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DETECTION OF BRAIN TUMOR USING NEURAL NETWORKS

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ABSTRACT
A brain tumor is a growth of abnormal cells in the brain or near it. Identifying brain tumor lately may cause serious issue to the person. So, to identify it in the initial stages we use convolutional neural networks. Convolutional Neural Networks (CNNs) is a popular and promising approach for medical image analysis. These networks can effectively learn features from medical images and provide accurate diagnoses for brain tumor. The general process for using CNNs for brain tumor detection and classification involves data acquisition, data preprocessing, data augmentation, model selection, model training, model evaluation and model deployment. They show promising solution for detecting brain tumors as they are more accurate and efficient in medical diagnosis. Through this, the types of brain tumor can be identified that can reduce the risk of people and can increase the chances of life expectancy, when started diagnosing in early stages. As these networks continue to evolve, they are expected to become an even more important tool for medical professionals in the future.

Index Terms: Convolutional Neural Networks (CNN), Magnetic Resonance Imaging (MRI), Rectified Linear Unit (ReLU), Computed Tomography (CT).

INTRODUCTION:
Medical imaging techniques are used to take pictures of the inside of the human body for diagnosing medical conditions. One challenging and important topic in image processing is classifying medical images, particularly for tumor detection or cancer detection. Brain tumors are especially concerning, as they have a high death rate and are a leading cause of cancer-related deaths in children and adults under 34 years old. Doctors use advanced methods like CT scans and MRI scans to detect tumors. MRI-based analysis for brain tumors is becoming more popular as it allows for efficient and objective evaluation of large amounts of medical data. This requires sophisticated computerized tools to analyze and visualize the images. Automatic brain tumor detection from MRI images can play a crucial role in alleviating the need for manual processing of large amounts of data. A brain tumor is an abnormal mass of cells that can be either benign (not cancerous) or malignant (cancerous), and it can occur in different parts of the brain. Brain tumors can start in the brain (primary) or spread to the brain from other parts of the body (secondary).They can cause different symptoms depending on their size, location, and type, such as headaches, seizures, changes in vision or hearing, difficulty with speech or movement, and mood changes.

Doctors usually use CT scans or MRI scans to diagnose brain tumors. Treatment options include surgery, radiation therapy, chemotherapy, and targeted therapies, and the prognosis depends on various factors like tumor type, size, location, and overall health of the patient. It's important for those who suspect a brain tumor to seek medical evaluation and appropriate care from a healthcare professional without delay.

EXISTING STRATEGIES: Brain tumors are a serious medical condition that can be difficult to detect. Current methods of diagnosis are often inaccurate and time consuming, leading to delays in treatment. Our goal is to find a better solution for this problem so that people no longer need to suffer for long periods of time. The existing system is using the CNNs and DNNs for detecting whether the person has cancerous or non- cancerous tumors and a certain type of tumor. The output for this system can be "TUMOR DETECTED" or "TUMOR NOT DETECTED" and Benign refers to non- cancerous tumor and Malignant refers to cancerous tumor.

Limitations of existing Solutions:

❖ Can only detect cancerous and non- cancerous tumors.

❖ Doesn't classify the type of tumor.

PROPOSED SOLUTION:

The proposed system for detecting brain tumors would use computer programs to look at medical images of the brain (MRI) and determine if there are any tumors present. The system would first clean up the images to make them clearer, then separate the brain from the rest of the image. It would then use a special type of computer program to find patterns in the image that could indicate the presence of a tumor. Once the computer program is trained to recognize the different types of tumors, it would be able to automatically detect and identify glioma, meningioma, and pituitary tumors in new images.

Advantages:

❖ The proposed system for detecting three types of brain tumors (glioma, meningioma, and pituitary tumors) has several advantages over traditional diagnostic methods:

❖ Accurate Diagnosis: The proposed system uses CNN to accurately detect and classify brain tumors. This can help doctors make more accurate diagnoses and plan more effective treatment strategies.

❖ Efficiency: The proposed system can quickly and efficiently process medical images, reducing the time it takes to diagnose and treat brain tumors. This can lead to faster treatment and better patient outcomes.

❖ Cost-effective: The proposed system can potentially reduce healthcare costs associated with the diagnosis and treatment of brain tumors. By accurately detecting brain tumors early on, the system can help avoid costly treatments and procedures later on.

IMPLEMENTATION:

The implementation process includes the uploading the image which is the random image to test the type of tumor. At first the model should be trained to detect the tumor. It will be trained by using a dataset from Kaggle that contains MRI images of brain with four categories (Glioma, Meningioma, Pituitary and No Tumor) of separation in it. The model is trained by taking each image through the CNN layer. After training the model with all the images in the dataset, it will be saved in a preferred location. Secondly, the image needs to be provided to test, an interface will be available to take the input from the user which is the MRI image of brain. This interface was designed using TKinter. The saved model will predict the presence of tumor and classify the type of tumor. Then this result will be displayed to the user.

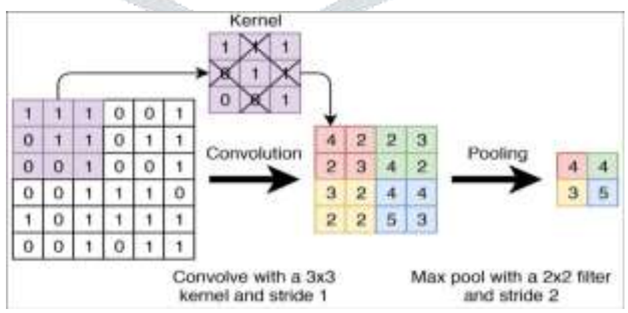
In the medical profession, recent technological advancements play an essential role in the early detection and categorization of many diseases that cause mortality. The technique rising on daily basis for detecting illness in magnetic resonance through pictures is the inspection of humans. Automatic (computerized) illness detection in medical imaging has found you the emergent region in several medical diagnostic applications. Various diseases that cause death need to be identified through such techniques and technologies to overcome the mortality ratio. The brain tumor is one of the most common causes of death. Researchers have already proposed various models for the classification and detection of tumors, each with its strengths and weaknesses, but there is still a need to improve the classification process with improved efficiency. However, in this study, we give an in-depth analysis of six distinct machine learning (ML) algorithms, including Random Forest (RF), Naïve Bayes (NB), Neural Networks (NN), CN2 Rule Induction (CN2), Support Vector Machine (SVM), and Decision Tree (Tree), to address this gap in improving accuracy. On the Kaggle dataset, these strategies are tested using classification accuracy, the area under the Receiver Operating Characteristic (ROC) curve, precision, recall, and F1 Score(F1). The training and testing process is strengthened by using a 10-fold cross- validation technique. The results show that SVM outperforms other algorithms, with 95.3% accuracy.

- A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.
- This network comprises of many layers. Out model consists of

1. Convolutional layer: A convolutional layer is the main building block of a CNN. It contains a set of filters (or kernels), parameters of which are to be learned throughout the training. These layers generate a feature map by sliding a filter over the input image and recognizing patterns in images.

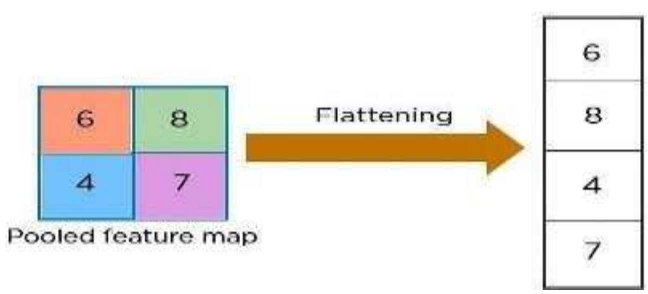
2. Max pooling layer: A convolutional layer is the main building block of a CNN. It contains a set of filters (or kernels), parameters of which are to be learned throughout the training. These layers generate a feature map by sliding a filter over the input image and recognizing patterns in images.

3. Fully connected layer: A fully connected layer refers to a neural network in which each neuron applies a linear transformation to the input vector through a weight's matrix. As a result, all possible connections layer-to-



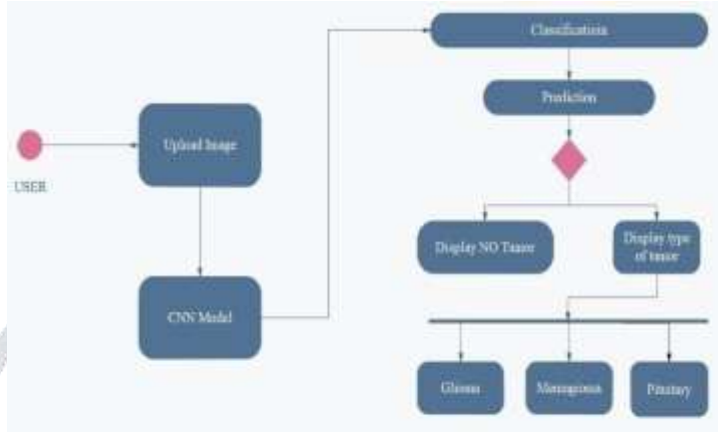
layer are present, meaning every input of the input vector influences every output of the output vector.

4. Dropout layer Flatten layer: The Flatten layer is used to convert the multi-dimensional output of a



convolutional or pooling layer into a one- dimensional vector. It "flattens" the input.

SYSTEM ARCHITECTURE:



Convolutional Neural Networks (CNN): Convolutional Neural Networks (ConvNets or CNNs) are a type of neural network that share their parameters. You can think of an image as a cuboid with length, width, and height (representing the dimensions of the image and its color channels). Convolutional Neural Networks (CNNs) have a different architecture compared to regular Neural Networks. Regular Neural Networks process inputs through hidden layers, where each layer has neurons that are fully connected to all neurons in the previous layer. Neurons in a layer function independently and do not share connections with each other. The output layer represents the predictions. However, regular Neural Networks do not work well with images. CNNs are different in that their layers are organized in three dimensions: width, height, and depth. Neurons in one layer do not connect to all neurons in the next layer, but only to a small region of it. The final output is a single vector of probability scores, organized along the depth dimension. Moreover, CNNs perform convolution operation in case of matrix multiplication. On the left side of the figure, there is a regular three-layer neural network. On the right side, there is a Convolutional Neural Network (CNN) that organizes its neurons in three dimensions: width, height, and depth. Each layer of the CNN transforms the 3D input volume into a 3D output volume of neuron activations. In this example, the red input layer represents the image, with width and height corresponding to the image dimensions, and depth representing the three-color channels (Red, Green, Blue).

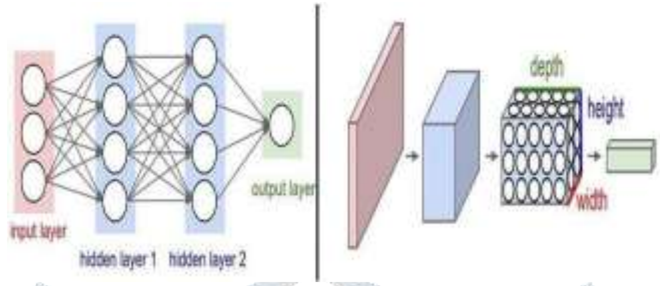


Figure 1: A simple neural network and A Convolutional Neural Network

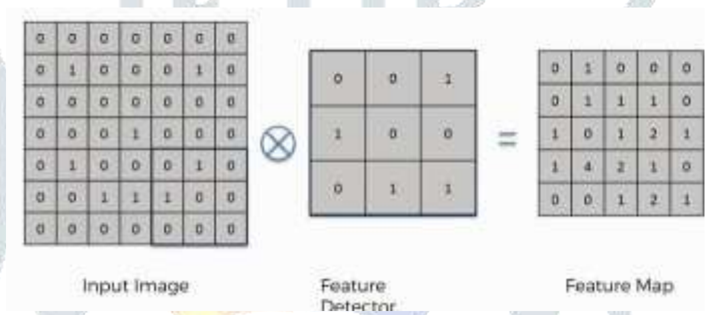


Figure 2: Convolution Operation

Excepted Results:

The implementation process includes the uploading the image which is the random image to test the type of tumor. At first the model should be trained to detect the tumor. It will be trained by using a dataset from Kaggle that contains MRI images of brain with four categories (Glioma, Meningioma, Pituitary and No Tumor) of separation in it. The model is trained by taking each image through the CNN layer. After training the model with all the images in the dataset, it will be saved in a preferred location. Secondly, the image needs to be provided to test, an interface will be available to take the input from the user which is the MRI image of brain. This interface was designed using TKinter. The saved model will predict the presence of tumor and classify the type tumor. Then this result will be displayed to the user. If there is an image that is not belonging to four classes then the matrix values closer to the values of particular class will be displayed.

Figure 3.1: Go to the folder that contains the required files.

Figure 3.2: Run the TC.py file

Figure 3.3: Model starts training

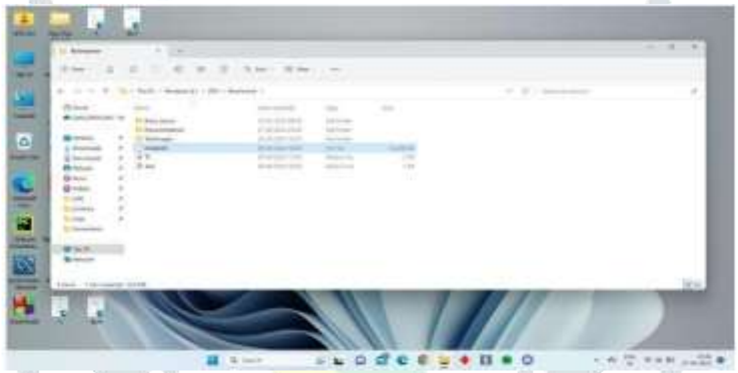


Figure 3.4: Upload the image to test

CONCLUSION:

In this project, we used Convolutional Neural Networks (CNN) to train the brain tumor classifying model by giving it the required dataset and after training we can use this model to predict the type of brain tumor from new brain MRI (magnetic resonance imaging) images. It is able to detect three types of tumors which are Glioma, Meningioma and Pituitary respectively. If there is no presence of tumor in it, it gives no tumor as output. So, it contains four classes. Our training accuracy was 86% and our prediction accuracy is nearly 100%. If there is presence of other type of tumor this model gives the nearest tumor class as output, with the right quality images our model can detect Glioma, Meningioma and Pituitary tumors accurately.

FUTURE ENHANCEMENT:

The future scope of detection of brain tumor involves in training the model to detect more than three types of tumors. Here are some potential future enhancements:

- Attention mechanism: Attention mechanisms can be used to enhance the CNN model's ability to focus on important regions of the image that are most indicative of a brain tumor. This can improve the model's accuracy and reduce false positives.
- Explainable AI: Explainable AI techniques can be used to make the CNN model more transparent and interpretable. This can help radiologists to understand the model's predictions and increase their confidence in the model's results.
- Online learning: Online learning techniques can be used to continuously update the CNN model with new data. This can improve the model's accuracy over time and enable it to adapt to new types of brain tumors.
- Integration with clinical workflows: Integrating the brain tumor detection system with clinical workflows can improve the efficiency of the radiology department. For example, the system can automatically flag potentially abnormal cases for immediate attention, or provide a second opinion on difficult cases. Overall, these future enhancements can improve the accuracy, efficiency, and effectiveness of brain tumor detection system. This can lead to better patient outcomes and help radiologists to make more informed decisions about treatment planning.

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