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BRAIN TUMOR DETECTION AND CLASSIFICATION ON MRI IMAGES USING MACHINE LEARNING TECHNIQUES

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Abstract: Automatic flaw detection in medical images is a rapidly growing subfield used in a variety of medical diagnostics. Automated tumor diagnosis in MRI is significant because it reveals information about aberrant tissues that is required for treatment planning. For this reason, reliable automatic classification systems are crucial for reducing human mortality. Since saving the radiologist's time and achieving a tested accuracy is a priority, automated tumor detection systems are being developed. We propose the use of the CNN machine learning method in this study to identify brain tumors

Index Terms **- Automatic flaw detection, Medical images, MRI, CNN.**

I. INTRODUCTION

The human brain is a crucial organ since it regulates the body's processes and plays a role in forming decisions. The brain acts as the body's command centre, orchestrating both voluntarily and involuntarily performed tasks. The tumor is an uncontrolled growth of fibrous, malignant tissue within our brain. In the United States alone, over 3,540 young people under the age of 15 are diagnosed with a brain tumor every year. Preventing and treating brain tumors requires a thorough familiarity of the disease's progression through its stages. Radiologists frequently utilize MRI for the evaluation of brain malignancies. Here, we use deep learning techniques to analyze brain images and determine whether they belong to a healthy or ill individual. To distinguish between healthy and diseased brain tissue, this study employs ANN and CNN. Similar to how the nervous system in the human brain works, an ANN (Artificial Neural Network) allows a digital computer to learn from experience by being fed data through a series of simple processing units that are then applied to the training set. It's made up of interconnected neuronal layers. The neural network can learn new information by being exposed to a data collection. There will only be one visible layer between the input and output layers, whereas the number of hidden layers is unconstrained. Neurons in each successive layer have their weight and bias adjusted based on the information received from the layer below it and the input features (for hidden layers and output layers). To get the desired result, a model is trained using the activation function applied to the input features and the hidden layers. Since this article employs an image as its input and since ANN operates with fully linked layers, where additional processing is required, the emphasis is on applying CNN as well. For those unfamiliar, convolutional is the name of the linear operation used in CNN (convolutional neural network). Without losing any of the essential training data, CNN's successive layers reduce the image's overall dimensionality. The model is constructed using a variety of processing techniques, including convolve, max pooling, dropout, flatten, and dense. In this study, we create our own ANN and CNN model architecture and compare their results when applied to an MRI dataset of brain tumors.

II. LITERATURE SURVEY

[1] The study recommends a CNN (Convolution Neural Network)-based automatic segmentation approach, which uses small 33 kernels to perform the segmentation. This method combines two processes into one, allowing for efficient segmentation and classification. CNN is a machine learning technology that derives from NN (Neural Networks) and uses a layer-based approach to classification outcomes. The proposed techniques consist of the following stages: (1) data collection; (2) preprocessing; (3) average filtering; (4) segmentation; (5) feature extraction; and (6) CNN by means of classification and identification. Important connections and patterns in the data can be extracted using DM (data mining) techniques.

[2] This review walked readers through the fundamentals of brain tumors, where to find data, how to improve it, how to enhance it, how to segment it, extract features for classification, how to use deep learning, transfer those features, and how to use quantum machine learning to analyze it. This overview also includes the benefits, drawbacks, advances, and forthcoming trends of all relevant literature for detecting brain cancers.

[3] When applied to disease detection, machine learning techniques such as SVM, KNN, Naive Bayes, and Decision tree can improve decision-making speed while simultaneously decreasing the number of false positives. Python is discussed as a realistic implementation language for these algorithms. Cancer, diabetes, epilepsy, heart attack, and other major disorders are all diagnosed with the help of these algorithms.

[4] Early discovery of cancers can reduce mortality rates. M.R.I., or magnetic resonance imaging, is the standard technique for detecting brain tumors (MRI). Because of the detailed information about the tumor's structure that MR images provide, they are being considered. An innovative method for detecting cancers in MR images is proposed, which makes use of machine learning techniques and, in particular, the CNN model.

[5] Noise reduction, segment-based morphological operation, feature extraction, and a Naive Bayes classifier are some of the project's stages. First, a picture of the patient's brain has to be taken. Pre-processing the captured image, then performing feature extraction and categorization. The rate of correct classification is improved by 60% over previous methods. With accurate prognostic information, the tumor's location and extent can be determined, and the brain cancer can be surgically removed.

,[6] The proposed method seeks to distinguish between healthy and malignant brain tissue (benign or malign). Brain MRI is used in the investigation of malignant brain tumours like glioblastoma, sarcoma, and metastatic bronchogenic carcinoma (MRI). Using a combination of wavelet transforms and support vector machines, MRI brain cancers can be detected and classified.

[7] In this study, we propose two deep learning based methods for identifying and categorising brain tumors by utilizing the state-of-the-art object detection framework YOLO (You Only Look Once) and the deep learning library FastAi. Part of the BRATS 2018 dataset (which included 1,992 Brain MRI images) was used for this investigation. The accuracy of the FastAi classification model was 95.78 percent, whereas that of the YOLOv5 model was 85.95 percent.

[8] The screening process for brain tumors has been greatly enhanced by new technologies that complement conventional imaging methods. Data on brain tumors are typically not made available to the general population. The BRAMSIT database is intended for use by those conducting studies on analyzing MRI images. The proposed MRI database is called BRAMSIT, and it aims to provide users with a set of both benign and malignant examples of brain tumors. Patient information is interpreted in the database, including demographic information and MRI axial positions (trans-axial, coronal, and sagittal).

[9] There are four steps to the proposed method: lesion enhancement, feature extraction and selection for classification, localization, and segmentation. Prediction scores for localization, segmentation, and categorization of brain lesions were all higher than 0.90 with the suggested method. Classification and segmentation results are also improved over prior approaches.

[10] The hybrid method for classifying brain tumors uses a support vector machine (SVM) in conjunction with a genetic algorithm to reduce the number of features and a discrete wavelet transform (DWT) for feature extraction. Pictures are retrieved from the SICAS Medical Image Repository, which has already categorized the pictures as either benign or malignant. The MATLAB 2015a environment is used to implement the proposed hybrid strategy.

III. ARCHITECTURE DESIGN

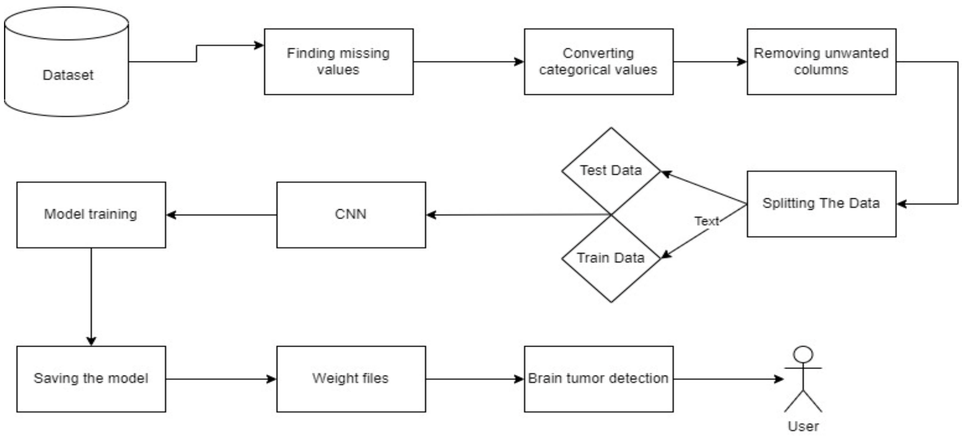

Figure 1: Block Diagram

IV. METHODOLOGY

The proposed system contains the following modules:

1) GUI Data Augmentation
2) Image Preprocessing
3) Feature Extraction Prediction

4.1 GUI Data Augmentation

To assist in the identification of brain tumors in medical photographs, a brain tumor detection GUI (Graphical User Interface) can be created. The automatic detection and segmentation of tumors in brain scans, such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans, can be accomplished using machine learning techniques.

You can use libraries like Tkinter, PyQt, or wxPython, which offer tools for making interactive interfaces, to build a GUI for detecting brain tumors. The user can submit medical photos, choose the type of scan, and select the algorithm that will be used to find the brain tumor using the GUI.

Data augmentation is a process that entails generating new data from the existing data by subjecting the original images to various transformations, such as flipping, rotating, or scaling. The amount and diversity of the dataset can be increased through data augmentation, which can raise the machine learning model's accuracy.

Use libraries like Augmentor or Augmentations to provide data augmentation to medical photos. In order to build fresh iterations of the original medical images, these libraries offer a variety of image augmentation capabilities. It is crucial to check that the alterations made do not change the diagnostic information in the medical images before performing data augmentation.

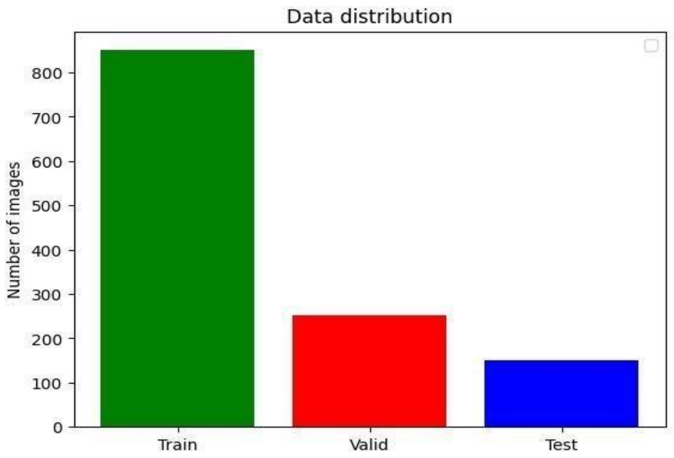

Figure 2: GUI Data Augmentation

In conclusion, creating a GUI for brain tumor detection can help with the quick and accurate identification of these lesions. By expanding the diversity and size of the dataset, the use of data augmentation techniques to medical images can also assist machine learning algorithms perform better.

The user or patient will interact with the application using this interface. This user interface was designed to be as straightforward as possible for the sake of its end-users. In this step, we train these input parameters and develop a model. Training these input parameters thoroughly is necessary for achieving high accuracy. The precision with which a machine learns to identify an outcome depends on both the features present in the training data and the quality of the labelled training data. Data cleaning and proper formatting are necessities for ML-based case prediction. Linear transformations, including random rotation (from 0 to 10 degrees), horizontal and vertical shifts, and horizontal and vertical flips, are all part of data augmentation. When just a small number of training samples are available, data augmentation is used to help the network learn the invariance and resilience features that were originally required.

4.2 Image Preprocessing

Any computer vision task that uses convolutional neural networks (CNNs) for image recognition or classification must start with picture preparation. Because they can automatically identify features from images, CNNs are commonly employed in image processing applications. However, pictures must first undergo preprocessing to guarantee that they are in a format compatible with CNNs before being trained on them. The most popular image preparation methods that can be used to get ready images for CNN-based applications are covered in this paragraph. Image normalization is the initial preprocessing method, and it entails scaling the pixel values of the images to a comparable range and distribution. In order to make the CNN converge more quickly during training, it is ensured that the input has a consistent scale and is centered around zero. Scaling the values of the pixels to the range [0, 1] or [-1, 1] is one of the normalization procedures. The second method is picture resizing, which is adjusting the photos' dimensions to a particular value. In order to ensure that the filters used in the convolutional layers match the image dimensions, CNNs require input images to have a fixed size. With libraries like OpenCV or PIL, resizing can be accomplished.

The third method, known as data augmentation, transforms existing photos by rotating, resizing, flipping, or altering brightness or contrast to create new ones. When a model performs well on training data but badly on new data, this is known as overfitting. Data augmentation helps to decrease overfitting and increase the diversity of the dataset. To add fresh variants to the photographs, augmentation techniques like random cropping, random flipping, or Gaussian blur might be used. The fourth method is image cropping, which entails choosing a certain area of interest within the image and removing everything else. When the photos contain unimportant or irrelevant information that could impair the performance of the model, this can be helpful. Cropping can aid in directing the model's emphasis to the important elements of the image, increasing the model's accuracy.

Image denoising, the fifth approach, involves taking out noise or artifacts from the image. Images in real-world situations may have noise or artifacts that can impair the performance of the model. To reduce this noise and enhance the image quality, denoising techniques like Median or Gaussian filtering can be used. Depending on the application, additional preprocessing methods can also be used, including edge detection, color normalization, and contrast enhancement. It's crucial to remember that the preprocessing methods shouldn't change the fundamental aspects of the image that the model needs to learn. In conclusion, the success of CNNbased computer vision applications depends critically on image preprocessing. Preprocessing methods including normalization, scaling, cropping, data augmentation, and denoising can be used to enhance model performance and lessen overfitting. The preprocessing methods chosen depend on the application, and they should not change the image features that the model needs to learn.

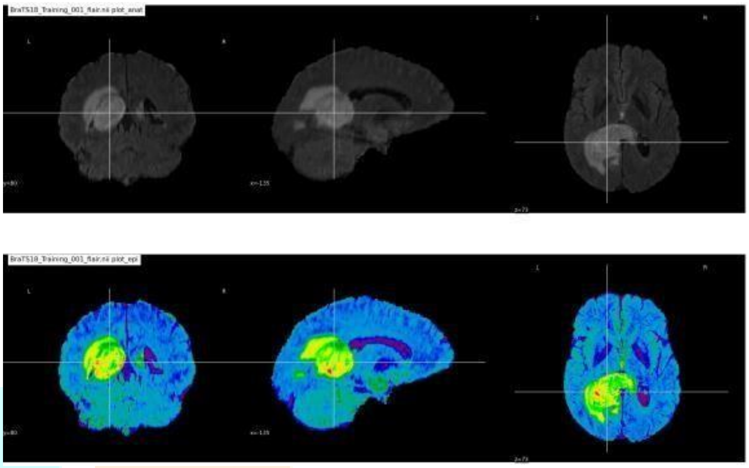

Figure 3: Image Preprocessing

4.3 Feature Extraction Prediction

Any machine learning system must have both feature extraction and prediction. Selecting the pertinent features from the data that can be utilized to train the model is known as feature extraction. Finding an image's essential traits that may be utilized to set it apart from other images is what feature extraction entails in the context of image processing. In image processing, methods like the histogram of oriented gradients (HOG), local binary patterns (LBP), and convolutional neural networks are frequently employed for feature extraction (CNNs).

Prediction is the following phase, which entails using the relevant features to create predictions on fresh, unforeseen data after the pertinent features have been extracted. This could involve categorizing a picture into one of several established categories in the context of image processing, such as determining whether or not an image contains a specific object. The best prediction algorithm for the task at hand must be chosen in order to create reliable forecasts. Support vector machines (SVMs), random forests, and neural networks are a few of the frequently used prediction techniques in image processing. The retrieved features and accompanying labels can be used to train these algorithms.

To improve accuracy, the prediction algorithm may occasionally need to be tweaked. This can involve tweaking the hyperparameters of the algorithm or utilizing techniques such as cross-validation to optimize the model's performance. To make sure the prediction model is performing as predicted, it is crucial to assess its performance. On both the training and test sets of data, performance metrics including accuracy, precision, recall, and F1 score can be used to evaluate the model's effectiveness.

In conclusion, any machine learning system, especially one used for image processing, must have both feature extraction and prediction. Prediction requires using these features to create predictions on fresh, unforeseen data. Feature extraction entails choosing the pertinent features from the data that may be used to train the model. Accurate predictions must be made by selecting the right prediction algorithm and optimizing it for performance. Finally, assessing the model's performance with the right metrics will assist pinpoint areas for development and guarantee that the model is operating as intended.

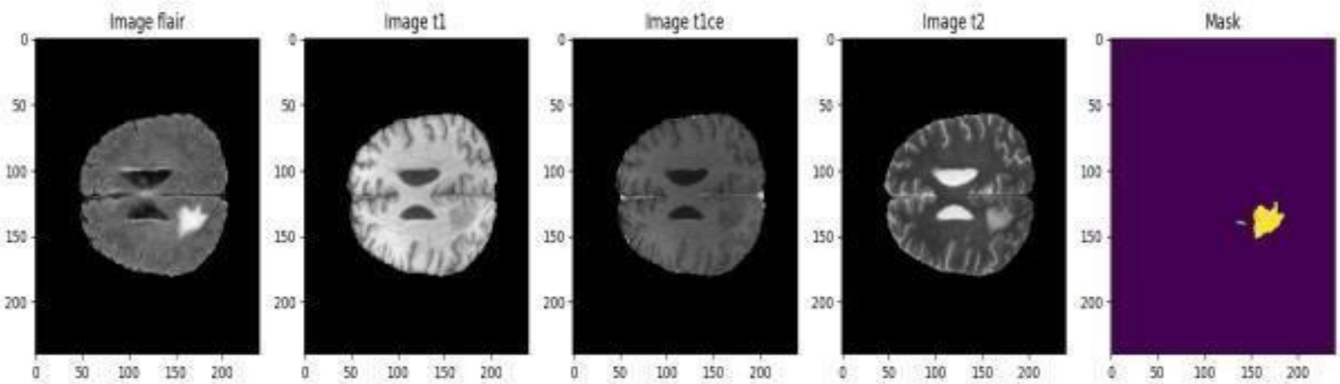

Figure 4: Feature Extraction

V. PERFORMANCE METRICS

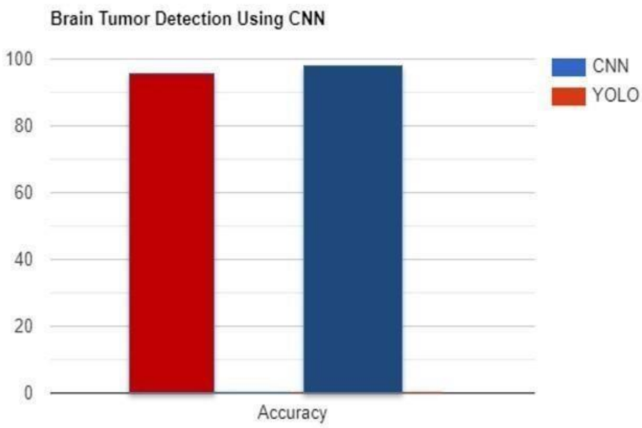

Figure 5: Performance Metrics.

VI. RESULT

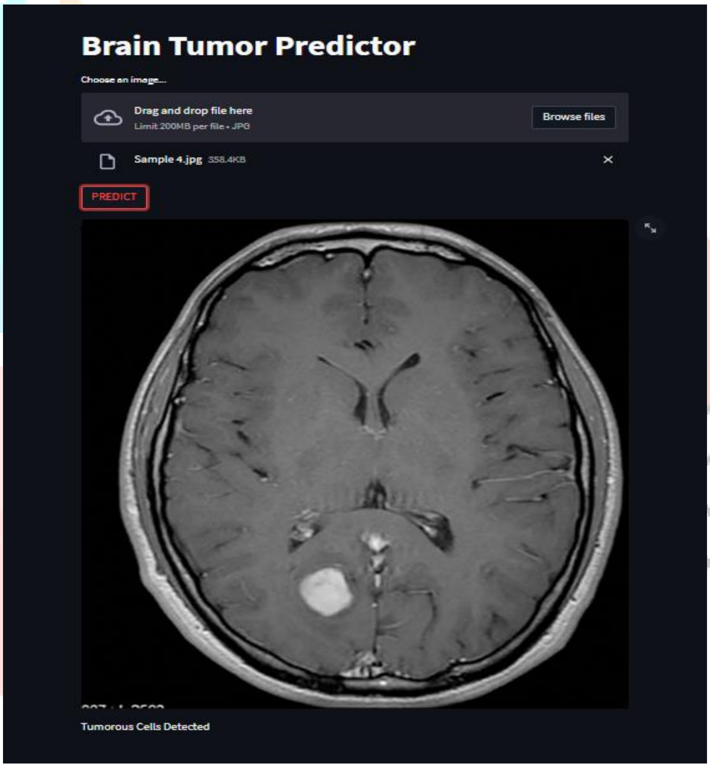

Figure 6: Brain Tumor Detected

However, the outcomes of these research frequently include accuracy metrics that show how well machine learning algorithms work in detecting and categorising brain tumours on MRI images. These metrics include sensitivity, specificity, and the area under the curve. Heat maps and segmentation maps are two examples of graphical representations of the expected output that can be included in the results and that can help with interpreting of the machine learning findings. The end goal of these studies is to increase the precision and effectiveness of brain tumour diagnosis and therapy, which can have a substantial impact on patient outcomes.

VII. CONCLUSION

To sum up, the implementation of machine learning approaches for brain tumour detection and categorization on MRI scans has shown considerable promise in enhancing the precision and effectiveness of brain tumour diagnosis and therapy. Algorithms for machine learning can learn to 5 recognise the features and patterns associated with various forms of brain tumours by being trained on an extensive set of labelled MRI images. This can help with the automatic categorization of new MRI pictures. The wide range of MRI images can be mitigated by preprocessing techniques and extraction of features approaches, which can serve to increase the precision of machine learning algorithms. The use of these methods may ultimately result in earlier identification and better management of brain tumours, which may significantly affect patient outcomes. However, more study is required to address the difficulties and restrictions of these methods, such as the requirement for a sizable volume of labelled data and potential algorithmic biases.

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