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 pre- processing, 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

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.

Problem statement
The objective of this project is to develop an accurate and reliable system for the detection of brain tumors using neural networks. Brain tumors are a significant health concern, and early detection plays a crucial role in effective treatment and improved patient outcomes. However, traditional methods of brain tumor detection, such

as manual inspection of medical images by radiologists, can be time-consuming, subjective, and prone to human error.

Scope

The International Association of Cancer Registries (IARC) reported that there are over 28,000 cases of brain tumours reported in India each year and more than 24,000 people reportedly die due to brain tumours annually. A brain tumours is a serious condition and can be fatal if not detected early and treated. The 5-year relative survival rate for a cancerous brain or CNS tumor is almost 36%. The 10-year survival rate is over 30%. The 5-year relative survival rate for people younger than age 15 is about 75%. For people age 15 to 39, the 5-year relative survival rate nears 72%. The 5-year relative survival rate for people age 40 and older is 21%.

Objective

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. Our objective is to create a model that can predict if medical images contain a brain tumor or not, and also identify the type of tumor. Collecting a dataset of brain tumor images is a challenging task as it is scarce and complicated to acquire. However, our approach is to develop a model that can perform all the necessary tasks to detect and analyze brain tumors efficiently and effectively without human assistance.

LITERATURE SURVEY

The literature survey on brain tumor detection focuses on reviewing existing research and studies related to the detection of brain tumors. This survey provides an overview of the current state of the field, including the methods, techniques, and algorithms used for brain tumor detection and also serve as the foundation for our research, guiding us in understanding the existing knowledge, identifying potential research directions, and building upon the work of previous researchers in the field of brain tumor detection.

Brain Tumor Detection and Classification using Convolutional Neural Network and Deep Neural Network:

For successful treatment of the disease, accurate and early detection of brain tumours is essential. Early detection not only helps to come up with better medications, it can also save a life in due time. Neuro-oncologists are benefiting in many ways by the advent of Computer-Aided Diagnosis and biomedical informatics. Computer-aided mechanisms are applied to obtain better results as compared with manual traditional diagnosis practices. This is generally done by extracting features through a convolutional neural network (CNN) and then classifying using a fully connected network. The proposed work involves the approach of deep neural network and incorporates a CNN based model to classify the MRI as " TUMOUR DETECTED & quot; or & quot; TUMOUR NOT DETECTED & quot;. The model captures a mean accuracy score of 90.14% with f- score of 97.3.

Detection and Classification of Brain Tumors From MRI Images Using a Deep Convolutional Neural Network Approach:

Brain tumor is a severe cancer disease caused by uncontrollable and abnormal partitioning of cells. Timely disease detection and treatment plans lead to the increased life expectancy of patients. Automated detection and classification of brain tumor are a more challenging process which is based on the clinician’s knowledge and experience. For this fact, one of the most practical and important techniques is to use deep learning. Recent progress in the fields of deep learning has helped the clinician’s in medical imaging for medical diagnosis ofbrain tumor. In this paper, we present a comparison of Deep Convolutional Neural Networks (DCNNs) models for automatically binary classification query MRI & CT scan images dataset with the goal of taking precision tools to health professionals based on fined recent versions of DenseNet, Xception, NASNet-A, and VGGNet. The experiments were conducted using an MRI & CT scan open dataset of 3,762 images acquired with three kinds of brain tumor, Meningioma, Glioma, and Pituitary tumor, precision, recall, F-score, and specificity. Finally, the accuracy and results of these algorithms are analyzed by comparing the effectiveness among them.

Machine Learning-Based Models for Magnetic Resonance Imaging (MRI)-Based Brain Tumor Classification:

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. 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 an eed 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 Net-works (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 90.14% accuracy.

Existing System

The existing system is using the CNNs and DNNs for detecting whether the person has cancerous or non-cancerous tumors. The output for this system would be “TUMOR DETECTED” or “TUMOR NOT DETECTED” and if the is presence of tumor in it, Benign refers to non-cancerous tumor and Malignant refers to cancerous tumor. The existing model can only detect benign or malignant tumors but do not classify the type of tumor. Classifying the type of tumor can be more beneficial for early diagnosis which can increase the chances of life after treatment.

Proposed System

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.

METHODOLOGY

Image Pre-Processing

Image pre-processing refers to the techniques and methods used to modify, enhance, or prepare digital images for further analysis or processing. It involves a series of image processing operations that are applied to raw images to improve their quality, remove noise, enhance features of interest, and standardize their format for further analysis.

Image pre-processing techniques typically include operations such as image resizing, color correction, contrast enhancement, noise reduction, image filtering, and image normalization. These operations are performed to remove any artifacts or inconsistencies in the images that may affect the accuracy of subsequent image analysis or computer vision algorithms.

Image Classification

Image classification is a type of computer vision task that involves categorizing images into predefined classes or categories based on their visual content. It typically involves the use of machine learning algorithms that are trained on labeled image data to learn patterns and features that are indicative of different classes. Once trained, these algorithms can then be used to automatically classify new, unseen images into the appropriate classes. Image classification has a wide range of applications, including object recognition, facial recognition, medical image analysis, and more. It is an important technique used in various fields to automatically and accurately classify images based on their visual features, making it a valuable tool for many real-world applications.

Image Processing for Brain Tumor segmentation:

Segmenting tumors from MRI brain images is a challenging task that requires accurately identifying the region of interest within an object. It is considered ambitious due to the complex nature of brain tumors and the large amount of data involved. Brain tumor segmentation is a critical step in medical image processing as tumors can have soft tissue boundaries and may not be well-defined. Image processing techniques are used to enhance the quality of MRI images and extract features for classification. The image processing steps for brain tumor segmentation include skull stripping, pre-processing, and tumor contouring, among others.

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 colour 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.

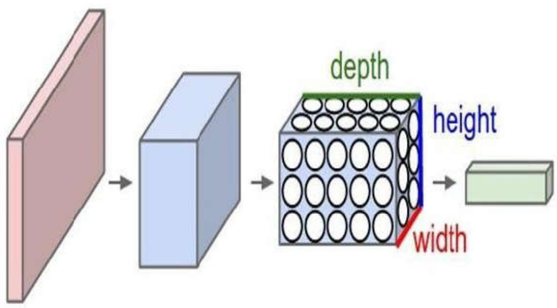
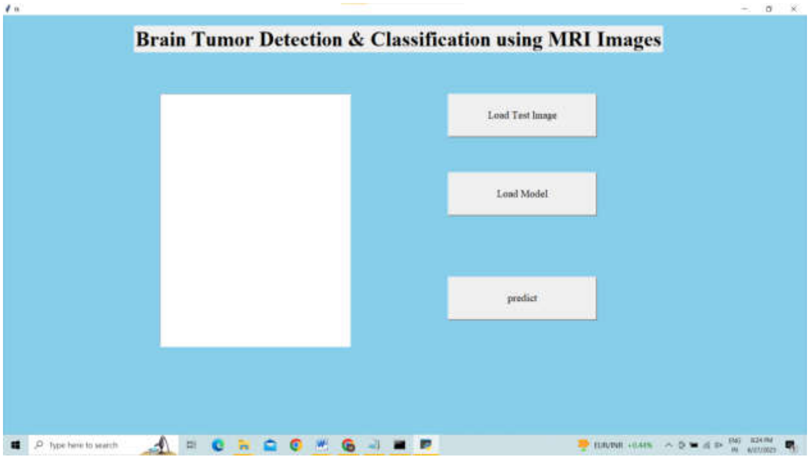


Figure.1. A simple neural network and A Convolutional Neural Network

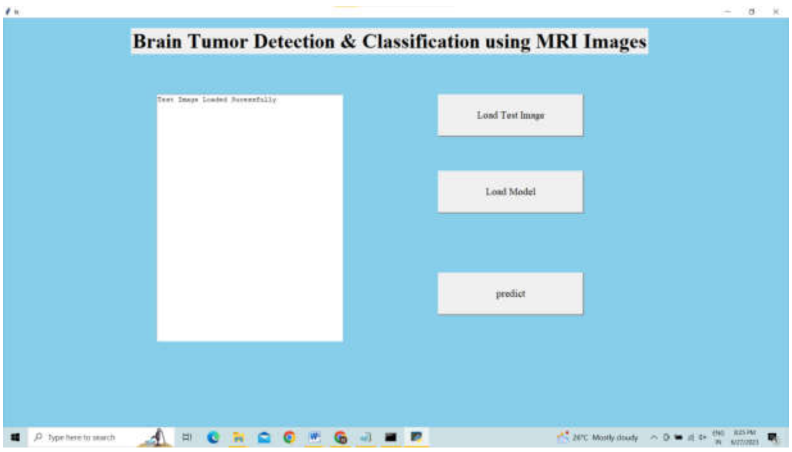
Convolutional Neural Networks (CNNs) use a mathematical operation called convolution. Convolution is a mathematical operation that combines two functions (f and g) to produce a third function. The convolution operation of f and g is denoted as f*g and is defined as the integral of the product of the two functions after one is reversed and shifted. This operation involves an input image, a feature detector (often called a "kernel&

quot; or "filter"), and a feature map (also known as an activation map) which indicates where a certain kind of feature is found in the image. The feature detector is typically a 5x5 or 7x7 matrix used to extract features from the input image.

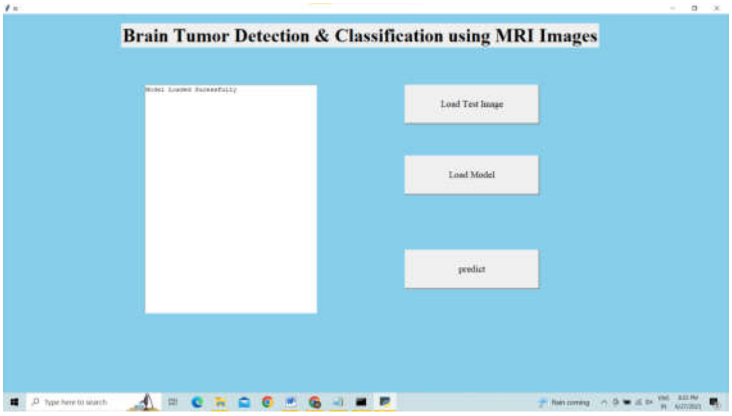
Results



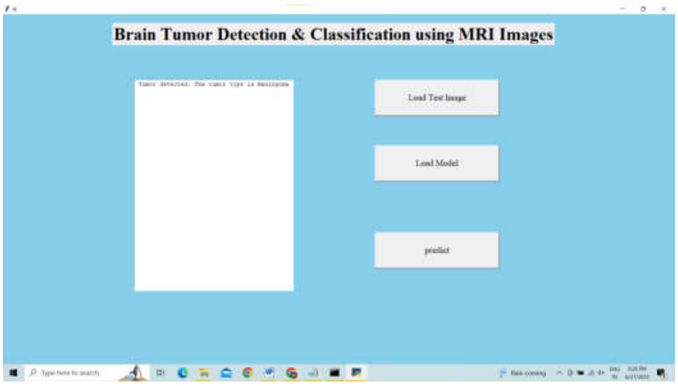
The above picture shown is the user interface of our application for detection of brain tumor. In the UI of application, we used methods to load test image, load model, and to predict the output.



After uploading the scanner of human brain, an output is shown that the test image loaded successfully by onclick on Load Test Image in User Interface of application for detection of brain tumor.



When the output is given as image loaded successfully, then our model is loaded to our scanned human brain image. Onclick on Load Model, an output will be given as Model Loaded Successfully.



Finally we predict the output as the tumor present in the scanned brain image or not. If the tumor is found the our application will detect that tumor is present and also the type of tumor is also shown.

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. In summary, the application of neural networks for the detection of brain tumors shows great promise in automating and improving the accuracy of tumor identification. By leveraging advanced neural network architectures, along with medical imaging techniques and preprocessing methods, this project aims to enable early detection, precise localization, and timely medical interventions for improved patient outcomes.

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