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DEEP LEARNING-BASED BRAIN TUMOR DETECTION IN PRIVACY PRESERVING SMART HEALTH CARE SYSTEMS

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Abstract: Deep learning has been widely used in medical image processing, which has sparked the development of a wide range of applications and led to a notable increase in the number of therapeutic and diagnostic options available for a range of medical imaging problems. In the era of the Internet of Things (IoT), safeguarding the security and privacy of medical data is crucial to the advancement of sophisticated diagnostic applications for medical imaging. Deep learning-based brain tumor detection in smart health care systems with privacy preservation is proposed in this paper. The system under consideration is organized into three discrete stages that are then combined to provide an all-encompassing blueprint. During the first phase, patients with brain tumors are the primary target of an efficient healthcare system that is introduced. A Microsoft-based operating system-compatible application has been developed to accomplish this. Patient data is secure and only available to the hospital and the individual patient, which enables patients to engage with the system both locally and virtually. To obtain the anticipated outcomes, the user must first submit the patient's MRI scan and then enter a special 10-digit code. In the second part, the authors develop a deep learning-based tumor identification platform which also incorporates the AES-128 algorithms and PBKDF2 for secure medical image storage on the server and data transmission via the internet from the client to the server and back to the client upon prediction..

Keywords: Brain tumor detection, classification, CNN, cryptography, deep learning algorithms, MRI, privacy preservation, smart healthcare systems.

I. INTRODUCTION

Brain-inspired computing has long been a nice theoretical research topic facing implementation issues. Even with powerful computing capabilities on some of the hardest problems, very few industrial applications have appeared. Some solutions have been proposed to cope with these issues. Analog neuron is an elegant implementation solution to reduce the number of transistors needed for a neuron. However, while reducing the number of transistors, large capacitances is needed for obtaining a good RC delay. On the connection purpose, time multiplexing is currently used, but it limits the overall performance while increasing the power consumption due to high frequency links. Moreover, the increasing capacitance of wires in advanced technologies limits this solution. A global conclusion of all these works is the relative inexpediency of standard CMOS with Neural Networks (NN) implementation.Generally, real-time images collected from scan centre and simulated images collected from publicly available database are used for image classification and segmentation. These are raw images which are unsuitable for analysis due to the various types of noises present in the images. Hence, suitable pre-processing methodologies must be used to enhance the quality of the images. Literature survey reveals the availability of several pre-processing and feature extraction techniques for MR brain image analysis.

II. LITERATURE SURVEY

Deep Learning Based Brain Tumor Segmentation.
Authors: Zhihua Liu, Lei Tong, Zheheng Jiang, Long Chen, Feixiang Zhou, Qianni Zhang.
Year: 2020.
Brain tumor segmentation stands as a pivotal challenge in medical image analysis, aiming to delineate tumor regions accurately within brain scans. The advent of deep learning has significantly advanced this field, offering automated solutions that surpass traditional methods in precision and efficiency. This overview delves into the evolution,

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methodologies, challenges, and future directions of deep learning-based brain tumor segmentation.Traditional image processing techniques, such as thresholding and region-growing, laid the groundwork for tumor segmentation. The introduction of machine learning brought about feature-based approaches, yet they still relied heavily on handcrafted features and expert knowledge. The breakthrough came with the advent of deep learning, particularly Convolutional Neural Networks (CNNs), which can automatically learn hierarchical features from data, eliminating the need for manual feature extraction.

III. METHODOLOGY

Deep learning based image processing healthcare system:

Deep learning-based image processing healthcare systems represent a cutting-edge approach to medical imaging and diagnostics, leveraging advanced artificial intelligence (AI) techniques to analyze and interpret medical images with unprecedented accuracy and efficiency. These systems have demonstrated remarkable performance across a wide range of medical imaging tasks, including disease diagnosis.

Privacy concerns in ai-assisted smart Healthcare systems:

Deep learning-based image processing healthcare systems epitomize a revolutionary method for medical imaging and diagnostics, providing unmatched accuracy, efficiency, and clinical significance. Through the utilization of AI capabilities,these systems hold the promise of transforming healthcare delivery by facilitating earlier detection, precise diagnosis, and personalized treatment strategies for patients globally.

Cryptography for medical images in smart Healthcare systems:

In smart healthcare systems, cryptography is vital for safeguarding the security and privacy of medical images [17]. For hackers, a patient's aggregated data is highly valuable.

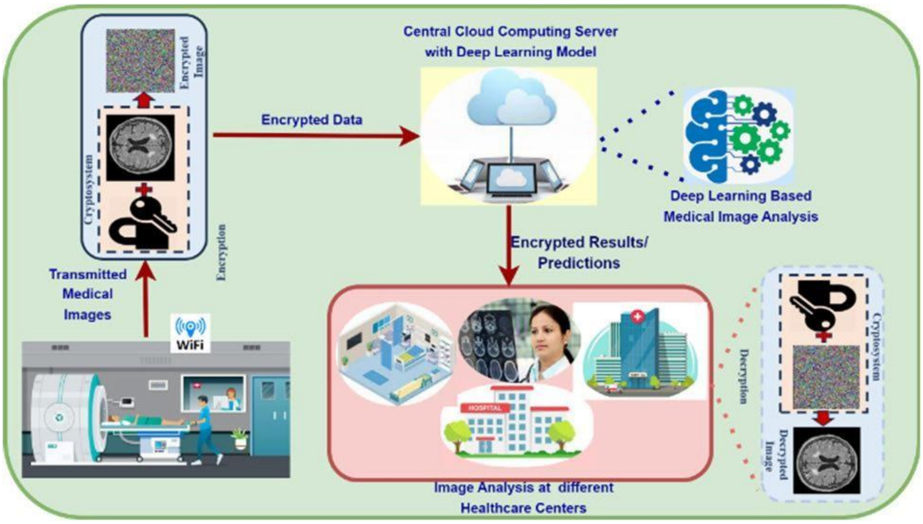

FIGURE 1. Smart hospital management system for secured brain tumordetection system.

Figure 1: depicts the methodology for developing a brain tumorr.The dataset is created by collecting all the questions asked about a particular technical university from various social media portals and the university's students and faculty. Answers are obtained for these questions from authorized sources from the university. The dataset has around 250 questions formed in differentways. The following methodology is used for using these questions and answers to design a chatbot. In the first step, raw data is pre-processed and converted into a format that is easier and more effective for further processing steps. It also normalizes the raw data in the dataset and reduces the number of features in the feature set. This leads to a decrease in the complexity of fitting the data to each classification model. Medical imaging and healthcare technology have advanced significantly with the development of a Secured Brain Tumor

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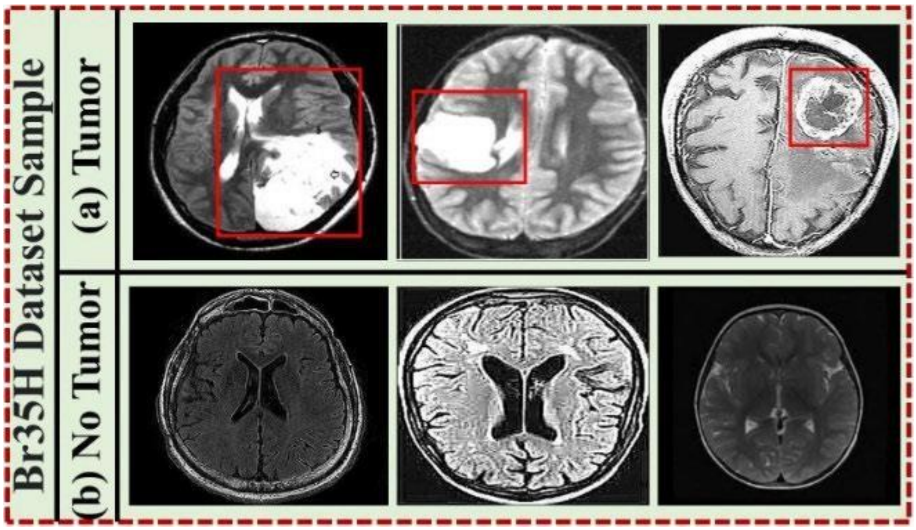

FIGURE 2. Selected sample images from dataset used in this study With Tumor (b) Tumor free sample.

Detection System This system has the potential to revolutionize brain tumor diagnosis by merging state-of the-art diagnostic capabilities with rigorous data security measures. It not only promises to enhance patient care by revolutionizing brain tumor diagnosis but also ensures the utmost privacy and confidentiality of critical medical data.AES-128 cryptographic method and PBKDF2 integrated for MRI scan encryption and decryption are used in the construction of a deep learning-based brain tumor detection system with secured data processing. Following four distinct steps,namely: 1) data set acquisition, 2) encryption and decryption using AES-128 along with PBKDF2, 3) deep learning model implementations,integration of entire work using Python based web framework, the proposed brain tumor.

Data Set Acquisition

CNN is trained using dataset Br35H::Brain Tumor Detection 2020 (BR35H) [51]. The dataset consists of 1500 twodimensional brain MRI images that are equally divided into two groups: pictures classified as ‘‘yes’’ (tumors and images classified as ‘‘no’’ (tumor-free). Every picture is skull-stripped and has a standard resolution of 256 ∗ 256 pixels.

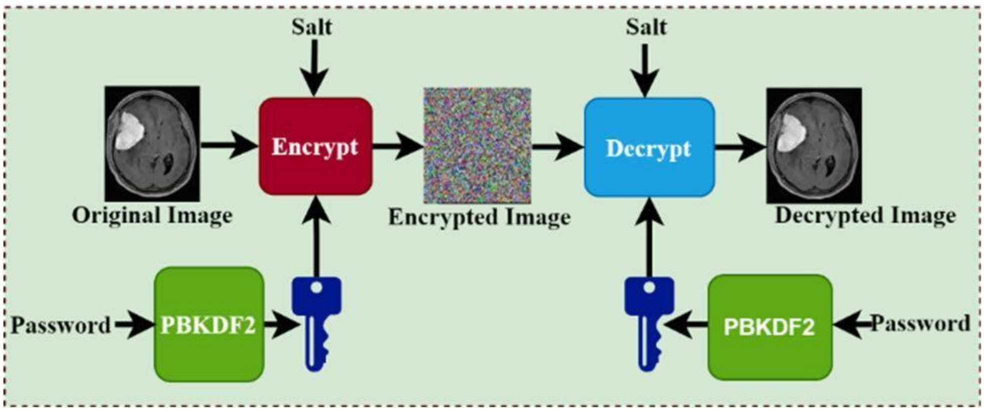

FIGURE 3: AES-128 cryptographic algorithm with PBKDF2**.**

Web Application’s Frontend Interface:

During the first stage, a web-based application is developed that enables users or patients to upload their MRI images and have the scans used to forecast whether a brain tumor is present. Algorithm 1 makes up this web application’s front-end interface.The approach used in the web application’s prediction phase is described as follows: There are three types of pre-trained CNN models used i.e. InceptionV3, VGG-16 and ResNet-50, with various optimizers used by each one of them. The ResNet-50 model is found to be performing better than the other models through reported results during the testing of the proposed system. These CNN models are implemented on the server used for the proposed system using

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Python. A base operating frequency of 3.80GHz and 16GB of installed RAM make up the server hardware, which is an Intel Core i7-10700K CPU. Running on a 64-bit operating system, the server makes optimal use of modern hardware architecture, and facilitates the effective use of all RAM installed. Improving memory management and processing speed is the reason behind the choice of an x64-based processor with a 64-bit architecture.

Algorithm 1 Web Application's Frontend Interface Inputs: I is an input MRI scans for tumor detection **Outputs**: Diagnosis of the input image I.
1 Home Page: Predict and Upload
Upload: submit the MRI scan for further analysis *Predict:* Access insights and forecasts related to brain tumor diagnosis.
2 Upload Page: Securely submit images for analysis. I'
<- Enter unique key of 10-digit number for encryption of image I
Encryption: AES-128 and PBKDF2
Upload: encrypted image (I') stores in the designated 'uploads' folder
3 Predict Page: Display forecast of upload MRI scan for review and analysis.
Access Encrypted Image: Enter the same initially entered key.
Decrypt: Decrypt the image using AES-128 and PBKDF2
Predict: Determine the tumor presence or absence in the uploaded MRI scan.
Display: Final prediction results displayed on the front end.

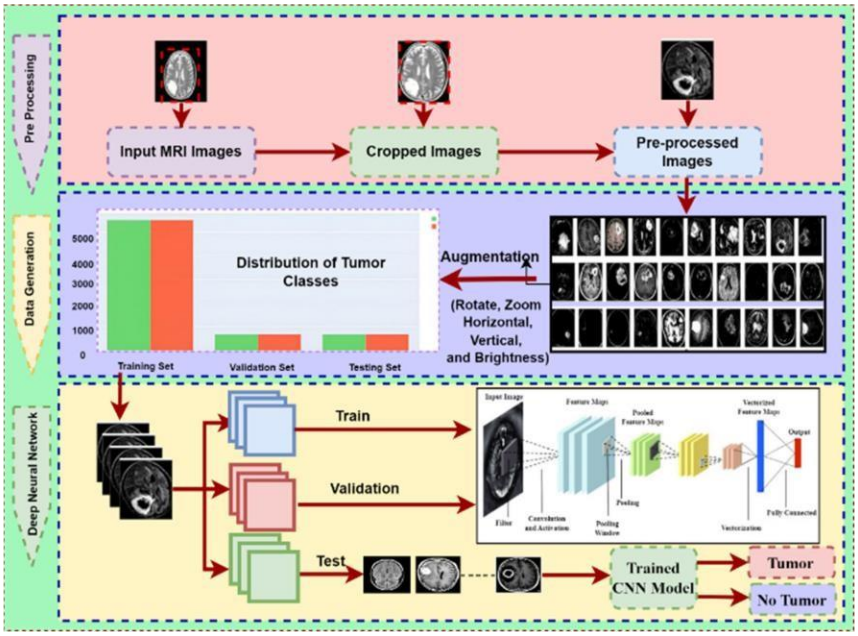

FIGURE 4. An overview of the system for diagnosing brain tumors using CNN.

The explanation of Algorithm 2 is given in the following paragraphs. The data is stored in *intents. json* file, and itcontains a list of intents. Each intent or class has a tag, a pattern, and a response. The ''tag'' defines the intent or class. The ''pattern'' is a list of possible questions for the corresponding class. The ''response'' is a list of possible answers to the questions of that ''tag.'' The chatbot will take the message from the user, identify the ''tag'' of the message, and give the corresponding response. Pre-processing steps are applied to the data. Every question of every intent is tokenized using *nltk.word_tokenize()* and is appended to the ''all_words'' list. Every unique tag is stored in the ''tags'' list. Now, ''all_words'' is a list that contains all the tokenized words of the dataset, and ''tags'' is a list that contains all the tags of the database. All the punctuation tokens are removed; every word in the dataset is converted to lower case using the *lower()* function, and the words are stemmed using *PorterStemmer().stem()* function from nltk. ''all_words'' list is sorted using *sorted(all_words)* function and all the duplicate words are removed using *set(all_words)* function. ''tags'' list is also sorted. To create a bag of words,

Algorithm 1: Deep Learning Based Brain Tumor Segmentation.

function varargout = BrainMRI_GUI(varargin) gui_Singleton = 1;
gui_State = struct('gui_Name', mfilename, ... 'gui_Singleton', gui_Singleton, ...

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```
'gui_OpeningFcn', @BrainMRI_GUI_OpeningFcn, ... 'gui_OutputFcn', @BrainMRI_GUI_OutputFcn, ...
'gui_LayoutFcn', [] , ...
'gui_Callback', []);
if nargin&&ischar(varargin{1}) gui_State.gui_Callback = str2func(varargin{1}); end
if nargout
[varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:}); else
gui_mainfcn(gui_State, varargin{:}); end
function BrainMRI_GUI_OpeningFcn(hObject, eventdata, handles, varargin)
% Choose default command line output for BrainMRI_GUI handles.output = hObject;
ss = ones(200,200); axes(handles.axes1);

imshow(ss); axes(handles.axes2) imshow(ss);
% Update handles structure guidata(hObject, handles);
% UIWAIT makes BrainMRI_GUI wait for user response (see UIRESUME)
% uiwait(handles.figure1);
% --- Outputs from this function are returned to the command line.
```

IV. SYSTEM MODULES

Input image

- First we need to produce a digital image from a paper envelope.
- This is being done using either a camera, or a scanner.

Preprocessing

- Preprocessing is used to remove the noise from the given input image by using median filter.
- Pre processing is done on the captured image to prepare it for further analysis.
- Such processing includes:Thresholding to reduce a grayscale or color image to a binary image, reduction of noise to reduce extraneous data, segmentation to separate various components in the image, and, finally,thinning or boundary detection to enable easier subsequent detection of pertinent features.

Segmentation process

- To partition the image into its constituent parts (objects).
- Autonomous segmentation (very difficult).

THRESHOLDING PROCESS

Image thresholding is a simple, yet effective, way of partitioning an image into a foreground and background. This image analysis technique is a type of image segmentation that isolates objects by converting grayscale images into binary images.

A test dataset having 144 queries is used to test the chatbot models. Confusion matrices and accuracies are calculated using sklearn metrics library. (using confusion_matrix and accuracy_score functions) The neural network was created using TensorFlow in this model, and multiple pre-processing steps were applied.
The Lancaster Stemming algorithm was used in the preprocessing phase, which is more accurate. Furthermore, the softmax activation function is applied to the output layer, increasing the neural network's performance.
In this model, the neural network is not created. Instead,TF-IDF Vectorization converts every sentence into a vector,and Cosine Similarity calculates the similarity between every sentence and the query. This model needs to understand the meaning of the query; it simply finds the most similar sentence. Table 1 is the confusion matrix of Big Mouth.

V. RESULT ANALYSIS

The performance of deep neural networks is evaluated using deep learning assessment measures. Using these metrics model's effectiveness is assessed for its benefits and drawbacks.The following are the metric parameters [56] used in the presented work for evaluating deep learning models Our study delved into exploring the classification performance of different types ofCNNmodels with the stability and variability of various optimization strategies. Concurrently, we endeavored to mitigate overfitting concerns and enhance classification accuracy by exploring alternative optimizers beyond default choices..

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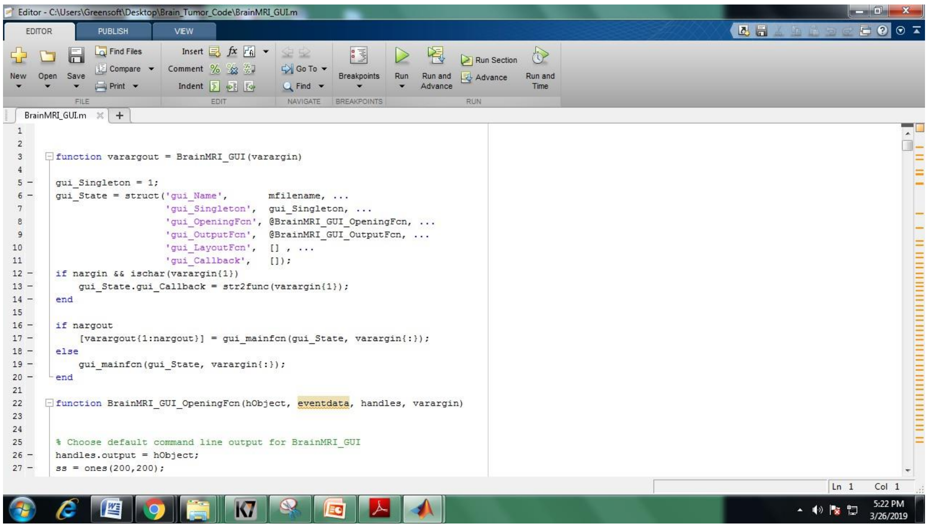
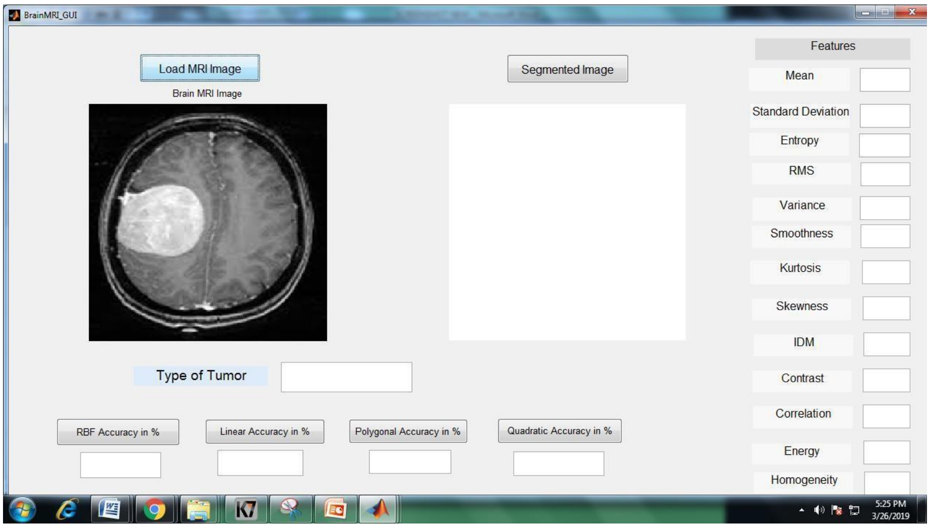


A brain tumor is a mass of cells that have grown and multiplied uncontrollable i.e. a brain tumor is an uncontrolled growth of solid mass formed by undesired cells either normally found in the different part of the brain such as glial cells, neurons, lymphatic tissue, blood vessels, pituitary and pineal gland, skull, or spread from cancers mainly located in other organs.



Brain tumors are classified based on the type of tissue involved in the brain, the positioning of the tumor in the brain, whether it is benign tumor or malignant tumor and other different considerations. Brains tumors are the solid portion permeate the surrounding tissues or distort the surrounding structures. There are different type of brain tumor they are Gliomas, Medulloblastoma, Lymphoma, Meningioma, Craniopharyngioma, Pituitary adenoma.

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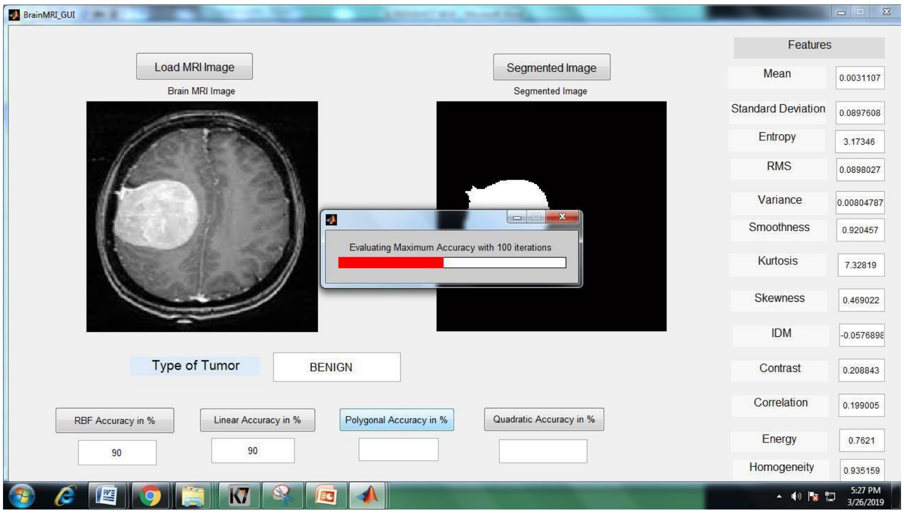
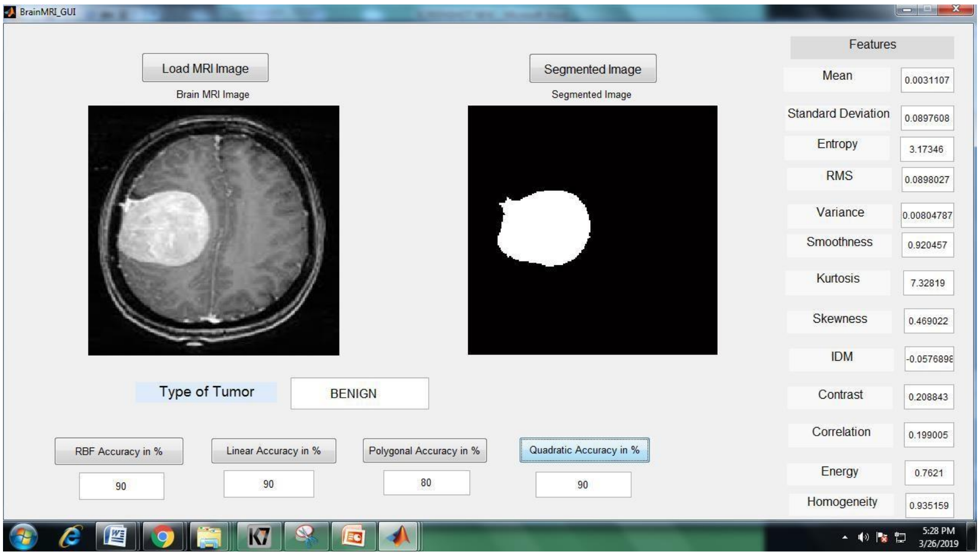


Brain areas were marked in white colour and the rest in black colour. Since this label is used for data-mining, it is called the fitness mask in this paper. A bit map editor is usually used for creating the fitness mask from the original image.



VI. CONCLUSION

As the healthcare landscape evolves in the age of the Internet of Things (IoT), ensuring the security and privacy of medical data is paramount to foster trust and facilitate the adoption of sophisticated diagnostic applications. This proposed work has focused on the implementation and evaluation of a deep learning-based tumor detection system with privacy preservation capabilities within smart health care systems. We are able to achieve the impressive performance metrics parameters while detecting the brain tumor using the proposed system. The proposed system is implemented in three phases, to provide more secure healthcare services towards tumor detection and classification systems. We have demonstrated the effectiveness of the proposed approach through rigorous experimentation and evaluation by applying different types of optimizers also. We are able to achieve the impressive performance metrics parameters while detecting the brain tumor using the proposed system. The proposed system is implemented in three phases, to provide more secure healthcare services towards tumor detection and classification systems. When have also shown that the integrated encryption mechanism enhances the security of medical while preserving the patient's privacy throughout the completed diagnostic process. In future, we would explore the incorporation of additional security features to migrate the emerging threats towards AI-assisted smart healthcare systems. We are able to achieve the impressive performance metrics parameters while detecting the brain tumor using the proposed system. Brain tumors, whether benign or malignant, represent a serious neurological condition with significant impacts on a patient's health and quality of life. Early diagnosis through imaging and clinical evaluation is crucial for effective treatment planning. When have also shown that the

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integrated encryption mechanism enhances the security of medical while preserving the patient's privacy throughout the completed diagnostic process. Advances.

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