Disease Detection by Canny Edge Detector using CNN

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***Abstract*— The field of image processing is highly challenging, and one of its most difficult aspects is image segmentation. Biomedical imaging heavily relies on the technique of object-background separation, which has proven to be quite beneficial. This research paper introduces a novel approach to segment brain tumors in medical images by leveraging the power of Convolutional Neural Networks (CNNs) and the Canny edge detection algorithm in combination. The proposed method seeks to enhance the effectiveness and efficiency of brain tumor segmentation in medical images by utilizing the strengths of both techniques in a synergistic manner. The current standard method for detecting brain tumor is through Magnetic Resonance Imaging (MRI). This approach combines image sharpening, double thresholding, and hysteresis with the Sobel operator, and employs Convolutional Neural Networks (CNNs) as a pre-segmentation pixel classifier to improve the accuracy and efficiency of brain tumor segmentation. Nevertheless, the efficiency of these techniques may not always be satisfactory. Therefore, a hit and trial approach is employed by combining the Canny edge detection algorithm with CNNs, which showed an improvement in efficiency.**

Keywords*— *Image segmentation, CNNs, canny edge detection, MRI, Sobel operator, double thresholding, hysteresis.

I. Introduction

A brain tumor is an aggregation of cells that divide and proliferate swiftly and continuously within the brain tissue. Early detection of brain tumors is vital for physicians to diagnose and treat the illness promptly. The differentiation of normal and abnormal brain cells is a daunting task in medical image processing, with brain tumor segmentation representing a significant challenge in this regard. Image segmentation plays a critical role in identifying objects, estimating borders, and compressing images. However, manually interpreting MRI images to separate brain tumors can be prone to errors and time-consuming. Therefore, automatic segmentation methods are highly desirable for precise and efficient detection of brain tumors in MRI images.

Recent research indicates that machine learning techniques, such as CNNs, have significant capabilities in automating the detection of brain tumors from MRI images.This study suggests an automated system that utilizes the Canny Edge detection method and CNNs to detect brain tumors from MRI images. The Canny Edge method is employed for preprocessing the images and also to extract tumor region's edges, which are subsequently analyzed by a CNN model that has been trained on a vast dataset of labeled MRI scans. The model is capable of accurately detecting and locating brain tumors in new MRI scans.

The proposed system has the ability to enhance the precision and speed of brain tumor detection, which can assist doctors in delivering timely and effective treatment to patients. This project showcases the application of advanced machine learning techniques in medical imaging and emphasizes the potential of AI to revolutionize healthcare. Detecting brain tumors in medical image processing involves various methods for determining the tumor region, and researchers worldwide are focusing on finding the most efficient and accurate approach. CNN and image segmentation methods are being explored in the quest for the most effective approach.

The authors of paper [1] have presented a technique for identifying brain tumor edges from MRI scan images.To enhance the accuracy of medical image diagnosis, the authors propose a method that employs various functions, including noise reduction, feature enhancement, and BCET. In the second step of their approach, they utilize FCM clustering to segment the image, after which they apply the canny edge detection technique to detect intricate edges. The experimental study involves using MATLAB software to detect and extract tumors from MRI scan images of the brain, including those with different tumor locations, pathologies, shapes, sizes, and densities. The proposed methodology has been found to be relatively resistant to noise, and the accuracy of the geometric analysis and segmentation of some tumor pathologies was found to be 10-15% better than corresponding expert estimates.

Currently, the usual way to find gliomas is through Magnetic Resonance Imaging (MRI). In Paper [2] the authors have presented a new method for accurate segmentation, which is fully automatic and reliable. This technique relies on CNN with 3x3 kernels to prevent overfitting. In the pre-processing stage, intensity normalization is implemented, which is an uncommon practice in CNN. Furthermore, the image undergoes edge detection using Canny and wavelet transform techniques. Ultimately, the PCNN method enhances the image. Collectively, this methodology presents a potentially better way of detecting gliomas through MRI scans.

In Paper [3], a new approach for edge detection in brain tumor segmentation is presented. The method relies on the Sobel technique and involves a thresholding process based on the image itself, along with a closed contour algorithm that identifies different regions. The intensity data within these closed contours is then utilized to extract the tumors. The algorithm is coded in C and is assessed using both objective and subjective measurements. Simulation outcomes suggest that this approach surpasses traditional segmentation methods, with multiple parameters indicating its superiority.

Paper [4] introduces a fresh automated segmentation approach that leverages CNN with small 3 x 3 kernels for both classification and segmentation. CNN is a category of machine learning method that involves classification based on the layer's outputs. The suggested technique consists of several stages, including data collection, pre-processing, average filtering, segmentation, feature extraction, and CNN for identification and classification. Data mining methods are employed to extract significant correlations and patterns from the data. The combined utilization of machine learning and data mining techniques proves effective in detecting and preventing brain tumors at an early stage.

The authors of paper [5] describe a novel approach for selecting the parameters in the Canny algorithm which is not computed during runtime. Instead, they are selected from a configuration table, which is based on the estimated noise intensity of the input image and the required level of performance for the specific application. By adopting this method, it exhibits greater resilience to noise under a variety of conditions and has a lower execution time compared to recent Canny algorithms. In essence, this paper presents an adaptive implementation of the Canny algorithm that delivers superior performance and faster execution times.

The authors of paper [6] discuss their implementation of CNN method for segmenting brain tumors in MRI images. This approach requires minimal preprocessing and is able to extract features directly from pixel images. The duration required for training was decreased by decreasing the quantity of parameters used.The CNN architecture is composed of data layers, convolutional layers, and output layers, which work together to automatically extract relevant features for the segmentation task. The main benefit of utilizing a CNN for this task is its high efficiency.

The authors of paper [7] present an automated diagnostic framework that incorporates anatomical features to improve accuracy. The method suggested utilizes the differences in intensity among distinct types of tissues to gather insights about the tissues neighboring the tumor. MRI segmentation is becoming increasingly popular in treatment monitoring, especially with the advancement of image-guided surgical techniques. To detect and segment gliomas, the proposed technique uses a CNN to learn specific features.

Paper [8] proposes a model that employs Convolutional Neural Networks (CNN) and deep learning methods for classifying three common categories of benign brain tumors using MRI images. The dataset utilized in this research includes labeled images of Meningiomas, Gliomas, and Pituitary Adenomas. The model is trained with a substantial amount of labeled data and can effectively classify any input MRI image into one of the three categories mentioned above.

The authors of paper [9] have presented a new method that is entirely automated and dependable for detecting the tumor edge's intensity. This approach employs CNN to extract the most suitable characteristics after pre-processing the MRI images. To identify the edge and evaluate its intensity, the method employs Canny edge detection and Wavelet transform techniques, followed by Hough transform. This paper's edge detection approach has numerous practical surgical applications.

The article [10] presents a system for identifying brain tumors from 2D MRI images using the FCM clustering algorithm, conventional classifiers, and convolutional neural networks. The research analyzed a dataset of actual-time images that exhibited varying tumor sizes, shapes, locations, and intensities. Initially, the researchers tested six conventional classifiers like SVM, KNN, MLP, Logistic Regression, Naïve Bayes, and Random Forest. Then, a CNN model was created using Keras and TensorFlow, which outperformed the traditional classifiers with a 97.87% accuracy rate. The study's primary goal is to differentiate between normal and abnormal pixels based on statistical and texture characteristics.

II. METHODOLOGY

In our proposed methodology, the brain tumor detection is done by using machine learning algorithms. The study is implementing image processing techniques such as edge detection and Convolutional Neural Network (CNN) to predict tumor edges with a specific intensity value. The process of detecting the edges of the tumor involves various steps, including data preprocessing, canny edge detection, feature extraction, splitting the data, and constructing a model, as demonstrated in Figure 1. The data set that are used for the detection are MRI scans of brain consisted of 500 images. The datasets are taken from Kaggle for the segmentation and detection. The brain tumor detection process involves MRI scans of two classes, one with tumors and the other without. The methodology can be broken down into three phases: data pre-processing, model design, and model evaluation. Figure 1 provides a visual representation of the actual process.

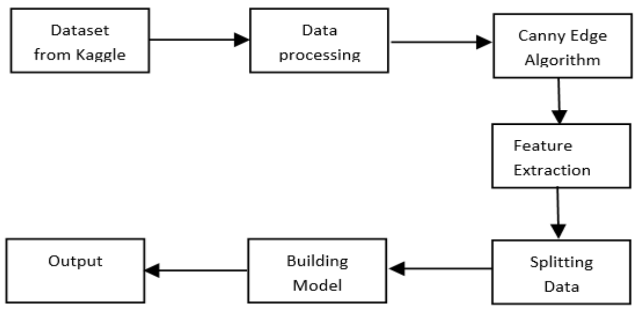

Fig.1. Proposed Methodology

III. TECHNOLOGY USED

PYTHON: Python is a high-level, interpreted programming language that prioritizes code readability and uses significant whitespace. Its object-oriented approach and multiple programming paradigms make it easy to write code for various project sizes. Python has robust scientific computing tools like NumPy, Pandas, and SciPy that reduce coding needs and speed up development. Although Python allows pseudocode-like programming, its dynamically typed nature and ambiguous return types in documentation can lead to compatibility issues with packages and require more testing when using new libraries.

JUPYTER NOTEBOOK: A Jupyter Notebook file is a JSON document that adheres to a standardized schema and includes a sequential list of input/output cells that can contain code, text, mathematical equations, plots, and multimedia elements. These files typically have a ".ipynb" extension.

KERAS: Keras is a Python-based open-source library for neural networks that can run on multiple platforms, including TensorFlow and Theano. It is user-friendly, modular, and extensible, and allows for fast experimentation with deep neural networks. Keras offers pre-built neural network building blocks, such as layers, objectives, activation functions, and optimizers, as well as tools to simplify working with image and text data.

OPENCV: OpenCV is a cross-platform library of programming functions designed for real-time computer vision. It's free to use under the BSD license and supports models from various deep learning frameworks like TensorFlow and PyTorch. It also promotes the use of Open Vision Capsules, a portable format compatible with other formats.

TENSORFLOW: TensorFlow is an open-source library for differentiable programming and dataflow that is utilized in various tasks, including neural networks and symbolic math.

IV. SYSTEM DESIGN

System design involves developing the structure, modules, and communication methods of a system that can fulfill the requirements of the end user. The process includes defining the overall architecture and interfaces that will be used in the system. The aim is to create a system that can effectively address the needs of the end user.

- In our project, we are using five-level architecture of CNNs for detecting the brain tumor.
- To begin with, the data is prepared and pre-processing is done then unwanted noise is removed by utilizing the canny edge algorithm
- Further the data is splitted into training and testing parts.
- Then the classifier undergoes training by combining the various details and newly identified features of each image from the dataset. The training data that has annonate specific objects are utilized by the classifier to understand and learn whether the tumor is present or not.
- The process of feature extraction is advantageous in identifying the location of a brain tumor with accuracy and aids in forecasting the subsequent stage.

The high level architecture for the above explained procedure is as follows:

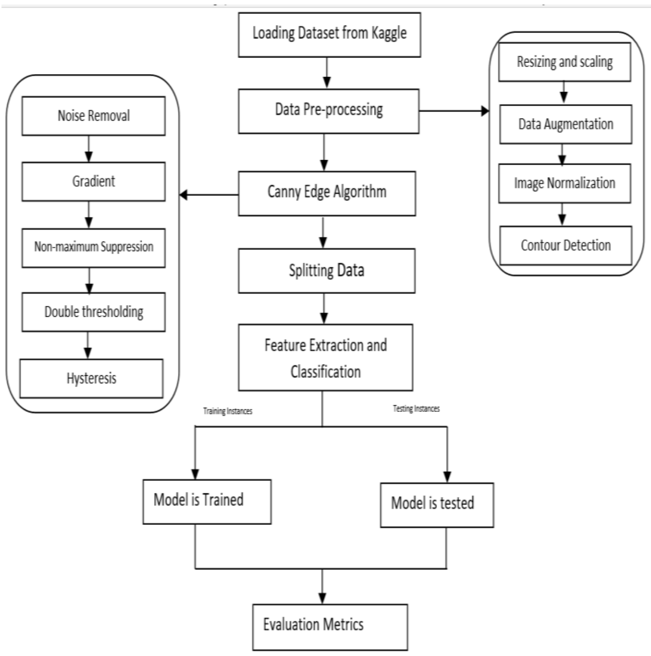

Fig.2. High level Architecture Model

A. Data Collection:

The dataset used for the proposed project was obtained from Kaggle and comprised MRI images of the brain. The dataset consisted of 350 images of brain having tumor and not having tumor. It contains MRI scans of two classes as follows:

- YES : means tumor is present, labelled as 1 (shown in Fig.3.1).
- NO : means tumor is not present, labelled as 0 (shown in Fig.3.2).

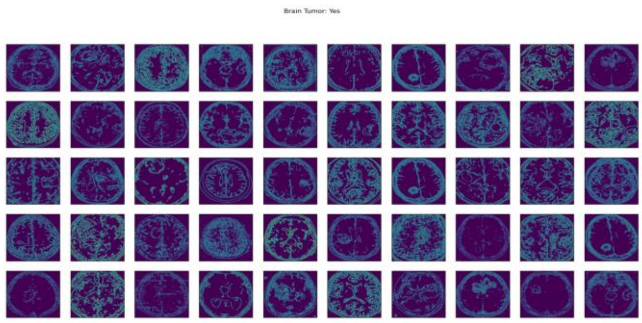

Fig.3.1.Yes Tumor

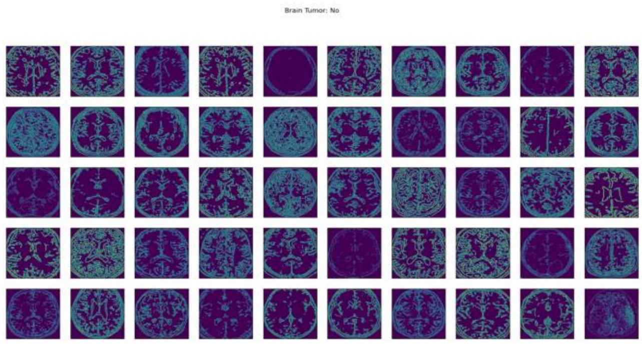

Fig.3.2.No Tumor

B. Data Pre-processing:

Due to the complexity of analyzing raw MRI images, pre-processing plays a critical role in MRI image analysis. The initial step involves converting the input image into grayscale to prepare it for further preprocessing. Then, a thresholding process is applied to differentiate the foreground and background regions, and erosion and dilation techniques are employed to refine the image and eliminate unwanted details. Additional techniques such as resizing, data augmentation, image normalization, and contour detection are also applied to facilitate further processing of the MRI images. The primary goal of these preprocessing techniques is to produce a sharper image with enhanced edges, which can lead to more precise image analysis. Ultimately, these techniques can improve the accuracy and reliability of MRI image analysis.

IMAGE RESIZING: In order to enhance the effectiveness of the model training, the dataset was modified by resizing the images to dimensions of (240,240). This standardization of image size promotes uniformity and enables efficient training of the model.

FILTERING: Our work involved the application of a Gaussian blur filter to mitigate the impact of Gaussian noise commonly found in brain MRI images. This technique proved to be instrumental in achieving successful segmentation outcomes.

DATA AUGMENTATION: This process entails generating novel training instances by implementing alterations to the initial data, which may involve image flipping, rotation, or displacement. The dataset consists of 350 images and after augmentation it becomes dataset of around 1500-2000 images approximately. This can help the model generalize better and reduce overfitting.

IMAGE SEGMENTATION: This methods include min-max scaling, where the pixel values are scaled to a range between 0 and

1,This adjustment can accelerate the convergence of the model during training.

CONTOUR DETECTION: Contours are defined as a line that connects all the continuous points that share the same color and intensity. They are commonly employed in various applications, including image foreground extraction, simple image segmentation, detection, and recognition. To identify the contours in an image, the findContours() function is used.

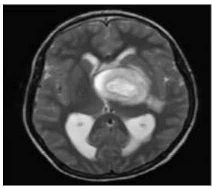

Fig.4.1MRI Image

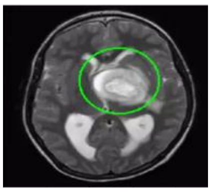

Fig.4.2Contoured MRI Image

C. **Canny Edge Algorithm:**

The Canny Edge algorithm is a method used to detect edges in images. The first step involves using a Gaussian function to smooth the image, which reduces noise and improves image resolution for more precise edge detection. The sobel operator is then used to calculate the image gradient, with separate kernels for horizontal and vertical edge detection known as sobel x and sobel y. In cases where edges may have multiple orientations, the sobel xy operator is preferred as it provides more accurate edge detection. This method is illustrated in the figures below.

Fig.5.1sobel x

Fig.5.2 sobel y

Fig.5.3 sobel x+y

LAPLACIAN TRANSFORMATION: The Laplacian transformation is used to detect double edges in an image that has been filtered with a Gaussian filter. By applying the Laplacian to the smoothed image, the zero crossings between the double edges are obtained, allowing for edge detection. The LoG edge detector utilizes horizontal and vertical kernels (Gx and Gy) to locate these edges. This process is illustrated in figure 5.4.

NON-MAXIMUM SUPPRESSION: It thins edges to a single pixel and retains only the strongest edges in an image. It involves comparing each pixel's gradient direction to its neighboring pixels along the gradient direction, retaining only those with the maximum gradient magnitude. This results in a thinned edge map with one pixel-wide line for each edge, eliminating false edges and preserving the strongest ones.

DOUBLE THRESHOLDING: The algorithm detects edges in an image by measuring the change in brightness between neighboring pixels. It uses a high and low threshold to determine which pixels are strong or weak edges, and discards those that are not edges at all. Weak edge pixels require further analysis in the next step of the algorithm.

HYSTERESIS: To perform Canny edge detection, two threshold values are set to differentiate strong, weak, and non-edge pixels based on their gradient magnitude. Weak edge pixels are further analyzed to determine if they are connected to strong edge pixels. This approach eliminates false and weak edges while retaining strong edges, making it a reliable edge detection method. The output of the Canny edge detection algorithm is shown in Figure 5.3.

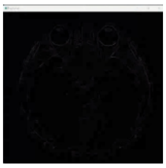

Fig.5.4 Laplacian

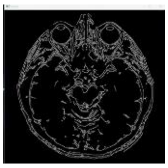

Fig.5.3 Canny

D. *Convolutional Neural Network(CNNs)*

A basic CNN is composed of multiple layers, with each layer transforming one volume of activation to another using a differentiable function. There are five main types of layers commonly used to construct CNNs.
Our project's model design consists of two phases: Data Splitting and Classification.

DATA SPLITTINGThe project's dataset was divided into training and testing data. The model was trained on the training data, and the testing data was used to evaluate its performance. The dataset was split 70/30, with 70% used for training and 30% for testing.

CLASSIFICATION: A five-layered Convolutional Neural Network (CNN) was created and utilized to detect tumors. The model included hidden layers and was found to be the most accurate in identifying tumors.

CONVOLUTION LAYER: The MRI images were standardized to a 64x64x3 size using a convolutional layer and then passed through a kernel with 32 filters of 3x3 size and 3-channel tensors. The output was prevented from overfitting by using an activation function called ReLU. Stride, a hyperparameter in convolution layers, is used to control the movement of the kernel. When set to 1, it moves one pixel at a time and produces output feature maps with the same spatial dimensions as input. But, when set to a value greater than 1, the kernel skips over some input pixels, resulting in smaller output feature maps.

POOLING: The Max Pooling layer is employed to avoid overfitting. In particular, the Max-Pooling 2D layer is applied to spatial data that corresponds to the input image. This layer operates on a dimension of 31x31x32 and uses a pool size of (4,4) to downscale the image in both vertical and horizontal directions.

FLATTENING: n this stage, the pooled feature maps are merged into a single vector to be passed on to the next layer. This is done using the Flatten function, which essentially reshapes the feature maps into a long column.

ACTIVATION FUNCTION: Activation functions add non-linearity to neural networks by limiting the output values to a specific range. Rectified Linear Unit (ReLU) is an activation function that sets the input value to zero if it's negative, and returns the input value if it's positive

DENSE LAYERThe model employed two Dense layers, named Dense-1 and Dense-2. Keras was used to implement the dense function for neural network processing, with the resulting vector serving as input for this layer. The hidden layer contains 128 nodes, which were chosen based on available computing resources, aiming to keep it as moderate as possible while still achieving substantial results.

E. *Model Evaluation:*

There are various evaluation metrics to assess the model's performance, but for this project, accuracy was utilized as the evaluation metric. Accuracy is a measure of how accurately the model predicts the class and is computed by dividing the correctly predicted instances by the total number of instances. The developed approach achieved a 94% accuracy rate for detecting brain tumors.

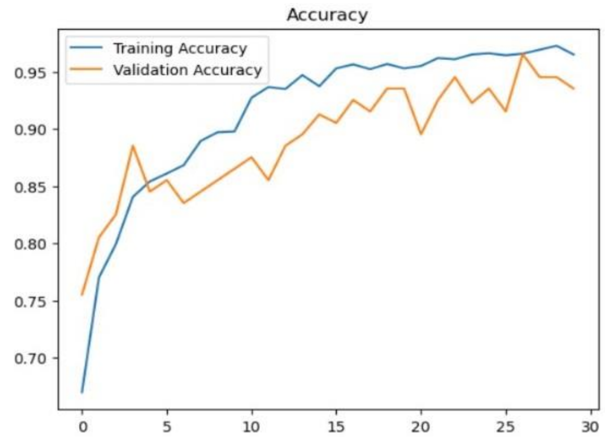

Fig.6 Training and Validation Accuracy

V. CONCLUSION

We presented a technique for the detection and segmentation of brain tumors using Convolutional Neural Networks. The images are initially read from the local device and transformed into grayscale. To eliminate noise in the image, an adaptive filtering technique is applied. Then, double thresholding is applied to the denoised image, followed by Convolutional Neural Network segmentation to identify the tumor region. The model achieved an accuracy of 94% and provided promising results with minimal computational time and no errors.

VI. FUTURE SCOPE

It has been observed that the proposed approach requires a large training set to obtain more accurate results. However, collecting medical data for this purpose can be challenging, and in some cases, datasets may not be available. Therefore, the proposed algorithm needs to be robust enough to accurately detect tumor regions in MR Images even with limited training data. To achieve this, weakly trained algorithms can be integrated, which can identify abnormalities with minimal training data, and self-learning algorithms can be used to enhance the accuracy and reduce computational time.

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