An Automatic Clinical System for Tumor Medical Image Classification Using Machine Learning Techniques

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Abstract: This study introduces an enhanced machine learning framework, referred to as the Robotic Clinical System for Brain MRI Image Classification (RCS-BMIC), and developed to enable automated detection of brain tumors from MRI scans. The architecture of the proposed system is organized into two fundamental stages: model training and performance evaluation. In the training stage, previously acquired brain MRI scans are compiled from clinical data sources to form a structured dataset. These images are then subjected to preprocessing procedures aimed at improving visual clarity and normalizing image dimensions through optimized computational techniques. Feature extraction is subsequently conducted using a Convolutional Neural Network (CNN), which learns discriminative representations such as structural boundaries and texture patterns within the brain images. The extracted features are further organized using the K-means clustering algorithm to group similar patterns into distinct clusters based on shared characteristics. During the evaluation stage, unseen MRI images are analyzed using the trained model. The classification process is performed through the K-Nearest Neighbor (K-NN) algorithm, which determines the presence or absence of a tumor based on feature similarity. The integration of deep feature learning, clustering, and instance-based classification provides a comprehensive and reliable framework for accurate brain tumor identification.

Keywords: Convolution Neural Network (CNN); K-means ; Robotic Clinical System for Brain MRI Image Classification (RCS-BMIC)

Introduction

Brain tumor detection is a critical medical procedure aimed at identifying abnormal growths within the brain that may disrupt normal neurological function. These growths, referred to as tumors, are broadly categorized as either present or absent, forming the basis of diagnostic evaluation. Early and precise detection is essential, as timely intervention significantly improves treatment outcomes and reduces the risk of severe complications. Magnetic Resonance Imaging (MRI) serves as a primary diagnostic tool, providing high-resolution images that enable clinicians to determine the presence, size, and exact location of tumors. In recent years, advancements in artificial intelligence and machine learning have further enhanced diagnostic accuracy by enabling automated analysis of medical images, thereby supporting radiologists in making faster and more reliable assessments. Clinical manifestations of brain tumors vary depending on their size and location, commonly including persistent headaches, nausea, seizures, visual disturbances, and cognitive or behavioural changes. Early diagnosis facilitates prompt therapeutic intervention such as surgery, radiation therapy, or chemotherapy ultimately improving patient prognosis and quality of life. The proposed brain tumor detection system employs advanced machine learning methodologies to analyze MRI-based medical imaging data for accurate and efficient diagnosis. By identifying abnormal structural patterns within brain images, the system assists clinicians and radiologists in improving diagnostic precision while minimizing manual effort. The framework integrates

Convolutional Neural Networks (CNNs) for deep feature extraction, K-means clustering for effective image segmentation, and the K-Nearest Neighbor (K-NN) algorithm for accurate classification through pattern matching. This hybrid approach leverages the complementary strengths of each technique, resulting in a robust, reliable, and comprehensive solution for early brain tumor detection and enhanced clinical decision-making.

Related work

In [1], the authors Kazihise Ntikurako Guy-Fernand et al., have been reported a medical system which used to identify the brain tumor over the given MRI picture. The paper discusses the use of a pre-trained attention mechanism for brain tumor classification, leveraging deep learning methods in medical image analysis. It Implements the architecture that achieved state-of-the-art performance on a brain tumor dataset. The study also references related works and studies in the field of medical image analysis and deep learning, providing valuable insights for the literature survey.

The authors **Swati Jayade et al.,** in [2] have Implemented a system called Review of Brain Tumor Detection Concept using MRI Images. The literature survey provides an overview of the significance of medical imaging in identifying and diagnosing brain tumors, with a focus on MRI images as the most reliable visualization tool for internal brain structures. It also discusses various segmentation methods, including thresholding and clustering, used for brain tumor detection, emphasizing the importance of accurate segmentation for precise diagnosis and treatment planning. Additionally, the survey highlights the development and successful testing of various algorithms and techniques for image segmentation in the context of brain tumor detection.

Gouskir et al., **in [3]** have designed a system called Automatic Analysis of Brain Tumor from Magnetic Resonance Images based on Geometric Median Shift. The paper presents an adaptive method that employs the mean shift algorithm over Riemannian manifolds for accurate segmentation of brain tumor regions in magnetic resonance images. It combines geometric median shift with K-means to improve the homogeny of both methods. The Implemented method presents efficient results in clustering brain regions and accurately segmenting different tissues. The quantitative evaluation is done using the Dice Similarity Coefficient (DSC) and shows high rates for T1-weighted sequences compared to T2-weighted sequences.

The author Deepak O. Patil et al., in [4] have reported a system called Monogenic Wavelet Phase Encoded Descriptors for Brain Tumor Image Detection. The Presented brain tumor detection algorithm utilizes monogenic wavelet phase-encoded features and CLBP textural descriptors, reduced using neighborhood component analysis. It employs a support vector machine for classification. Evaluation using two popular MR imaging databases demonstrates enhanced performance compared to existing algorithms. The algorithm efficiently extracts abnormality details from input images and achieves better accuracy in detecting brain tumor images.

The author Akshaya TA M et al., in [5] have been Implemented a system called Identification of Brain Tumor on MRI Images With And Without Segmentation Using DL Techniques. The literature survey explores the use of computer-based systems to enhance the accuracy and speed of brain tumor detection. It discusses the potential of convolutional neural networks (CNNs) in accurately detecting and classifying brain tumors based on MRI images. The process involves pre-processing MRI images, segmenting the tumor, and extracting relevant features for training the CNN. Additionally, studies have been conducted to enhance brain tumor segmentation and detection using deep learning frameworks. There is potential for further improvement in the accuracy of the model with the inclusion of more diverse data and fine-tuning of the hyper-parameters.

Md. Ahasan Kabir et al. [6] have designed a system called Early-Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique. The document presents an algorithm for enhancing MRI images to aid in the detection and classification of brain tumors. It discusses the use of contrast limited adaptive histogram equalization (CLAHE) and outlines the various stages of the algorithm, including intensity smoothing, image enhancement, SVM-based segmentation, feature extraction, and classification. The algorithm in tumor classification, outperforming existing algorithms. It was tested on the BRATS dataset image, and the results were compared with those of existing algorithms in terms of accuracy.

In [7], The author Levente Kovacs et al. have reported a system called A Feature Ranking and Selection Algorithm for Brain Tumor Segmentation in Multi-Spectral Magnetic Resonance Image Data. The study presents a feature selection algorithm for brain tumor segmentation in multi-spectral magnetic resonance image data. It focuses on reducing computational load while maintaining segmentation accuracy. An ensemble learning solution using binary decision trees and a feature set is employed. The algorithm iteratively eliminates low-ranked features, resulting in a reduced set of 13 features that provides the same accuracy as the initial set but three times faster. The reduced feature set can be extracted in 7-8% of the time necessary for the full feature set. This approach offers a significant contribution to optimizing the processing speed of medical image.

The author Kim Mey Chew et al., in [8] have Implemented a system called Human Brain Modeling Tumor Detection in 2D and 3D Representation Using Microwave Signal Analysis. The literature survey in the document covers the human brain structure, dielectric properties of human tissues, and the microwave imaging system. It also discusses brain cancer incidence rates and metastases. Additionally, it provides information on signal processing and the use of window functions and superposition technique functions. The survey is comprehensive and provides valuable insights into the relevant background information for the study.

Polly et al., in **[9]** have designed a system called Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning. The literature survey discusses various methodologies and algorithms for brain tumor detection and classification using MRI images. It covers the use of Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), k- means clustering, Probabilistic Neural Network (PNN), FCM clustering, SVM classifier, PCA, and other techniques. The survey also evaluates the performance of different systems based on parameters such as accuracy, sensitivity, and specificity. Overall, it provides a comprehensive overview of the existing research in this field.

In [10] the author Ahasan Iban Aziz et al., have reported a system called Effective Modeling of GBC Based Ultra-Wideband Patch Antenna for Brain Tumor Detection. The paper presents the design of a special ultra-wideband (UWB) patch antenna using graphene-based conductor (GBC) for the detection of human brain tumors. The presented antenna operates within a frequency band of 3.15 - 9.15 GHz and is designed to be located at a 20 mm distance from the human head. The study includes biocompatibility analysis of the head tissue using CST MWS software, and the developed antenna ensures protection of the patient from electromagnetic radiation. Microwave-based techniques are highlighted as fast, cost-effective, and portable for head investigation and brain tumor detection. The antenna's performance is optimized by determining the length of the ground patch, and the gain of the antenna is shown to be greater when simulating with a cancerous head phantom compared to a healthy phantom.

The authors Jemimma et al., in [11] have been Implemented a system called Watershed Algorithm based DAPP features for Brain Tumor Segmentation and Classification. The paper presents a brain tumor detection technique using the Watershed Dynamic Angle Projection - Convolution Neural Network (WDAPP-CNN). This method achieves 94.2% sensitivity, outperforming existing techniques. It involves segmentation, feature extraction, and classification of MRI brain images. The implemented algorithm is compared with other methods using the BRATS database and shows efficient execution time. The Watershed algorithm and CNN classification are key components of this approach.

Anandkumar et al., in [12] have been designed a system called Human Brain Tumor Detection and Classification by Medical Image Processing. The literature survey covers the detection and extraction of brain tumors from MRI images. It includes studies on brain tumor segmentation, image processing techniques, and the use of MATLAB for tumor extraction. The survey emphasizes the importance of accurate detection and separation of brain tumors from MRI scans for clinical studies. Additionally, it highlights the need for pre-processing of MRI images to enhance image quality and features. The implemented algorithm for brain tumor detection and separation using MRI scans has shown promising results.

In [13],The author Hemanth et al., in [13] have been reported a system called Design And Implementing Brain Tumor Detection Using Machine Learning Approach. The literature survey discusses the use of machine learning and data mining techniques for brain tumor detection and prevention at an early stage. It includes a comparison of various classification techniques, such as CRF, SVM, and GA, and highlights the output of the presented CNN. The document also presents simulation results and references related research papers, providing valuable insights into the current state of the art in MRI brain tumor segmentation.

The author Mostafa Soleymanifard et al., in [14] have been Implemented a system called Segmentation of Whole Tumor Using Localized Active Contour and Trained Neural Network in Boundaries. The document discusses a presented method for automatic segmentation of brain tumors from MRI images, utilizing a combination of active contour and trained neural network. The approach is based on training patches on tumor boundaries as random points, resulting in faster training and improved accuracy in segmentations. The segmentation performance is evaluated using the DICE coefficient, showing promising and satisfactory results. Suggestions for improvement include learning combinatorial mask coefficients and using intensity inhomogeneity for segmentation. The proposed method is compared to state-of- the-art segmentation methods, demonstrating competitive performance.

Kasi Tenghongsakul et al., in [15] have been designed a system called Deep transfer learning for brain tumor detection based on MRI images. The study focuses on deep transfer learning methods for brain tumor detection using MRI images. It compares pre-trained models such as Inception ResNet- V2, ResNet50, MobileNet-V2, and VGG16, and evaluates their efficiency using various metrics. The results indicate that VGG16 with RMSprop using CLAHE MR images for brain tumor detection provides the best efficiency, with 100% accuracy, precision, recall, and F1-score.

Key Contribution

The proposed RCS-BMIC framework is engineered to divide brain MRI scans into two separate clusters by adaptively computing centroid positions through the K-means clustering technique. In addition to segmentation, the system categorizes MRI images into tumor and non-tumor classes to support precise diagnostic outcomes. The methodology is structured into a sequence of processing phases, including image enhancement and preprocessing, extraction of edge-oriented features, clustering of relevant regions, and subsequent classification. A schematic representation of the complete operational architecture of the RCS-BMIC model is presented in Figure 1.

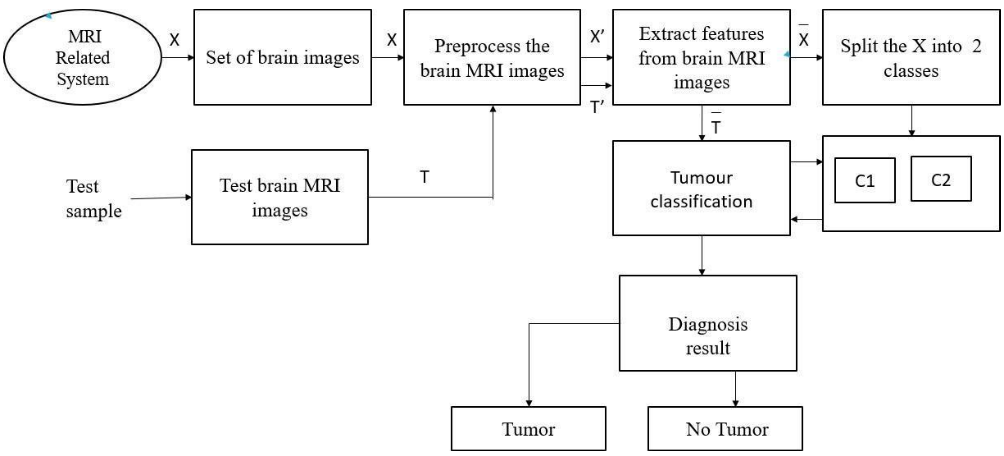

Figure 1: Proposed (RCS-BMIC) System Architecture

Preprocessing of brain MRI images involves a sequence of refinement steps designed to improve image consistency and analytical reliability. The images are first standardized by adjusting their dimensions while maintaining proportional scaling to preserve anatomical integrity. To further enhance image quality, denoising techniques are applied to suppress random artifacts that may obscure diagnostically significant details.

The proposed framework subsequently concentrates on extracting boundary-oriented characteristics from MRI scans to detect distinguishing markers between abnormal and normal brain tissues. A Convolutional Neural

Network (CNN) is utilized to automatically derive multi-level feature representations from the images. Through

layered processing, the network identifies meaningful visual cues, including structural irregularities, texture disparities, and intensity fluctuations that may indicate the presence of a tumor.
In the training phase, the model is supplied with annotated datasets to learn the distinction between pathological and healthy image patterns. The learning process iteratively adjusts internal parameters to reduce misclassification and enhance predictive performance. Additionally, a K-means clustering approach is implemented to partition the MRI data into two defined categories namely C1 (tumor) and C2 (non-tumor), thereby supporting structured grouping and improving overall classification effectiveness.

Method, Experiments and Results

The historical brain MRI images are collected from the medical related system as a image dataset. A total of 253 images were collected from a Kaggle platform with different size including count of 155 tumor images and 98 no tumors images respectively. For the demonstration purpose, we have randomly selected few number of images from the image data set and the sample medical pictures are presented in the Figure.1.

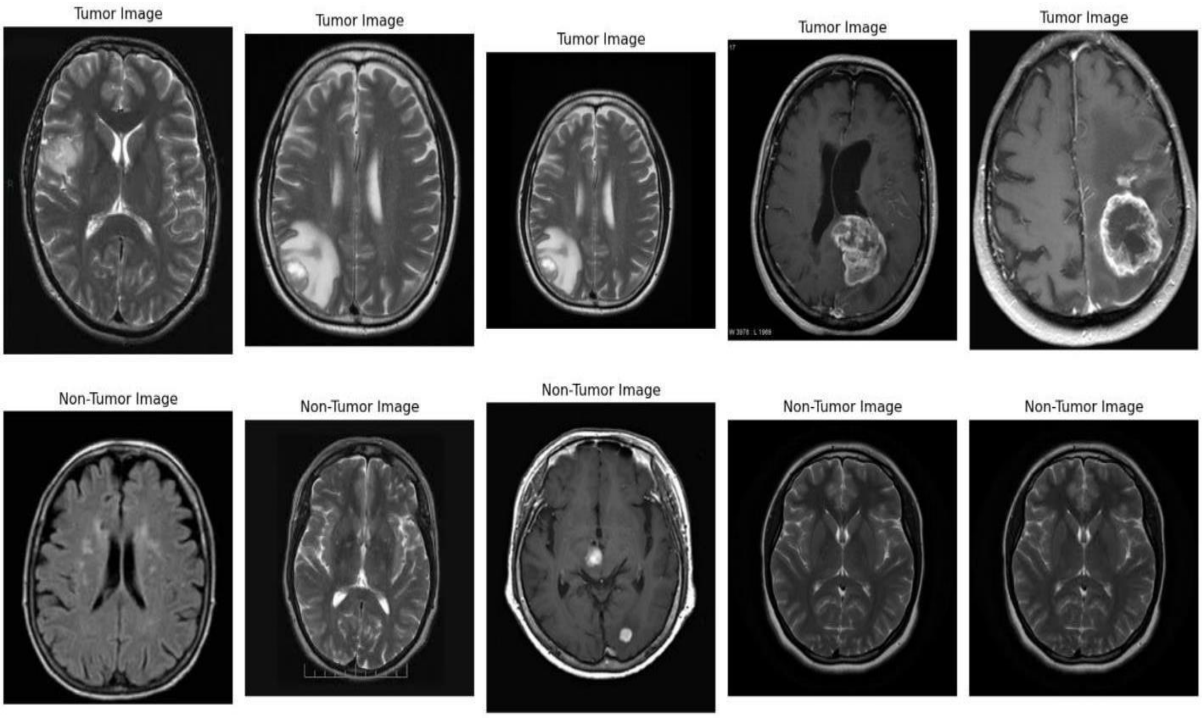

Figure. 1: Sample Input Medical Image Set

Brain MRI images preprocessing involves several steps to enhance the quality of the images. Resizing ensures that you adjust the dimensions of the image while keeping the aspect ratio constant Gaussian blur is a smoothing technique that helps reduce this noise. The result of the MRI samples pre-processed as presented in the Figure. 2

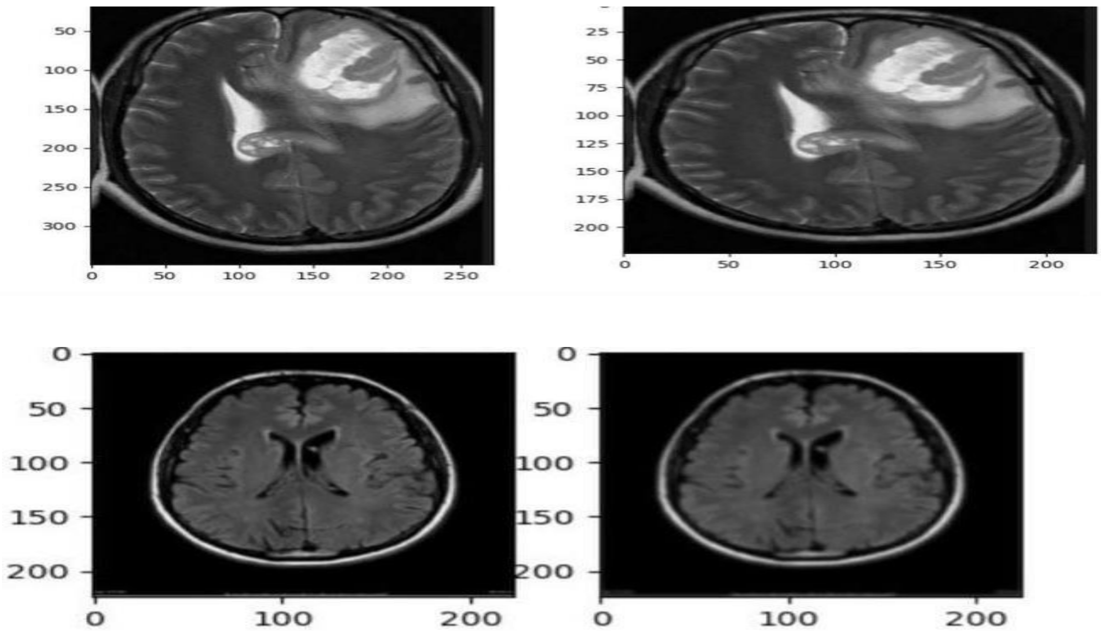

Figure. 2: Result of MRI Images Pre Processed Including Re-sizing and Blurring Operation

System is currently focused on extracting edge features from brain MRI images with the goal of identifying unique patterns that distinguish tumor regions from non-tumor areas using CNN. The proposed system is applying edge detection using the Sobel operator and then trains a convolution neural network (CNN) model for edge detection. It pre-process the images and labels, creates a CNN model with convolution and pooling layers, and compiles the model. Finally, it trains the model on the pre-processed images and indicating that the CNN model has been trained for edge detection. clusters. The organization of images into output directories based on their cluster assignments further streamlines data management and analysis.

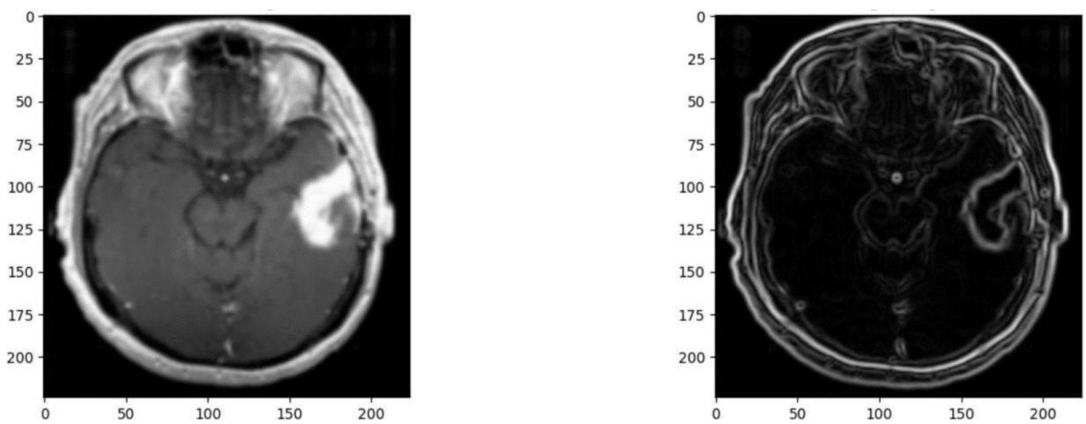

Figure. 3: Result of CNN Process Over the Sample MRI Images

In the next stage, the proposed system is following to train the result of CNN model by k-means and PCA techniques respectively. This stage aims to cluster grayscale images into two categories, representing tumor and non- tumor images, using k-means clustering after preprocessing them with PCA for dimensionality reduction. Initially, it organizes the images from two directories (**Cluster_1** and **Cluster_2**) into lists along with their corresponding labels, tumor images labeled as 1 and non-tumor images as 0. It then standardizes the features and reduces dimensionality through PCA, retaining 150 principal components. Subsequently, it trains a k-means model on the transformed data, with the number of clusters set to 2. After training, it assigns each image to the cluster with the nearest centroid and computes the accuracy of the clustering results. Finally, it saves the trained k-means model to a file. The printed warnings indicate potential issues related to future changes in default parameters and a known memory leak on Windows with MKL, which can be addressed by setting environment variables appropriately. The script reports a high accuracy of 98.02% for the clustering and confirms the successful saving of the trained model and the result is presented in the Figure. 5.

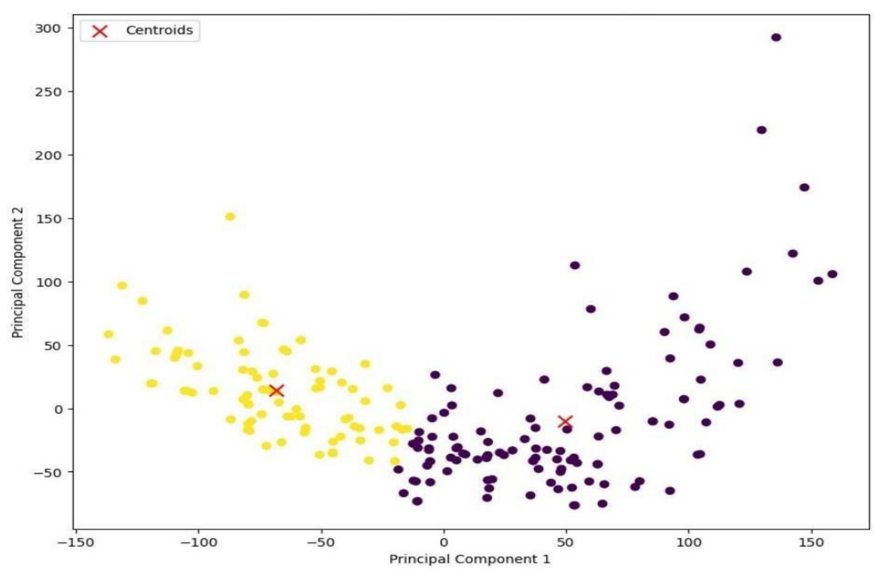

Figure. 5: Result of Training Process Using k-means and PCA over the Feature of MRI Samples

Finally, the proposed system has been demonstrated the classification of a new MRI image into one of two clusters, "Cluster_1" representing tumor images and "Cluster_2" representing non-tumor images, using a previously trained k-means model. Initially, the image is loaded, per-processed by re-sizing and flattening it, then normalized using the scale trained on the training data. Subsequently, the PCA transformation is applied to reduce the image's dimensional to match the training data set format. The script then employs the trained k-means model to predict the class of the new image based on its PCA transformed features. Finally, it prints out the predicted class, indicating whether the new MRI image belongs to "Cluster_1" or "Cluster_2." In this instance, the output suggests that the new MRI image belongs to "Cluster_2."

Conclusions

The Phase-2 work of a Robotic Clinical System to Classify Brain MRI Images Via Improved Machine Learning Technique has come to a successful conclusion with the completion of the Introduction, Literature Survey, System Requirement Specification and System Design. The requirements for the system have been effectively identified and the design of the system has been formulated. The literature survey conducted for the project provides a clear overview of the existing Machine Learning techniques and how they can be used to Classify Brain MRI Images With the completion of this phase of the project, the groundwork has been laid for the development of the system. The next phase will involve implementation of the system followed by testing and evaluation of the system. After successful completion, it is expected that the system will be able to classify brain MRI images as tumor or no tumor accurately and efficiently.

References

1. Kazihise Ntikurako Guy-Fernand, Juan Juan Zhao, Fredy Malack Sabuni, Jiawen Wang, “Classification of Brain Tumor Leveraging Goal-Driven Visual Attention with the Support of Transfer Learning", Information Communication Technologies Conference, pp 328-332,2020.
2. Ms. Swati Jayade, Dr. D. T. Ingole, Prof. Mrs Manik D. Ingole, "Review of Brain Tumor Detection Concept using MRI Images", International Conference on Innovative Trends and Advances in Engineering and Technology, pp 206-209,2019.
3. Deepak O. Patil, Satish T Hamde, "Monogenic Wavelet Phase Encoded Descriptors for Brain Tumor Image Detection", Proceedings of IEEE Third International Conference on Multimedia Processing, Communication & Information Technology, pp 40-44,2020.
4. M. GOUSKIR, M. BOUTALLINE, M.A. ZYAD, "Automatic Analysis of Brain Tumor from Magnetic Resonance Images based on Geometric Median Shift", 2nd Inter-national Conference on Knowledge-Based Engineering and Innovation, vol. 8, no. 4, pp 11-17,2020.
5. Sneha Grampurohit, Venkamma Shalavadi, Vaishnavi R. Dhotargavi, Megha Kudari" Brain Tumor Detection Using Deep Learning Models", IEEE India Council International Subsections Conference , pp 129-134,2020.
6. Md. Ahasan Kabir, Agnes Gy orfi, Levente Kovacs and Laszl o Szil agyi, "Early-Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique", IEEE Region 10 Symposium, pp 1828-1831,2020.
7. Agnes Gyorfi, Rubita Sudirman, Syvester Tan Chiang Wei, "A feature ranking and selection algorithm for brain tumor segmentation in multi spectral magnetic resonance image data", Biomed.Sign.Proc. Contr, pp 804-807,2019.
8. Kim Mey Chew, S. K. ShilM. A. Hossain, A. Ayman, Y. M. Jang, "Human Brain Modeling Tumor Detection in 2D and 3D Representation Using Microwave Signal Analysis",

Neuroscience. 4th. Sinauer Associates, United States of America, pp 310-316,2018.
9. F. P. Polly1, Ahasan Ibna Aziz, Md. Masud Rana, Md. Ariful Islam and Reefat Inum, "Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning", Expert Systems with Applications, pp 813-817,2018.
10. Md. Ahasan Ibna Aziz, Y. Jacob Vetharaj,"Effective Modeling of GBC Based Ultra Wideband Patch Antenna for Brain Tumor Detection "9th European Conference on Antennas and Propagation (Eu-CAP), pp 6-10,2018.
11. T. A. Jemimma, Anandkumar, R. Dhayalan,"Watershed Algorithm based DAPP features for Brain Tumor Segmentation and Classification",International Conference on Smart Systems and S. Gobhinath, P. Ezhilbharathi R. Haridharan, "Human brain tumor detection and classification by medical image processing", 7th International Conference on Advanced Computing & Communication Systems , pp 561-564,2021.
12. G. Hemanth, Janardhan L. Sujihelen, "Design and implementing brain tumor detection using machine learning approach" ,Proceedings of the Third International Conference on Trends in Electronics and Informatics, pp 1289-1294,2019.
13. Mostafa Soleymanifard, Mohammad Hamghalam, "Segmentation of Whole Tumor Using Localized Active Contour and Trained Neural Network in Boundaries "5th Conference on Knowledge-Based Engineering and Innovation, Iran University of Science and Technology, pp 739-744,2019.
14. Suraj Patil, Dnyaneshwar Kirange, "Ensemble of deep learning models for brain tumor detection", International Conference on Machine Learning and Data Engineering , pp 2468-2479,2023.