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DETECTION AND LOCALIZATION OF BRAIN TUMOR USING DEEP LEARNING AND COMPUTER VISION

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Abstract: **Brain tumor detection plays a crucial role in healthcare, significantly impacting patient survival rates. Brain cancer is one of the most severe and life-threatening conditions, necessitating early and accurate detection for effective treatment. Unfortunately, many patients in remote areas cannot access advanced diagnostic tools and treatment options, exacerbating the severity of the disease. Timely detection of brain tumors is essential to improve prognosis and survival rates. In this study, we explore the application of machine learning, particularly deep learning techniques, in detecting brain tumors from medical images. Our research focuses on the comparative analysis between convolutional neural networks (CNN) and the AlexNet architecture for brain tumor detection. The study demonstrates that CNN algorithms are highly effective, achieving an accuracy of 96.15%, while the AlexNet architecture, a specific type of CNN, achieved an even higher accuracy of 98.03%. The results indicate that AlexNet outperforms the standard CNN in terms of accuracy. Additionally, an Android application has been developed to facilitate brain tumor detection. This mobile app allows users to upload medical images, which the app analyzes to predict the presence of a tumor and provides relevant information to guide further medical consultation.**

Keywords: **Brain Tumor Detection, Image Preprocessing, AlexNet, Convolutional Neural Network, Deep Learning, Web App.**

1. INTRODUCTION

Brain tumors are a significant health concern in India, leading to a high mortality rate due to late diagnosis and the unavailability of specialized medical care. Brain tumors represent a serious medical condition in India, with many cases being diagnosed at advanced stages, thus complicating treatment and reducing survival chances. The lack of access to specialized neurosurgeons and advanced diagnostic tools in remote and rural areas exacerbates the issue, highlighting the urgent need for improved healthcare infrastructure and awareness. However, there is a problem of 40-50% chance of death in patients due to misdiagnosis and untimely detection of tumor. Brain tumor needs to be diagnosed as early as possible for formulating appropriate treatment plans. Due to High exposure to ionized radiation, growth of cancer cells, Mutations in specific genes, such as TP53, PTEN, and IDH1, genetic syndromes, such as neurofibromatosis, Li-Fraumeni syndrome, and tuberous sclerosis, immunosuppressant diseases patients develop cancerous growths in the brain. It is essential to conduct research for automating diagnostic techniques because of advancements in healthcare technology and the application of machine learning in the diagnosis of brain tumors [12], [14]. The existing modern MRI machines rely on healthcare professionals to enter important information in MRI images and reports Our proposed system can readily identify regions of interest and give a brief information on the area and location needed for further treatment. This, can be implemented as an advanced feature into imaging systems and integrate the system with machine learning for achieving accessible healthcare objectives.

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Ensuring effective containment of brain tumors and facilitating optimal treatment outcomes heavily relies on timely detection and accurate classification of pathological brain tissues [14]. Glioblastoma multiform, meningioma, pituitary adenoma, and astrocytoma represent prevalent types of brain tumors, each posing distinct challenges in diagnosis and treatment. Failure to promptly identify these tumors can lead to extensive neurological damage and diminished patient prognosis. Employing advanced machine learning techniques such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) has shown promising results in automating the detection and classification of brain tumors from medical imaging data. Brain Tumors can be recognized by the shape and distinct white color area on MRI T1 and T2 images. However, brain tumor extraction usually extracts un necessary areas and contours along with the ROI, making it very difficult to recognize and extract tumor region by computer systems. It is very important to identify the mass at an early stage and provide appropriate solutions to prevent further damage to brain and body function. The patients may not always be able to get access to oncologists and cancer experts in remote and impoverished areas, causing loss of lives and increased mortality of rural patients. The main task in machine learning in the field of healthcare is to detect diseases at an early stage. It is essential to identify the presence of brain tumor early on and provide the right solutions to avoid future health complications and increase the chances of the patient to survive and recover from cancer.

In this paper, we designed a system by using deep learning techniques for the identification and classification of brain tumor. The innovation of the proposed system lies in its capacity to aid doctors and patients in the detection and management of brain tumors. CNN [13] and VGG16 [10], [11] architecture are used to detect presence of brain tumor in patients and Compare these architecture's accuracy and efficiency. The image dataset used in this work was obtained from the Kaggle website, and some images are downloaded from Google via the Internet. The dataset contains 2,533 images. We used the CNN algorithm which is most widely used deep learning algorithm and achieved an accuracy of 96.15% and TumoVision is a process developed to manipulate images for a clear view of the tumor and accurate extraction of the image of the cancerous mass present in brain. In this work, a web application allows patients to take a photo of the MRI scans or upload from the device. When a user captures or uploads a photo of a MRI T2 scan, the application processes the image to reveal the tumor and offers details about location and area of spread of the mass.

2. LITERATURE REVIEW

This section includes a review of previous studies that have been done based on the requirements of our project. We studied the following recently published research papers. Different machine learning methods are used in healthcare applications like brain health checking, diagnosing cervical and breast cancer, and detecting tumors. Techniques such as RF, SVM, and AdaBoost1 RUSBoost are applied to find tumors in MRI or FLAIR scans, using brats 2012 dataset for natural and syntactic image types. The suggested model yields outcomes with a dice score of 0.88%, 0.98% accuracy, 0.92% sensitivity, 0.96% specificity, and 0.88% precision.

Another system is suggested in [2] for automatically classifying brain tumors. This uses the K-nearest neighbour algorithm to decide if MRI images are normal or abnormal. The fuzz C-means clustering technique helps in identifying tumor regions. The experiment, using MICCAI and brats12 datasets, reveals 96.5% The findings revealed 93% specificity, 100% sensitivity, and accuracy.

In [3], they introduce a manual optimization model crafted by a machine learning expert. This is compared with a machine learning tool called Tree-Based Pipeline optimizer to see how well the model performs. They put this model to the test using MRI pictures from 288 persons. The outcomes reveal the highest accuracy of 0.88% and AUC value of 0.94%.

When it comes to deep learning techniques, although these models are used in various areas, they need adjustments before being used in advanced and fragile fields like medical imaging. The GAN architecture stated in [4], whereby various DL models, including CNN, resnet152v2 are utilized for the purpose of creating and classifying MRI brain pictures. Deep transfer models are trained using DCGAN and Vanilla GAN to generate these images. After that, the performance is assessed using a test set of actual MRI scans. Based on the MRI brain pictures, the experimental results demonstrate that ResNet152V2 outperforms the other models with 99.09% precision, 99.12% recall, 99.51% AUC, 99.09% accuracy, and a 0.196 loss were recorded.

A novel concept for a transfer deep learning model can be found in [5]. Early detection of brain tumors is advised, with particular attention paid to subclasses such as glioma, pituitary, and meningioma. CNN models are created from scratch and tested on MRI brain images to determine their effectiveness. Next, a binary classification with 22 layers (tumor or no tumor) Tumor sub classification is achieved by using an isolated-convolutional neural network model to classify the MRI brain images. This model uses the transfer learning technique to modify the weights of its neurons. The authors of [6] present a novel model for identifying brain cancer. They make use of quantum variational classifiers (QVR) and ensemble transfer learning. The inceptionv3 model extracts the deep features, and SoftMax is used to calculate the score vector. Next, pituitary tumor, no tumor, meningioma, and glioma are distinguished using QVR. Three datasets are used in the study: Kaggle, local images, and 2020-BRATS. A detection score of more than 90% is achieved by the proposed model.

In [7], there's a new idea called the NeuroXAI framework. It's designed to help people understand deep learning networks better, especially medical experts. This framework uses seven methods like GradCAM, Smooth-Grad, guided Grad-CAM, steerable backpropagation, vanilla gradient, integrated gradients. These techniques generate trustable maps that illustrate the functioning of the deep learning model.

An automated system named Ultra-Light Brain Tumor Detection (ULBTD) is mentioned in [8]. The new Ultra-Light Learning Architecture (UL-DLA) is the foundation of this system. It blends textural features from the Gray Level Co-occurrence Matrix (GLCM) with in-depth features. Using a support vector machine, they create a Hybrid Feature Space (HFC) to locate brain tumors. Using a T1-weighted MRI dataset, they test it and find an astounding average detection rate of 99.23% with a 0.99% F1 measure. A number of experiments combining deep learning and machine learning techniques were carried out in [9] to diagnose brain tumors. ResNet-18 and AlexNet were combined with support vector machine techniques. to identify and categorize brain cancers. The average filter method was used to improve the MRI images of brain tumors, and DL techniques were then used to get important deep convolutional layers for features. SVM and SoftMax were then used to sort these features. An MRI dataset comprising 3,060 images—three classes representing tumors and one class representing normalcy—was used for the study. AlexNet with SVM demonstrated the best results, with 95.10% accuracy, 98.50% specificity, and 95.25% sensitivity, according to the findings. Alsaif et al. In 2022 conducted a thorough analysis of CNN architectures, outlining the features of several models, including VGG, ResNet, and AlexNet. The MRI dataset was used to test the CNN-based data augmentation method for the identification of brain tumors. The VGG model performed exceptionally well, as evidenced by its 0.93% accuracy, 0.93% F1-score, 0.94% precision, and 0.93% recall.

Brain tumor detection and recognition could be enhanced by using machine learning techniques, ensemble classifiers, and a variety of datasets, such as the T1-weighted MRI dataset and the BRATS dataset. The existing literature, summarized in Table 1, reveals ongoing efforts in brain tumor detection, with the caliber of his or her harvest. In this investigation, crop diseases and other issues are the main focus of the researchers. Early detection and control of crop diseases can help prevent crop loss and fertilizer waste because they have a detrimental impact on crop quality. In the past, crop diseases might be found using techniques like image processing. For detection and classification in this work, the machine learning method and image processing technologies are both used. Aspects of the image processing method include feature categorization, feature extraction, and other processes [4].

References	Focus	Technique	Performance
Rehman (2020) [8]	Brain tumor	AdaBoost and RUSBoost	Low
Alsaif (2022) [10]	Brain tumor	CNN	Low
Shokry and Salama (2022) [14]	Brain tumor	CVG	Low

Table.1. Literature summary table

3. MATERIALS AND METHODS

The implementation is broken down into several phases. The steps utilized to create a Brain Tumor Detection model that detects tumor regions in the human brain are covered in this section. We started by gathering the image dataset, importing the necessary libraries, processing the dataset with image preprocessing and data augmentation, divided it into training and test sets, built the model, and then trained the model to see which one best fit the data and can predict the precise result.

3.1 IMAGE ACQUISITION

The Kaggle website provided the image dataset for this project, while some of the photographs were downloaded from Google's website. We used a variety of data augmentation approaches to enhance the diversity and robustness of the brain tumor image dataset. There are 253 images in the collection. The dataset includes T2 weighted MRI images of the human brain in black and white format. The data set was split 80:20 between training and testing. There are 155 images in the yes tumor class and 98 images in the no tumor class. Each image that is downloaded by default is saved in the JPG file format and uses the RGB color space.

Characteristic	Value
Number of Images	2533
Image Type	T2 weighted MRI (human brain)
Color Format	Black and White
Split (Training:Testing)	80:20:00
Yes Tumor Class Images	155
No Tumor Class Images	98
Default File Format and Color Space	JPG , Grayscale

Table.2. Dataset details

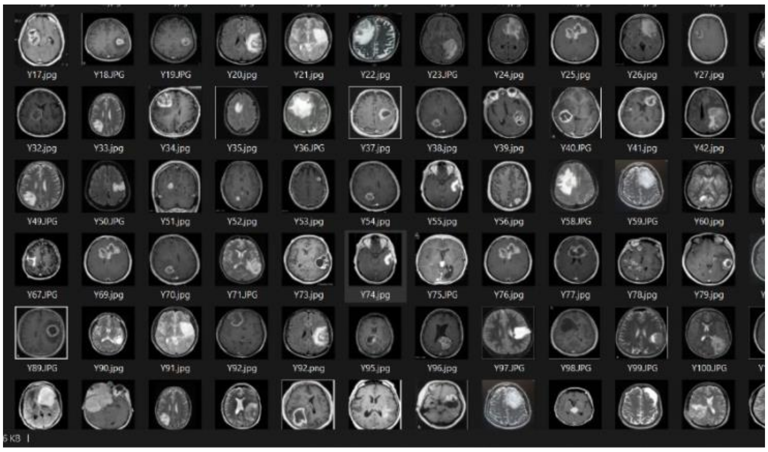

Fig.1. Different Images from Dataset

3.2 IMAGE PREPROCESSING AND DATA AUGMENTATION

To prepare raw data and make it acceptable for creating and training deep learning models, image pre-processing is a vital effort. This enhances the effectiveness and accuracy of the model. It enables you to enhance the quality of your data and derive important insights from it. All of the photos in our dataset have an RGB coefficient that ranges from 0 to 255. So, we changed the images' sizes and scales. The dataset has many formats with various resolutions and quality because some photographs were downloaded from Google and others from Kaggle. Therefore, in order to enhance feature extraction, save training time, and achieve consistency, we resize the images to to 270 × 270 x 1. for CNN architecture. The pre- processing stage resizes all of the photos in accordance with the model's specifications and rescales each image's pixel values to lie between 0 and 1. Numerous image augmentation techniques were utilized to increase the dataset's size because it was so little. Some picture augmentation techniques include rotation, vertical and horizontal image flipping, shearing, and random zooming.

3.3 MODEL BUILDING

In model building phase, we employed a deep learning architecture and an image processing technique for the purpose of detecting and extracting Brain tumor presence in images: Convolutional Neural Network (CNN) and TumoVision method. These techniques in combination with one another give rise to an accurate and novel imaging technique to identify brain tumors.

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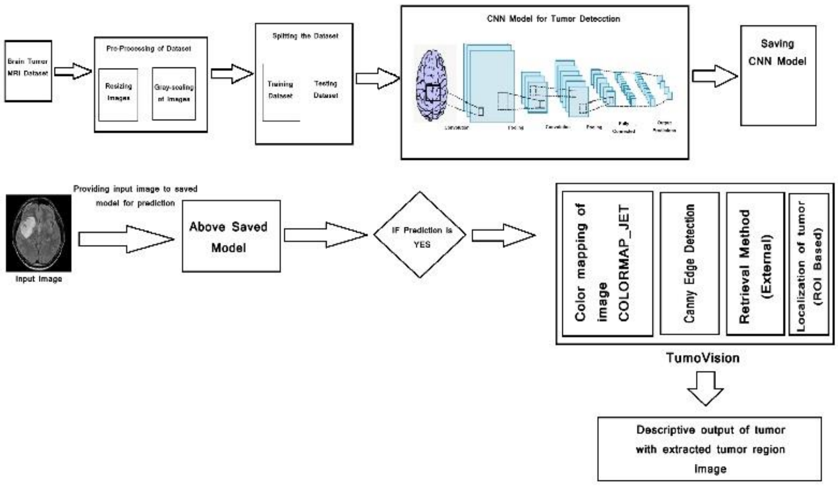

Fig.2. Proposed system Architecture

3.3.1 Convolutional Neural Network (CNN):

The convolutional neural network is a well-known deep learning approach that successfully trains many layers. There are nine layers in our CNN architecture, including three convolution layers, three max pooling levels, one dropout layer, and one output layer. The supplied image is scaled down to 270 × 270 x 1. Most calculations are done in the convolutional layer, which is the first layer of the CNN architecture.

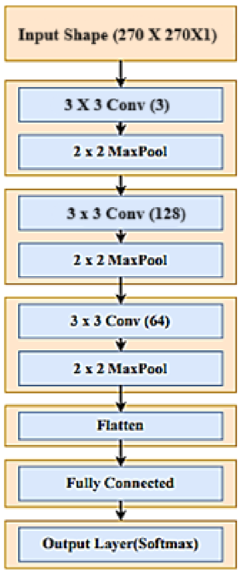

Fig .3.Shows the architecture of convolutional neural network.

The first convolutional layer utilizes 3 filters with a kernel size of 3 x 3 and a 270 × 270 input image with a relu activation function as its input. The size of the feature map is then decreased by applying this pooling layer with a filter size of 2 x 2. The second convolutional layer, which employs 128 filters of size 3 x 3, uses the output of the first convolutional layer as its input and employs the relu activation function. The feature map is then reduced by applying a pooling layer with a 2 x 2 filter size a second time. The third convolution layer, which has a kernel size of 3 x 3, 64 filters, a relu activation function, and is fed the output of the second convolution layer. The lower function separates the image into six different categories and delivers the candidate that fits the target class the best.

dimension feature map is after that made smaller using a pooling layer with a 2 x 2 filter size. Before transmitting the resulting array to the fully connected layer, the flatten layer will convert the input from the multidimensional array into a single-dimensional array. Two fully connected layers, each containing 64 and 6 neurons, were used. The dropout layer is used to exclude the neurons that were selected at random with 0.2 probabilities in order to avoid the issue of overfitting. The output layer's softmax activation

3.3.2 TumoVision (ROI extraction method):

TumoVision is the method proposed to extract tumor region. TumoVision is a process which works in cohesion by leveraging image manipulation techniques and ROI extraction methods that are most frequently utilized. This method has been newly proposed to solve problems with traditional contouring methods used for extracting tumor area from the MRI images. Upon using contouring for extraction of tumor from the image, contouring algorithm recognizes all edges in the image and not just the tumor area. It utilizes Color-mapping or Pseudo-Coloring technique using OpenCV to highlight the tumor area pixels using colors, as the gray scale images do not indicate regions based on intensities in color spaces like HSV,RGB etc.

The Pseudo-coloring method COLORMAP_JET is the best suited color map for the detection of tumor area. It assigns color to the image pixels according to the intensity values observed in the image.

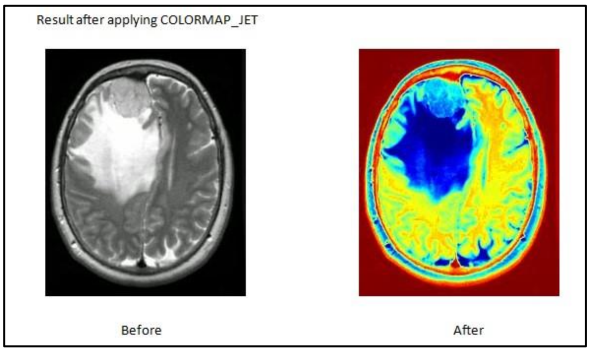

Fig.4. Pseudo-coloring of images

By applying Canny edge method onto the Color mapped image, the ROI is narrowed down to the area consisting the tumor. Final extraction is done based on the pixel values of a certain color here, Blue colored pixels in the range [110, 50, 50] [130, 255, 255] carry the same intensity as tumor cell area. Thus, extraction of pixels within the range of the blue pixels gives us the entire tumor region. Masking of extracted tumor image and original image using bitwise And-ding.

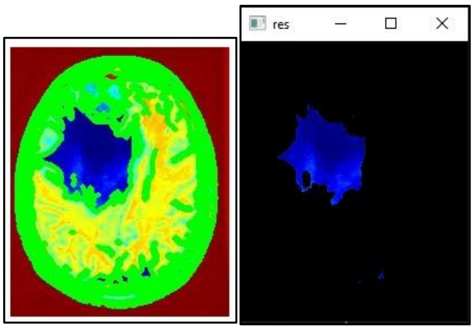

Fig.5. ROI Extraction and results

4. RESULTS AND DISCUSSION

We used 253 images for training and testing. The training accuracy of VGG16 is 92.31%, while that of CNN is 96.15%. The model's classification efficiency is evaluated using a loss accuracy graph (Fig. 6 and Fig. 8). True positive, true negative, false positive, and false negative values can be found in the confusion matrix. In the confusion matrix, higher diagonal values represent the model's more accurate predictions. The accuracy, precision, and recall figures from the confusion matrix produced from the CNN and VGG16 architectures are provided in Fig. 8 and Fig.10. When compared to VGG16's (92.31 percent) accuracy, the outcome demonstrates that CNN architecture achieves the highest accuracy (96.15 percent).

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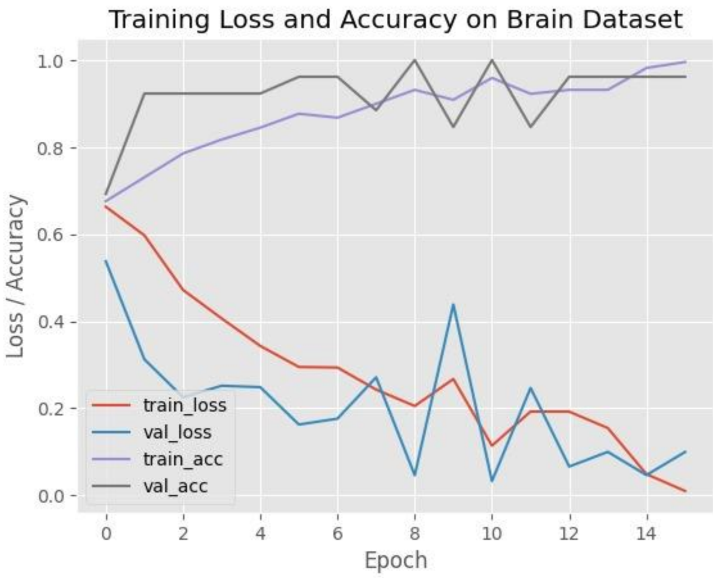

Fig.6. Loss Accuracy Graph CNN

	precision	recall	f1-score	support
no	0.91	1.00	0.95	10
yes	1.00	0.94	0.97	16
accuracy			0.96	26
macro avg	0.95	0.97	0.96	26
weighted avg	0.97	0.96	0.96	26

COnfusion Matrix is : [[10 0]
 [1 15]]

Fig.7.Accuracy Metrics CNN

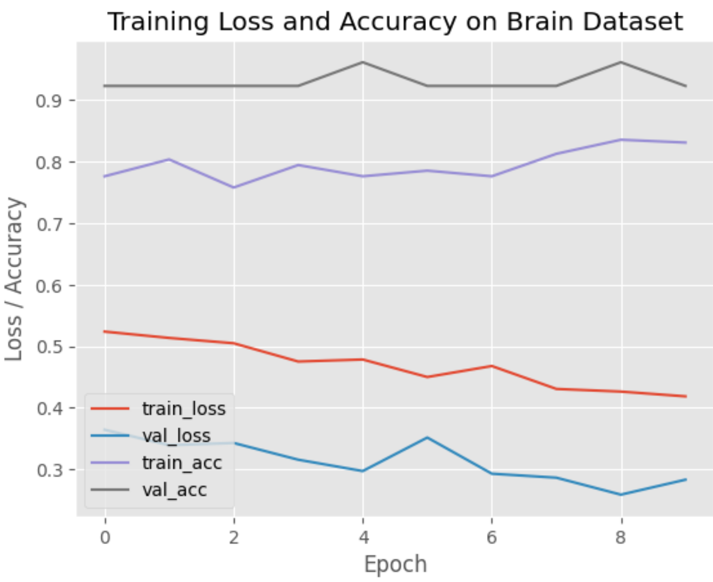

Fig.8. Accuracy graph of VGG16

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	precision	recall	f1-score	support
no	0.90	0.90	0.90	10
yes	0.94	0.94	0.94	16
accuracy			0.92	26
macro avg	0.92	0.92	0.92	26
weighted avg	0.92	0.92	0.92	26

```
[[ 9  1]
 [ 1 15]]
```

Fig.9. Accuracy metrics of VGG16

After categorizing and contrasting the deep learning-based work, Fig. 8 and Fig.9 clearly demonstrate that accuracy may be increased by utilizing different layers. When compared to CNN, it has been observed that VGG16 architecture takes longer to train because it has more layers. Both models are able to identify the tumor and classify it after training. In our experiment, we found that the model can be executed on the GPU. The filter sizes used by the CNN architectures are smaller, and there are fewer training parameters. As a result, the model offers a straightforward and effective results of tumor.

In this paper, the web application has been designed using flask for the detection of brain tumor in images. The web app allows patients or users to capture a photo or upload photo from the device. When user uploads the image to be analyzed, web application recognizes the tumor, extracts tumor region and gives information about its spread. Fig. 10 shows the system UI or user interface of proposed system.

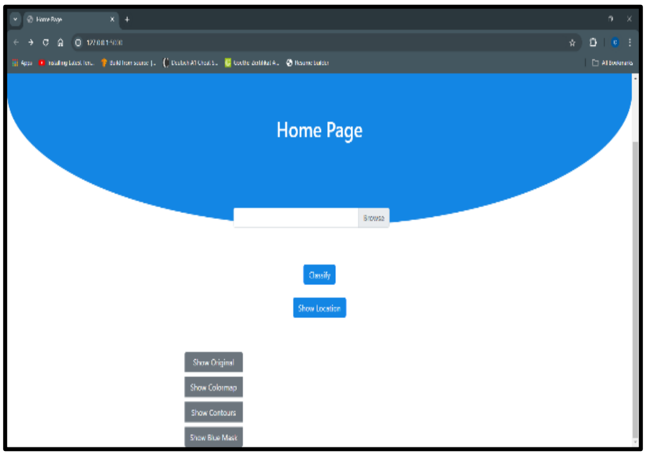

Fig.10. System User interface

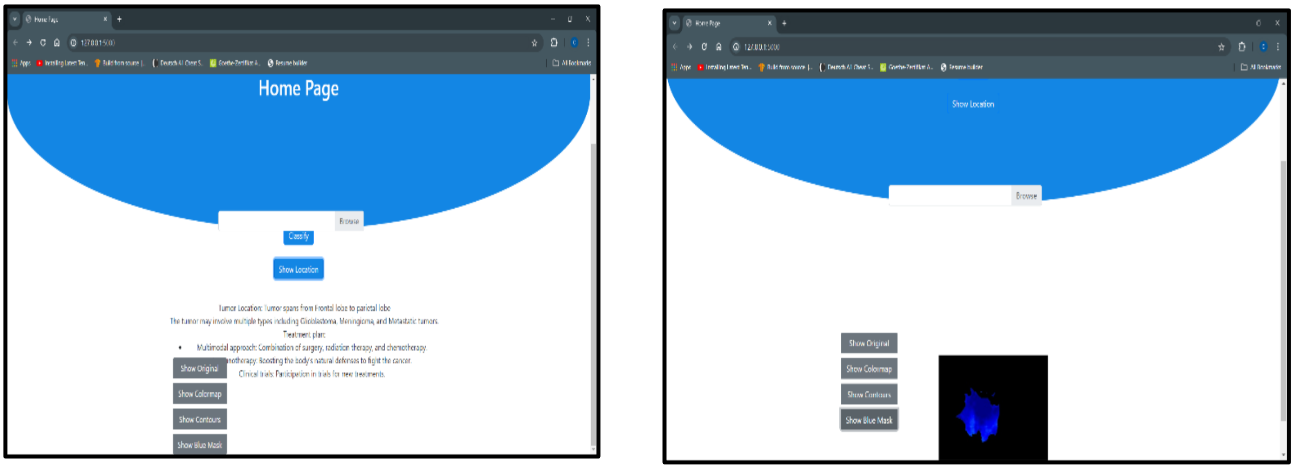

Fig.11. Screenshots Output for Detecting Brain Tumor

The Fig.11 shows some screenshots of the achieved results. The proposed system would allow users to upload MRI images of the brain, Once the image is chosen, the app will preprocess that image and feed that image to the model that detects the whether a tumor is present or not and displays the result of the tumor region along with details and description of tumor in text format.

5. CONCLUSION

In this paper, a CNN architecture is used to perform brain tumor detection in combination with TumoVision method for extraction of tumor region. For this research, as a result, CNN design outperforms VGG16 architecture in terms of accuracy and precision. This work shows that deep learning architectures can distinguish between most important and less important features in images. After 15 epochs of fine-tuning with various hyper parameters, a straightforward CNN model achieved an accuracy of 96.15 percent. Using 30 epochs. In conclusion, the paper presents the model's comprehensive analysis and outcomes. Images of both healthy and brain tumor MRIs were used in the experiments. It is concluded that the proposed approach successfully classifies images on basis of presence of tumors and gives information regarding the localization of tumor.

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