e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH

IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 8, August 2024

INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.521

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Tumor Brain Detection and Stage Prediction using Deep Learning

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ABSTRACT: Brain tumors are dangerous and serious disorders affected by uncontrolled cell growth in the brain. Brain tumors are one of the most challenging diseases to cure among the different ailments encountered in medical study. Early classification of brain tumors from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify tumors in the brain. MRI is commonly used for such tasks because of its unmatched image quality. The traditional method of identifying tumors relies on physicians, which is time-consuming and prone to errors, putting the patient's life in jeopardy. Identifying the classes of brain tumors is difficult due to the high anatomical and spatial diversity of the brain tumor's surrounding region. An automated and precise diagnosis approach is required to treat this severe disease effectively. The relevance of artificial intelligence (AI) in the form of deep learning (DL) has revolutionized new methods of automated medical image diagnosis. As a result, good planning can protect a person's life that has a brain tumour. Using the 2D Convolution Neural Network (CNN) technique, this project proposes Computer-Aided Diagnosis (CAD) a deep learning-based intelligent brain tumour detection framework for brain tumour type (glioma, meningioma, and pituitary) and stages (benign or malignant). CNN is used to classify tumors into pituitary, glioma, and meningioma. Then its classify the three grades of classified disease type, i.e., Grade-two, Grade-three, and Grade-four. The performance of the CNN models is evaluated using performance metrics such as accuracy, sensitivity, precision, specificity and F1-score. From the experimental results, our proposed CNN model based on the Xception architecture using ADAM optimizer is better than the other three proposed models. The Xception model achieved accuracy, sensitivity, precision specificity, and F1-score values of 99.67%, 99.68%, 99.68%, 99.66%, and 99.68% on the MRI-large dataset. The proposed method is superior to the existing literature, indicating that it can be used to quickly and accurately classify brain tumors.

I. INTRODUCTION

The brain is a complex organ that controls thought, memory, emotion, touch, motor skills, vision, breathing, temperature, hunger and every process that regulates our body. Together, the brain and spinal cord that extend from it make up the central nervous system, or CNS.

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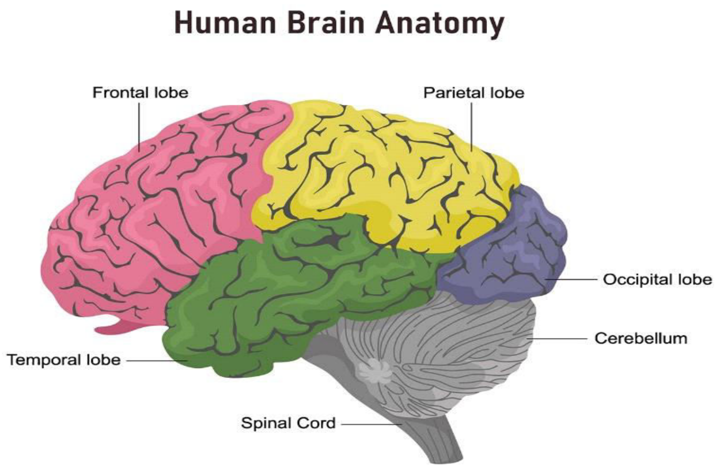

Weighing about 3 pounds in the average adult, the brain is about 60% fat. The remaining 40% is a combination of water, protein, carbohydrates and salts. The brain itself is a not a muscle. It contains blood vessels and nerves, including neurons and glial cells

Brain Tumour

A brain tumour is a growth of abnormal cells in the brain. The anatomy of the brain is very complex, with different parts responsible for different nervous system functions. Brain tumours can develop in any part of the brain or skull, including its protective lining, the underside of the brain (skull base), the brainstem, the sinuses and the nasal cavity, and many other areas. There are more than 120 different types of tumours that can develop in the brain, depending on what tissue they arise from.

II. EXISTING SYSTEM

Region Based Method - The region-based classification method divides an image into related areas by applying homogeneity criteria to the collection of pixels. Region based methods are classified into: region growing, region splitting and merging, thresholding, watershed and clustering.

Thresholding method- Thresholding is a straightforward and effective method for image segmentation. Thresholding is used to transform a multilevel image to a binary image. To segment image pixels into different regions, a suitable threshold is selected. The thresholding approach has two limitations: it generates only two classes and cannot be extended to multichannel images. Furthermore, threshold does not take into account an image's spatial characteristics. As a result, it is susceptible to noise.

Region growing method- This is a traditional approach in which segmentation begins with the manual sorting of seeds from the image of interest. The manual dealings to attain the seed point are the area growing's restriction. However, split-and-merge is a region-growing algorithm that does not need a seed point. Region growth is also vulnerable to noise, resulting in gaps in partitioned areas. This problem is solved by the hemitropic region-growing algorithm. However, this technique requires user intervention for seed selection.

Watershed algorithm- Watershed is a segmentation system dependent on gradients. Similar gradient values are analysed as heights. When a hole is drilled into each local minimum and immersed in water, the water rises before it reaches the local maximums. When two bodies of water intersect, a barrier is constructed between them, and the water level increases before both points are combined. The picture is segmented by dams, which are referred to as watersheds.

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Clustering method- Clustering is an unsupervised learning task that groups items based on a similarity criterion. There are two types of clustering algorithms: hard clustering and fuzzy clustering. The hard clustering process seldom assigns a pixel to a single cluster. Due to the presence of partial volume effects in MRI, this cannot be used for MRI segmentation. In fuzzy clustering, a single pixel may be allocated to several clusters. Fuzzy C Means (FCM) is a common fuzzy clustering tool. Although the FCM algorithm performs very quick and simple segmentation, it does not guarantee good accuracy for noisy or irregular images.

Edge-based method—changes in the intensity between edges of voxels are used as the boundaries of the tumours.

Prewitt- The "Prewitt Mask" is one of the unmistakable separation activities. As needs be, approximated subsidiary qualities in both the headings, with the end goal that even and vertical, are determined utilizing two 3 × 3 veils. Prewitt veils provide an approximation to both flat subsidiary and the vertical subordinate.

Robert- By using the "Robert's edge" location activity, the picture inclination is evaluated by means of unmistakable separation. Likewise, "Robert Mask" is a network and the districts of high spatial recurrence are featured, that are frequently compared to edges in the image.

Sobel- The "Sobel Mask" generally function as the "Prewitt veil". It must be taken into account as the Sobel administrator has values; '2' and '- 2' which are assigned to the focal point of first and the third segments of the flat veil and first and third columns of the vertical cover. Henceforth it gives high edge intensity.

Canny Edge Detector- The calculated temperature distribution (thermal image) in this study showed that a large gradient in tumour borders is the reason to use an edge detection method to track the tumour contours. An edge in the image represents a strong local variation in pixels' intensity, usually, arising on the boundary between two different regions within an image. Edge detection is the process of objects boundaries detection within an image by finding the changes in discontinuities intensities.

Histogram of Oriented Gradient- The extraction technique of the "Histogram of Oriented Gradient" (HOG) will take the calculations given below in consideration. In the first place, the pre-arranged cell picture shall be coursed as "32 × 32" pixels. The power of each pixel is '1' or '0'. By then the result will be added to "Crowd".

III. PROPOSED SYSTEM

The main goal behind the development of our proposed model is to automatically distinguish people with brain tumors, while reducing the time required for classification and improving accuracy. We propose a novel and robust DL framework CNN for detecting brain tumors using MRI datasets. The proposed model is a four step process, in which the steps are named:
1). Pre-processing,
2). Features Extraction,
3). Features Reduction,
4). Classification.

Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull, in the pre-processing step. During this stage, the images are converted from grey scale to coloured images for further processing. In second step, it uses Grey Level Co-occurrence Matrix GLCM) technique to extract different features from the images. In third stage, Color Moments (CMs) are used to reduce the number of features and get an optimal set of characteristics. Images with the optimal set of features are passed to CNN classifiers for the classification of BT Type and their grades.

Region Proposal Network: This region proposal network takes convolution feature map that is generated by the backbone layer as input and outputs the anchors generated by sliding window convolution applied on the input feature map.

© 2024 IJMRSET | Volume 7, Issue 8, August 2024| DOI: 10.15680/IJMRSET.2024.0708020

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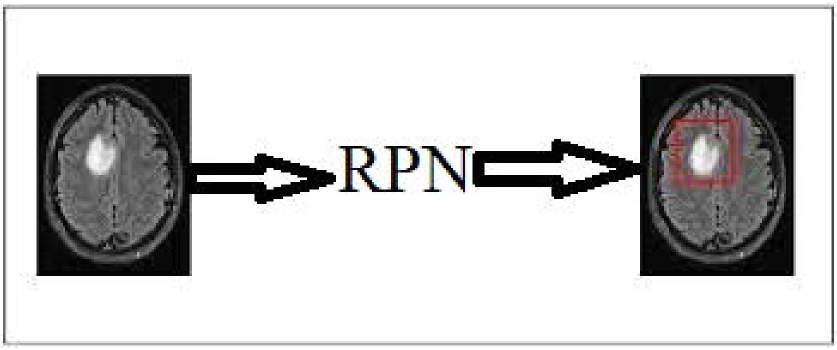
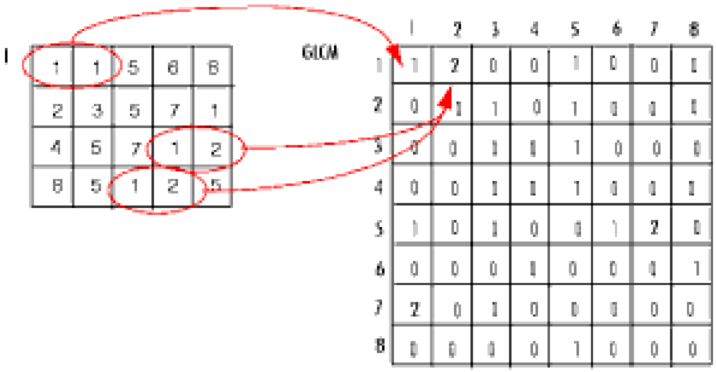


Grey Level Co-occurrence Matrix: Grey Level Co-occurrence Matrix (GLCM) based texture analysis of kidney diseases for parametric variations. The investigations were carried out using three Pyoderma variants (Boil, Carbuncle, and Impetigo Contagions) using GLCM. GLCM parameters (Energy, Correlation, Contrast, and Homogeneity) were extracted for each colour component of the images taken for the investigation. Contrast, correlation, energy, and homogeneity represent the coarseness, linear dependency, textural uniformity, and pixel distribution of the texture, respectively. The analysis of the GLCM parameters and their histograms showed that the said textural features are disease dependent. The approach may be used for the identification of CKD diseases with satisfactory accuracy by employing a suitable deep learning algorithm.



Convolutional Neural Network (CNN): A CNN is a type of deep learning used to analyse visual scenes. It is characterized by having one or more hidden layers, which extract the attributes in videos or images, and a fully connected layer to produce the desired output. Whereas for the computer, the image is a 3D array (width × height × depth) of values ranging from 0 to 255. It is simply pixels of colour; if the number of channels is one, the image is grayscale, black, and white. Besides, the channels are three colours (if images are RGB). CNN Deep Network has shown outstanding performance in many competitions related to image processing due to its accurate results. CNN is a hierarchical structure that contains several layers.

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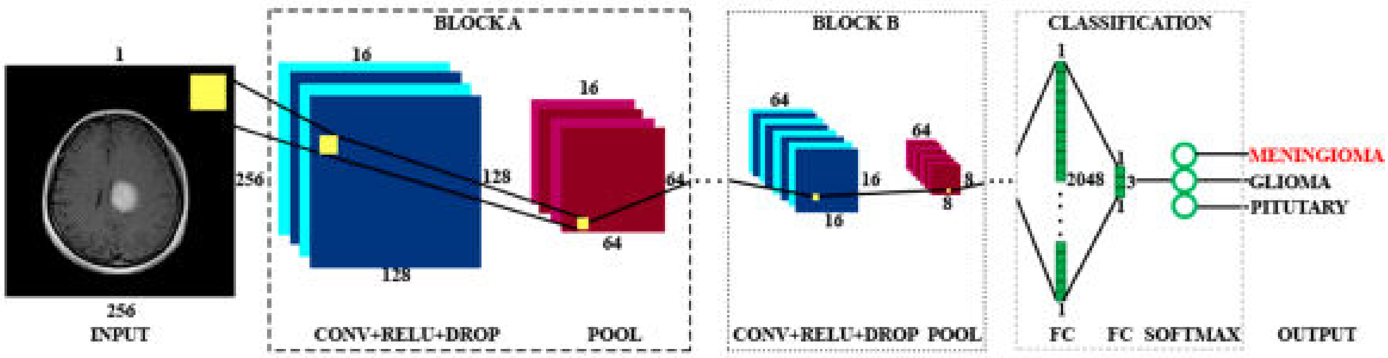

Figure 3.1. Architecture of CNN

The basic components of the basic convolutional neural networks are: The Convolutional Layer, the Activating function, the Pooling Layer, and the Fully-connected Layer.

Convolutional Layer: In the convolutional layer, a filter (known as a kernel) is used to determine the existence of patterns in the input images (original image), after which several filters can be employed to extract different features. The filter is a small size to have the ability to scan the whole image and apply the appropriate arithmetic between the filter and the pixels to extract the features. The filter settings are reset during the periodic training phase, and when the network has been trained for a retinacula number of epochs (epochs imply all training samples have been entered simultaneously), these filters start looking for different characteristics in the image. Simple and evident features, such as edges in various directions, are extracted using the first hidden layers. The complexity of the attributes which must be recognized and extracted rises as we go deeper into the network's hidden levels.

Pooling Layer: The purpose of the pooling is to reduce the size of the activation maps. This is not necessary but prevents you from falling into an overfitting situation. The idea behind clustering is simple, as large arrays are scaled down.

Fully-connected Layer: This layer is the last, where neurons are fully connected to all nodes of the previous layer. The final classification process takes place in it.

To design the network model, first, an image is inserted into a conv layer, and an activation function is applied to the output of the conv layer, such as ReLu. The function's output is sent to another conv layer; the process is repeated several times, sending the output to an assembly layer. The steps are repeated several times, and trainable classifiers are produced. The output is also sent to the fully connected layer, which has the probability of each class we want to train the network on. In the input layer, the range can be from 0 to 1. Each neuron is treated as a filter where the filter is computed for the data network depth; in the conv layer, the neurons are filters in image processing to detect edges, curves, etc. Each filter of the conv layer will have its image features, such as vertical edges, horizontal edges, colors, textures, and density.

All neurons add to the feature extractor array for the entire image. In addition, the pooling layer is sandwiched between successive convolutional layers to compress the amount of data and parameters and reduce overfitting. In short, if the input is an image, then the main function of the pooling layer is to compress the image by resizing the image. When the information removed when the image is compressed is just some irrelevant information, we can remove it.

Benefits of the Proposed System

- A fast and accurate fully automatic method for brain tumor classification which is competitive both in terms of accuracy and speed compared to the state of the art.

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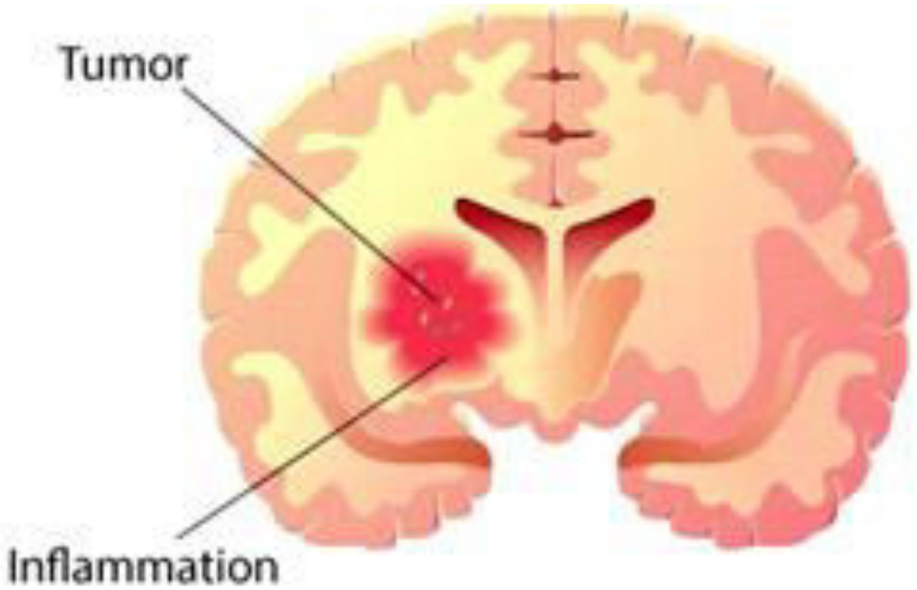
- The method is based on deep neural networks (DNN) and learns features that are specific to brain tumor types.
- Segmentation technique accomplishes the better segmentation results with the maximum accuracy of 99%.
- Automatic Feature Extraction
- Low Computational Overhead
- This method in clinical oncology can help radiologists and oncologists to get various tumor regions, sizes and shapes, and assist them in improving tumor diagnosis, treatment plan and prognosis.
- Cancer Rehabilitations program to the infected patients with brain tumor.



IV. FUTURE ENHANCEMENT

Expanding the dataset by increasing the number of MRI images is a crucial step in enhancing the accuracy and robustness of the proposed model. With a larger and more diverse dataset, the model can learn from a broader range of examples, capturing the variability present in real-world clinical scenarios. This expansion allows the model to better generalize to unseen data and improves its ability to accurately classify brain tumors across different patients, imaging modalities, and disease manifestations. Furthermore, extending the proposed approach to other types of medical images, such as x-ray, computed tomography (CT), and ultrasound, presents an exciting avenue for future research. Each imaging modality offers unique insights into various medical conditions and pathologies, complementing the information provided by MRI scans. By adapting the deep learning model to analyze different types of medical images, researchers can create a versatile and comprehensive diagnostic system capable of detecting a wide range of diseases and abnormalities beyond brain tumors. Integrating x-ray, CT, and ultrasound images into the proposed CAD system requires additional preprocessing techniques, model adjustments, and validation steps tailored to each imaging modality's characteristics. Moreover, comprehensive datasets containing labeled medical images across different modalities will be essential for training and evaluating the performance of the extended model effectively. In summary, increasing the dataset size and diversifying the types of medical images analyzed are essential steps in advancing the proposed approach for automated medical image diagnosis. By incorporating multiple imaging modalities, researchers can develop a more comprehensive and versatile diagnostic system with broader clinical utility and impact.

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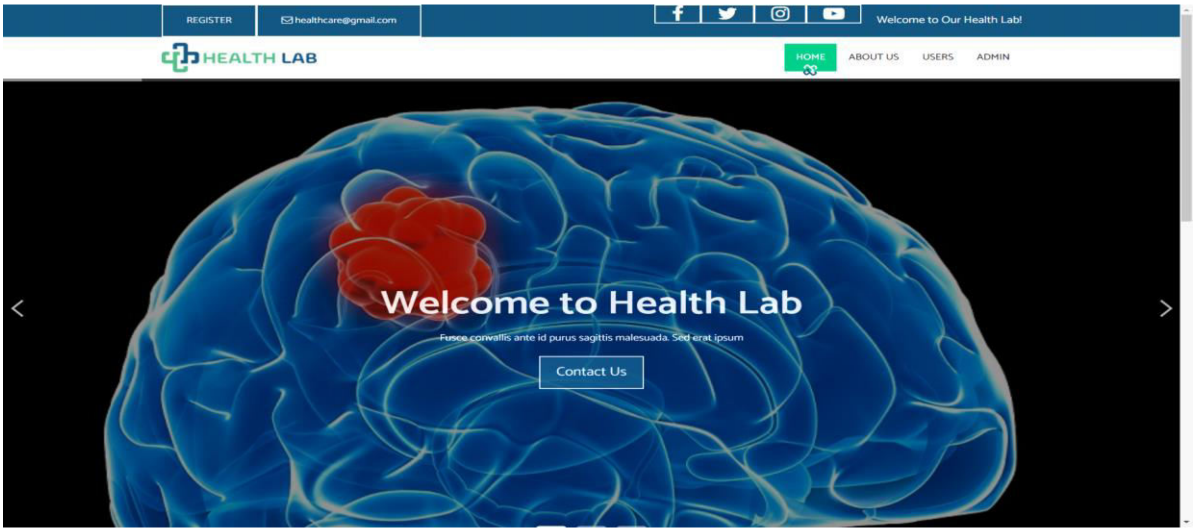
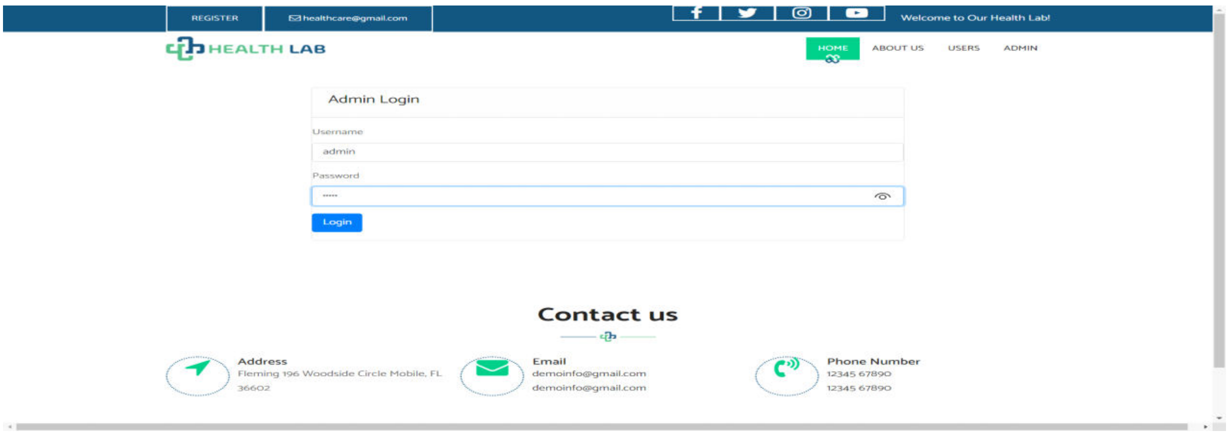
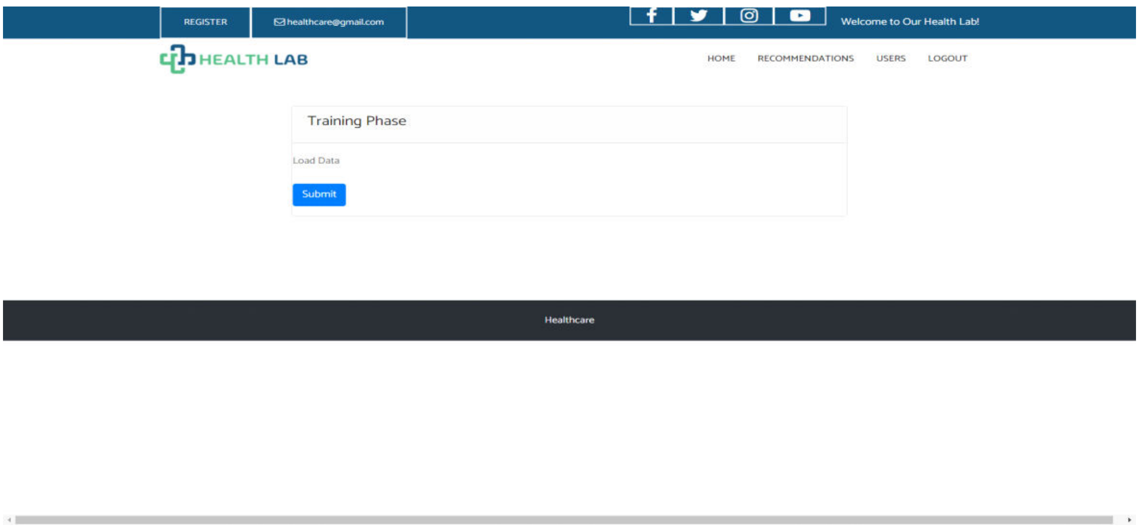
SAMPLE SCREENSHOT







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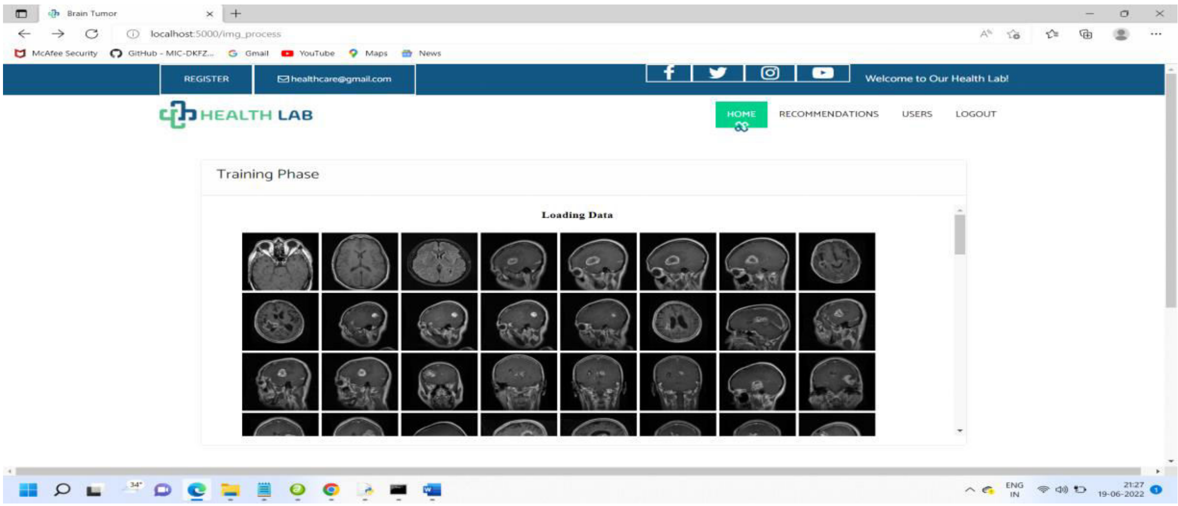

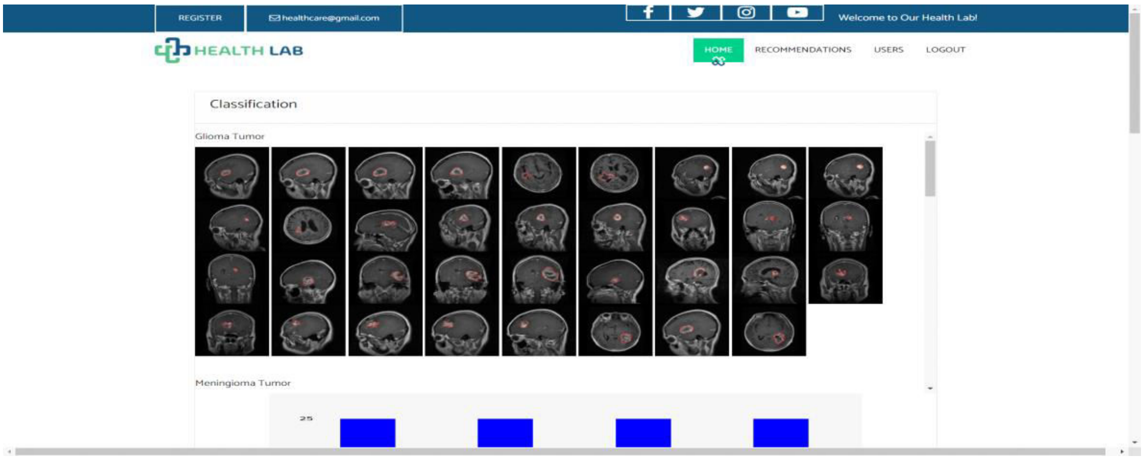

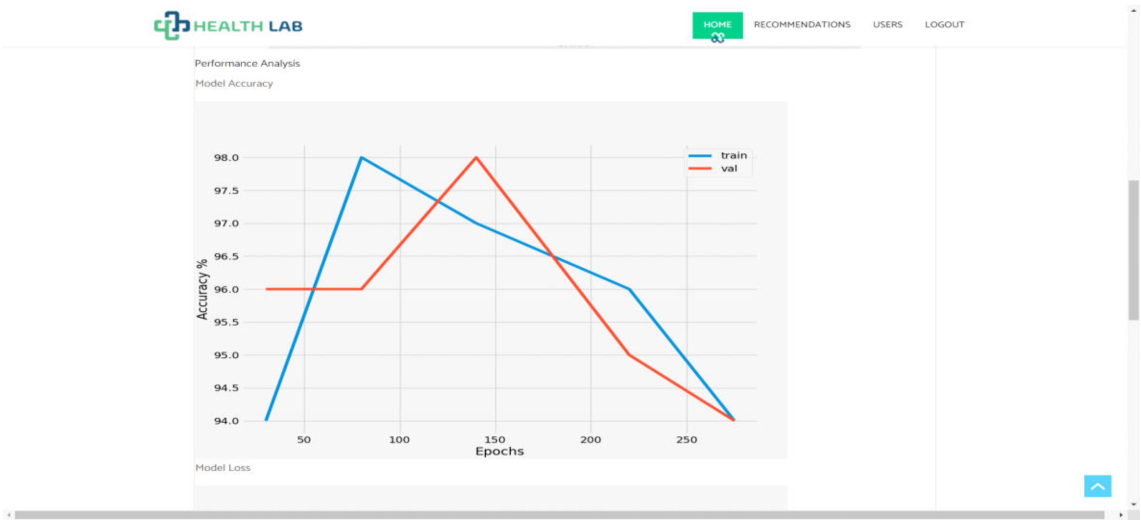

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V. CONCLUSION

The latest developments in medical imaging tools have facilitated health workers. Medical informatics research has the best options make good use of these exponentially growing volumes of data. Early detection options are essential for effective treatment of brain tumors. This project presented a CAD approach for detecting and categorizing BT's radiological images into three kinds (pituitary-tumor, glioma-tumor, and meningioma-tumor). We also classified glioma-tumor into various categories (Grade-two, Grade-three, and Grade-four) utilizing the DCNN approach (i.e., our proposed work). Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inceptionv3 model and concatenated and then, passed to the softmax for the classification of brain tumors. The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor. The outcome of the presented architecture shows high training and validation accuracy with low training and validation loss. Moreover, the testing phase determines the overall portable EM imaging system's capability and potential of CNN architecture in detecting and localizing the brain tumor with high accuracy.

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