

Hardware approach to brain tumour detection using AI concepts using real time embedded systems with Raspberry pi

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Abstract

Tumors have become the second leading cause of cancer nowadays, posing significant risks to numerous patients. The medical field is in urgent need of rapid, automated, efficient, and reliable techniques to detect tumors, especially brain tumors. Early and accurate detection plays a crucial role in successful treatment and keeping patients safe. To address this challenge, various image processing techniques are employed in the medical domain. These advancements have allowed doctors to administer appropriate treatments, leading to the successful recovery of many tumor patients.

Tumors are characterized by the abnormal growth of cells, which proliferate uncontrollably. Brain tumors, in particular, can be devastating as they compete with healthy cells and tissues for essential nutrients, ultimately resulting in brain dysfunction. Traditionally, doctors have relied on manual examination of MR images to identify the location and extent of brain tumors. Unfortunately, this approach is prone to errors and can be extremely time-consuming. To overcome these limitations, we have implemented a cutting-edge deep learning architecture known as Convolution Neural Network (CNN), a type of Neural Network (NN) that utilizes Transfer Learning. This CNN-based model enables us to automatically detect the presence of brain tumors in medical images with high accuracy. If a tumor is detected, the model outputs a positive result; otherwise, it indicates the absence of a tumor.

In our approach, we use K-means clustering in conjunction with Raspberry Pi to precisely pinpoint the location of the brain tumor. This ensures targeted and efficient treatment planning. Additionally, we have integrated an Arduino controller to facilitate the movement of robotic wheels, allowing for precise navigation to the exact location of the tumor during medical interventions. Overall, our system represents a significant advancement in tumor detection and localization, offering faster and more reliable results compared to manual methods. By leveraging state-of-the-art technology and innovative techniques, we strive to enhance patient outcomes, ultimately saving more lives in the fight against brain tumors.

Keywords: Ardunio, ANN, Raspberry Pi.

1. Introduction

Tumors have become the second leading cause of cancer nowadays, posing a significant threat to a large number of patients. To address this issue, the medical field is in dire need of fast, automated, efficient, and reliable techniques for tumor detection, especially in the case of brain tumors, where



timely detection is crucial for effective treatment and patient safety. Various image processing techniques are being employed to aid in the early identification of brain tumors.

In the quest to improve tumor detection, a groundbreaking approach is being used, leveraging Deep Learning architectures such as Convolutional Neural Networks (CNNs) and Transfer learning. This innovative method allows doctors to predict the presence of a tumor in brain images accurately. By detecting tumors in their early stages, doctors can proactively keep patients out of harm's way and administer timely and appropriate treatment, saving numerous lives.

Tumors are essentially an abnormal growth of cells that proliferate in an uncontrolled manner. In the case of brain tumors, these abnormal cells consume essential nutrients meant for healthy brain tissues, leading to brain function impairment and failure.

Traditionally, doctors manually locate the position and area of brain tumors by analyzing MR Images of the patient's brain. However, this manual approach often results in inaccuracies and consumes a considerable amount of time. To overcome these challenges, the current system employs advanced techniques using a Raspberry Pi for K-means clustering to identify the tumor's location accurately.

To further enhance the process, robotic wheels, controlled by an Arduino controller, are utilized to navigate precisely to the identified tumor location. This integration ensures that medical professionals can access and treat the tumor with high precision and efficiency.

In summary, by combining cutting-edge Deep Learning algorithms with smart robotic assistance, the medical community is making significant strides in detecting brain tumors swiftly and accurately. This collaborative approach between technology and medical expertise promises to improve patient outcomes and save lives in the battle against tumors.

2. Brief description of the works

Fig. 1 depicts the importance of early detection in the battle against tumor disease. Detecting tumors at an early stage is a critical factor in ensuring successful treatment and saving precious human lives. The project outlined in this M.Tech. synopsis focuses on an application-oriented approach using Convolutional Neural Networks (CNN) and Neural Networks (NN) for tumor cure therapy and diagnostic applications in human beings. The study involves simulation using software tools to aid in the identification and treatment of tumors. One of the primary challenges in tumor detection lies in the limitations of conventional disease diagnostic techniques, such as Magnetic Resonance Imaging (MRI). While MRI can indicate the presence of a tumor in the brain, it often fails to precisely determine the exact location of the tumor. This lack of precision can have detrimental effects on healthy tissues surrounding the tumor site.

To address this issue, the project aims to leverage advanced deep learning techniques like CNN and NN to improve the accuracy and early detection of tumors. By employing these state-of-the-art algorithms, the system can potentially pinpoint the location of tumors with greater precision, enabling more effective and targeted treatments. The project's simulation-based approach using software tools offers a safe and controlled environment to study and refine the tumor detection and cure therapy methods. This allows researchers and medical professionals to fine-tune the algorithms and ensure their effectiveness before applying them to real-life scenarios.

In conclusion, the project's focus on applying CNN and NN for tumor detection and cure therapy is a promising step towards enhancing the early identification of tumors. By overcoming the limitations of traditional diagnostic techniques, such as MRI, this research can significantly improve the outcomes of tumor treatment and positively impact human lives.



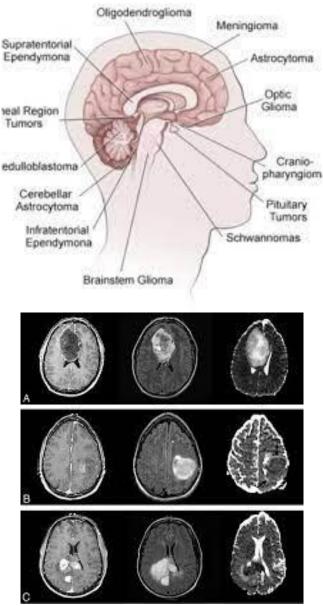


Fig. 1: Tumor in the Brain

3. Early detection process

A tumor is an abnormal mass of tissue that grows uncontrollably, making it the second leading cause of cancer. In the human body, the brain serves as the primary controller of the humanoid system. Brain tumors are characterized by the excessive and uncontrolled growth of cells. These abnormal cells in brain tumors consume vital nutrients that are meant for healthy brain cells and tissues, ultimately resulting in brain failure. The unregulated division of cells in the brain leads to the formation of brain tumors, and if left unchecked, they can progress into brain cancer. The early detection of brain tumors plays a crucial role in their treatment and management. When tumors are detected promptly, doctors can take necessary actions to safeguard patients from potential dangers. In this context, various image processing techniques are employed to aid in the detection of brain tumors. These techniques assist medical professionals in analyzing brain images and identifying any abnormal growth or patterns that might indicate the presence of a tumor.

By leveraging advanced image processing methods, medical experts can improve the accuracy and efficiency of tumor detection, leading to better treatment outcomes and enhanced patient safety. The timely identification of brain tumors allows for timely interventions and appropriate medical



strategies to be implemented, potentially saving lives and improving the overall quality of care for individuals facing this challenging condition. The medical field needs fast, automated, efficient and reliable techniques to detect tumors like brain tumor. In the area of human health, Computer Vision plays a significant role, which reduces the human judgment that gives accurate results. CT scans, X-Ray, and MRI scans are the common imaging methods among magnetic resonance imaging (MRI) that are the most reliable and secure. MRI detects every minute objects. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming.

4. Detection & Classification Process

To address the challenges of brain tumor detection and classification, the proposed solution involves leveraging Deep Learning architectures, specifically Convolutional Neural Networks (CNNs) or Neural Networks (NNs). The model's objective is to predict whether a brain tumor is present or not in an image, providing a binary classification of "yes" or "no" for tumor presence.

The brain tumor detection process comprises four main stages:

Image Pre-Processing: The initial step involves preparing the MRI images for analysis by applying various pre-processing techniques. These techniques may include noise reduction, image enhancement, and normalization to ensure that the input data is well-suited for further processing.

Image Segmentation: In this stage, the MRI images are segmented to identify and separate the regions of interest, i.e., the tumor region, from the background and healthy brain tissues. Image segmentation helps focus the analysis on the specific area of concern, enhancing the accuracy of tumor detection.

Feature Extraction: Extracting relevant features from the segmented images is a crucial step in understanding the tumor's characteristics and differentiating it from the healthy brain tissues. The extracted features serve as the input to the subsequent classification stage.

Classification: The extracted features are fed into the CNN or NN model, which has been trained to classify the input images as either tumor-positive or tumor-negative. The model's performance is evaluated on a test dataset, ensuring its accuracy in predicting tumor presence in new, unseen images. The motivation behind this brain tumor detection approach extends beyond mere detection; it also encompasses tumor classification and localization. By employing image processing techniques and deep learning, the system can not only detect tumors but also identify their types and precisely pinpoint their locations within the brain.

The use of K-means clustering, facilitated by a Raspberry Pi, aids in determining the exact location of the tumor within the segmented images. This information is crucial for planning treatment strategies and ensuring precision in tumor removal or treatment procedures.

To enable precise navigation to the tumor location, robotic wheels controlled by an Arduino controller are employed. This integration allows the system to move accurately along a particular axis to reach the identified tumor location.

In summary, the proposed approach combines advanced image processing techniques, deep learning, and robotic assistance to achieve accurate brain tumor detection, classification, and localization. This innovative solution has the potential to greatly improve the management and treatment of brain tumors, providing valuable insights to medical professionals and enhancing patient care.

5. Proposed Method - Block diagram

The proposed methodology that is adopted in the present work is shown here in a very highly abstracted manner with various blocks in the vertical & horizontal fashions.



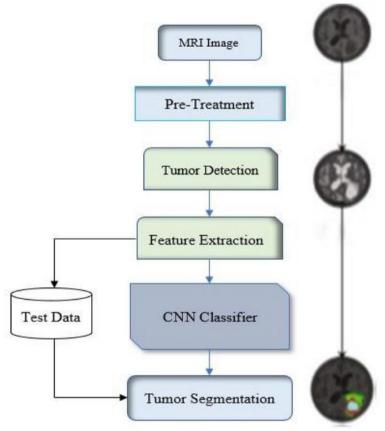


Fig. 2 : Use of CNN approaches for the training and testing purposes, CNN Architecture and Segmentation of MRI

Medical imaging techniques are utilized to generate clinically accurate images of the human body, following medical standards for diseases, physiology, anatomy, and other relevant aspects. These images are used for viewing, treating, and analyzing various conditions. While the examination of organs and tissues after their removal is performed for medical purposes, it falls under diagnostic pathology and not medical imaging.

Medical imaging techniques often draw upon scientific principles and may incorporate industry advancements. The primary purpose of medical imaging is to produce non-invasive pictures of the internal structures and organs of the body. This allows healthcare professionals to visualize and diagnose medical conditions without the need for surgical intervention.

One of the powerful tools used in medical image analysis is the Convolutional Neural Network (CNN). A CNN typically consists of three main layers:

Convolution Layer: This layer is responsible for extracting features from the input image using convolutional filters. These filters identify specific patterns and features within the image, such as edges, textures, and shapes.

Pooling Layer: After the feature extraction by the convolutional layer, pooling layers are used to downsample the feature maps, reducing the dimensionality and computational complexity of the network. Pooling helps retain the most salient information while discarding irrelevant details.

Fully Connected Layers: The final layers of the CNN are fully connected layers that analyze the extracted features and produce the final output, which can include classification or regression results. By employing CNNs in medical image analysis, healthcare professionals can leverage the network's ability to automatically learn relevant features from the images. This facilitates tasks such as tumor detection, disease classification, and anomaly identification in medical imaging.

Overall, medical imaging techniques and CNNs play a crucial role in modern healthcare, enabling non-invasive and accurate visualization of internal body structures, aiding in diagnosis, treatment planning, and patient care.



6. Integration of Hardware with Software

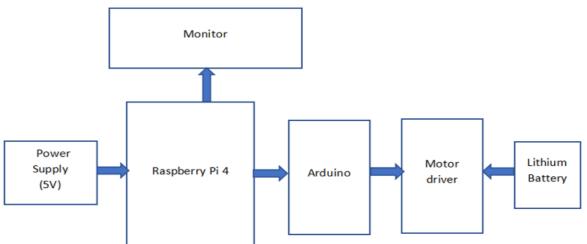


Figure 6: Block diagram of Hardware Integrated with software

7. Results

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8. Conclusions

In brain tumor detection, the existing work involves studying feature-based approaches. These approaches encompass various image processing techniques, including image pre-processing, image segmentation, feature extraction, and classification. Additionally, deep learning techniques like Convolutional Neural Networks (CNNs) and Neural Networks (NNs) are also studied in this context. The process of brain tumor detection starts with image pre-processing, which involves preparing the MRI images for analysis. This step may include tasks such as noise reduction, image enhancement, and normalization to improve the quality and consistency of the input data. Next, image segmentation is employed to identify and isolate the tumor region from the healthy brain tissues. By segmenting the image, the analysis can focus solely on the specific area of interest, enhancing the accuracy of tumor detection. Feature extraction follows image segmentation, where relevant characteristics of the



tumor are extracted from the segmented image. These extracted features serve as important information for differentiating between tumor and healthy brain tissue.

Using the extracted features, a classification model, such as a CNN or NN, is trained to determine whether the tumor is present or not in the image. The model is trained on a labeled dataset, where each image is associated with the corresponding label of "tumor" or "no tumor." Once the model is trained, it can be used to predict the presence of a tumor in new, unseen images. If the model predicts that a tumor is present, it returns "yes"; otherwise, it returns "no." Furthermore, the system incorporates robotic wheels to act upon the detection results. When a tumor is detected (resulting in a "yes" prediction), the robotic wheels are activated and move towards the position of the tumor in a precise and controlled manner. This combined approach of feature-based analysis, deep learning, and robotic assistance enhances the accuracy and efficiency of brain tumor detection. By leveraging cutting-edge technologies, medical professionals can achieve early and precise diagnosis, leading to improved patient outcomes and better treatment planning.

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