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Automated Brain Tumor Detection from MRI Scans using Deep Convolutional Neural Networks

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Abstract

The brain, as the central nervous system's most critical part, can develop abnormal growths of cells known as tumors. Cancer is the term used to describe malignant tumors. Medical imaging modalities, such as computed tomography (CT) or magnetic resonance imaging (MRI), are commonly used to detect cancerous regions in the brain. Other techniques, such as positron emission tomography (PET), cerebral arteriography, lumbar puncture, and molecular testing, are also utilized for brain tumor detection. MRI scans provide detailed information concerning delicate tissue, which aids in diagnosing brain tumors. MRI scan images are analyzed to assess the disease condition objectively. The proposed system aims to identify abnormal brain images from MRI scans accurately. The segmented mask can estimate the tumor's density, which is helpful in therapy. Deep learning techniques are employed to automatically extract features and detect abnormalities from MRI images. The proposed system utilizes a convolutional neural network (CNN), a popular deep learning technique, to analyze MRI images and identify abnormal brain scans with high accuracy. The system's training process involves feeding the CNN with large datasets of normal and abnormal MRI images to learn how to differentiate between the two. During testing, the system classifies MRI images as either normal or abnormal based on the learned features. The system's ability to accurately identify abnormal brain scans can aid medical practitioners in making informed decisions and providing better patient care. Additionally, the system's ability to estimate tumor density from the segmented mask provides additional information to guide therapy. The proposed system offers a promising solution for improving the accuracy and efficiency of brain tumor detection from MRI images, which is critical for early detection and treatment.

Keywords: Abnormality Detection, Brain Tumor, Convolutional Neural Network, Deep Learning, Early Detection, Medical Imaging, MRI, Patient Care, Therapy Guidance, Tumor Density, Tumor Segmentation.

I. Introduction

The brain is a crucial organ of the nervous system that comprises two hemispheres, namely the left and right sides. These hemispheres are connected by a bundle of fibers called the corpus callosum. The cerebrum, which is the largest part of the brain, is divided into four lobes, namely the frontal, parietal, temporal, and occipital lobes. The cerebellum, on the other hand, has a larger number of neurons and is responsible for controlling important body functions such as balance, coordination, and posture.

A brain tumor is an abnormal growth or mass of cells that develops in or around the brain. Possible causes of brain tumors include gene mutation or chromosomal abnormality and exposure to radiation. There are two main types of brain tumors: benign tumors and malignant tumors. A benign tumor is a non-cancerous growth that tends to grow slowly in the brain. It may cause symptoms such as severe, persistent headaches, seizures, persistent nausea, vomiting, and drowsiness. A malignant tumor, on the other hand, is a cancerous growth that tends to worsen progressively and can potentially lead to death. The abnormal cells that form a malignant tumor multiply at a faster rate compared to benign tumors. called a neural network. It consists of several layers of interconnected nodes that process information to extract meaningful features and make predictions.

Deep learning has shown promising results in the field of medical image analysis, including the detection and diagnosis of brain tumors. Deep learning algorithms can learn from a large number of MRI images and identify patterns that are indicative of tumors. They can also improve the accuracy of tumor detection compared to manual detection by radiologists. The proposed system for brain tumor detection using deep learning would involve training a neural network on a large dataset of MRI images with annotated tumor regions. The trained model can then be used to automatically detect tumors in new MRI images. This would not only improve the accuracy of tumor detection but also reduce the time and cost involved in manual detection by radiologists. In conclusion, the use of deep learning for brain tumor detection has great potential in improving the accuracy and efficiency of diagnosis. It is a promising area of research that can greatly benefit patients and healthcare providers.

Keras is a popular high-level Python deep learning API that simplifies the implementation of neural networks. It supports

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multiple low-level backends, including TensorFlow, PyTorch, and others, for fast computation. Keras provides various types of models, including sequential models, which are a linear stack of layers where one layer's output leads to the next layer's input. In the context of MRI image analysis for brain tumor detection, Keras can be used to develop a deep learning model for segmentation and classification of reconstructed magnitude images. The model can be trained on a large dataset of annotated MRI images to automatically detect and segment tumors in new images. Sequential models in Keras are simple and easy to implement, making them suitable for simple classifier or de-classifier models. However, for more complex tasks, other types of models such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) may be more appropriate.

The main objective of the proposed project is to develop a deep learning-based system that can automatically detect the presence of brain tumors in MRI images. The system aims to automate the manual process of brain tumor detection, which can be time-consuming and error-prone. The system is based on convolutional neural networks (CNNs), a type of deep learning model that is particularly well-suited for image analysis tasks. The system will be trained on a large dataset of MRI images with annotated tumor regions, enabling it to learn to detect tumors in new images. The development of deep learning applications for brain tumor analysis has become an active area of research in recent years. There are many different approaches to brain tumor analysis, including prediction and classification, and these can be driven by different methodologies and applications. A comprehensive review of the field can help researchers and practitioners better understand the state of the art and identify promising directions for future research.

II. Literature Survey

Various research studies have proposed different techniques for brain tumor detection using MRI images through machine learning and deep learning methods. Anand Deshpande et al. [1] presented a DCT-CNN-ResNet50 architecture that uses super-resolution, convolutional neural network, and ReNet50 to classify brain tumors. The experiment showed improved accuracy in classification compared to other methods. Dhanashri Joshi et al. [2] conducted a survey on brain tumor detection using machine learning and deep learning techniques on structural MRI images. They focused on digital image processing methodologies in the preprocessing, segmentation, and classification stages of MRI images to develop CAD systems. Their approach used SVM to classify images as normal or abnormal, and their system showed promising results in terms of reliability, accuracy, and computation time.

Praveen Gamage et al. [3] proposed a system that identifies brain tumors in MRI images using image processing techniques. Their system consisted of four components: pre-processing, image segmentation, feature extraction, and image classification. Devendra Somwaanshi et al. [4] presented an efficient mechanism for brain tumor detection from MRI images using entropy measures. They conducted a survey on different entropy functions for tumor segmentation and detection from various MRI images. They found that the segmented results were dependent on the threshold values derived from different entropy functions. These studies highlight the potential of machine learning and deep learning techniques in automating the manual process of brain tumor detection from MRI images, reducing the need for human intervention and improving accuracy in classification.

Nilesh Bharaskarrao Bahadure et al. [5] proposed an approach for MRI-based brain tumor detection and feature extraction using Berkely Wavelet Transform (BWT) and Support Vector Machines (SVM). The survey highlights the importance of segmenting brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid, and tumor-infected tissues. To improve the skull stripping performance, the authors used a skull stripping algorithm based on threshold techniques. Luxit Kapoor and Sanjeev Thakur [6] conducted a survey on brain tumor detection using various Image Processing Techniques. The survey covers the different medical image processing techniques used in discovering brain tumors from MRI images, where segmentation is considered the most significant step in the process of detecting tumors.

Deepa and Akansha Singh [7] conducted a literature review on machine learning-based brain tumor detection from MRI images. They found that the automation of brain tumor detection and segmentation from MRI images is a rapidly growing area of research in the medical field. In a separate study, S. Banerjee et al. [8] evaluated the accuracy of seven standard classifiers on the BRaTS 2015 dataset (which is a subset of the BRaTS 2017 dataset). The dataset consisted of 200 HGG and 54 LGG cases. They manually extracted 56 three-dimensional quantitative MRI features from each patient MRI and used them for classification. The classifiers tested included Adaptive Neuro-Fuzzy Classifier (ANFC), Naive Bayes (NB), Logistic Regression (LR), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Classification and Regression Tree (CART), and K-Nearest Neighbours (k-NN).

Swapnil R. Telrandhe [9] proposed a tumor detection method that involves segmenting an image into regions or objects. In order to properly analyze an image and classify its content, the item must be segmented from the background. Edge detection is an important tool for image segmentation and the performance of commonly used edge detection techniques were studied and compared through an experiment.

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Arun Kumar et al. [10] proposed an improved automated brain tumor segmentation and detection method using an Artificial Neural Network (ANN) model. They utilized MR data without human intervention and applied the best qualities for the initial detection of brain tumors. Their brain tumor segmentation technique included three main improvement focuses. First, they used K-means clustering to distinguish the areas of the region based on their grayscale. Second, ANN was used for correct object selection through the training step. Third, the tissue characteristics of the brain tumor area were removed to the mitotic stage. Gray-scale features were analyzed to recognize and diagnose brain tumors and distinguish between benign and malignant tumors. Their model was evaluated and compared to the SVM method segmentation outcomes and brain detection, achieving an accuracy of 94.07%, sensitivity of 90.09%, and specificity of 96.78%.

III. Problem Statement

The primary objective of this project is to enhance the performance of brain tumor detection using Convolutional Neural Network (CNN). Tumors are abnormal cell growths in the brain, and cancer refers to malignant tumors. The current practice of machine learning involves linear classifiers on top of hand-engineered features. However, image data requires an input-output function that is insensitive to irrelevant variations, such as changes in position, orientation, or illumination of an object. ConvNets have become the leading approach for recognition and detection tasks, achieving great success in the detection, segmentation, and recognition of objects and regions in images.

The existing system has limitations due to the small size of tumors in comparison to the rest of the brain, resulting in imbalanced brain imaging data. Consequently, existing networks tend to be biased towards one overrepresented class. The existing system also exhibits lower accuracy, higher false rates, longer processing time, and complexity in implementing real-time applications.

IV. System Architecture

The objective of the proposed method is to improve brain tumor detection in MRI images through the utilization of convolutional neural network (CNN) approach. The efficacy of this method is evaluated by testing its accuracy and comparing it with existing classification techniques. The proposed system encompasses several stages, including image acquisition, pre-processing, feature extraction, and classification. CNN architecture leverages convolution for automatic feature extraction from the entire image, and the number of feature maps increases with each additional convolutional layer. Additionally, the pooling layer downsamples the feature dimension, while the fully connected layers manipulate the score of each label. The softmax layer prepares the model with feature and class scores. The use of deep learning techniques, such as CNN, has demonstrated better accuracies than traditional methods. The proposed method employs lightweight libraries such as Matplotlib, Flask, and Keras in Python for image processing, which enhances the speed of execution. The proposed method employs various parameters for the classification of normal and brain tumor images.

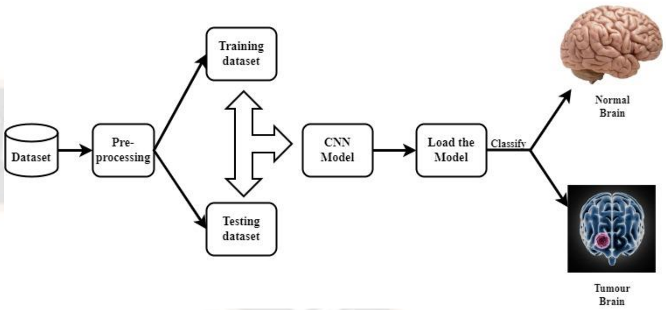

Figure 1 Architecture diagram for detecting the Tumorous Brain.

The successful implementation of a new system design is a critical phase in the overall system development life cycle. Implementation refers to the process of converting a new or revised system design into an operational one. This term can have different connotations, ranging from a simple application conversion to a complete replacement of a computer system. In this context, implementation denotes the process of translating a system design into a functional and operational system.

V. Convolution Neural Networks

The proposed system employs a Convolutional Neural Network (CNN/ConvNet) model for genre classification. CNN is a deep learning algorithm that is specifically designed for classifying images based on their spatial features [12]. Compared to other classification algorithms, CNN requires minimal pre-processing. The algorithm can efficiently capture the spatial and temporal characteristics of an image. The basic architecture of a ConvNet consists of an input layer, convolution and pooling layers, and a fully connected activation layer, as illustrated in Figure 2. The convolution layer comprises several filters or kernels that assist in extracting the primary features of an image. The main objective is to extract high-level features such as edges, color, gradient, and orientation from an input image. There can be multiple convolution layers, where the first filter captures low-level features, and the subsequent layers capture higher-level features. The pooling layer reduces the spatial size of the convolved feature to decrease the computational power required for data processing through dimensionality reduction. It also extracts the dominant features of the input. Max pooling is generally preferred over average pooling since it performs noise suppression, which is a beneficial feature. The fully connected activation layer is an inexpensive way of learning non-linear combinations of high-

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level features represented by the output of the convolution layers. Over multiple epochs, the model can distinguish between dominant and low-level features in the image and classify them using the SoftMax classification technique. The SoftMax function or normalized exponential function takes a vector of K real numbers as input and normalizes it into a probability distribution consisting of K probabilities.

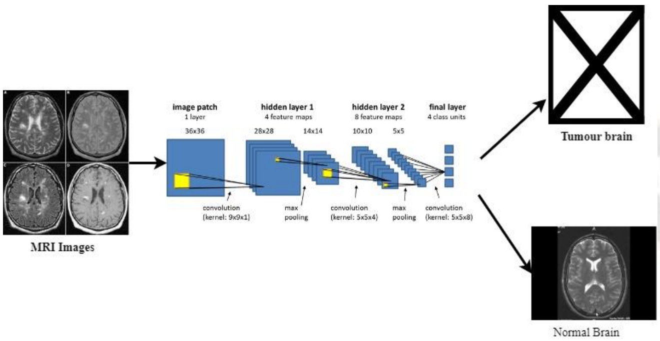

Figure 2 Convolution Neural Network Architecture**.**

Algorithm 1: CNN classification

Input: Dataset X Output: Trained model M

1. Apply pre-processing techniques to X to enhance desired features or reduce artifacts, and save the pre-processed dataset as X'.
2. Resize each image in X' to 24x24.
3. Split X' into training and validation sets, with a specified ratio (e.g., 80:20). Let X_train be the training set and X_val be the validation set.
4. Train a machine learning model M using X_train:

   a. Choose a model architecture and hyperparameters. b. Initialize the model with the chosen architecture and hyperparameters. c. Train the model on X_train using a suitable optimization algorithm and loss function. d. Evaluate the model's performance on X_val using a suitable metric (e.g., accuracy). e. Repeat steps b-d until satisfactory performance is achieved on X_val or a stopping criterion is met.
5. Evaluate the performance of the trained model M on a test set X_test using suitable metrics (e.g., confusion matrix and precision).

Note: This algorithm assumes a supervised learning problem with image data, where the goal is to classify the images into one of several predefined categories. The pre-processing techniques and model architecture/hyperparameters should be chosen based on the specific problem and data characteristics.

VI. Parameters of Convolutional Neural Network

1. The Keras deep learning framework was chosen to develop a convolutional neural network (CNN) for MRI image classification.
2. The input to the CNN consisted of MRI images with a spatial resolution of 224x224 pixels and 3 color channels (RGB).
3. The CNN architecture included three convolutional layers, each followed by a rectified linear unit (ReLU) activation function and a 2D max pooling layer. The first convolutional layer had 32 filters of size 5x5, while the second and third convolutional layers had 32 and 64 filters of size 3x3, respectively.
4. The max pooling layers had pooling sizes of 3x3, 2x2, and 2x2, respectively, to downsample the feature maps and reduce the spatial dimensionality.
5. A flatten layer was added to convert the output of the convolutional layers into a 1D vector.
6. A fully connected layer with 128 neurons and ReLU activation was added to perform feature extraction and dimensionality reduction.
7. To prevent overfitting, a dropout layer with a dropout rate of 25% was inserted after the fully connected layer.
8. The output layer consisted of two neurons with a softmax activation function, representing the binary classes of "Tumor" and "No Tumor".
9. The CNN was compiled using the categorical cross-entropy loss function, the Adam optimization algorithm, and the accuracy metric.
10. The CNN was trained on a dataset of MRI images with a batch size of 32 and for 10 epochs.
11. The performance of the CNN was assessed on a separate test dataset using various evaluation metrics, including accuracy, precision, recall, F1-score, and the confusion matrix.
12. The CNN was applied to predict the class of new unseen MRI images by computing the output probabilities of the final dense layer and selecting the highest one as the predicted class label.

The proposed system utilizes the Keras Sequential Model, a linear stack of layers, for the CNN architecture model. The Conv2D layer creates a convolution kernel that is applied to layers to produce a tensor of outputs. The MaxPooling layer is used to reduce the spatial dimensions of the output volume by selecting the maximum value of every 2 x 2 area of the image. The Dropout layer randomly sets input units to 0 with a frequency of rate during training time.

To build the system, the sequential model from the Keras library is used and layers are added to create the convolutional

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neural network. In the first two Conv2D layers, 32 filters are used with a kernel size of (5, 5). The MaxPool2D layer has a pool size of (2, 2) which reduces the image dimension by a factor of 2. The Dropout layer has a rate of 0.25, meaning that 25% of neurons are randomly removed. These three layers are applied again with some changes in parameters. The Flatten layer is then used to convert the 2-D data to a 1-D vector, followed by a dense layer, dropout layer, and another dense layer. The last dense layer outputs 2 nodes for brain tumor classification, using the SoftMax activation function to predict which of the 2 classes has the highest probability.

To acquire the necessary data for training and testing, the system takes input datasets. To build the model, libraries such as keras, sklearn, PIL, pandas, numpy, matplotlib, and tensorflow are imported. The images are retrieved and their labels are assigned. To ensure that all images are of the same size for recognition, they are resized to (224,224) and converted into numpy arrays. The dataset is then split into training and test data, with 82% used for training and 18% for testing.

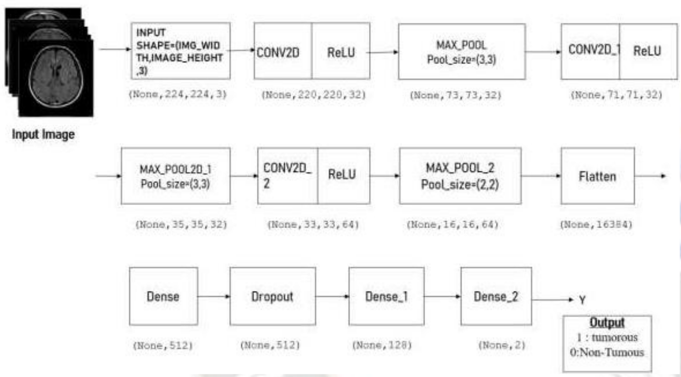

Figure 3 Keras Sequential Model on Brain Tumor MRI Images.

The sequential model is built using keras library. Two Conv2D layers are used with 32 filters and a kernel size of (5,5). The MaxPool2D layer has a pool size of (2,2) which reduces the image dimension by a factor of 2. The dropout layer is used with a dropout rate of 0.25, randomly removing 25% of neurons. These layers are then applied again with some changes in parameters. The flatten layer is used to convert 2-D data to a 1-D vector. This layer is followed by a dense layer, dropout layer, and another dense layer. The last dense layer has 2 output nodes indicating the presence or absence of a brain tumor. The SoftMax activation function is used to provide probability values and predict which of the 2 classes has the highest probability.

The model is applied for training using the fit function, with a batch size of 24. Graphs are plotted for accuracy and loss. Accuracy on the test set is calculated using the compile function with three parameters: loss, metrics, and optimizer. Finally, the trained model is saved using the pickle module. Let TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively. Then the evaluation metrics can be defined as follows:

i. Accuracy score : Accuracy score is a statistical measure that evaluates the performance of a classification model by calculating the proportion of correctly predicted samples out of the total number of samples in the dataset. This metric is used to measure how well a model can predict the correct class for a given input of brain images. The accuracy score is calculated by dividing the number of correctly classified samples by the total number of samples in the dataset.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Where TP is the true positive results, TN true negative results, FP is False positive and FN is false negative results obtained.

ii. Precision score: Precision is a performance metric that is used to evaluate the accuracy of a Convolutional Neural Network (CNN) model in classifying brain images. In the context of brain image classification, precision measures the proportion of true positive predictions out of all the positive predictions made by the model.

$$precision = \frac{TP}{TP + FP}$$

Here, true positives refer to the number of correctly predicted positive samples, while false positives refer to the number of negative samples that were incorrectly predicted as positive by the model. In brain image classification, precision is an important metric as it helps in assessing the model's ability to correctly identify positive cases while minimizing the number of false positive predictions.

iii. Recall score: In the brain image classification, recall score is a performance metric that measures the proportion of true positive cases that are correctly identified by the CNN model out of all the actual positive cases present in the dataset.

$$recall = \frac{TP}{TP + FN}$$

Here, true positives refer to the number of correctly predicted positive samples, while false negatives refer to the number of positive samples that were incorrectly predicted as negative by the model.

iv. F1-score: F1 score is a performance metric that combines both precision and recall to provide a more comprehensive evaluation of a CNN model's performance in brain image classification. F1 score is the harmonic mean of precision and recall, and it ranges from 0 to 1, with a higher score indicating better performance of the model.

$$F1 - score = 2 * \frac{precision * recall}{precision + recall}$$

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Table 1 The confusion matrix can be represented as follows.

	Predicted: Yes	Predicted: No
Actual: Yes	TP	FN
Actual: No	FP	TN

VII. Result Analysis

The proposed system takes MRI images as input and uses the train model function to load the dataset and generate a model. The test model function is then utilized to allow user interaction with the system. A User Interface provides a form for the user to upload an image file, and after a few seconds of analysis, the Interface outputs the corresponding class for the identified image file. The accuracy of the model on the test set is 99% when comparing the mean output distribution to the correct class. The dataset utilized in the project was sourced from the coding website Kaggle, and it comprised of fundus images. The training dataset contained a total of 7024 images, which were all obtained from the Kaggle dataset. The fundus images were categorized into two distinct classes, namely Tumor and No Tumor.

Confusion Matrix

A confusion matrix is a table that is commonly used to evaluate the performance of a classification model on a set of known test data. By presenting the number of correct and incorrect classifications for each class, it allows for easy identification of misclassifications between classes. This enables the visualization and summary of the performance of the algorithm, making it easier to calculate performance measures. The confusion matrix of the brain tumor classification model is shown in Figure 4, representing the performance of the proposed system's classification model. It provides a visual and concise summary of the algorithm's predicted and true labels, thus allowing for an effective evaluation of the model's performance.

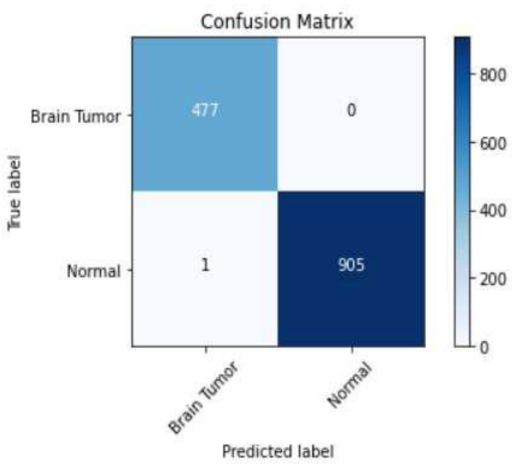

Figure 4 Confusion Matrix of Classification Model

Accuracy and loss

Accuracy and loss are important metrics used to evaluate the performance of a model. The loss is defined as the difference between the predicted and true values. The accuracy should increase as the loss decreases. Figure 5 represents a sequential model of training and testing loss and accuracy. The graph plots the values of loss and accuracy against the epoch number for the dataset used in training and testing the model. The graph shows that the loss significantly decreases over the first six epochs. The training loss and testing loss are quite similar, indicating that the model performs well. Additionally, Figure 6 shows there is an increase in accuracy over six epochs, and the graph shows an accuracy greater than 99%.

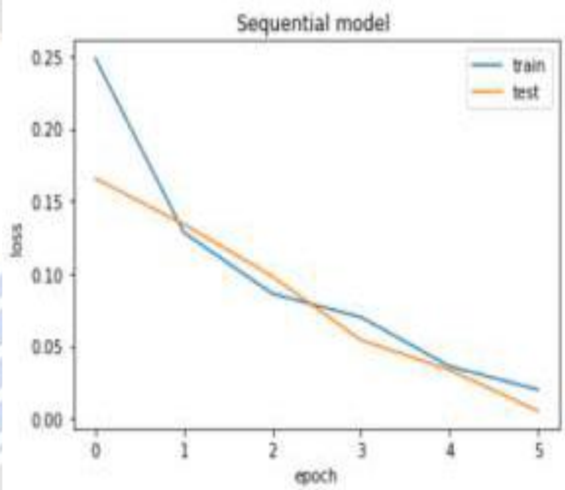

Figure 5 Loss over epochs During Test and Train

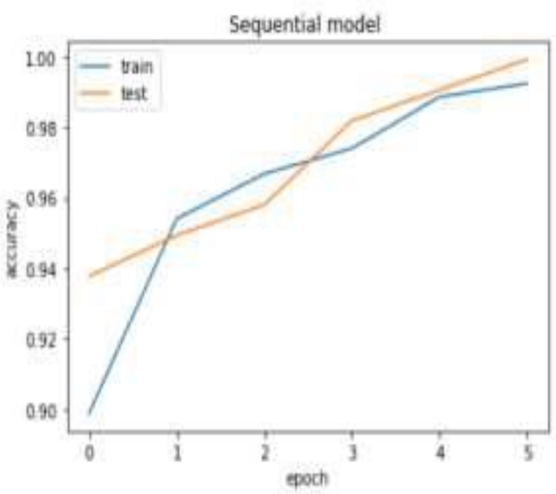

Figure 6 Accuracy over epochs During Test and Train

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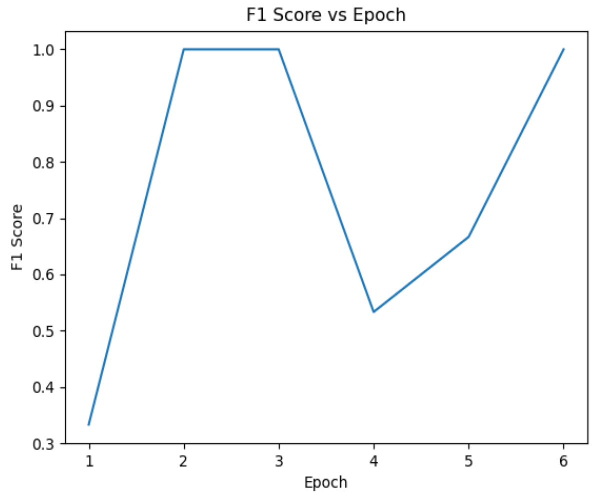

Figure 7 F1-score over 6 epochs

VIII. Conclusion

The proposed methodology utilizes deep learning techniques, specifically Convolutional Neural Networks (CNN), to automate the manual process of brain tumor detection from MRI images. This system is implemented in Python and aims to save time and reduce human effort in the detection process. The system is intended for use primarily in medical institutions. The CNN-based model is trained to detect the presence of brain tumors from MRI images, achieving an accuracy of 99.2% during training and 99.9% during testing, using the Keras sequential model. The performance of the classification model is assessed using a confusion matrix, providing an objective evaluation of the model's accuracy. This system can assist medical practitioners in accurately identifying brain tumors, saving time and effort compared to traditional manual detection methods. Additionally, it has the potential to reduce the occurrence of false negative diagnoses, which can be critical in ensuring early detection and treatment of brain tumors. The proposed system offers a promising solution for improving the accuracy and efficiency of brain tumor detection from MRI images.

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