Enhanced Brain Stroke Detection with Raspberry Pi Using Advanced CNN Architecture

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Abstract—The Raspberry Pi-based brain tumor detection and alert system is designed to streamline training for stroke prediction. It employs a modified CNN architecture with three convolutional layers and two hidden layers. Initially, input images are resized to 32x32 pixels and processed through three convolutional layers using a 3x3 kernel and ReLU activation, with max-pooling after each layer for feature extraction. The subsequent two hidden layers, each with 128 nodes, use softmax activation. This model is trained on a specific dataset to create a CNN model file. During testing, if a brain tumor is detected, a buzzer alert is triggered, and the detected stages are displayed and sent to a web application. The system aims to improve stroke classification efficiency and accuracy.

Keywords— Brain Stroke, Raspberry pi, Pi camera, Magnetic Resonance Imaging, Modified Convolution Neural Network.

I.INTRODUCTION

Brain stroke is a common and serious brain disease that affects many people worldwide, often with devastating effects. Brain cancer, on the other hand, occurs when cancer cells grow in brain tissue. Recent studies suggest that more than one hundred thousand people worldwide are diagnosed with brain strokes annually. Despite ongoing efforts to manage the complexities of brain strokes, the outcomes for patients are often unsatisfactory.

These imaging methods are preferred for their convenience and detailed tissue imaging capabilities. Treatment options for strokes encompass surgery, radiation therapy, and chemotherapy. The choice of treatment is determined by factors like the size, type, and grade of the stroke visible in the MR image, as well as the presence of cancer in other body regions.

The primary goal of computer vision in this context is to provide reliable output that assists medical professionals in interpreting images and reduces the time needed for image analysis. These advancements significantly enhance the reliability and accuracy of medical diagnoses.

However, segmenting a brain stroke from an MR image and identifying its location pose significant challenges. The presence of strokes in specific brain areas without distinct differences in image intensities further complicates the automated detection and segmentation of brain strokes.

The main objective of this project is to simplify the representation of stroke information extracted from MR brain images for a broad audience, including medical professionals. The aim is to create an algorithm that can extract stroke images from MR brain images and present the information in an easily understandable format.

The extracted image will include details such as the size, dimensions, and position of the stroke, providing valuable information for medical decision-making. Additionally, the algorithm will use a Convolutional Neural Network to detect the presence of a stroke in a given MR brain image.

II.RELATED WORK

In [1], the author Yuehao Pan and colleagues utilized brain MRI images to extract valuable information for classifying brain tumors. Their approach involved employing Convolutional Neural Networks (CNN) algorithms to develop a brain tumor detection system. They evaluated the performance of their CNN model based on sensitivity and specificity parameters, demonstrating improvements over the Artificial Neural Networks (ANN) method.

In [2], the author Roy et al. (2012) conducted research on calculating the tumor-affected area for proportional analysis. They validated their software using various datasets with different tumor sizes, intensities, and locations. The algorithm they developed could automatically detect and segment brain tumors from input images. Image pre-processing involved filtering the images to remove distractions. Their approach included tumor detection, segmentation, and area calculation, aiding in assessing disease progression. They proposed a multi-step and modular approach to address the complex MRI segmentation problem, with tumor detection as the initial step. Despite challenging scenarios, they achieved good results. The authors emphasized that while MRI segmentation is crucial in medicine, manual segmentation is tedious and time-consuming, highlighting the appeal and efficiency of automated analysis.

In [3], According to the author, T.U. Paul and S.K. Bandyopadhyay introduced a brain segmentation method that automates the Dual Localization technique. Their approach begins by generating skull masks. Finally, their method evaluates tumor dimensions, including length and breadth.

In [4], the author S. Pereira and colleagues emphasized the significance of reducing physical segmentation time in medical applications, specifically in magnetic resonance imaging. The inherent complexity of brain images, characterized by their three-dimensional nature and underlying intricacies, poses a significant challenge for segmentation. Therefore, the researchers chose CNN for its robustness in handling such complexities.

I. PROPOSED WORK

The proposed system offers a streamlined approach to reduce training time while maintaining crucial features for stroke prediction. It involves a modified convolutional architecture with three convolution layers and two hidden layers. The input image resolution is transformed to 200x200 pixels and processed through three consecutive convolution layers with a 3x3 kernel and ReLU activation, followed by maxpooling for feature optimization. The subsequent two hidden layers, each with 128 nodes, use softmax activation. This architecture is trained on a specific dataset, creating a CNN model file. During testing, the model accurately classifies strokes, enhancing prediction system efficiency. The implementation on Raspberry Pi leverages its computational capabilities, with prediction results displayed on an integrated LCD screen and accessible via a web application interface.

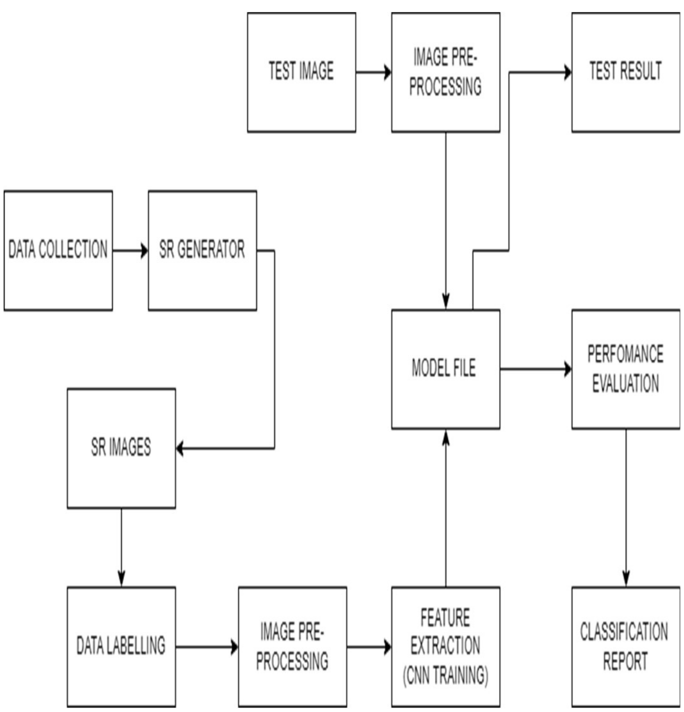

Fig 3.1 Simulation diagram

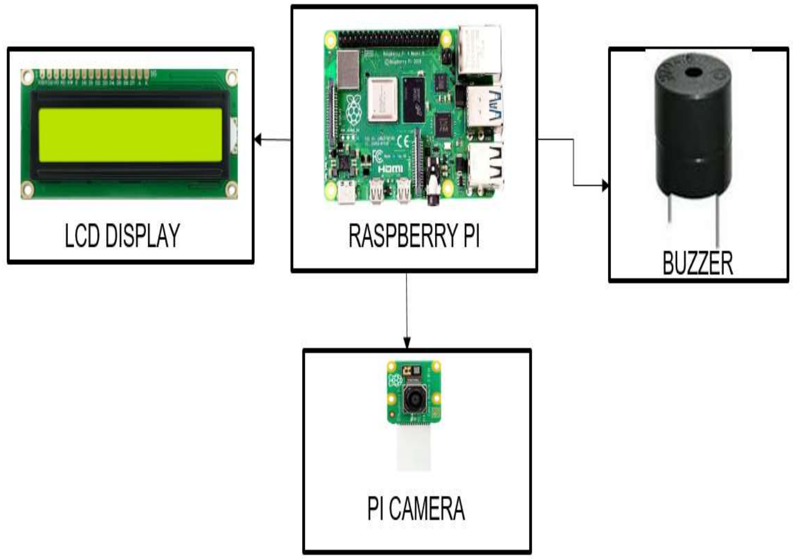

Fig 3.2 Hardware Block diagram

IV.SOFTWARE DESCRIPTION

PYTHON 3.7:

Python, a programming language as versatile as it is powerful, has captured the hearts of developers worldwide. Launched in 1991 by the ingenious Guido van Rossum, Python stands out for its elegance and readability, owing much to its unique use of whitespace. This high-level, interpreted language boasts efficient data structures and robust support for object-oriented programming. Python's adaptability knows no bounds; it can be freely distributed and seamlessly extended with new functions and data types, often implemented in languages like C or C++. This versatility also makes Python a popular choice as an extension language for customizable applications.This tutorial acts as a gateway to Python's world, offering a glimpse into its fundamental concepts and features. While it doesn't delve into every nook and cranny of Python, it lays a sturdy groundwork for further exploration of the language's expansive library modules.

THONNY IDE:

Thonny is a lightweight Integrated Development Environment (IDE) known for its speed and minimal dependencies. It is designed to be desktop environment agnostic, relying only on the GTK2 toolkit and runtime libraries for operation. The compilation process involves running the `./configure`, `make`, and `make install` commands. Thonny's `configure` script supports common options (accessible via `./configure --help`), and additional compile-time options can be found in `src/Thonny.h`. For systems lacking dynamic linking loader support, the `--disable-vte` option can be used to prevent Thonny from automatically loading `libvte.so.4` on various platforms, including Debian, Fedora, Linux From Scratch, FreeBSD, and Microsoft Windows.

V.HARDWARE DESCRIPTION

RASPBERRY PI:

The Raspberry Pi 4 Model B+ is the latest addition to the Raspberry Pi 4 lineup, featuring a 64-bit quad-core processor clocked at 1.4GHz. It includes dual-band 2.4GHz and 5GHz wireless LAN, Bluetooth 4.2/BLE, faster Ethernet, and PoE capability via a separate PoE HAT. The board has modular compliance certification for its wireless LAN, simplifying the process of designing the board into end products and reducing the cost and time required for wireless LAN compliance testing.

Fig 5.1 Raspberry Pi

PI CAMERA SENSOR:

The Raspberry Pi Camera Board connects directly to the CSI connector on the Raspberry Pi, providing a clear 5MP resolution image and 1080p HD video recording at 30fps. This latest version, 1.3, is custom-designed and manufactured by the Raspberry Pi Foundation in the UK. It features a 5MP Omnivision 5647 sensor in a fixed-focus module. The module attaches to the Raspberry Pi using a 15-pin ribbon cable to the dedicated 15-pin MIPI Camera Serial Interface (CSI) designed for camera interfacing. The CSI bus supports high data rates and exclusively carries pixel data to the BCM2835 processor.
The board is compact, measuring around 25mm x 20mm x 9mm and weighing just over 3g, making it suitable for mobile and weight-sensitive applications. The sensor has a native resolution of 5 megapixels with a fixed-focus lens onboard. For still images, the camera can capture 2592 x 1944 pixel static images. It also supports video recording at 1080p @ 30fps, 720p @ 60fps, and 640x480p @ 60/90fps. The camera is supported in the latest version of Raspbian, the Raspberry Pi's preferred operating **system.**

Fig 5.2 PI Camera

LIQUID CRYSTAL DISPLAY (LCD):

A Liquid Crystal Display (LCD) is a flat, thin panel containing an array of coloured or monochrome pixels filled with liquid crystals. It is commonly used in battery-powered electronic devices due to its low power consumption. Liquid crystals possess properties of both liquids and crystals, with molecules that are nearly as mobile as in a liquid but arranged in an ordered form like a crystal. LCDs are used in applications similar to LEDs. The LCD structure includes two glass panels with liquid crystal material between them. Transparent electrodes on the inner surfaces control the orientation angle of the crystal molecules. When a potential is applied across the cell, it disrupts the molecular alignment, causing turbulence and scattering light in all directions, making the cell appear bright and displaying the desired image or text. In the off state, the polarizers and liquid crystal align to allow light rays to pass through without orientation, making the LCD appear transparent.

Fig 5.3 LCD Display

BUZZER:

A buzzer is an electronic device that creates sound by vibrating a diaphragm when an electric current flows through it. It consists of a coil of wire wrapped around a magnet, with the diaphragm attached to the coil. The electric current, whether alternating (AC) or direct (DC), produces a magnetic field in the coil, causing it to move back and forth rapidly. This movement causes the diaphragm to vibrate, producing the buzzing sound. Buzzers are commonly used in alarms, timers, and notification systems due to their simple yet effective design.

Fig 5.4 BUZZER

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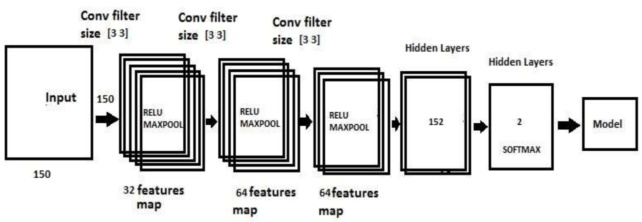
VI.WORKING OF MODIFIED CNN



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Data Preprocessing:

This dataset should reflect the variability and complexity encountered in real-world scenarios. Standardize and preprocess the images to ensure uniformity in input dimensions. Resize all images to a consistent resolution, such as 200x200 pixels, to facilitate effective model training and comparison. Implement data augmentation techniques to enrich the dataset and improve the model's performance. These techniques can include rotation, flipping, and scaling of images, helping the model generalize better to unseen data while reducing the risk of overfitting.

Convolutional Neural Network (CNN) Architecture Design:

Developing a customized Convolutional Neural Network (CNN) architecture tailored for medical image analysis involves several key steps. This setup helps in effectively capturing relevant features from the medical images. Additionally, integrating maxpooling after each convolutional layer helps in downsampling the feature maps, reducing computational complexity while retaining important information. The architecture also incorporates two hidden layers with a density of 128 neurons each. These layers use the softmax activation function, enabling accurate classification opotential stroke risks based on the extracted features. Overall, this modified architecture aims to enhance the model's ability to analyze medical images and improve stroke risk prediction.

Model Training and Optimization:

After preprocessing the dataset, it's crucial to divide it into training and validation sets to effectively train and evaluate the model. This partitioning ensures that the model can generalize well to new, unseen data. Using an optimization algorithm such as stochastic gradient descent (SGD) or Adam is essential for adjusting the model's parameters and minimizing the loss function iteratively. Monitoring the training process is key to prevent overfitting, which can be achieved through regularization techniques like dropout or L2 regularization, and adjusting hyperparameters such as learning rate and batch size as needed. Lastly, saving the trained CNN model file is important for future deployment and use in stroke prediction

Deployment and Evaluation:

Implement the trained CNN model on the Raspberry Pi platform to facilitate instant stroke prediction in healthcare scenarios. Assess the model's efficacy using a distinct test dataset, evaluating key metrics like accuracy, precision, recall, and F1 score. Validate the proposed system's performance by comparing it against established stroke prediction methods. Enhance the model iteratively based on evaluation outcomes to improve its predictive accuracy and reliability in identifying potential stroke cases.

ALGORITHMS:

Customized Convolutional Architecture: The architecture is tailored with convolutional layers using a 3x3 kernel and ReLU activation to efficiently extract key features from medical images while minimizing training time.
Maxpooling: Applied after each convolution layer, maxpooling reduces and enhancing feature extraction efficiency.
Softmax Activation: The two hidden layers, each comprising 128 neurons, utilize softmax activation for classifying potential stroke risks by providing probability distributions across multiple classes.
Training Algorithm: An algorithm optimizes CNN model parameters using a specific dataset, ensuring precise prediction and classification of brain strokes based on learned features.

TRAINING RESULTS OF MODIFIED CNN

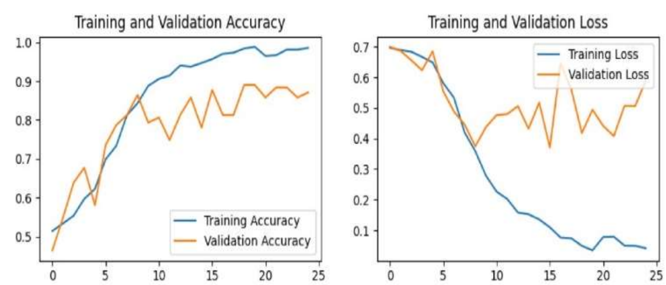


Fig 6.1 TRAINING GRAPH OF MODIFIED CNN

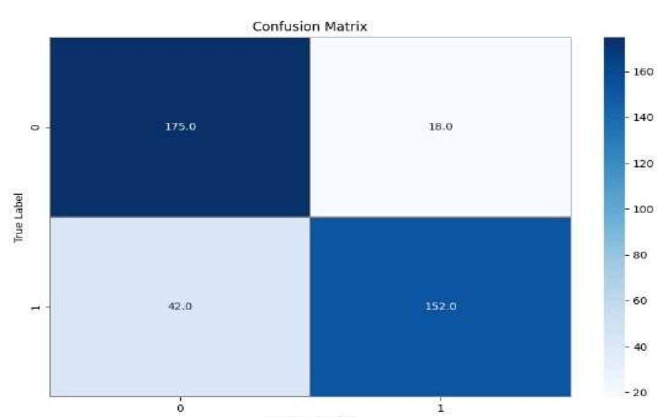
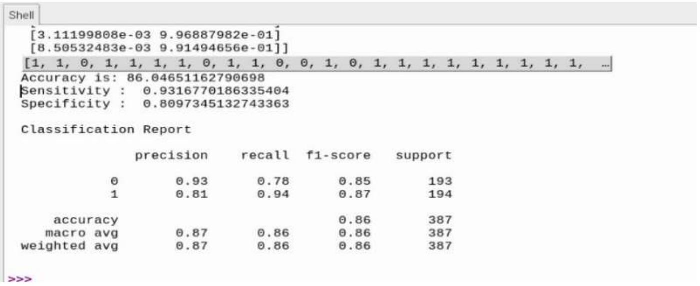


Fig.6.2 Modified CNN Classification Report



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Shell
 [3.11199808e-03 9.96887982e-01]
 [8.50532483e-03 9.91494656e-01]]
[1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,  ...
Accuracy is: 86.04651162790698
Sensitivity :  0.9316770186335404
Specificity :  0.8097345132743363

Classification Report

              precision    recall  f1-score   support

           0       0.93      0.78      0.85       193
           1       0.81      0.94      0.87       194

    accuracy                           0.86       387
   macro avg       0.87      0.86      0.86       387
weighted avg       0.87      0.86      0.86       387

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Fig.6.3 Modified CNN Classification Report

The training results reveal that Modified CNN achieved remarkable test accuracy of 93%, demonstrating their capability to accurately classify brain stroke images.

HARWARE RESULTS:

LEVEL 1: INITIAL STAGE

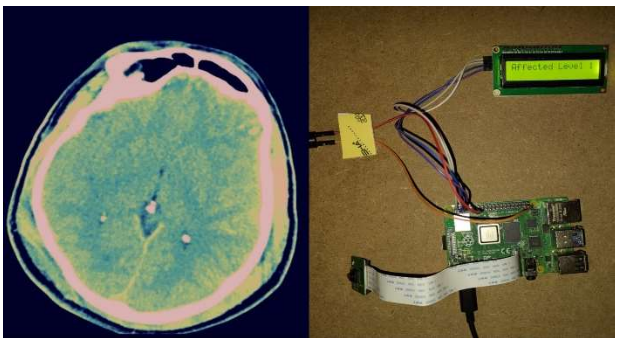

Fig 6.4 (a) This image predicts the initial stage of brain stroke. Lightish pink region predicts the stroke affected areas.

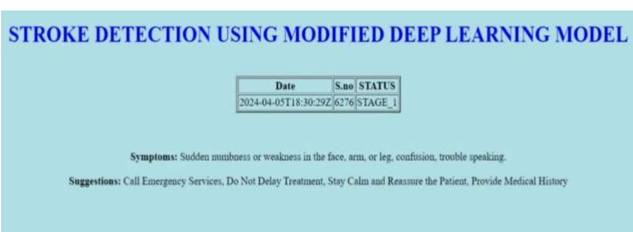

Fig 6.4 (b) This picture depicts Level 1 symptoms and Suggestions

LEVEL 2: INTERMEDIATE STAGE

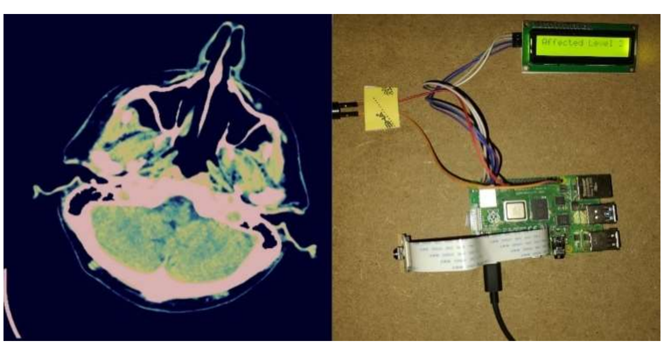

Fig 6.5 (a) This image predicts the minor and intermediate Stage of Brain stroke

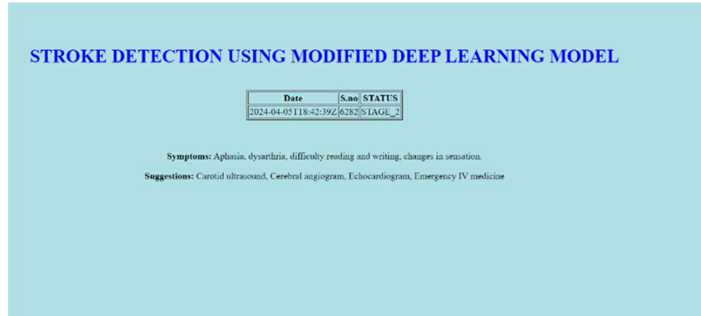

Fig 6.5 (b) This image depicts the Level 2 symptoms and Suggestions from the doctor

LEVEL 3: FINAL STAGE

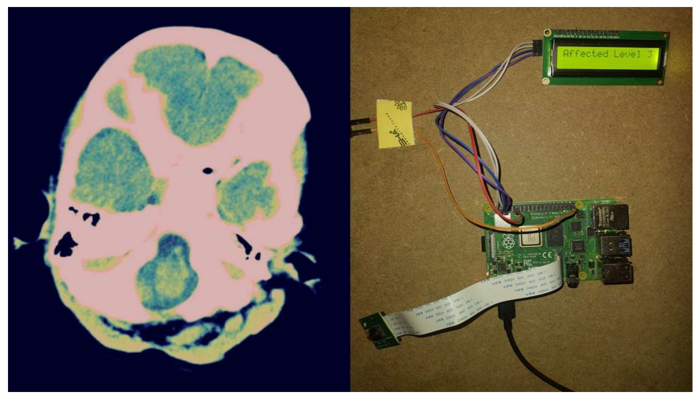

Fig 6.6 (a) This image predicts the major and final stage of Brain Stroke.

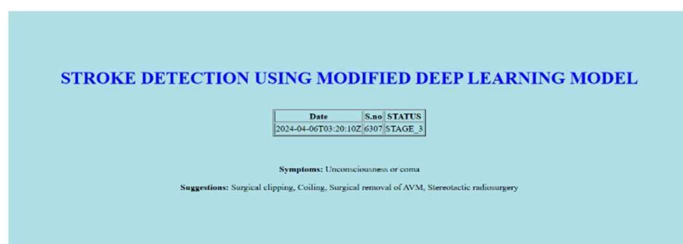

Fig 6.6 (b) This image depicts the Level 3 symptoms and suggestions.

VII . CONCLUSION

In Conclusion,The Raspberry Pi-based brain tumor detection and alert system is a significant advancement in medical technology, especially for stroke prediction. Its use of a modified Convolutional Neural Network (CNN) architecture enables precise and efficient brain tumor detection by analyzing input images and extracting key features. Integrating real-time alert mechanisms and seamless communication with a web application enhances its utility, providing immediate notifications and detailed insights into detected anomalies. This empowers healthcare professionals to take proactive measures, potentially revolutionizing early stroke diagnosis and treatment.

The system's streamlined stroke classification process and ability to facilitate prompt intervention offer promise in improving patient outcomes and reducing stroke-related morbidity and mortality. The Raspberry Pi-based system signifies a hopeful step forward in medical technology, hinting at a future where advanced diagnostics and interventions transform healthcare delivery.

VIII . FUTURE SCOPE

In Future, The proposed approach appears to necessitate a sizable training set for optimal accuracy. However, acquiring medical data for use in medical image processing can prove challenging, with datasets occasionally being unavailable. In such circumstances, it becomes crucial for the proposed algorithm to exhibit robustness in accurately detecting stroke regions from MR images. One potential enhancement to the proposed method involves integrating weakly trained algorithms capable of identifying abnormalities with minimal training data.

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