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"BRAIN TUMOR DETECTION AND CLASSIFICATION USING QUADRATIC DETERMINANT ANALYSIS"

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Abstract: A definitive diagnosis of a brain tumour is essential for enhancing treatment success and patient survival. However, it is difficult to manually evaluate multiple magnetic resonance imaging (MRI) images generated in a clinic. Therefore, more precise computer-based tumour detection methods are required. In recent years, many efforts have investigated on classical machine learning methods to automate this process. Deep learning techniques have recently sparked interest as a means of diagnosing brain tumours more accurately and robustly. The goal of this project is to analyse the medical test data set, which includes the whole Blood picture test results as well as the tests listed above, using QDA classification and Gaussian process classification methods. In addition, the tumour size in an MRI picture is estimated using Python's Pillow. The project comprises of four modules. The first module deals with adding the Complete Blood Picture test results and other test results to the database. The Gaussian Processes Classifier is a classification machine learning algorithm. Gaussian Processes are a generalization of the Gaussian probability distribution and can be used as the basis for sophisticated non-parametric machine learning algorithms for binary classification tasks and regression.

Introduction :Every day, a great number of magnetic resonance (MR) pictures are generated as a result of technical advancement. These photos are used to monitor the physical state of humans. Their study by specialists, on the other hand, is a

challenging task because it aids in the medical diagnosis and treatment of the patient's medical judgment. In other words, medical image analysis is an important stage in disease diagnosis and treatment. As a result, medical image analysis has turn out to be an exciting subject matter with a significant role in current clinical applications. Early brain tumour diagnosis is a difficult

undertaking that serves as impetus for additional research. Stroke lesions and cerebral tumours are difficult situations in medical imaging because their precise recognition has a significant impact on clinical diagnosis. A brain tumour is an abnormal cell that grows in or around the brain and causes changes in brain structure and behaviour. According to National Brain Tumor Foundation (NBTF) study studies, brain tumours are the leading cause of death worldwide and have more than tripled in the last three decades (El-Dahshan et al., 2014). The human brain is distinguished by an organized complexity that makes analysis extremely difficult. Compared to a vast number of MR images, in addition, the analysis and viewing expertise are quite limited. Manual process in analyzing these images has various drawbacks, including the fact that it takes time. Furthermore, maintaining a high level of concentration throughout categorization is tiring, which contributes to an increase in the faulty detection accuracy. As a result, an automated system with high accuracy is needed to analyse MR images, and computer aided diagnosis (CAD) is a possible answer. One of the remarkable attempt in utilizing

AI in detecting brain tumour via MRI images is Deep learning (DL) architecture (Abd-ellah et al., 2019). DL is also employed in various CAD systems and medical imaging purposes, which shows the great potential of such techniques in automating diagnosis. On the other attempt, convolutional neural network (CNN) (Ghassemi et al., 2020) is one of the other methods that has maintained effective performance in classifying radiological images in recent decades. These types of techniques are deep learning algorithms that have been employed in a variety of applications, including pattern recognition (Litjens et al., 2017). These benefits prompted us to develop a CNN algorithm for brain tumour diagnosis using MRI images in this study. Traditional machine learning methods solve problems by breaking them down into various parts, such as modelling the problem mathematically, gathering and clearing data, extracting and selecting features, training, optimization, and model evaluation. For large-scale problems, the lengthy process of modelling problems with these types of methods increases simulation time and computational expense. In contrast to these methods, DNN is a deep end-to-end learning method that may combine several processing steps into a single DNN to lower the cost of developing and extracting complicated features (Ertugrul, 2020). To obtain accurate and competitive performance, DNN merely requires sufficient data and proper tweaking of its hyper-parameters.

LITERATURE REVIEW :Numerous experts in medical tomography and complex processing have obtained significant advancements in brain tumour identification over the recent years. There have been proposals for both fully automatic and semi-automatic solutions. The level of supervision involvement in the diagnosing procedures has mostly dictated the clinical acceptance of the used approach (Yanase & Triantaphyllou, 2019). The method of detecting the existence or absence of a tumour utilizing MRI image databases is known as detection. One of the most common issues in the healthcare profession is detection. The tumour detection method produces an MRI image that is designated as normal or abnormal (Rehman et al., 2020). To discover the best detection approach, a big standard database must be used as a benchmark to train the classifier and determine the optimum method for feature extraction and detection. As most lesions are small and have many changes in color intensity, shape, and texture, interpreting MR

images by qualified physicians for the identification of a brain tumour surgical procedure is a time-consuming, and challenging undertaking. As a result, even well-trained neurologists or surgeons may find it difficult to make the right judgment. The other two reasons of misunderstanding are noisy visuals and a weary clinician. Quantitative image analytics are potential ways for coping with MRI scan defects. Deep learning architectures are the most prominent among machine learning methods. Although deep learning approaches for detecting brain tumours are a relatively new field of study, with few academic works on the subject, we covered in this part a brief synopsis of recently published studies on the diagnosis of brain tumours using machine learning (J. S. ; Paul et al., 2017).

Paul et al. (J. S. Paul et al., 2017) looked into the use of convolutional neural networks. They classified the photos using three classifiers: CNN, fully connected neural network (FCNN), and random forest. The CNN was configured with two convolutional layers (each with 64 filters of size 5×5), MaxPool layers, two fully connected layers with 800 neurons, and a SoftMax layer as the output layer.

Recently, an automated multi-modal diagnosis system was proposed in (Abd-Ellah et al., 2018) to detect and localize the different types of brain tumours using a deep CNN and an error-correcting output code combined with a support vector machine (ECOC-SVM). This hybrid model played the role of a feature classifier and extractor. In the second step of the proposed system from (Abd-Ellah et al., 2018), a deep CNN was used that includes five layers region-based (R-CNN) to localize the brain tumour within 4 the abnormal MRIs. According to the results reported in (Abd-Ellah et al., 2018), the proposed system (used an AlexNet) achieved a high accuracy at 99.55%. It was also able to beat other non-deep learning models. Gao et al. (X. W. Gao et al., 2017) proposed 2D and 3D convolutional deep learning models with seven layers, and in each layer, the convolution and sub-sampling were applied to classify the CT brain image. The average classification precision was 87.6% in the best modelling. However, the CNN's hyper-parameters were not considered in these studies, which is essential to ensure maximum performance of the learning algorithm. In another study, Rehman et al. (Rehman et al., 2020) introduced a computer-aided tumour detection model consisting of three various

CNN models (VGG16, GoogLeNet, and AlexNet) with an embedded transfer learning and data augmentation technique in order to classify the tumours of the brain. From (Rehman et al., 2020), the highest accuracy proposed by the VGG16 model was up to 98.69%. However, in most classification case studies, the performance of VGG19 was better than VGG16. Although deeper Convolutional Neural models can extract more complex nonlinear interactions and decode and enhance the model accuracy, most of them are faced with issues such as exploding or vanishing gradients. One of the most effective modifications is Residual Network (ResNet). ResNet is a popular CNN architecture introduced by He et al. in (He et al., 2016). One significant benefit of ResNet models is that it lets the training of intense CNNs using the shortcut connections in order to ignore one layer or more. One application of the ResNet for segmenting and classifying brain tumours based on MRI images can be seen in (Ismael et al., 2020); The applied ResNet with a set of augmentation methods such as zooming, shifting and rotating performed better than previous studies CNN (Abiwinanda et al., 2019; J. S. ; Paul et al., 2017), CapsNets (Afshar; et al., 2018, 2019), and KELM-CNN (Pashaei; et al., 2018). Another instance of the application of modern convolutional deep learning models in detecting brain disorders is that Ehret et al. (Ehret et al., 2022) introduced an automated technique to detect and segment the multi-sequence brain MRI using a GoogLeNet architecture, and also the classification results represented that the GoogLeNet performance outweighed other machine learning methods. Later work by Amin et al. (Amin et al., 2020) used a stacked sparse auto encoder (SSAE) model with two fine-tuned layers hybridized with a high pass filter plus a median filter in recognizing brain tumours. Additionally, extensive experiments were used to adjust the hyper-parameters. However, the hyper-parameter optimizer in (Amin et al., 2020) was not fast and effective. In (Raj; et al., 2020), to develop an accurate classifier for detecting brain disorders and Alzheimer's disease, a hybrid deep learning model was formed consisting of Restricted Boltzmann Machine (RBM), optimal feature selection model (GLCM and GLRLM) cooperated with the Crow Search optimization approach. Based on the reported accuracy results in (Raj; et al., 2020), the proposed model proposed the highest accuracy, sensitivity and specificity compared with CNN, NN, and

SVM. Nevertheless, the importance of the characteristics of the architecture and hyper-parameters were not assessed in (Raj; et al., 2020). Furthermore, Noreen et al. (Noreen; et al., 2020) presented the performance of the deep learning model can be improved using the pre-trained CNN models such as Inception-v3 and DensNet201 in the classification of brain tumour intensity. The findings in (Noreen; et al., 2020) represented that both models performed better than fine-tuned VGG16 (Rehman et al., 2020) and CNN-ELM (Pashaei; et al., 2018). Recently, the application of meta-heuristic optimization algorithms has been substantially increased to improve the performance of medical deep learning models. An alternative approach was suggested by Hu et al. (Hu & Razmjooy, 2021) in diagnosing various types of brain tumours employing a deep 5 belief network was combined with a meta-heuristic (seagull optimization algorithm) for improving the feature selection process. Another investigation of the meta-heuristics application in enhancing the performance of the brain tumours diagnosis was done by Aly et al. (Aly et al., 2019). They depicted a comparison of three optimisation algorithms: Ant colony (ACO) (Dorigo et al., 2006), Binary Particle Swarm Optimization (BPSO) (Khanesar; et al., 2007), and Artificial Bee colony (ABC) (Basturk & Karaboga, 2007) to develop the effectiveness of the group method of data handling (GMDH) (Amiri & Soleimani, 2021). The prediction results show that the ACO performance is better than the two other methods. In another recent research (Bezdan; et al., 2021), a hybrid system was proposed in classifying the glioma brain tumour, including a convolutional neural network that was modified by the elephant herding optimization (EHO) (Wang; et al., 2015) method. The EHO was applied to calibrate hyper-parameters of CNN, and also it resulted in a classification improvement rate. However, the computational budget was not reported in order to optimise the CNN's hyper-parameters. There are a considerable number of studies in the application of meta-heuristics to tune the hyper-parameters of the medical deep learning models. However, the majority of meta-heuristic optimizers have some control parameters that need to be initialized and adjusted during the optimization process. Initializing these control parameters is challenging, and we can see a high level of sensitivity in initializing these parameters with different values. Another issue associated with the control

parameters of the meta-heuristic algorithm is that there is not a smart and effective strategy to update these parameters in the most of optimization methods. Meanwhile, providing an outstanding balance between the exploration and exploitation ability of the meta-heuristics is another critical challenge in this way.

METHODOLOGY

Hardware Requirements

1. It requires a minimum of 2.16 GHz processor.
2. It requires a minimum of 4 GB RAM.
3. It requires 64-bit architecture.

4. It requires a minimum storage of 500GB.

Software Requirements

- 1.It requires a 64-bit Ubuntu/windows Operating System.
- 2.Python Qt Designer for designing user interface.
- 3.MY SQL server for storing database Entities.
- 4.Pyuic for converting the layout designed user interface (UI) to python code.
- 5.Python language for coding.

SYSTEM DESIGN

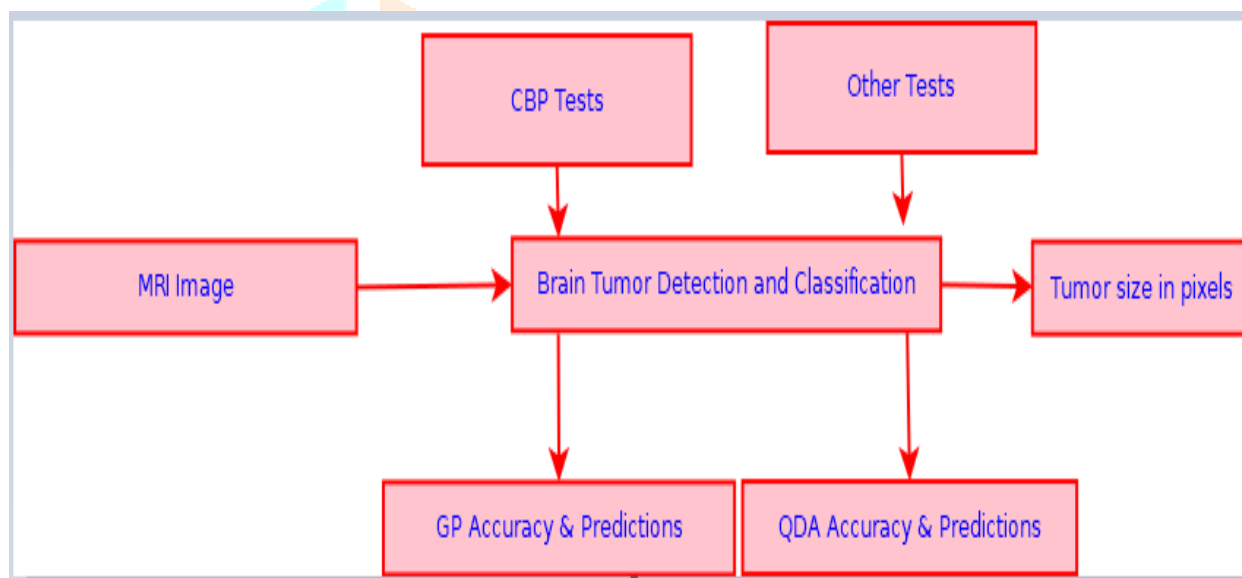


Fig : Data Flow Diagram

MRI image,CBP Test results as well as other test results are to be provided as Input to the system, using the corresponding user interfaces. The system then calculates, QDA Accuracy & Predictions, GPC Accuracy & Predictions.

SOFTWARE USED INSTALLATIONS

- 1) If the system don't have Python, then install Python by down loading itfrom the following site.
<https://www.python.org/downloads/release/python-371/>

IMPLEMENTATION

Go to the above site, come to the bottom of the page, and click on ‘ Windows x86-64 executable Installer ‘, as shown in the above figure.

Sample Code:

Python Code(To be filled in after coding)

Btumor1.py

```

import sys
import os
from btumor import *

from PyQt5 import QtWidgets, QtGui, QtCore

```



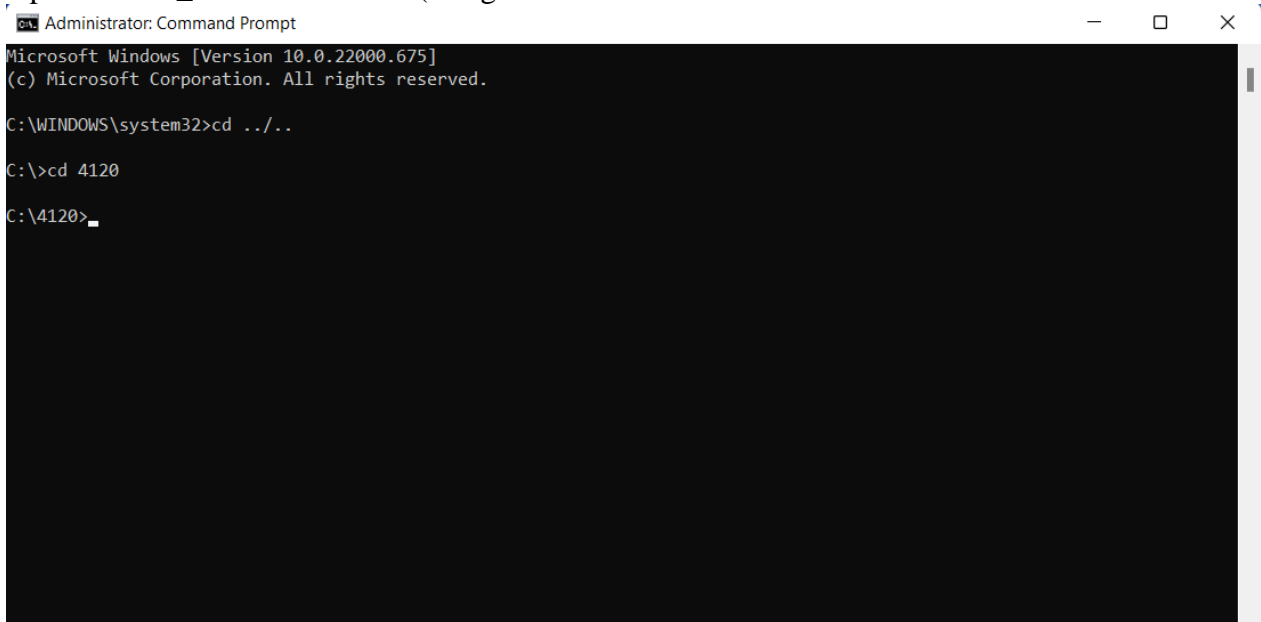
```
class MyForm(QtWidgets.QMainWindow): def
init_(self,parent=None):
QtWidgets.QWidget.__init__(self,parent)
self.ui=Ui_MainWindow() self.ui.setupUi(self)
self.ui.pushButton.clicked.connect(self.otests)
self.ui.pushButton_2.clicked.connect(self.qdac)
self.ui.pushButton_3.clicked.connect(self.g
```

```
c) self.ui.pushButton_4.clicked.connect(self.img1)
self.ui.pushButton_5.clicked.connect(self.cbpic)
self.ui.pushButton_6.clicked.connect(self.img2)
```

System Testing Results:

Testing Results(To be filled in after coding):

Change the directory to the project folder for it to run.



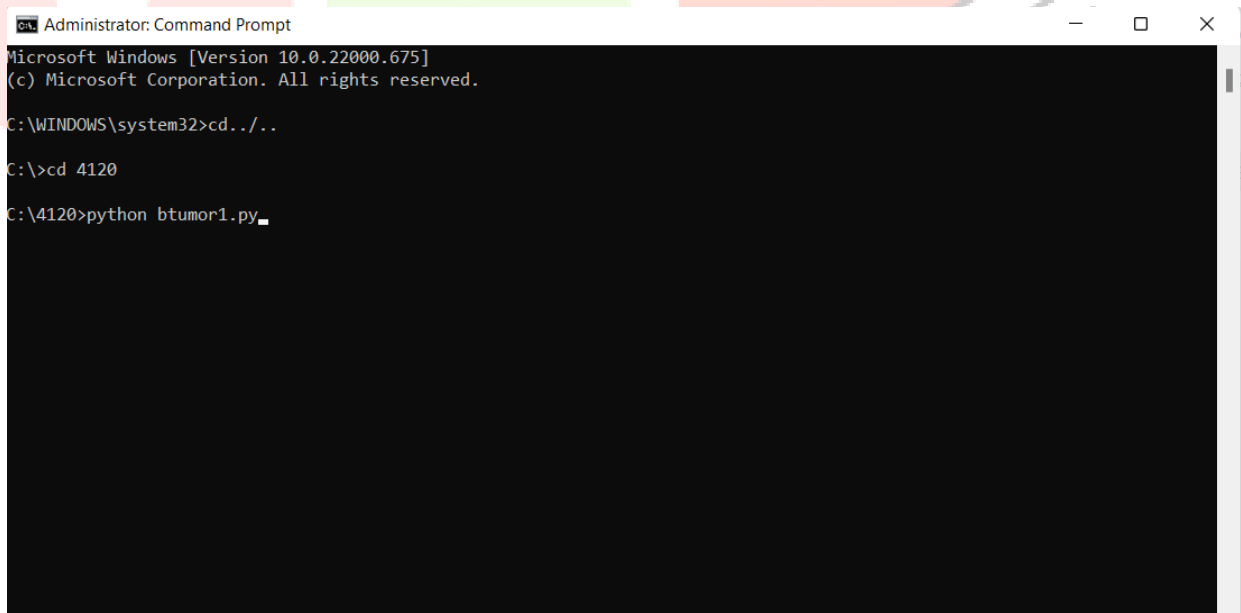
```
Administrator: Command Prompt
Microsoft Windows [Version 10.0.22000.675]
(c) Microsoft Corporation. All rights reserved.

C:\WINDOWS\system32>cd ../../

C:\>cd 4120

C:\4120>
```

For running the application, we give the following command



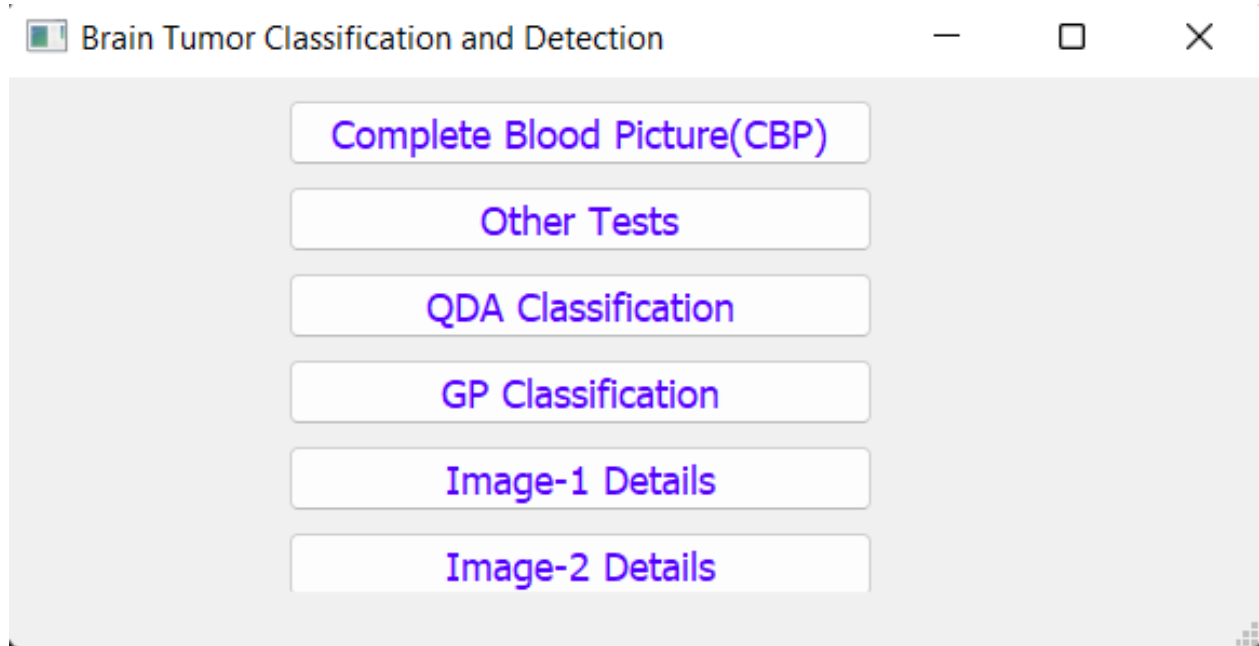
```
Administrator: Command Prompt
Microsoft Windows [Version 10.0.22000.675]
(c) Microsoft Corporation. All rights reserved.

C:\WINDOWS\system32>cd ../../

C:\>cd 4120

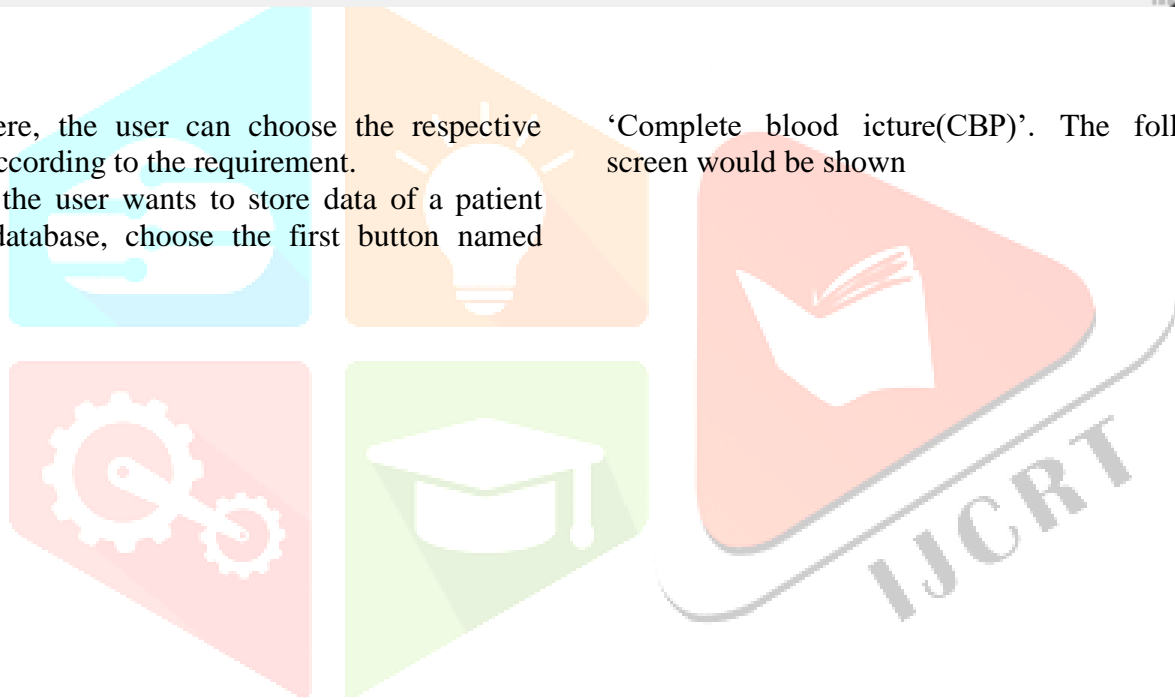
C:\4120>python btumor1.py
```

The following screen would appear, as the command given is processed



From here, the user can choose the respective option according to the requirement. First, if the user wants to store data of a patient in the database, choose the first button named

'Complete blood icture(CBP)'. The following screen would be shown



The screenshot shows a web form titled "Complete Blood Picture". It contains several input fields for patient and test data. The fields are as follows:

Parameter	Value
Patient ID:	001
Red Blood Cells Count (Value between 1.01 to 5.99)	5.26
Hemoglobin (7.1 to 17.0)	14.5
Hematocrit(Enter a value between 30.0 to 50.0)	44.5
White blood cell count: (1.1 to 9.9)	4.3
Platelet count(80 to 450)	258
Lymphocytes(10.00 to 50.00)	33.59
Monocytes (1 to 10)	2.34
Basophils(0.1 to 1.0)	0.54
Eosinophils(0.01 to 5.00)	2.43
Neutrophils(20.00 to 80.00)	51.89
Young neutrophils(0.001 to 3.000)	2.53

At the bottom of the form is a button labeled "Store CBP Details in Data base".

The tables present in the database are shown below

```

SQLite version 3.38.5 2022-05-06 15:25:27
Enter ".help" for usage hints.
Connected to a transient in-memory database.
Use ".open FILENAME" to reopen on a persistent database.
sqlite> .open btumor1
sqlite> .tables
cbp      image1   image2   othrtests
sqlite>

```

CONCLUSION

This project entitled “**Brain Tumor Detection and Classification.**” is useful in the early prediction and detection of Brain tumors. Early detection of brain tumors leads to the saving of valuable patients lives. Automated analysis of medical test results is useful to the neurologists, as they need not remember the thresholds of each and every medical test.

FUTURE SCOPE

As of now, the project is implemented on a data set comprising of the Austrains male patients data. The project needs to be futher tested with other data sets, including Female patients data.

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