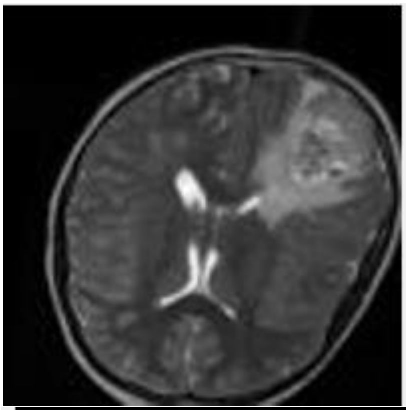
The training process was verified after 100 epochs.

VII. Concept

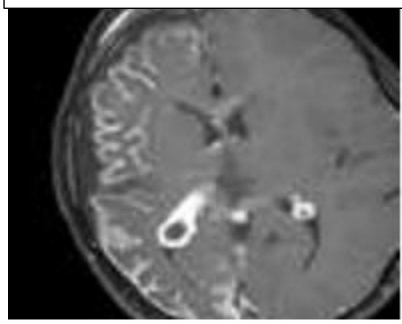
We tackled the complex challenge of detecting brain tumors in MRI scans by leveraging a substantial dataset of brain tumor images. Through transfer learning and fine-tuning a cutting-edge CNN model, we observed a notable enhancement in its ability to detect gliomas, meningiomas, and pituitary brain tumors. Our deep learning model exhibited promising outcomes, accurately pinpointing the presence and exact location of brain tumors in MRI images.. The proposed approach achieved better accuracy compared to standard techniques, with a remarkable 90% accuracy in our analysis.



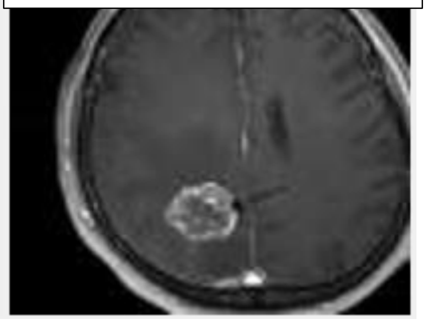
Normal Brain



Meningioma Tumor



Gliomas Tumor



Pituitary Tumor

VIII. Technology

Python is a versatile programming language utilized for various purposes including server-side web development, software development, mathematical computations, system scripting, and more. It is renowned for its high-level nature, built-in data structures, dynamic typing, and dynamic binding. Python's readability and easily learned syntax contribute to reduced program maintenance costs. Its support for modules and packages encourages modular programming and code reuse, while being an open-source language fosters a thriving community of developers constantly enhancing its libraries and functionalities.

In professional settings, Python shines in backend web development, data analysis, artificial intelligence, and scientific computing. Developers leverage Python to create productivity tools, games, desktop applications, and more.

Features and Benefits of Python:

- Cross-platform Compatibility: Python runs on various platforms such as Windows, macOS, Linux, Raspberry Pi, and others, making it versatile and accessible.

- Simple Syntax: Python uses a straightforward syntax similar to English, allowing developers to write code with fewer lines compared to other languages, enhancing readability and reducing development time.
- Interpreter System: Python operates on an interpreter system, enabling immediate code execution and facilitating rapid prototyping and development cycles.
- Multiple Programming Paradigms: Python supports procedural, object-oriented, and functional programming paradigms, providing flexibility and adaptability to different coding styles.

However, Python also has its limitations:

- Maintenance Challenges: Python's dynamically typed nature can lead to ambiguity in code, making maintenance challenging as projects grow in size and complexity. Designing code with clear definitions and writing unit tests can mitigate these challenges.
- Performance Issues: Python's flexibility and dynamic typing can impact performance, requiring additional referencing and slowing down execution. Alternative implementations like PyPy can help improve performance in certain scenarios.

Software Requirements Specification

- Coding Language : Python
- Operating System : Windows 10

Hardware Requirements Specification

- Processor : Pentium-IV
- RAM :512 MB(min)
- Hard Disk : 40 GB
- Key Board : Standard Windows Keyboard
- Mouse : Two or Three Button Mouse
- Monitor : LCD/LED

IX. Algorithm

A Convolutional Neural Network (CNN) is a specialized type of neural network commonly used in the field of Computer Vision within Artificial Intelligence. It allows computers to interpret and understand visual data such as images.

In a typical neural network, there are three main types of layers:

1. Input Layers: This layer receives the input data for the model. For images, the number of neurons in this layer is usually equal to the total number of features, which corresponds to the number of pixels in the image.
2. Hidden Layers: The input from the Input layer is then processed through one or more hidden layers. Each hidden layer can have varying numbers of neurons, typically more than the number of features. The output from each layer is computed through matrix multiplication with learnable weights and biases, followed by an activation function that introduces nonlinearity to the network.
3. Output Layer: The output from the hidden layers is then fed into an output layer, where a logistic function such as sigmoid or softmax is applied. This converts the output into probability scores for each class, providing a prediction or classification result.

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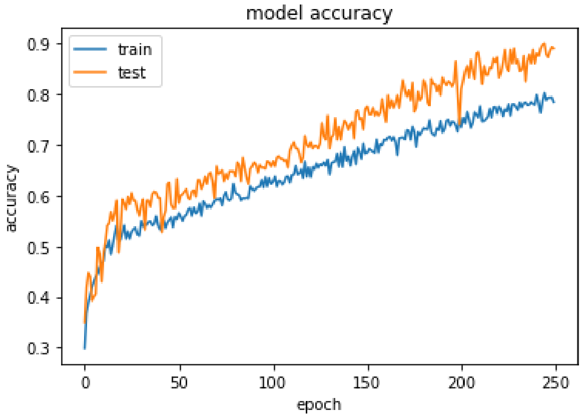
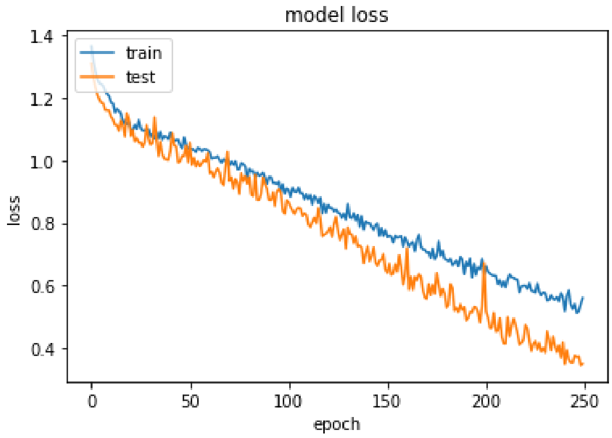
X. Implementation Stages/python

```python
import functools
import operator


def convert_str_to_tuple(tup):
    s = functools.reduce(operator.add, (tup))
    return s

def test_model_proc(fn):
    from keras.models import load_model
    # from keras.optimizers import Adam

#    global fn

    IMAGE_SIZE = 100
    LEARN_RATE = 1.0e-4
    CH=3
    print(fn)
    if fn!="":
        # Model Architecture and Compilation

        model = load_model('brain_model.h5')

        # adam = Adam(lr=LEARN_RATE, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0)
        # model.compile(optimizer=adam, loss='categorical_crossentropy', metrics=['accuracy'])

        img = Image.open(fn)
        img = img.resize((IMAGE_SIZE,IMAGE_SIZE))
        img = np.array(img)

        img = img.reshape(1,IMAGE_SIZE,IMAGE_SIZE,3)

        img = img.astype('float32')
        img = img / 255.0
        print('img shape:',img)
        prediction = model.predict(img)
        print(np.argmax(prediction))
        brain=np.argmax(prediction)
        print(brain)



        if brain == 0:
            Cd="Normal_Brain"
        elif brain == 1:
            Cd="Brain_Tumor_Glioma Level"
        elif brain ==2:
            Cd="Brain_Tumor_Meningioma Level"
        elif brain ==3:
            Cd="Brain_Tumor_Pitutorial"


        A=Cd
        return A
```

XI. Result Output





Testing Accuracy:80%
Training Accuracy:80%

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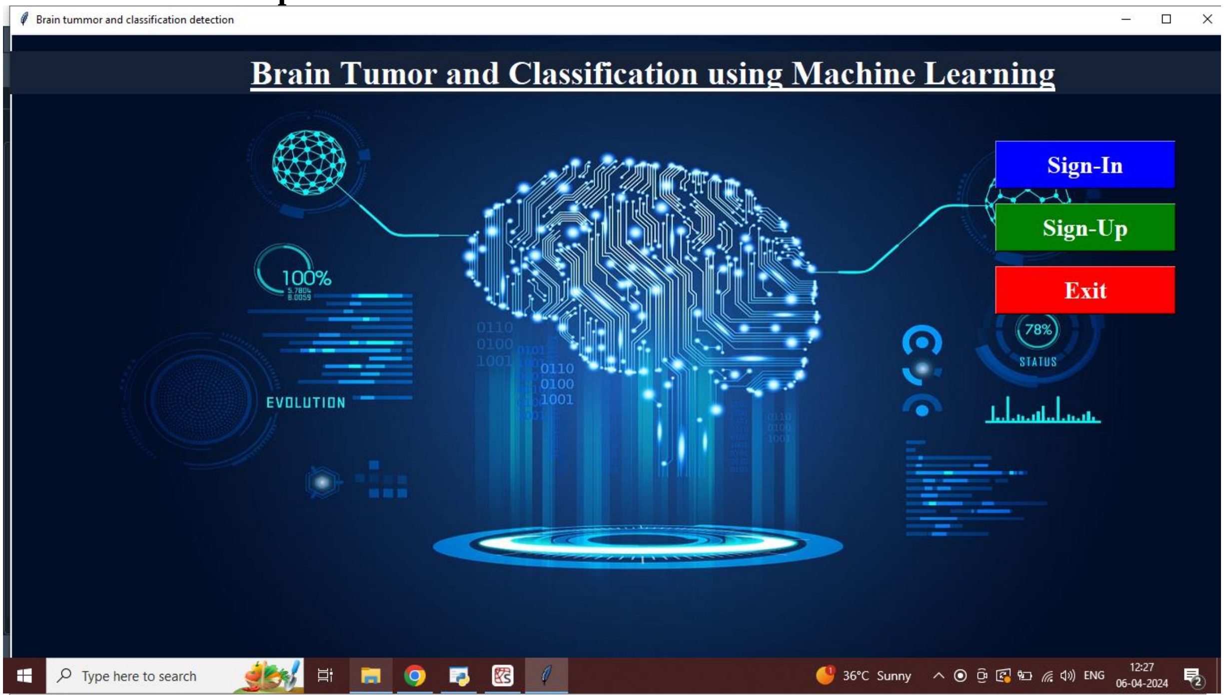
XII. Screenshot Output



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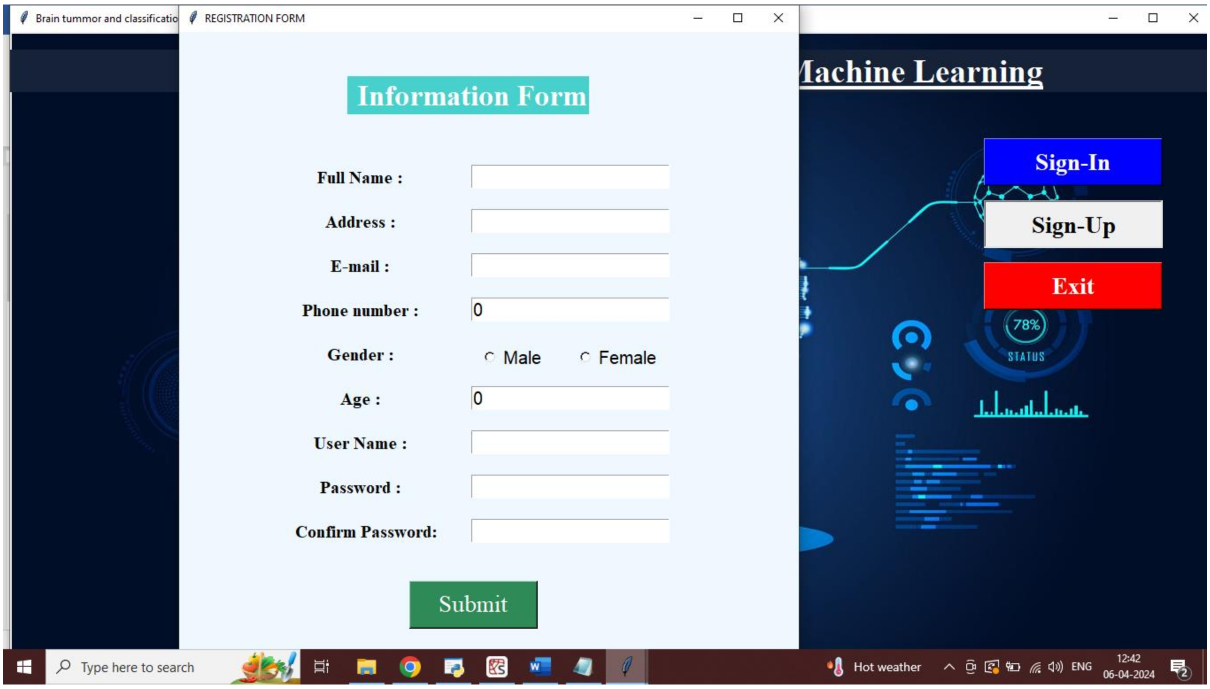
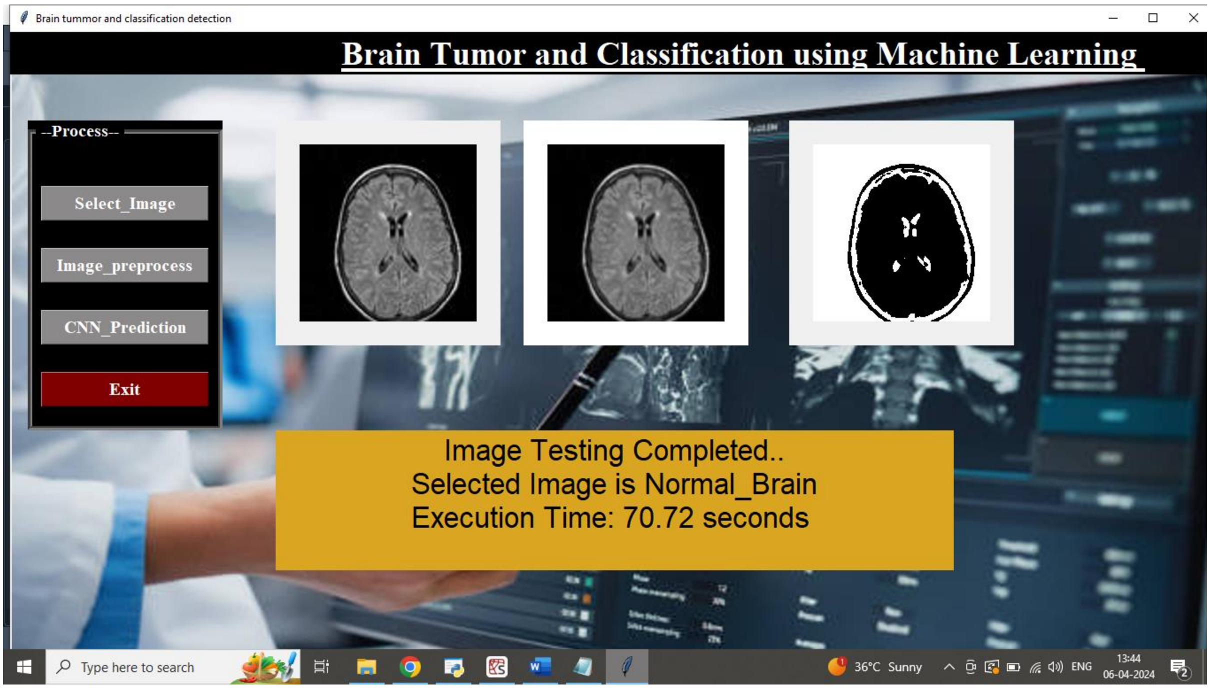
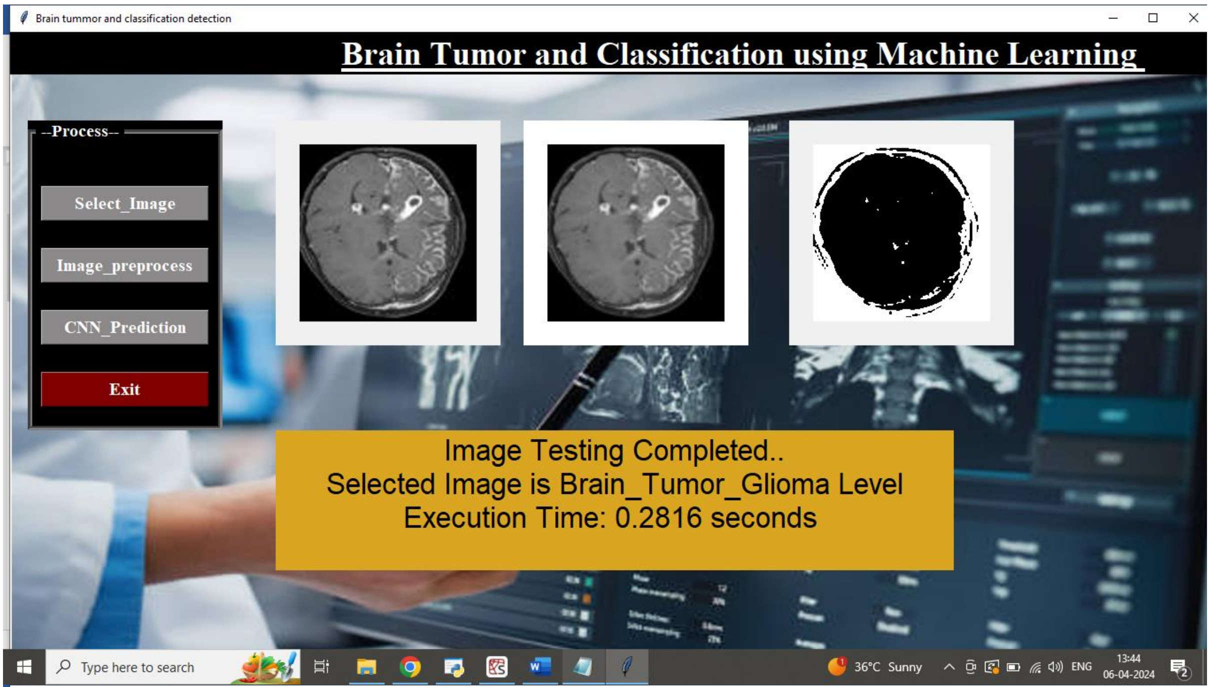
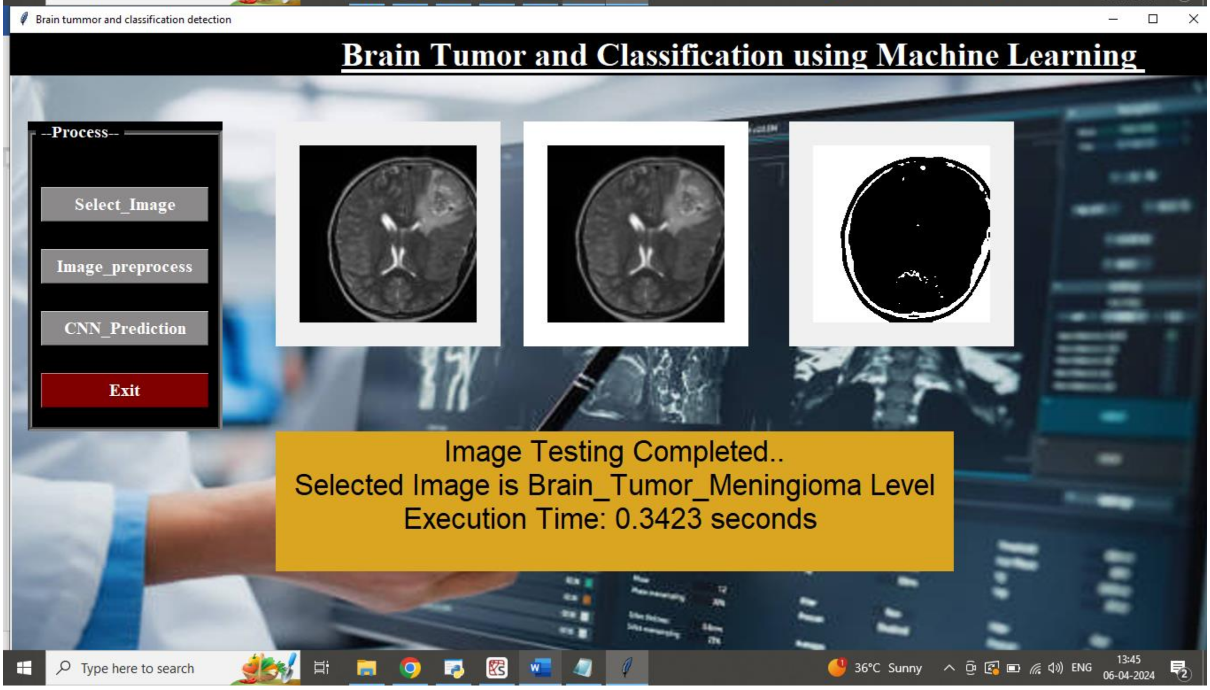
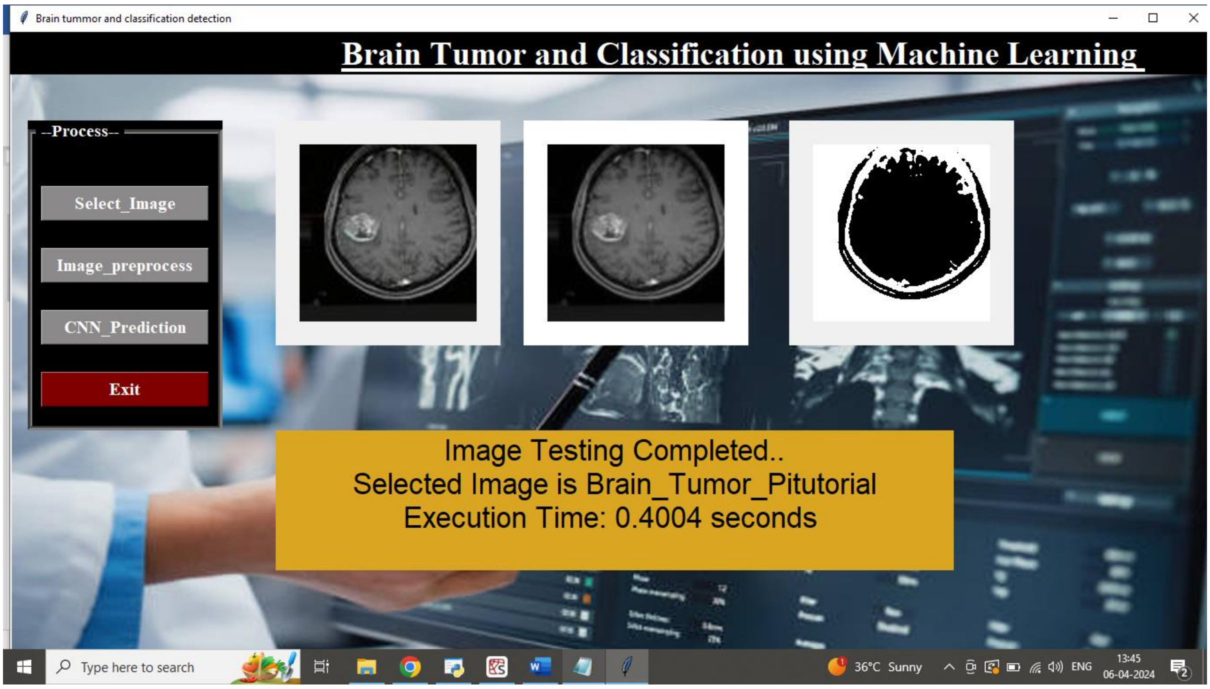





Brain tummor and classification detection
Brain Tumor and Classification using Machine Learning
--Process--
Select_Image
Image_preprocess
CNN_Prediction
Exit
Image Testing Completed..
Selected Image is Brain_Tumor_Glioma Level
Execution Time: 0.2816 seconds
Type here to search
36°C Sunny
ENG
13:44
06-04-2024


Brain tummor and classification detection
Brain Tumor and Classification using Machine Learning
--Process--
Select_Image
Image_preprocess
CNN_Prediction
Exit
Image Testing Completed..
Selected Image is Brain_Tumor_Meningioma Level
Execution Time: 0.3423 seconds
Type here to search
36°C Sunny
ENG
13:45
06-04-2024



XIII. Conclusion

In the domain of brain tumor diagnosis, the fusion of cutting-edge medical imaging, deep learning, machine learning, and expert knowledge has paved the way for groundbreaking solutions. The implementation of an expert brain tumor detection and classification system, incorporating a meticulous two-level diagnosis approach, marks a significant advancement in this field. Through our research, we have showcased the potential to transform brain tumor diagnostics, leading to substantial improvements in accuracy, interpretability, and clinical relevance.

Our approach combines the strengths of artificial intelligence with the expertise of medical professionals, offering a pathway to more precise, interpretable, and personalized brain tumor diagnoses. This integration has the potential to enhance patient outcomes and redefine the standards of neuroimaging diagnostics, ultimately making a positive impact on the lives of patients.

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