CONVOLUTIONAL NEURAL NETWORK MODEL FOR BRAIN LESION DETECTION

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Abstract

The detection of brain lesions is crucial in various aspects of neuroscience and neurology. It plays a vital role in diagnosis, treatment planning, prognosis, disease monitoring, prevention, and research advancements. Brain lesions serve as indicators of underlying conditions such as tumors, infections, strokes, and neurodegenerative disorders, facilitating timely and accurate diagnosis for appropriate management. Lesions also provide prognostic insights, shedding light on disease outcomes and progression. Monitoring lesions over time aids in treatment adjustments and interventions. Early detection enables preventive measures, minimizing the impact of conditions. In this work, we present a Convolutional Neural Network (CNN) model specifically designed for brain lesion detection using MRI images. The proposed model aims to provide improved accuracy in tumor detection, further enhancing patient care, management, and quality of life.

Keywords: Brain Lesion Detection, Acquisition, Filtering, Segmentation, CNN classification

I. Introduction

The brain is a complex organ that serves as the central command center of the nervous system in humans and other vertebrates. It is responsible for controlling various bodily functions, including thoughts, emotions, movement, and sensory perception [1]. Any harm to the brain could affect the complete functioning of the body. This harm is called as “Brain Lesions.” Brain lesions refer to abnormal or damaged areas in the brain caused by injury, disease, infection, or other pathological conditions [2]. They can be focal or diffuse, with focal lesions affecting specific regions and diffuse lesions causing widespread damage. Brain tumors, vascular issues, and infections can all lead to the formation of brain lesions [3]. These lesions can disrupt normal brain function, resulting in various neurological symptoms [4]. Moreover, the brain lesions can occur due to various factors and conditions. The causes include traumatic brain injuries from impacts or accidents, vascular disorders like strokes from blood vessel blockages or ruptures, infections, brain tumors that compress nearby tissue, neurodegenerative diseases like Alzheimer's or Parkinson's, autoimmune disorders such as multiple sclerosis, genetic factors that predispose individuals to lesion formation, and toxic exposure to substances like heavy metals or drugs [5]. Diagnosis typically involves medical imaging scans like MRI or CT, and further investigations may be required to determine the underlying cause [6]. Treatment options depend on the specific condition and may include surgery, medication, radiation therapy, or rehabilitation.

The detection of brain lesions is essential for diagnosis, treatment planning, prognosis, disease monitoring, prevention, and research advancements [7]. Brain lesions indicate underlying conditions like tumors, infections, strokes, or neurodegenerative disorders, enabling timely and accurate diagnosis for appropriate management [8]. Treatment decisions are guided by lesion detection, considering surgery, radiation therapy, medication, or rehabilitation [9]. Lesions provide prognostic information, offering insights into outcomes and disease progression [10]. Monitoring lesions over time informs treatment adjustments and interventions [11]. Early detection allows for preventive measures, minimizing the impact of conditions. Research on brain lesions contributes to diagnostic tools, treatment modalities, and therapeutic advancements [12]. Overall, detecting brain lesions improves patient care, management, and quality of life in the field of neuroscience and neurology. Hence in the contribution of this work is as follows

- Present a Convolutional Neural Network (CNN) model for detection the brain lesion using the MRI images.
- Provide better accuracy for the detection of the tumor in the MRI images.

II. Literature Survey

In [13], Brain tumor detection and removal have been suggested using a Fuzzy C-Means clustering technique, conventional classification algorithms, as well as a CNN to process 2D MRIs of the brain. Experiments were conducted using a real-time dataset consisting of tumor images of a variety of intensities, dimensions, and positions. K-Nearest-Neighbor (KNN), Support-Vector-Machine (SVM), Logistic-Regression (LR), Multilayer Perceptron (MLP), Random Forest (RF), and Naive Bayes were the six classical classification algorithms which were used for comparison. All of them were developed in scikit-learn. Following that, they developed the CNN built with TensorFlow and Keras due to its superior performance compared to more conventional methods. Their approach resulted in an impressive 97.87% accuracy for CNN. The primary goal of this work was to use texture-based and statistical characteristics to identify abnormal and healthy pixels. In [14], Twenty studies reported between the years 2000 and 2020 were reviewed using a two-stage methodology to discover additional information regarding tumor identification in MRI images. Multiple processes were analyzed side by side. Image enhancement as well as restoration were identified as two primary issues following a thorough examination approach. Using this they have proposed an approach. TensorFlow as well as Python library were used for implementing the proposed approach. The advantages and drawbacks of the approaches and techniques were also presented in this study. In [15], Utilizing the data augmentation technique, an CNN algorithm, as well as a pre-trained approach, the researchers of this study created an algorithm for identifying brain tumors in conventional MRI scans. Various tumors of varied dimensions, forms, as well as intensity were taken from the data set provided by Kaggle and used in the course of the study. For quite some time, doctors have relied on deep learning, among the latest cutting-edge technological technologies, to eradicate malignant tumors throughout the brain. It is possible that sophisticated AI as well as Neural Network categorization algorithms could aid with the early diagnosis of brain tumors. CNN models in this work were constructed utilizing the VGG 16 to detect tumors in the brain. A method of using MRI for rapid, reliable, and accurate diagnosis of brain tumors was also uncovered in the study. A total of 253 MRI scans of the brain were used to evaluate the new method, including 155 of those scans showing malignancies. The proposed work has the potential to detect tumors in brain MRI scans. VGG 16 had a 99.94% accuracy, CNN had a 97% accuracy, RestNet50 had a 45.75 % accuracy, as well as InceptionV3 had a 48.85 % accuracy.

In [16], This research demonstrates how CNN can be used for the diagnosis of brain tumors. The experimental findings demonstrate that the proposed approach is more accurate than existing systems for tumor classification, and it is applicable to images of varying resolutions. They have suggested that, the effectiveness of CNNs can be tweaked in a number of ways, including by changing the method of optimization used, the number of epochs, the size of the batches, the rate at which the network learns, and so on. The purpose of this research was to demonstrate the value of CNN in detecting brain tumors more effectively. In [17], They have created a CNN that does not require any preprocessing or augmentation of the raw data. The suggested approach achieved comparable testing accuracy of 98.5% when compared to state-of-the-art models; it was developed using the BRATS dataset, which contains 2065 brain MRI images. In [18], CNNs, a type of deep learning algorithm, has been used in this study, specifically for the Image Dataset. For this investigation, both unhealthy and healthy images of chronic brain tumors were obtained under ideal lighting conditions to reveal any underlying differences. Grayscale, black and white, resize, power-transform, complement and robert, were among of the methods used to alter the image samples. Next, a CNN textural extraction of features method is applied to the data. Seventy percent of the data was utilized for training, ten percent

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for validation, and twenty percent for testing. For a given number of cycles or epochs, the detected efficiency was 92.78 percentage, and the total processing time was 5.33 seconds.

In [19], In this study, they present a computerized brain tumor identification method that uses a CNN to examine MRI scans and label them as either benign or malignant. The GoogleNet, Alexnet, RNN, VGG-16 and CNN architectures were among those investigated and evaluated. The work centers on fine-tuning hyperparameters that are part of VGG-16 and Alexnet architectures. Initial testing on 125 images utilizing CNN Alexnet for automatic identification of brain tumors validated a precision of 98.67% utilizing the BRATS-2015, BRATS-2013, and OPEN I dataset, totaling 621 images. In [20], In order to distinguish between benign and malignant brain tumors, the authors of this research proposed two deep-learning algorithms. Here, they employ two open-source collections, totaling 152 MRI scans and 3064 MRI scans, respectively. In order to construct their model, they begin by applying a 23-layers CNN onto the first dataset. This is done because the initial set has a significant amount of MRI images that are used for training purposes. Nevertheless, the suggested "23-layers CNN" design runs into an overfitting issue while working with small quantities of data. They employ transfer learning techniques to integrate the VGG16 architecture using their suggested "23 layers CNN" design in order to solve this problem. According to their experiments, their models outperform all existing state-of-the-art approaches by achieving up to 97.8% and 100% accuracy in classification, respectively, for their used datasets. In [21], This study presents a successful approach for brain Tumor identification using the Enhanced Residual Networking (ResNet), which solves the gradient-based problem of DNN. In addition to saving time and money, this method also reduces computing complexity. As shown by empirical study of BRATS 2020 MRI sample information, the suggested approach outperforms state-of-the-art alternatives by a margin of at least 10% in terms of accuracy, recall, and f-measure.

III. Methodology

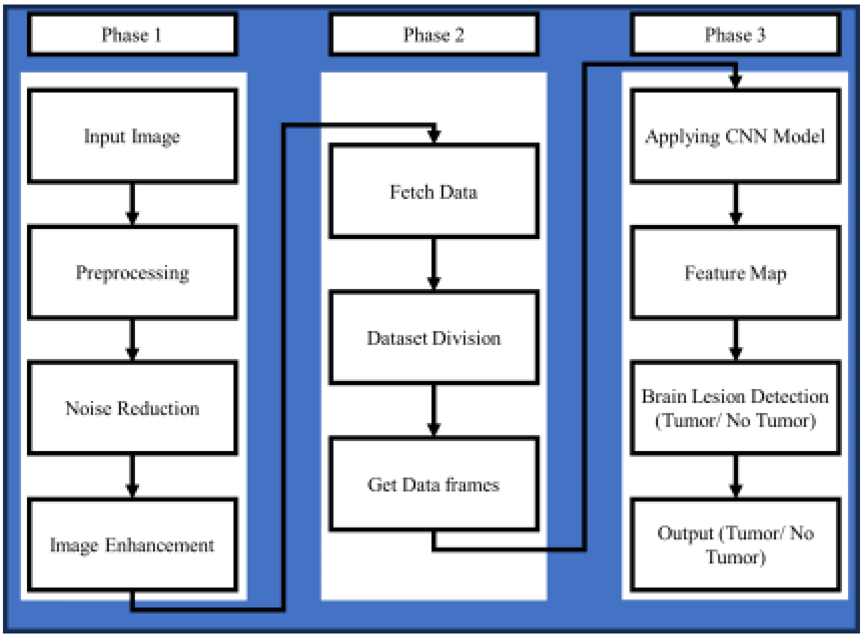

Figure 1. Architecture of the Proposed CNN Model.

In Figure 1, the architecture of the proposed model has been given. The brain lesion detection process involves three essential phases. In Phase 1, the input image of the brain undergoes preprocessing steps like resizing, normalization, and format conversion to prepare it for analysis. Noise reduction techniques such as denoising filters are applied to enhance the image's clarity, while image enhancement methods like contrast adjustment and histogram equalization improve the visibility of brain lesions. Phase 2 focuses on data preparation and dataset division. Brain imaging data, such as MRI scans, is collected, and the dataset is split into training, validation, and testing sets. The training set is used for model training, the validation set aids in hyperparameter tuning, and the testing set evaluates the final model's performance. In Phase 3, a convolutional neural network (CNN) model is designed, consisting of convolutional layers, pooling layers, and fully connected layers. Preprocessed brain images are fed into the CNN to extract meaningful features through feature mapping. The extracted features are then used to classify the presence of brain lesions, involving training the CNN model on a labeled dataset. Finally, the CNN model predicts the presence or absence of a brain lesion, providing a binary classification output of tumor or no tumor.

IV. Proposed CNN Model

In the recent years, the CNN model is most widely used for the detection of the brain lesion using the MRI medical images [22]. The CNN model depends solely on MRI scans for lesion detection and ignores the matching masks. This means that CNN evaluates only the Magnetic Resonance Imaging (MRI) images to create predictions with respect to the existence or features of tumors, without including extra information given by the matching masks, that might include tumor-related segmented or labeled data. Typically, a Convolutional layer serves as the first layer, and its filters are used to extract important information from the images. This layer will produce a series of feature maps as its output. These feature maps will every indicate how every filter responds to the image which was fed into the layer. To prevent overfitting, it is common practice to include an additional layer consisting of the pooled mechanism to reduce the dimensions of the feature mapping all while maintaining the most important characteristics. After each layer's output has been compressed, it is sent to fully connected-layers for final feature extraction classification. The result of the CNN is a distribution of probabilities across the several classification labels that can be assigned; using this distribution of probabilities, a threshold is determined to determine if or not a tumor is detected. Throughout the training phase, the CNN improves the total number of the Convolutional layer as well as the fully connected-layers. This is done commonly by back-propagation as well as stochastic-gradient-descent. The goal of this optimization is to minimize the disparity among the class that is predicted as well as the actual truth-class from the training data. The trained CNN is able to identify and categorize brain tumors within the medical images by first producing a score that represents the probability indicating the existence of the tumor, and then categorizing the image as having a tumor if the resultant probability is higher than the threshold value [23]. The complete process has been given in the Figure 2.

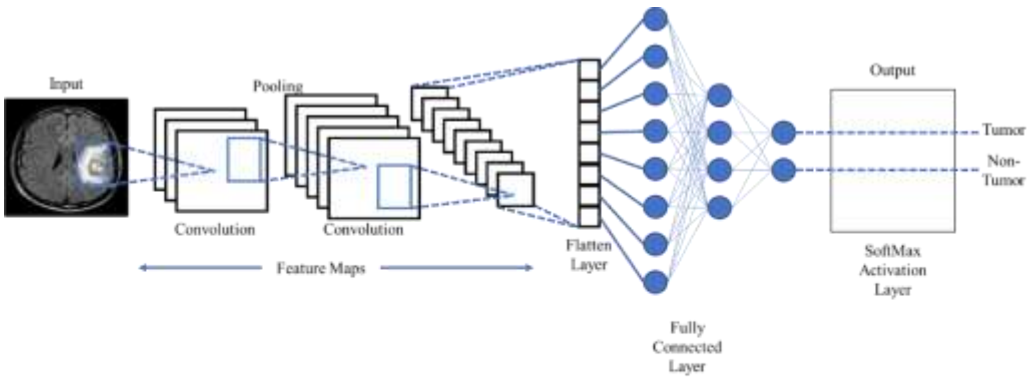

Figure 2. CNN Layers for the proposed model.

In order to extract features, the convolutional layer is essential. This layer applies a variety of filters in order to get the relevant information. The size and output of the convolutional layers is evaluated utilizing Eq. (1) and Eq. (2).

$$FM_b^a = \Delta\,(K_b^a - I_L + Y^i) \quad (1)$$

$$size = \left(\frac{input - filter\ size}{stride}\right) + 1 \quad (2)$$

where, FM_b^a in Eq (1) is used for defining the feature maps of the images, Δ is used for defining the activation-function, IL is used for defining the width of the input, and $K_L^{i\epsilon f}, Y^{i\epsilon f}$ are used for defining the filter channels (f).

Overfitting can occur in CNNs; hence the pooling stage is employed to regulate parameters and ensure that the final output is truly unique and independent of any problems of duplication. Different types of pooling, such as maximum, minimum, as well as average pooling, are all accomplished by using pooling layers. The most popular type of layer is max pooling [24]. The pooling stage output and size are evaluated utilizing the Eq. (3) and Eq. (4).

$$P_{i,j} = max_{p,s\in R} \quad (3)$$

$$Pooling\ Layer\ Output\ Size = \left(\frac{convo\ output - Pooling\ Size}{stride}\right) \quad (4)$$

where, s is used for representing the final output and p is used for denoting the pooling area. In the final phase of processing, three interdependent layers are incorporated. The evaluation of the proposed CNN model has been done in the next section.

V. Results and Discussions

For the experimentation of the proposed CNN model, in this work we have considered the Kaggle dataset [25]. This dataset consists of brain tumor and healthy patient images. The dataset consists of 2513 brain tumor MRI images and 2084 healthy patient MRI images. The proposed model was coded in Python language and the was run using the Anaconda 3 platform.

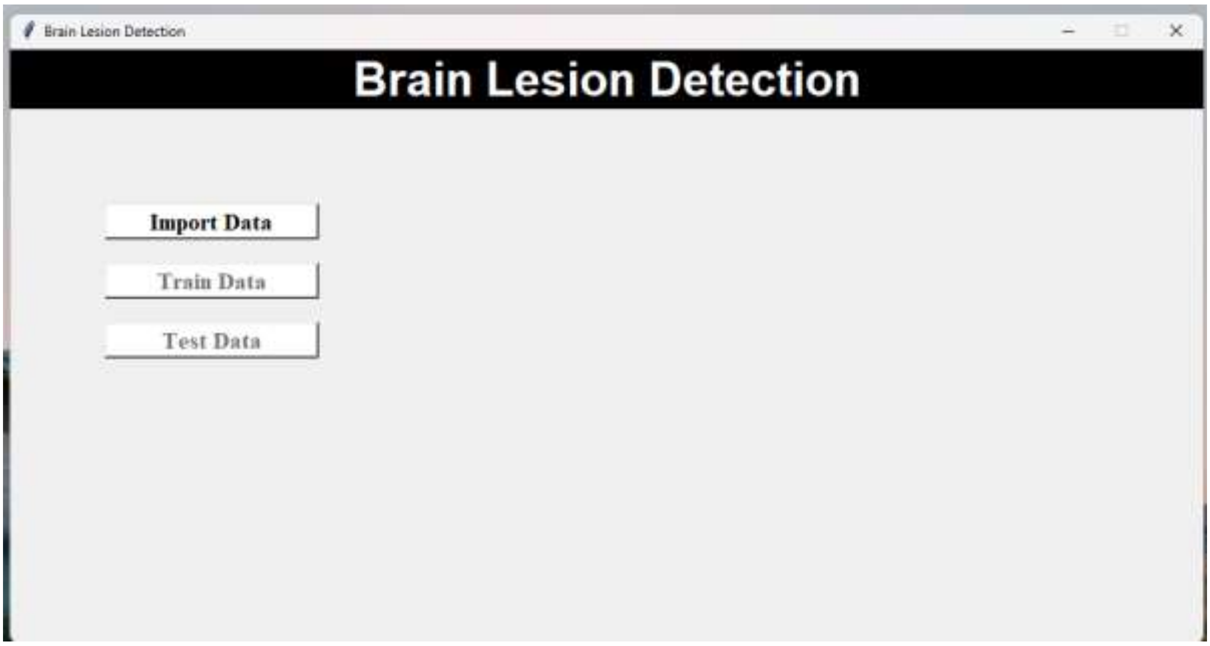

Figure 3. User Interface.

In Figure 3, the user interface for the brain lesion detection has been shown. The brain lesion detection interface consists of three boxes, import data, train data and test data. First, the complete Kaggle dataset consisting of the MRI images is imported which has been shown in Figure 4.

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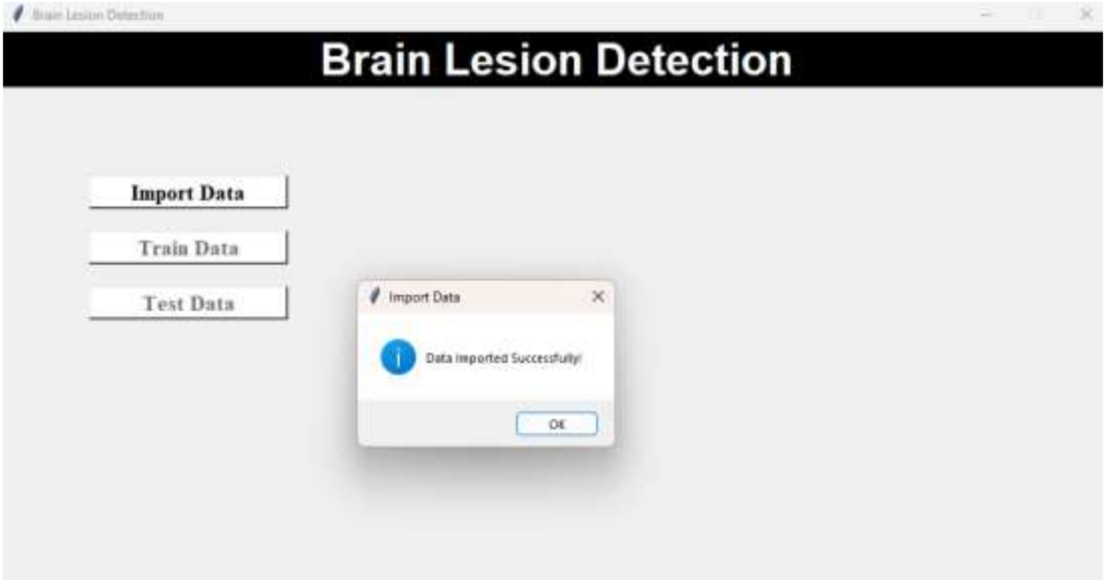

Figure 4. Importing Brian Images.

After importing, the dialog box appears which states "Data imported successfully." After the successful import of the dataset, the dataset is trained. By clicking on the train data, the dataset is trained. The similar operation has been shown in the Figure 5.

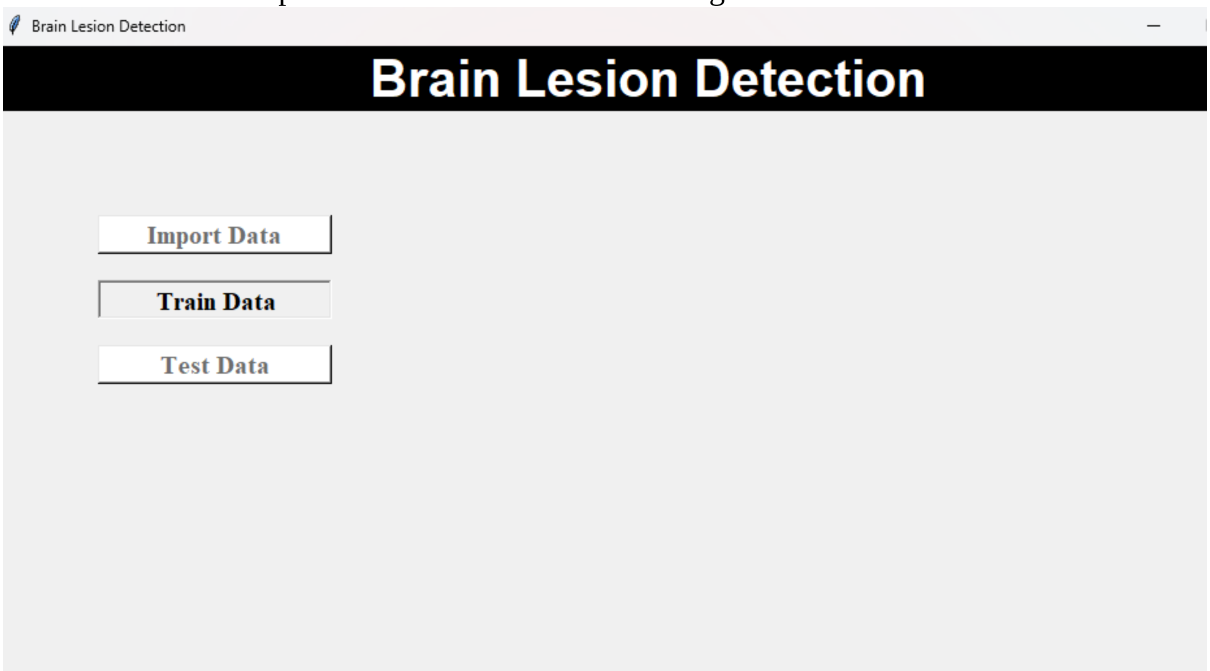

Figure 5. Training Images to Model.

The complete process of training has been shown in the Figure 6. During training the proposed CNN model is trained for 9 epochs. During training the proposed CNN model has attained an accuracy of 100.00% which has been shown in the Figure 7.

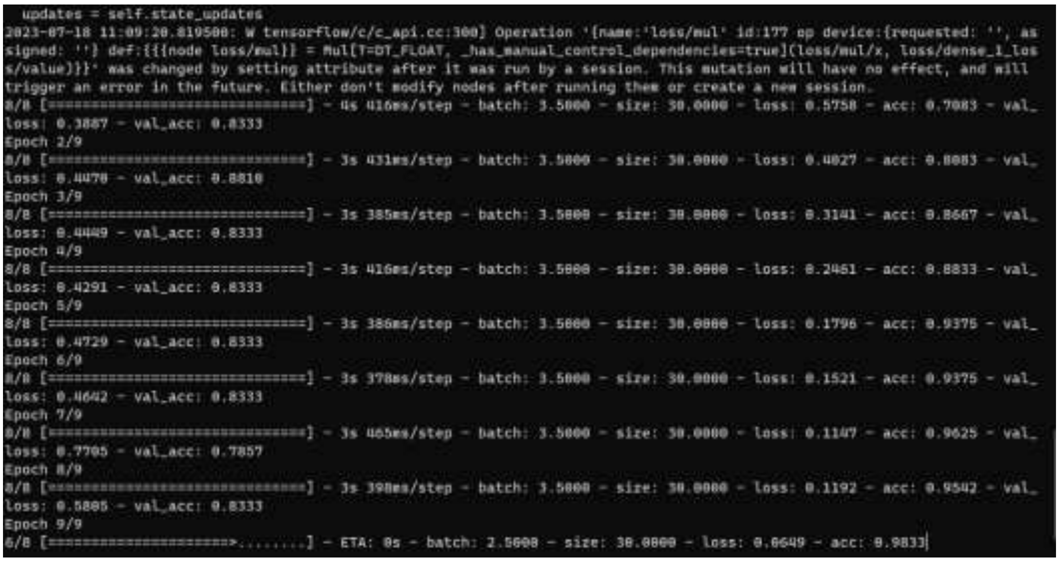

Figure 6. Trained Model.

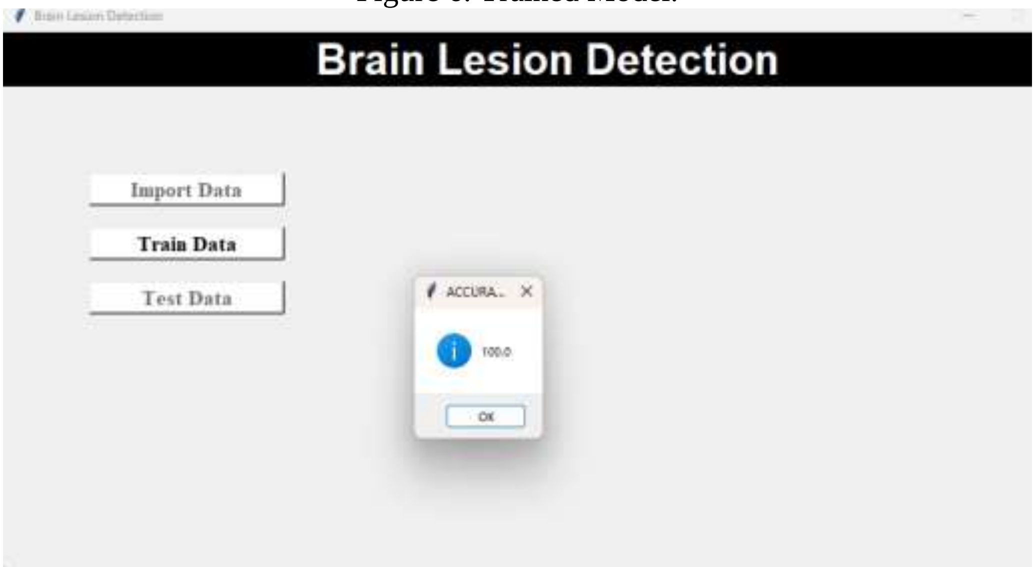

Figure 7. Model Accuracy.

Further, after the successful training of the CNN model, which has been shown in the Figure 8, the CNN model is tested.

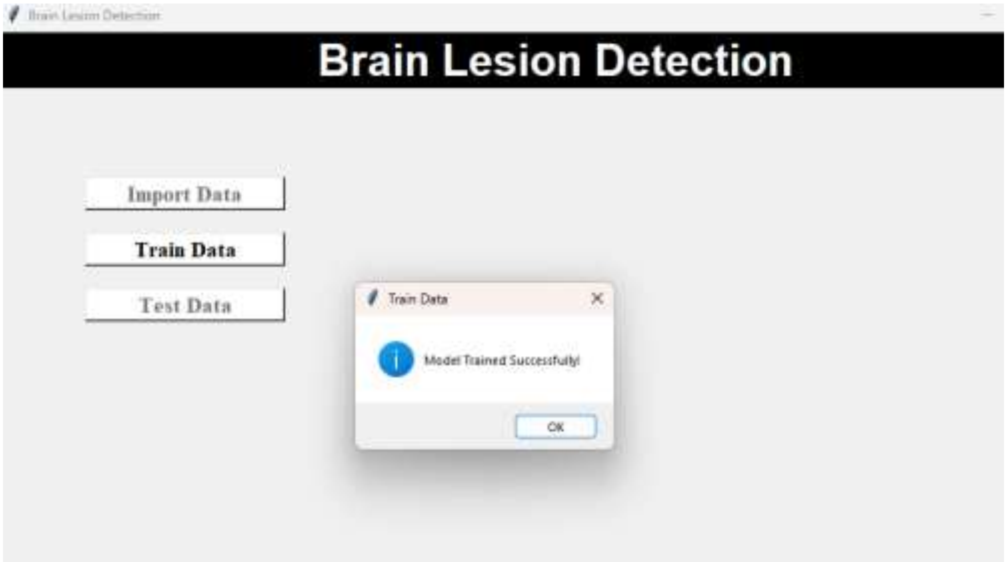

Figure 8. Trained Model Confirmation.

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For testing the proposed model, first, a random image is selected from the dataset which has been shown in the Figure 9. The selected figure would open and would be analyzed and compared with the dataset as shown in the Figure 10 and Figure 12. Finally, the output would be given as “Tumor Detected” or “No Tumor Detected” as shown in the Figure 11 and Figure 13.

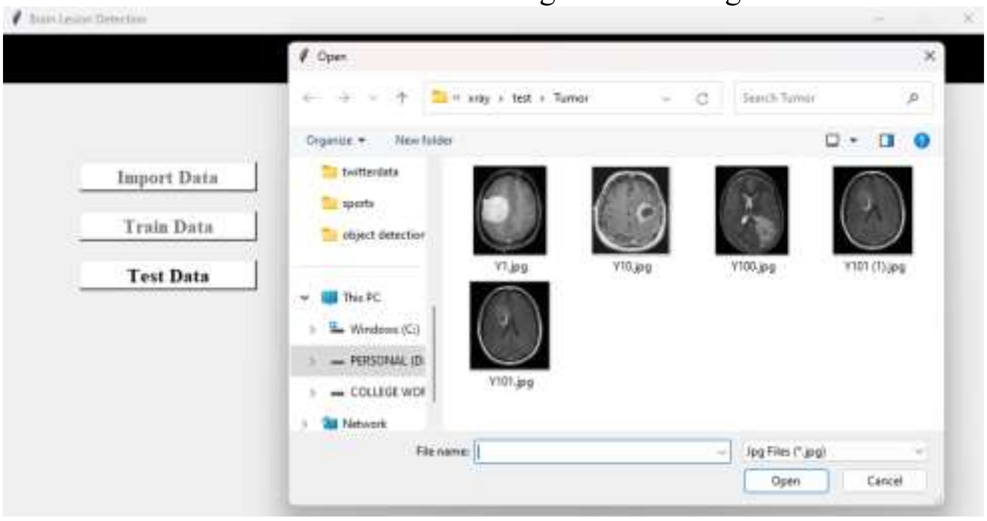

Figure 9. Testing Model.

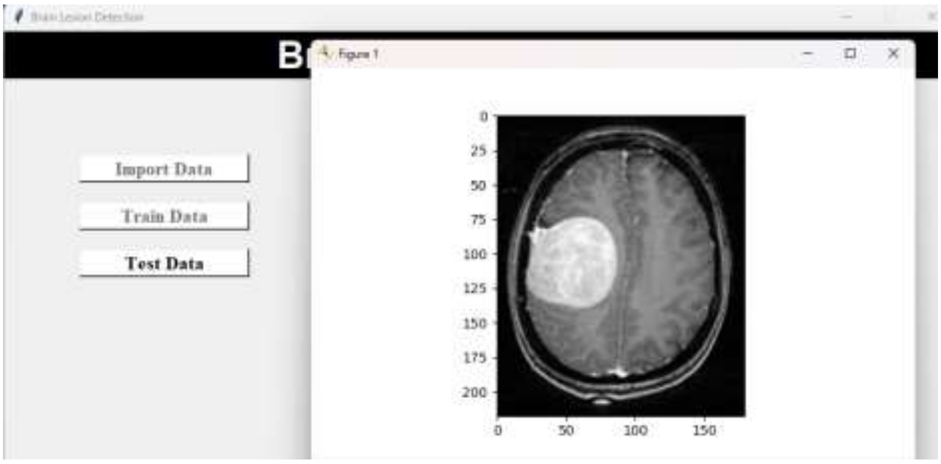

Figure 10. Testing Model with Tumor image.

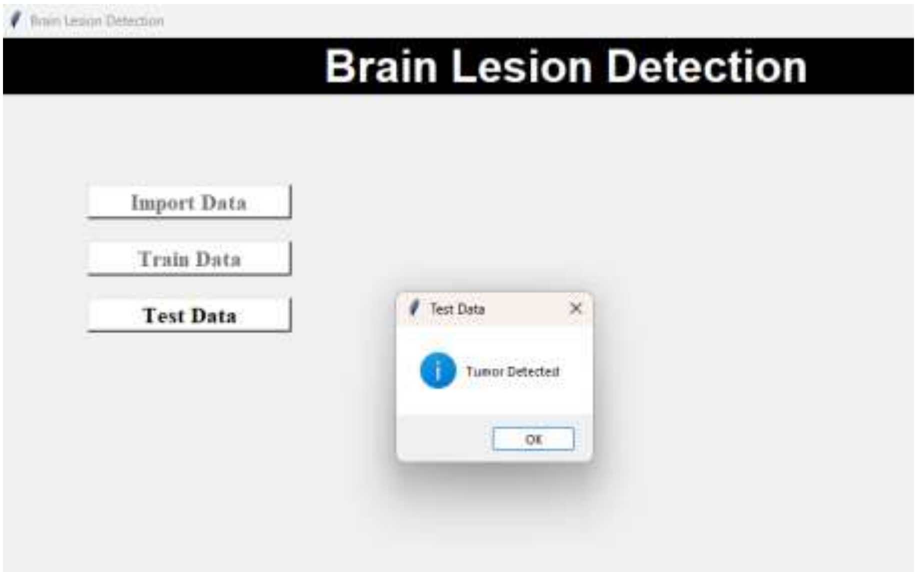

Figure 11. Predicted Result.

Figure 12. Testing Image with No Tumor.

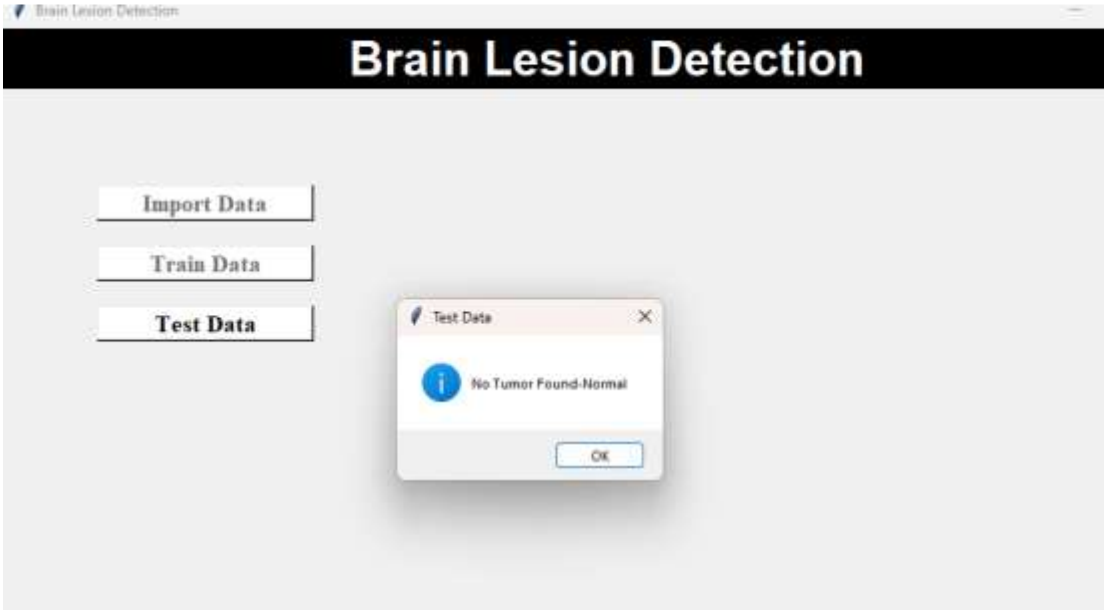

Figure 13. Predicted Result.

VI. Conclusion

The detection of brain lesions is of most importance in the field of neuroscience and neurology. Brain lesions serve as critical indicators of underlying conditions such as tumors, infections, strokes, and neurodegenerative disorders, allowing for timely and accurate diagnosis. The presence of brain lesions guides treatment planning, enabling healthcare professionals to make informed decisions regarding surgery, radiation therapy, medication, or rehabilitation. Additionally, brain lesions provide valuable prognostic information, offering insights into disease outcomes and progression. Monitoring lesions over time facilitates the adjustment of treatment strategies and interventions. Early detection of brain lesions enables preventive measures, minimizing the impact of conditions on patient's well-being. This work presents a Convolutional Neural Network (CNN) model for brain lesion detection using MRI images, this work aims to improve accuracy, ultimately benefiting patients and their quality of life. The ongoing efforts in detecting and understanding brain lesions continue to shape the field, driving advancements in neuroscience and neurology for better healthcare outcomes. For the future work, this work can be extended for classifying the brain lesions into different types.

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