Don Bosco Institute of Technology

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SYNOPSIS

On

Registration of MRI Brain Tumor classification based on Genetic Algorithm and Convolutional Neural Network

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ABSTRACT

Brain tumors are fatal for majority of the patients, the different nature of the tumor cells requires the use of combined medical measures, and categorizing such tumors is a difficult task for radiologists. The diagnostic structures based on PCs have been offered as an aid in diagnosing a brain tumor using magnetic resonance imaging (MRI). General functions are retrieved from the lowest layers of the neural network, and these lowest layers are responsible for capturing low-level features and patterns in the raw input data, which can be particularly unique to the raw image. To validate this, the pre-trained model is utilized to classify three types of brain tumors: glioma, meningioma, and pituitary tumor. Three types of brain tumor datasets are used to assess each approach. Compared to the existing deep learning models, the concatenated functions and genetic algorithms give better accuracy. Tensor flow 2 and Nesterov-accelerated adaptive moment estimation (Nadam) are also employed to improve the model training process by making it quicker and better. The proposed technique using CNN attains an accuracy of 99.56%.

Keywords: Deep Learning, Convolutional Neural Network, Genetic Algorithm, Brain tumor classification.

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1. INTRODUCTION

In the disciplines of biomedicine and artificial intelligence, progress is being made at unprecedentent rate. Many individuals are affected by cancer. Because of its unpredictability, it poses a severe threat to their livelihood. A brain tumor is one of the most severe and life-threatening diseases. Nearly 23000 people were diagnosed with brain tumors in 2015. The use of MRI in detecting and treating brain tumors is critical. It generates diagnostic images of the brain free of tissue damage or skull anomalies, and it provides clinicians with critical information for identifying brain tumors and other brain diseases. It is used in CNN models to classify brain tumor MRI images. The proposed framework correctly identified three types of brain tumors, grades II, III and IV with an accuracy of 98.14%. The suggested CNN models can be used to help radiologists and doctors in confirming their first screening.

As a result, the deep learning model achieves a 97.3% accuracy, and this is higher than the other approaches using the same database. The primary goal of their work was to identify medical images in the early stages of brain tumors and clarify diagnostic images for cancer therapy, both before and after surgery, by bridging the gap between the radiologist and the computer. The difficulty of recognizing a brain tumor early was confirmed by evaluating image segmentation and classification algorithms on brain MRI images.

The suggested model employs ResNet 50 and Inception V3 to achieve 89% and 75% accuracy, respectively, and this approach demands relatively little processing resources while achieving the highest accuracy and efficiency. Medical imaging has emerged as a critical tool in the early detection and diagnosis of various diseases, with Magnetic Resonance Imaging (MRI) playing a pivotal role in the field of neurology. Among the many applications of MRI, the detection and classification of brain tumors have garnered significant attention due to their potentially life-threatening nature. Timely and accurate identification of brain tumors is essential for effective treatment planning and patient outcomes.

To enhance the accuracy and efficiency of brain tumor classification using MRI scans, the integration of advanced computational techniques has become imperative. This research focuses on the development of a novel approach that combines Genetic Algorithms (GAs) and Convolutional Neural Networks (CNNs) to address the challenges associated with MRI brain tumor classification.

1.1 Motivation

The motivation for the registration of MRI brain tumor classification based on Genetic Algorithm and Convolutional Neural Network is deeply rooted in the urgent need to improve the accuracy, speed, and accessibility of brain tumor diagnosis. This research holds the potential to transform the way brain tumors are detected and classified, ultimately improving the lives of patients and advancing the field of medical imaging and artificial intelligence in healthcare. Brain tumors represent a critical health concern, often requiring prompt and accurate diagnosis for effective treatment. MRI scans are a primary imaging modality for detecting brain tumors, and improving their classification accuracy can lead to earlier interventions and better patient outcomes. Manual interpretation of MRI scans is time-consuming, and the demand for radiologists often exceeds their availability. Automating the classification process with advanced techniques such as Genetic Algorithms and Convolutional Neural Networks can expedite the diagnosis, reducing patient waiting times and anxiety.

1.2 Background

The background for the registration of MRI brain tumor classification based on Genetic Algorithm and Convolutional Neural Network is grounded in the clinical importance of accurate brain tumor diagnosis, the challenges posed by MRI image variability, and the potential of advanced machine learning techniques to revolutionize this vital aspect of neuroimaging and healthcare. This research builds upon previous work in medical image analysis and leverages cutting-edge technologies to improve patient care and outcomes. Brain tumors are abnormal growths of cells within the brain or the central nervous system. They can be benign or malignant and have serious clinical implications. Timely and accurate diagnosis is crucial for treatment planning and patient outcomes.

Machine learning techniques have gained significant prominence in the analysis of medical images, including MRI scans. These methods can learn and extract relevant features from images, enabling automated classification and diagnosis. Accurate brain tumor classification has a direct impact on treatment decisions, including surgery, radiation therapy, and chemotherapy. Misclassification can lead to inappropriate treatments or delays, highlighting the clinical significance of this research. Automated clinical diagnosis, detection of clinical phenotypes, and forecasting of biomedical attributes and health phenotypes can be subjective and error-prone. AI methods can augment human experts by deriving unbiased, reliable (low variability) and quick computer models that can assist medical professionals with identifying patterns (such as tumors) and suggesting optimal interventions. The applications of AI in medicine are advancing swiftly.

Brain is the controlling center of our body. With the advent of time, newer and newer brain diseases are being discovered. Thus, because of the variability of brain diseases, existing diagnosis or detection systems are becoming challenging and are still an open problem for research. Detection of brain diseases at an early stage can make a huge difference in attempting to cure them. In recent years, the use of artificial intelligence (AI) is surging through all spheres of science, and no doubt, it is revolutionizing the field of neurology. Application of AI in medical science has made brain disease prediction and detection more accurate and precise.

Twenty-two datasets are discussed which are used most frequently in the reviewed articles as a primary source of brain disease data. Moreover, a brief overview of different feature extraction techniques that are used in diagnosing brain diseases is provided. Finally, key findings from the reviewed articles are summarized and a number of major issues related to machine learning/deep learning-based brain disease diagnostic approaches are discussed. Through this study, we aim at finding the most accurate technique for detecting different brain diseases which can be employed for future betterment.

1.3 Literature Survey

- **Deep Learning Approach for 2D MRI Brain Tumor Segmentation: MOHAMMAD ASHRAF OTTOM, HANIF ABDUL RAHMAN, AND IVO D. DINOV: Date of publication 23 May 2022.**

In this work, we proposed a new approach for MR images segmentation based on the deep learning concept of convolutional network and data augmentation to utilize the available labeled images. The architecture relies on auto encoder-decoder, the concept of skip-connections, and residual neural networks, which requires combining the output of the previous layer with the next layer. Also features maps are required to map the dimensions between the input and the output of each layer. The benefit of skip-connections is to find alternative and further paths for the learning process and the gradient, which increase the probability of model convergence and avoid vanishing gradients dilemma. We can confirm the ability of deep learning methods and the proposed Znet framework to detect and segment tumors in MR images. Furthermore, pixel accuracy evaluation may not be a suitable evaluation measure for semantic segmentation in case of class imbalance in MR images segmentation. This is because the dominant class in ground truth images is the background. Therefore, a high value of pixel accuracy can be misleading in some computer vision applications. On the other hand, alternative evaluation metrics, such as dice and IoU (Intersection over Union), are more factual for semantic segmentation. Acquiring such large-scale testing and validation data is resource-intensive and time-consuming. We are also working on deep learning strategies to generate realistic high dimensional and multimodal neuroimaging data along with ground truth labels. The transfer learning approach can be utilized along with the proposed Znet to optimize the training and minimize the costs of developing, validating, and embedding AI techniques in clinical practice.

- **Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances PROTIMA KHAN1, MD. FAZLUL KADER, S. M. RIAZUL ISLAM, (Member, IEEE), AISHA B. RAHMAN, MD. SHAHRIAR KAMAL1, MASBAH UDDIN TOHA, AND KYUNG-SUP KWAK: Date of publication February 26, 2021.**

In this paper, we have presented a survey on the four most dangerous brain disease detection processes using machine and deep learning. The survey reveals some important insights into contemporary ML/DL techniques in the medical field used in today's brain disorder research. With the passage of time, identification, feature extraction, and classification methods are becoming more challenging in the field of ML and DL. Researchers across the globe are working hard to improve these processes by exploring different possible ways. One of the most important factors is to improve classification accuracy. For this, the number of training data needs to be increased because the more the data is involved, the more accurate the results will be. This slight change in a part of the system eventually resulted in superior performances. Based on the discussion on different types of brain disease data sources and feature extractions methods, it is apparent that the accuracies differ based on different classifiers used and feature extraction processes applied in the systems. To uncover the limitations of existing ML/DL-based approaches to detect various brain diseases, the paper provides a discussion focusing on a set of open research issues. To design effective AI systems for medical applications, the inclusion of XAI approaches is the ultimate necessity. Brain cancer is one of the life-threatening diseases at present and detecting the tumor at an early stage is very much important to save lives. Brain tumor is basically the abnormal growth of cells. There are two types of brain tumor: benign and malignant. Brain tumors are of different varieties based on appearance and it is hard to differentiate between tumor and normal brain tissues. For this, the extraction of tumor regions becomes very difficult. Manual detection systems were performed before by Radiologists. However, these manual systems may lead to errors which can be serious for the patients.

- **Convolutional Neural Network Based on Complex Networks for Brain Tumor Image Classification With a Modified Activation Function ZHIGUAN HUANG, XIAOHAO DU LIANGMING CHEN YUHE L, MEI LIU, YAO CHOU, AND LONG JIN : Date of publication May 11, 2020**

The convolutional neural network based on complex networks with a modified activation function for image classification of brain tumors, abbreviated as CNNBCN, generated by ER, WS, and BA algorithms has been presented in this paper. Experimental results have shown that the classification accuracy of the original CNNBCN model and modified model are better than some manually designed neural networks. In addition, its performance is comparable to one of the best current image classification models. The CNNBCN model has not only achieved satisfactory results in the field of brain tumor image classification, but also provided a reference for the design of network structures. The construction of neural networks by using connectomes of animals and even humans will be considered in our future work. Medical image analysis is a revolution of practicability and innovative concepts due to the rapid development of hardware, and the use of complex mathematical tools, which can obtain clearly visible medical images. Based on these medical images, effective image analysis can help doctors diagnose and treat patients. The application of machine learning in medical image analysis, such as support vector machines (SVMs) and random forests, has greatly promoted the development of computer-aided medicine. Image classification for traditional machine learning algorithms, for example, SVM, is hard to implement for large scale training samples. In addition, they are quite likely to fail to solve multi-classification problems. The performance of a convolutional neural network is determined by the depth, width, and residual connections of the network. At present, models used for image classification are generally composed of convolutional neural networks and are almost regularly connected.

- **Registration of MRI to Interventional US for Brain-Shift Compensation Using Convolutional Neural Networks: RAMY A. ZEINELDIN (Member, IEEE), MOHAMED E. KARAR (Member, IEEE), ZIAD ELSHAER, MARKUS SCHMIDHAMMER, JAN COBURGER, CHRISTIAN R. WIRTZ, OLIVER BURGERT, AND FRANZISKA MATHIS-ULLRICH: Date of publication October 14, 2021**

We presented iRegNet as an automated fast and robust deformable method for pre-operative MRI to pre-resection iUS registration for compensating brain-shift phenomenon. In six experiments, our proposed method has been successfully tested and evaluated on 36 cases from two multilocation datasets, validating the registration performance qualitatively and quantitatively. Notably, iRegNet achieved considerable performance and computational efficiency even with untrained cases, demonstrating the generality of our proposed method. Image registration is the process of finding spatial correspondences between two or more images. Within the medical field, image registration is attractive for providing more information when the imaging data come from different sources and/or different modalities. The term deformable denotes that the images are related through non-linear spatial deformation and the resultant transformation not only includes rigid operations (such as rotation and translation) but also non-uniform operations like shearing. Accurate and safe neurosurgical intervention can be affected by intra-operative tissue deformation, known as brain-shift. In this study, we propose an automatic, fast, and accurate deformable method, called iRegNet, for registering pre-operative magnetic resonance images to intra-operative ultrasound volumes to compensate for brain-shift. iRegNet is a robust end-to-end deep learning approach for the non-linear registration of MRI-iUS images in the context of image-guided neurosurgery.

1.4 Problem Statement

Brain tumors are a significant health concern, and Magnetic Resonance Imaging (MRI) is a vital diagnostic tool for their detection and classification. However, the accurate and timely classification of brain tumors from MRI scans remains a challenging task due to the following problems:

- **Complex Image Variability:** MRI images of brain tumors exhibit substantial variability in terms of tumor size, shape, location, and appearance.
- **Dimensionality Challenges:** MRI scans typically generate a large volume of data, which can overwhelm classification algorithms.
- **Lack of Automated Solutions:** While machine learning and deep learning techniques have shown promise in medical image analysis, there is a need for an automated and robust solution that can handle the diversity and complexity of MRI brain tumor images efficiently.
- **Inefficient Feature Extraction:** Extracting meaningful and discriminative features from MRI images is a critical step in tumor classification.
- **Manual Diagnosis Limitations:** Manual interpretation of MRI scans by radiologists is time-consuming and can be subject to human error.

2. METHODOLOGY

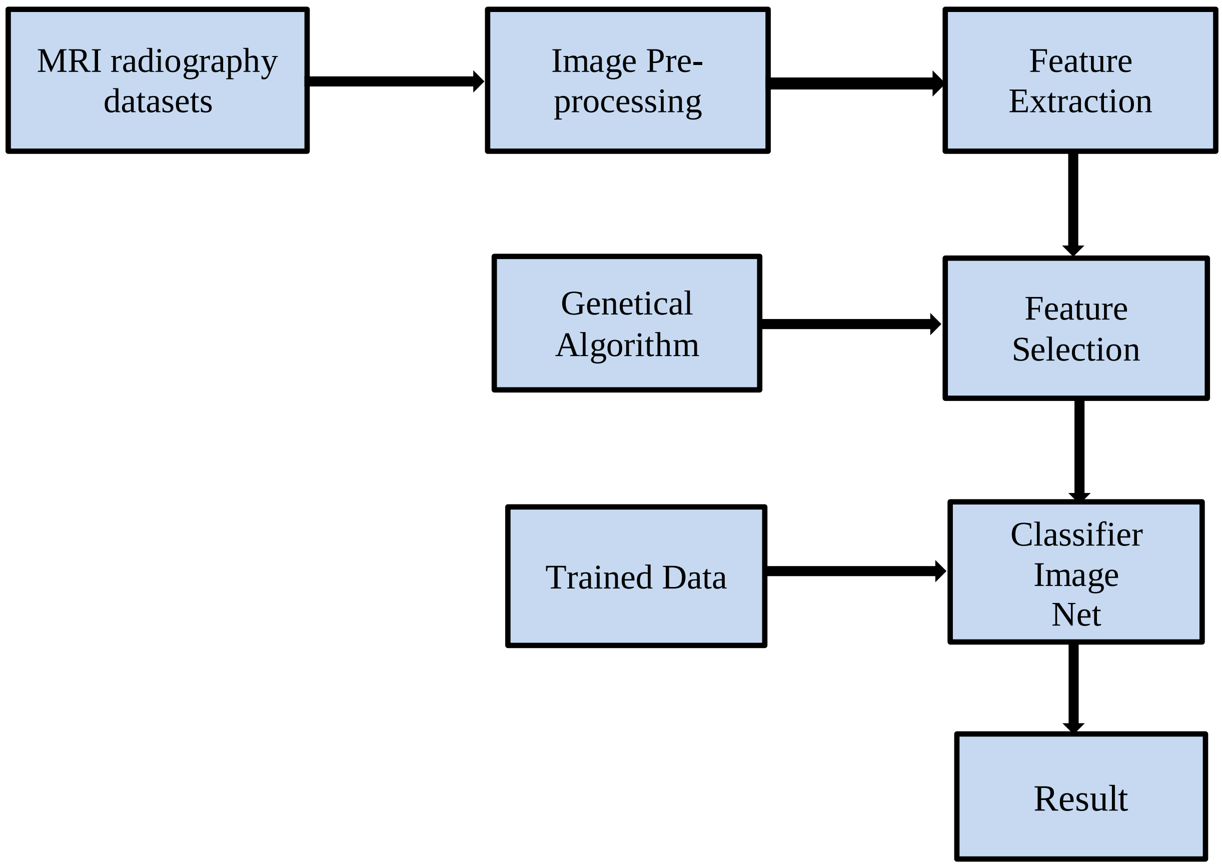

Figure: Overview of Proposed Deep Learning Model

The proposed model with multiple layers and predetermined models is explained in the following subsections. The suggested deep learning model overview is shown in Figure. Image Preprocessing allows running many deep learning algorithms and machine learning parallel to choosing the best algorithm. Image classification datasets are often more significant. Feature extraction is a technique to reduce the number of features in a dataset by creating new features from existing ones. This research uses a SVM to evolve the CNN's ideal structure by selecting suitable network parameters. In this scenario, Proposed CNN technique is applied to achieve optimal learning.

2.1 Module Specification

Module Specification is the way to improve the structure design by breaking down the system into modules and solving it as independent task. By doing so the complexity is reduced and the modules can be tested independently. The number of modules for this model is two, namely hazed data collection set, data set de-hazing module.

2.1.1 Image Pre-Processing Module

Name of the Module: Image Pre-Processing

Actors: User, System

Use Cases: Captured Image, Generate RGB matrix, Grey to binary image

Functionality: The main functionality of this module is to convert the RGB image to binary format for faster processing.

Description:

Figure 2.1 shows the use case diagram of the pre-processing module. In this use case diagram, there are four use cases and two actors. In the first use case, image is captured and is used as input for this module. In second use case, the captured image is complexity using "rgb2gray" function. At last, fourth use case the grey image is converted to binary image.

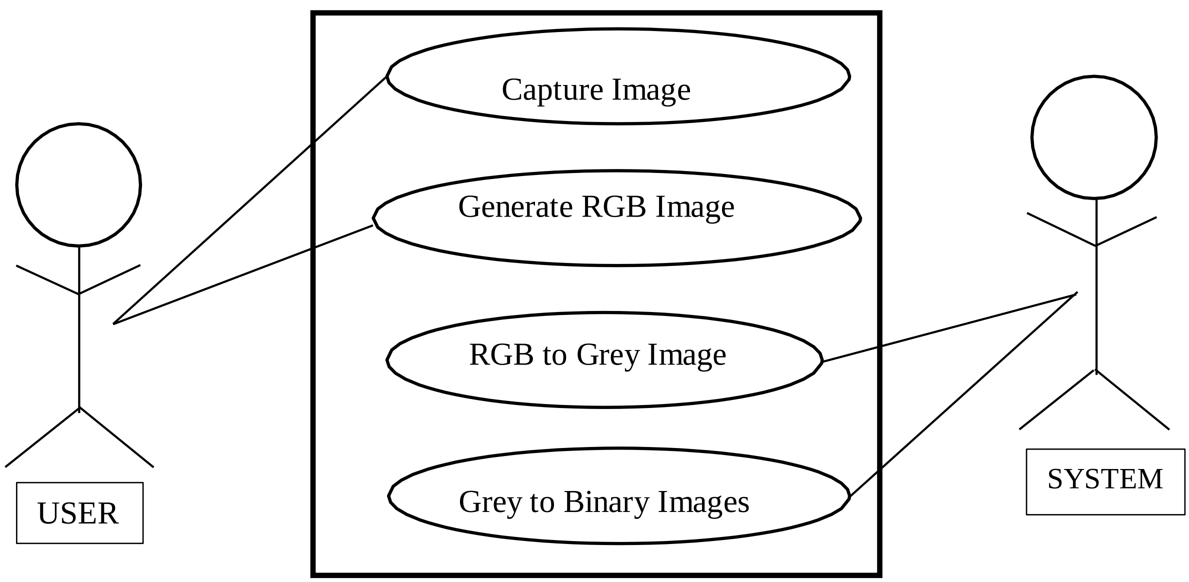

Figure 2.1: Use Case Diagram of pre-processing module.

2.1.2 Segmentation Module

Name of the Module: Segmentation

Actors: System

Use Cases: Binary image, Thresholding, segmented matrix

Functionality: The main functionality of this module is to obtain segmented matrix from binary image performing masking.

Description: Figure 2.2 shows the use case diagram of segmentation of binary image module. In this use case diagram, there are three use cases and one actor. In the first use case, the system takes the binary image as input. In second use case, the image is used as the original RGB image. At the end of third use case Segmentation of image is done to divide image into two regions, background and the foreground. Further the image is resized to reduce size of the matrix used for there cognition process.

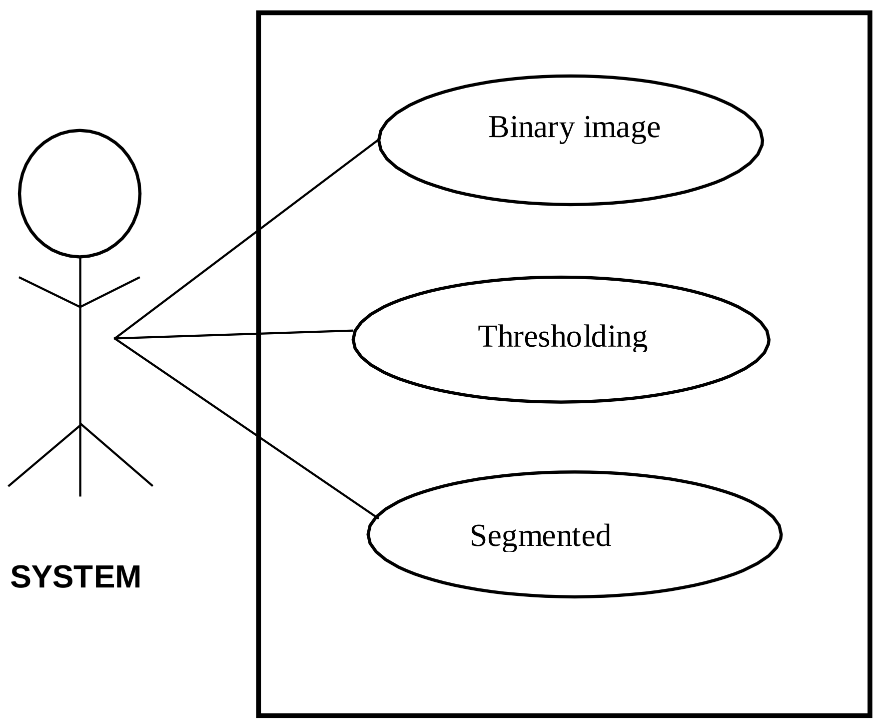

Figure 2.2: Use Case Diagram of Segmentation module

2.1.3 Feature Extraction Module

Name of the Module: Feature extraction

Actors: System

Use Cases: Segmented matrix, Apply GLCM, Generate Statistical values.

Functionality: The main functionality of this module is to apply principle component analysis and obtain Statistical values

Description: Figure 2.3 shows the use case diagram of Feature Extraction module. In this use case diagram, there are three use cases and one actor. In the first use case, the system GLCM, where we can get Statistical Values and Statical Vectors. At the end of third use case to calculate this Statistical Values and Statistical Vectors, column matrix of all the images is formed and concatenated to form single matrix.

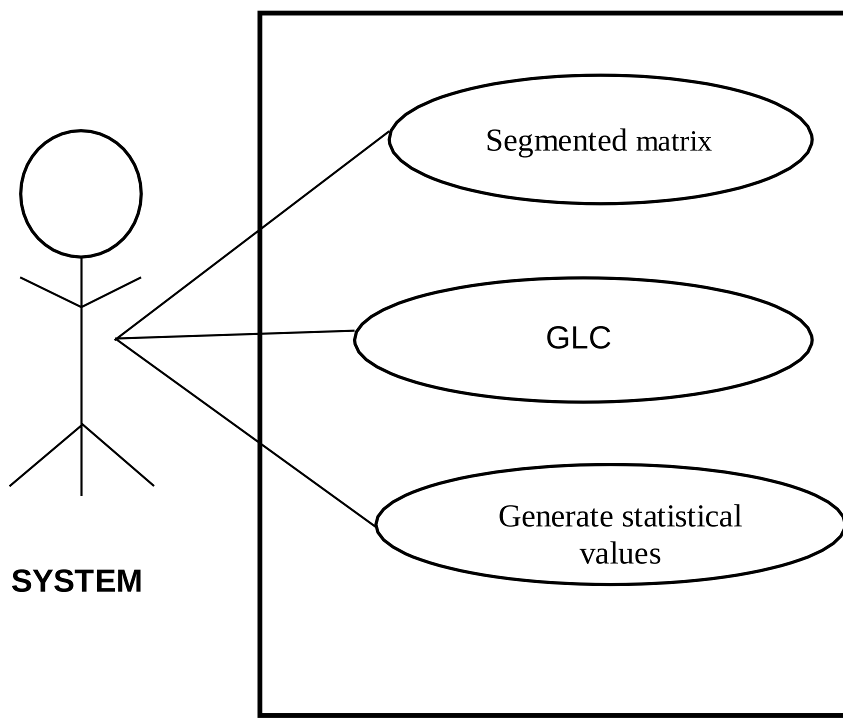

Figure 2.3: Use Case Diagram of Feature Extraction Module.

2.1.4 Classification Module

Name of the Module: Classification Actors: System

Use Cases: Statistical values, obtain feature vector

Functionality: The main functionality of this module is to calculate minimum distance.

Description: Figure 2.4 shows the use case diagram of classification module. In this use case diagram, there are three use cases and two actor. In the first use case, the system takes vectors are obtained which is used to classify the skin gestures. At the end of third use case Feature vectors are calculated for the dataset and the Feature vector calculated for the input image are used to classify the character related to the input gesture.

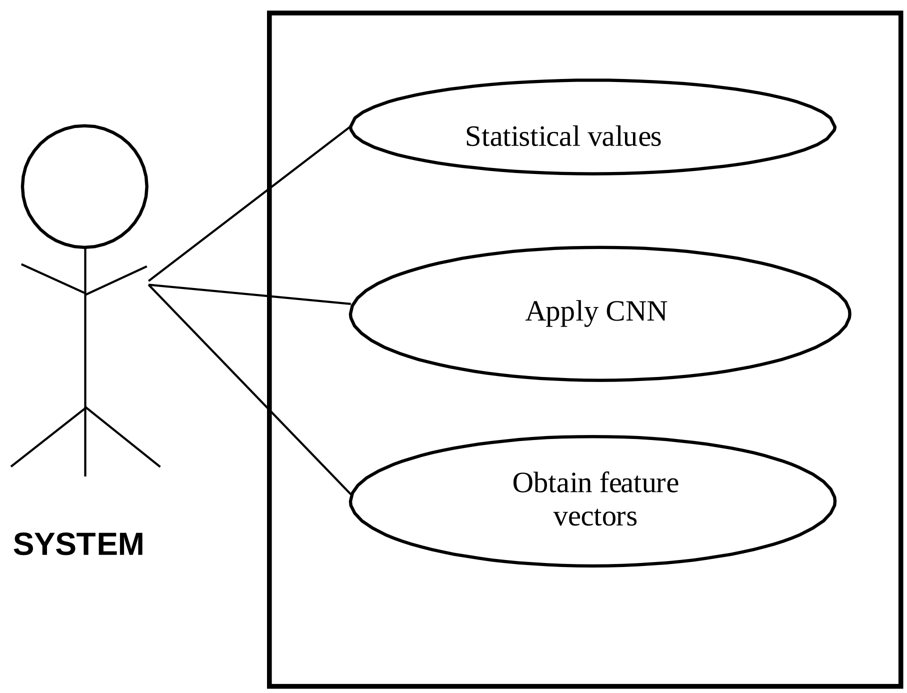

Figure 2.4: Use Case Diagram of Classification Module.

2.1.5 Convolution Matrix

Name of the Module: Convolution

Actors: System

Use Cases: Feature vectors matched with dataset, calculating minimum distance value,

Functionality: The main functionality of this module is to calculate minimum distance value and to recognize the corresponding image.

Description: Figure 2.5 shows the use case diagram of convolution matrix. In this use case diagram, there are three use cases and two actor. In the first use case, the feature vectors. matched with dataset is taken as input. In second use case, the minimum value between the input image and segmented image is obtained after matching. At the end of third use case the sign is recognized as output.

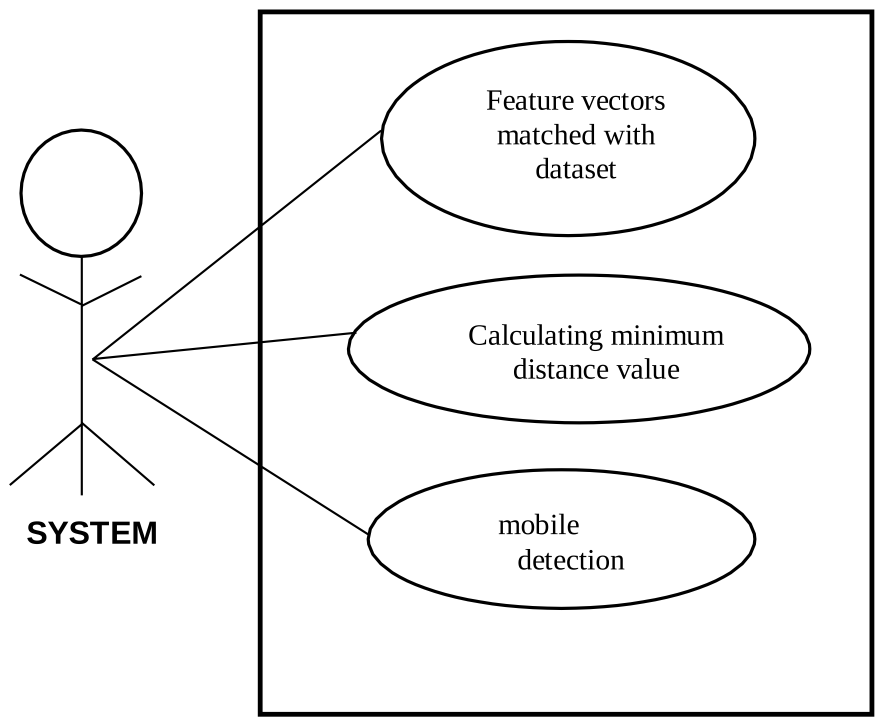

Figure 2.5: Use Case Diagram of Convolution Matrix

In the following subsections, the proposed model with multiple layers and predetermined models is explained:

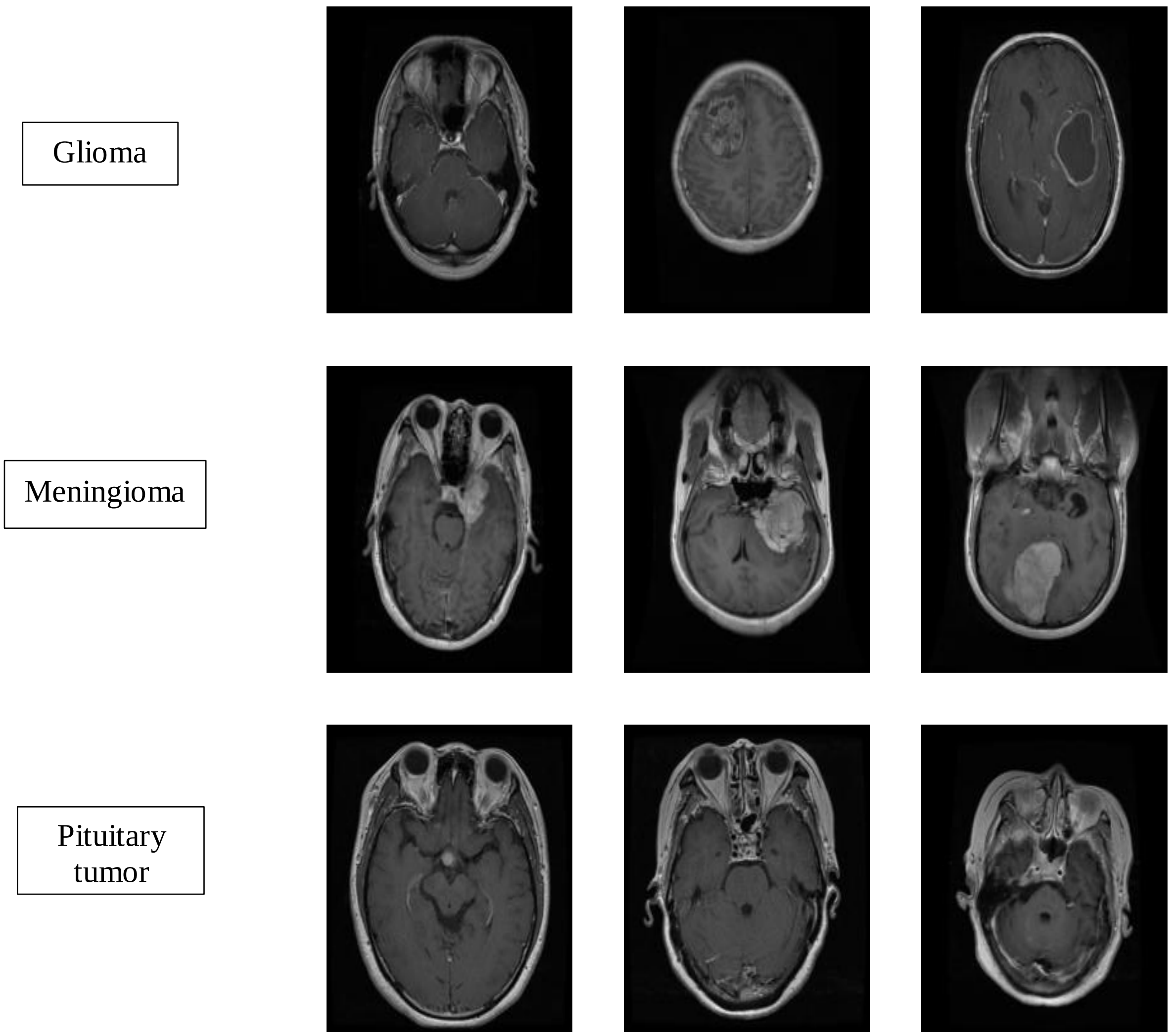

Figure: Sample test images from the Radiography dataset

2.2 Limitations of Existing System

The existing systems for the registration of MRI brain tumor classification based on Genetic Algorithm and Convolutional Neural Network (CNN) have made significant strides in improving accuracy and efficiency. However, they are not without their limitations: MRI datasets for brain tumor classification may suffer from class imbalance, with some types of tumors being significantly rarer than others. This imbalance can lead to biased models that perform well on the majority class but poorly on minority classes. The existing system's ability to generalize to data from different sources or patient populations may be limited. Models trained on a specific dataset may not perform well on scans from different MRI machines, acquisition protocols, or patient demographics. Both CNNs and Genetic Algorithms involve tuning hyperparameters, and the performance of the system can be sensitive to these settings. Finding the optimal hyperparameters can be a time-consuming and iterative process.

2.3 Proposed System/Approach

The proposed system aims to provide an advanced and robust solution for the registration of MRI brain tumor classification, offering improved accuracy, interpretability, and ethical compliance while addressing the challenges of data diversity and computational resources. It represents a significant step toward enhancing patient care and outcomes in the field of neurology.

- To address the limitations of existing systems and further enhance the accuracy and efficiency of MRI brain tumor classification, we propose an advanced system that integrates Genetic Algorithms (GAs) and Convolutional Neural Networks (CNNs).
- Our proposed system aims to overcome the challenges of data limitations, computational resources, interpretability, data imbalance, and generalization while improving the overall diagnostic performance.
- Implement techniques for model interpretability and explain ability to provide insights into why the model makes specific classification decisions. This is crucial for gaining trust from medical professionals.
- Ensure compliance with ethical standards and regulatory requirements for medical AI systems, including patient data privacy, informed consent, and adherence to healthcare regulations.

3. Tools or Languages Used

Python is the predominant programming language in machine learning. Its simplicity, extensive libraries like NumPy and TensorFlow, and a vibrant community make it the top choice for ML practitioners. Python's versatility and ease of use make it well-suited for tasks like data preprocessing, model development, and deployment in the field of machine learning.

HTML, CSS and JavaScript play essential roles in web development, the core work of designing, training, and deploying AI and ML models typically relies on other programming languages and frameworks, such as Python, TensorFlow, PyTorch, or scikit-learn. These technologies are better suited for the computational and data manipulation tasks inherent in AI and ML development.

Image processing is a fundamental component of artificial intelligence (AI) and machine learning (ML) applications. It involves techniques for analyzing, enhancing, and extracting information from images. In AI and ML, image processing is crucial for tasks like computer vision, object detection, facial recognition, and medical image analysis. Algorithms and neural networks are trained on large datasets of images to learn patterns and make sense of visual data. This enables AI systems to perform tasks such as identifying objects in photos, detecting anomalies in medical scans, and powering autonomous vehicles. Image processing is a cornerstone of AI and ML, enabling machines to understand and interpret the visual world.

4. Applications and Advantages

Applications:

The registration of MRI brain tumor classification based on Genetic Algorithm and Convolutional Neural Network has multifaceted applications that span diagnosis, treatment planning, research, education, and healthcare optimization.

- **Early and Accurate Diagnosis:** This technology aids medical professionals in swiftly identifying the presence, type, and location of tumors, enabling timely treatment decisions.
- **Treatment Planning:** By knowing the tumor type and location, healthcare providers can determine the most appropriate treatment approach, whether it involves surgery, radiation therapy, chemotherapy, or a combination of these.
- **Education and Training:** MRI brain tumor classification systems can serve as educational tools for medical students and residents, helping them understand the intricacies of brain tumor identification and classification.
- **Assisting Radiologists:** Radiologists can benefit from the system as a supportive tool in their diagnostic workflow.

Advantages:

The registration of MRI brain tumor classification based on Genetic Algorithm and Convolutional Neural Network (CNN) offers several notable advantages over traditional methods and even some existing machine learning approaches. These advantages include:

- The integration of Genetic Algorithms and CNNs allows for more accurate brain tumor classification.
- Genetic Algorithms intelligently select the most discriminative features from MRI scans, reducing the dimensionality of the data while preserving critical information.
- Radiologists can benefit from the system as a supportive tool in their diagnostic workflow.
- The proposed system automates the process of brain tumor classification, reducing the reliance on manual interpretation by radiologists.

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