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BRAIN TUMOR DETECTION USING CNN

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Abstract: NeuroDigiScan introduces a paradigm shift in medical imaging by automating defect of modern diagnostics. Identifying tumors in MRI scans is pivotal for treatment planning, yet conventional methods, reliant on human inspection, falter due to data volume. To mitigate this, NeuroDigiScan Proposes Convolutional Neural Network(CNN) algorithms, surmounting traditional classifier limitations in detecting brain tumors. The intricate and diverse nature of tumors presents a formidable challenge in MRI brain tumor detection, underscoring the necessity for automated systems to bolster diagnostic precision and mitigate human mortality rates.

Keywords:NeuroDigiScan,MRI,CNN,Brain,Tumor,Medical

I. INTRODUCTION

Brain tumor poses a significant challenge in medical science, with effective early analysis being paramount for successful treatment. The gold standard for tumor grading, stereotactic biopsy, involves risks such as bleeding, infection, seizures, and even death. However, its accuracy remains imperfect, leading to potential diagnostic errors and mismanagement. Non-invasive techniques like MRI have gained prominence in brain tumor diagnosis due to the risks associated with biopsies. Yet, interpreting MRI data accurately presents challenges, including low illumination, vast data volume, and tumor complexities like unstructured shapes and unpredictable locations. Automated defect detection using machine learning has emerged as a vital tool in medical diagnostics, in MRI-based brain tumor detection, providing crucial information for treatment planning. Recent studies advocate for computerized detection and diagnosis, which not only saves radiologists time but also ensures tested accuracy. Robust computer algorithms capable of quantitatively assessing tumor characteristics can significantly enhance clinical management by relieving physicians of manual tumor depiction tasks.

II. RELATED WORK

[1]Brain Tumor Detection Using Deep Learning The goal of the paper "Brain tumor detection using deep learning Approaches" by Razia Sultana outlines a research initiative focused on improving brain tumor detection through deep learning, using the ResNet50. The motivation stems from the need for accurate and timely diagnosis, aiming to automate and enhance the precision of brain tumor identification. The objective is to identify the most suitable transfer learning model among VGG16, VGG19, DenseNet121, ResNet50, and YOLO V4, considering factors like precision, computing efficacy, and real-world adaptability. The expected outcome is the selection of a model, such as ResNet50, with the highest accuracy, along with insights into its advantages, disadvantages, and computational efficiency, contributing to the broader knowledge in transfer learning. The ultimate goal is to provide actionable insights for improving the accuracy and efficacy of applications using deep learning models in brain tumor.

[2] MRI Image Classification with Support Vector Machine(SVM) The paper Image Classification using Robust brain Image With SIBO-SVM , introduces SIBO-SVM, for brain tumor MRI image classification. It combines the BoF(Bag-of-Features) model, Scale-Invariant Feature Transformation (SIFT) technique, and weighted Support Vector Machines(WSVM) for efficient and accurate classification, addressing challenges faced by deep learning methods like CNNs. SIBOW-SVM not only classifies images but also estimates class probabilities, providing a confidence measure. The article compares SIBOW-SVM with CNNs and emphasizes its computational efficiency, scalability, and parallelizability.

The paper is organized into branches detailing image classification systems, pre-processing techniques, the proposed methodology, numerical results, and concluding remarks.

[3] The paper "Convolutional Neural Network(CNN) for Image Detection and Recognition" by Rahul Chauhan, Kamal Kumar Ghanshala, and R.C.Joshi explores the application and implementation of CNN in tasks such as image recognition. for - Evaluation on MNIST and CIFAR-10 datasets, with a focusing on to reduce overfitting - Performance evaluation of the models and discussion of the results - Literature survey of related works and future directions for research - Use of Convolutional Deep belief network on CIFAR-10 dataset, achieving accuracy of 78.90% on GPU unit - Exploration of different filters and their performance in different

models - References to other works such as Ensemble of classifiers on K-Nearest Neighbor(KNN) and an introduction to deep learning and its algorithms. Detailed information about the use of CNN and RNN in various applications and the MNIST and CIFAR-10 datasets - Discussion of the architecture, layers, pooling, dropout, activation functions, batch size, optimizer, and data augmentation techniques used in a CNN model - Mention of overfitting and underfitting in deep neural networks, and the need for fine-tuning learning rates - Conclusion with the results of experiments showing accuracy of the CNN model on MNIST dataset - Exploration of deep learning and CNN techniques for image recognition and detection of the MNIST and CIFAR10 datasets Techniques such as increasing the number of epochs, using dropout for regularization, data augmentation, and RMS prop optimizer for improving accuracy - Achievement of the 99.6% accuracy on MNIST dataset and 80.17% on CIFAR-10 datasets. - Potential for further improvement through Training with larger Epochs and GPU unit - Discussion of deep learning and convolutional neural networks to improve training accuracy of CIFAR-10 dataset - Implement as support system for machine vision to detect natural language symbols. - References to other research papers and resources related to deep learning and image recognition Pos"

III. PROPOSED SYSTEM

The data was sourced from Kaggle. This dataset contains MRI images of brain tumors. The pictures come in different dimensions(e.g.,630*630, 225*255) and are resized to 256*256 pixels.

In this approach, preprocessing is employed to improve the image quality without changing its information content. The primary sources of image include relices. poor resolution, low contrast, and geometric distortion. Feature extraction is then utilized to obtain image features from the datasets. This method produces moderate results, accurately detecting tumors using the CNN algorithm.

IV. METHODOLOGY

The following are the steps involved in applying CNN on the brain tumor dataset:

- Import required packages
- Open the data folder and import it (Yes and No)
- Assign image labels to the appropriate classes
- Assemble the photos into a form (256X256)
- Make the image normal.
- Separate the photos into three sets: train, validation, and test.
- Create the sequential model in step
- Put the model together.
- The training dataset should be validated using a validation set to assess the performance during training.

- Use the test images to evaluate the model.
- Create a graph that compares training and validation accuracy.
- Create a confusion matrix that compares the actual output to the projected output.
- The CNN sequential model incorporates multiple layers, starting with resizing the original image to 256*256 pixels. Each convolutional layer applies 32, 32, 64, and 128 filters successively, followed by a 20% dropout rate. Max pooling with a 2*2 window size is applied after each convolutional layer. The feature maps are flattened into a one-dimensional array using the flattened method. A dense layer with 256 units and connects the flattened feature, while the output layer uses sigmoid activation for binary classification. This design encompasses both training and testing phases, implemented in python.

Algorithm for CNN based Classification

1. The first layer applies a convolution filter.
2. The sensitivity of the filter is lowered by smoothing the convolution filter (i.e., subsampling) ¬ The activation layer is in charge of signal transfer from one layer to the next.
3. Using a rectified linear unit can shorten the training period (RELU)
4. Every neuron in the preceding layer is coupled to every neuron
5. Feedback is provided to the neural network through a loss layer added at the end of the training process.

Table 1 Performance metrics used in CNN.

No.	Metrics	Calculation
1	Accuracy	TP+TNTP+TN+FP+FN
2	Sensitivity	TPTP+FN
3	Specificity	TNTN+FP
4	Precision (PPV)	TPTP+FP
5	Negative Predictive Value (NPV)	TNTN+FN
6	F1-score	2×PPV×TPRPPV+TPR

V. SYSTEM ARCHITECTURE

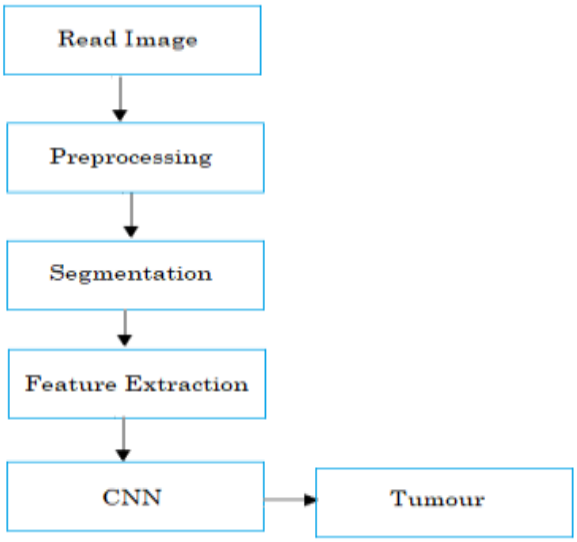

Figure 1: System Architecture

In the above architecture, the stages to detect brain tumor using CNN are as follows :

 Read Image: Gather a dataset consisting of brain images, with labels indicating normal brains and brains with tumors. Read an input image as a test image.

 Preprocessing: Clean the data, handle missing values, and standardize image sizes and formats. This might involve normalization, resizing, and data augmentation to increase variability.

Segmentation: Divides the image into number of parts.

Feature extraction : It extracts the features of an image and finds the edges using canny edge.

Splitting Data: Splitting the dataset into training and testing sets.

CNN Model: The Architecture of Convolutional Neural Network entails specifying layers including convolutional, pooling, and fully connected layers.

 Training Data: Train CNN model using the labeled training data. This step involves feeding the training images through the network, adjusting the model's weights to minimize the prediction error.

Testing Data: Assessing the performance of the trained model with the testing dataset helps determine its ability to generalize unseen data.

 Loading Model: Once model is trained and saved, load it for further use in classification tasks.

 Classification: Use the loaded model to classify new brain images into two categories: ”Normal Brain” or “Tumor Brain” based on patterns learned from the training data.

 Results: Display or analyze the classification results to understand the model's accuracy and performance.

VI. IMPLEMENTATION

Figure 2: doctor registration

this module registers the doctors in the hospital

figure 3:doctor login

it is use to login the doctors by entering their username and password

figure 4: menu

this is menu

Figure 5: add patient

using this the doctors are adding patient details with the scan brain image

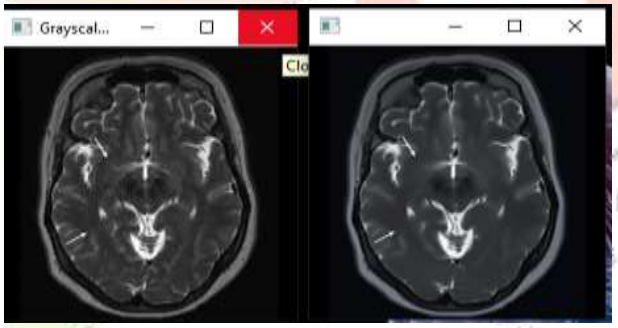

Figure 6: gray scale and denoised images

this module converts the image into gray scale and denoises the images

Figure 7: segmentation

It divides the image into number of parts such as foreground and background.

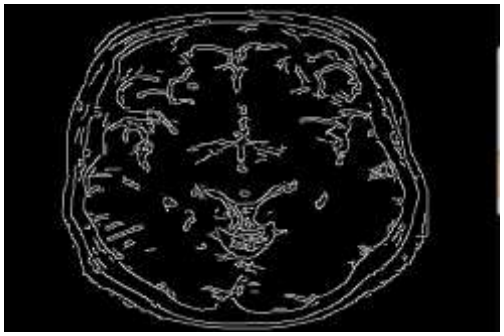

Figure 8: Feature Extraction

Using Canny Edge algorithm finds the edges of an image

The Canny edge detection algorithm consists of 5 stages:
1. Reducing noise
2. Calculating gradients
3. Suppressing non-maximum values
4. Applying dual thresholds
5. Hysteresis-based edge tracking

The initial stage of the Canny edge detection algorithm involves applying a Gaussian filter to the input image. The **Gaussian filter** is a smoothing operation that helps to reduce noise in the image. Noise can introduce false edges, which could compromise the accuracy of the edge detection process. The Gaussian filter smooths The image is smoothed by convolving it with a Gaussian kernel, effectively reducing high-frequency noise. while preserving the edges' sharpness.
Mathematically, the Gaussian kernel is defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} . \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

The Gaussian filter is applied to each pixel in the image by sliding the kernel across the entire image and taking the weighted average of the neighboring pixels' intensities. This means it takes into account the brightness of surrounding pixels and gives more importance to the closer ones. So, if the kernel is larger, it involves more pixels in the calculation, resulting in a stronger blurring effect on the image.

Figure 9: Report

VII. CONCLUSION

CNN is highly effective for analyzing image dataset, as it reduces image size while retaining essential information for accurate predictions. The model presented here was developed through trial and error. Future work will focus on optimization techniques to determine the optimal number of layers and filters for the model. For the current dataset, CNN has proven to be a superior method for predicting the presence of brain tumors.

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