A Robotic Clinical System to Classify Tumor MRI Images Via Improved Machine Learning Techniques

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Abstract: An improved machine learning technique called Robotic clinical system for brain MRI image classification (RCS-BMIC). The proposed (RCS-BMIC) system automatically classifies tumor MRI images using machine learning techniques. The proposed (RCS-BMIC) system contains 2 phases namely training phase and testing phase, in the first stage of training phase, the historical brain MRI images are collected from the medical related system as a image dataset. In second stage, the system preprocesses the brain MRI images to improve the quality and optimize size of the image using improved arithmetic operation. In third stage feature extraction involves identifying unique brain characteristics like edges and texture using Convolution neural network (CNN) algorithm. Fourth stage used to group similar data points together into a clusters based on certain features using Kmeans clustering Algorithm. In testing phase, the proposed system classifies the brain MRI image based on its features or characteristics using k nearest neighboring algorithm resulting whether the tumor is present or not.

Keywords: CNN Algorithm, K-Means Algorithm, KNN Algorithm, Tumor Detection and Machine Learning Technique.

I. INTRODUCTION

Finding abnormal growths in the brain is the goal of the critical medical procedure known as brain tumor identification. These growths, also referred to as tumors, may interfere with normal brain activities and may be cancers or not. Early brain tumor detection is crucial for successful therapy. Tumor location, size, and presence are all determined in large part by a variety of imaging methods, including magnetic resonance imaging (MRI) scans. Machine learning algorithms and other advanced technologies are being used more and more to improve detection speed and accuracy. Brain tumors can cause a wide range of symptoms, from nausea and headaches to impairments in cognitive function. Early detection increases the likelihood of a successful course of therapy and lowers the risk of complications by allowing medical personnel to act quickly.

Since brain tumor patients sometimes find tumor biopsy difficult, non-invasive imaging methods such as Magnetic Resonance Imaging (MRI) have been widely used for brain tumor diagnosis. Thus, it is now essential to build algorithms for the identification of tumors and the estimation of their grade using MRI data. However, upon initial observation of the imaging modality, such as Magnetic Resonance Imaging (MRI), accurately visualizing the tumor cells and differentiating them from the surrounding soft tissues is a challenging task. This could be because of the low illumination in imaging modalities, the abundance of data they contain, or the complexity and variability of tumors, such as their unstructured shape, viable size, and unpredictable locations.

In several medical diagnostic applications, automated flaw detection in medical imaging by machine learning has emerged as a new discipline. Its use in MRI brain tumor identification is critical because it gives information about aberrant tissues, which is needed to plan the course of treatment.

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According to studies published recently in the literature, automatic computerized illness identification and diagnosis based on medical image analysis may be a good substitute because it would reduce radiologists' time and provide tested accuracy.

II. RELATED WORK

Classification of Brain Tumor Leveraging Goal Driven Visual Attention with the Support of Transfer Learning is a system that was reported by Kazihise Ntikurako Guy-Fernand et al. in [1]. 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, offering insightful information for the literature survey.

The Review of Brain Tumor Detection Concept using MRI Images system was implemented by the author, Ms. Swati Jayade, and her colleagues in [2]. With an emphasis on MRI scans as the most trustworthy visual aid for interior brain structures, the literature review gives a general review of the importance of medical imaging in detecting and diagnosing brain malignancies. It also goes over other segmentation techniques, including as clustering and thresholding, that are used to detect brain tumors, highlighting how crucial exact segmentation is to a precise diagnosis and treatment plan. Furthermore, the survey emphasizes the creation and efficacious evaluation of diverse algorithms and methodologies for picture segmentation within the framework of brain tumor identification.

A technique named Automatic Analysis of Brain Tumor from Magnetic Resonance Images based on Geometric Median Shift was created by M. GOUSKIR et al. [3]. The study offers an adaptive technique for precise brain tumor zone segmentation in magnetic resonance imaging that makes use of the mean shift algorithm across Riemannian manifolds. In order to increase the homogeneity of both approaches, it combines K-means with geometric median shift. The adopted technique yields precise tissue segmentation and effective grouping of brain areas. The Dice Similarity Coefficient (DSC) is used for the quantitative evaluation, which reveals higher rates for T1-weighted sequences than T2-weighted sequences..

An approach known as Monogenic Wavelet Phase Encoded Descriptors for Brain Tumor Image Detection was described by Deepak O. Patil and colleagues in [4]. The proposed brain tumor identification system makes use of CLBP textural descriptors that are reduced using neighborhood component analysis and monogenic wavelet phase-encoded features. For categorization, a support vector machine is used.

An evaluation against two widely-used MR imaging databases shows improved performance over current techniques. The system improves the accuracy of brain tumor picture detection while effectively extracting information of abnormalities from input images.

A method named Identification of Brain Tumor on MRI Images With and Without Segmentation Using DL Techniques has been implemented by the author Akshaya TA M et al. in [5]. The use of computer-based technologies to improve the precision and speed of brain tumor detection is investigated in the literature review. It talks about how convolutional neural networks, or CNNs, can effectively identify and categorize brain cancers using magnetic resonance imaging (MRI) data. Pre-processing MRI scans, tumor segmentation, and feature extraction are the steps in the process that prepare the pictures for CNN training. Furthermore, research has been done to improve the deep learning frameworks' capabilities for brain tumor segmentation and detection. By adding additional varied data and adjusting the hyperparameters, the accuracy of the model might potentially be increased even more.

A system named Early-Stage Brain Tumor Detection on MRI Image Using a Hybrid Technique was created by Md. Ahasan Kabir et al. [6]. An strategy for improving MRI pictures is presented in the paper to help in brain tumor identification and categorization. It describes the stages of the technique, including intensity smoothing, picture improvement, SVM-based segmentation, feature extraction, and classification, and talks about using contrast limited adaptive histogram equalization (CLAHE). The tumor classification method outperforms current algorithms. It was evaluated on a picture from the BRATS dataset, and the accuracy of the results was compared with those of other algorithms that were already in use.

A Feature Ranking and Selection Algorithm for Brain Tumor Segmentation in Multi-Spectral Magnetic Resonance Image Data is the system that the author Levente Kovacs et al. published in [7]. A feature selection approach for segmenting brain tumors from multi-spectral magnetic resonance image data is presented in the paper. Its main goal is to keep segmentation accuracy while lowering computational burden. A feature set and binary decision trees are used in an ensemble learning solution. Low-ranked features are iteratively removed by the algorithm, leaving a reduced set of 13 features that performs three times faster with the same accuracy as the original set. It takes 7-8% less time to extract the reduced feature set than it does to extract the entire feature set. This method makes a substantial contribution to processing optimization.

A method named Human Brain Modeling Tumor Detection in 2D and 3D Representation Using Microwave Signal Analysis has been implemented by the author Kim Mey Chew et al. in [8]. The anatomy of the human brain, the dielectric characteristics of human tissues, and the microwave imaging system are all covered in the literature review in this publication. It also covers metastasis and incidence rates of brain cancer. It also offers details on signal processing, including how to employ superposition technique functions and window functions. The survey is thorough and offers insightful information about essential background data for the investigation.

A system named Detection and Classification of HGG and LGG Brain Tumor Using Machine Learning was created by F. P. Polly et al. [9]. The review of the literature addresses different approaches and algorithms for MRI image-based brain tumor identification and categorization. The use of k-means clustering, PCA, FCM clustering, Probabilistic Neural Network (PNN), Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), SVM classifier, and other approaches are covered. Additionally, the study assesses the effectiveness of various systems using metrics like specificity, sensitivity, and accuracy. All in all, it offers a thorough summary of the body of work that has already been done in this area.

The system named Effective Modeling of GBC Based Ultra-Wideband Patch Antenna for Brain Tumor Detection was reported by Md. Ahasan Iban Aziz et al. in [10]. The invention of a unique ultra-wideband (UWB) patch antenna for the detection of brain cancers in humans utilizing graphene-based conductors (GBC) is presented in this study. The proposed antenna is intended to be placed 20 mm away from the human head and operates in the 3.15 - 9.15 GHz frequency range. The study involves a biocompatibility analysis of the head tissue with CST MWS software, and the patient is protected from electromagnetic radiation by the constructed antenna. Microwave-based methods are emphasized as being quick, affordable, and portable for head exams and brain tumor identification. By adjusting the ground patch length, the antenna's performance is maximized. It is demonstrated that simulating with a cancerous head phantom yields a higher gain than a healthy phantom.

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The Watershed Algorithm based DAPP features system was implemented by the author T. A. Jemimma et al. in [11] for the purpose of brain tumor segmentation and classification. The Watershed Dynamic Angle Projection - Convolution Neural Network (WDAPP-CNN) is a brain tumor detection technology that is presented in this research. This approach outperforms previous methods with 94.2% sensitivity. MRI brain pictures are segmented, features are extracted, and the images are classified. Using the BRATS database, the built algorithm is compared against alternative techniques and demonstrates an efficient execution time. Two essential elements of this strategy are the CNN classification and the Watershed algorithm.

A method named Human Brain Tumor Detection and Classification by Medical Image Processing was created by S. Anandkumar et al. [12]. The identification and extraction of brain tumors from MRI images are covered by the literature review. It covers research on image processing methods, brain tumor segmentation, and MATLAB tumor extraction. The survey highlights how crucial it is for clinical research to accurately identify and isolate brain tumors from MRI imaging. It also emphasizes how MRI image preparation is necessary to improve picture characteristics and quality. Promising results have been observed with the built algorithm for brain tumor detection and separation utilizing MRI data.

A system named Design and Implementing Brain Tumor Detection Using Machine Learning Approach has been reported by the author G. Hemanth et al. [13] in [13]. The application of data mining and machine learning methods for early brain tumor prevention and detection is covered in the literature review. It compares a number of classification methods, including CRF, SVM, and GA, and it shows the results of the CNN that was given. Along with simulation findings and relevant research publications, the document offers insightful information about the state of the art in MRI brain tumor segmentation at the moment.

A technique named "Segmentation of Whole Tumor Using Localized Active Contour and Trained Neural Network in Boundaries" was implemented by Mostafa Soleymanifard et al. in [14]. The paper describes a system that combines active contour and trained neural network to automatically segment brain tumors from MRI images. The method is based on using tumor boundaries as random sites for training patches, which leads to faster training and better segmentation accuracy. The DICE coefficient is used to assess the segmentation performance, and the results are encouraging and satisfactory. Using intensity inhomogeneity for segmentation and learning combinatorial mask coefficients are two recommendations for improvement. The suggested approach performs competitively when compared to cutting-edge segmentation techniques.

A system known as Deep transfer learning has been developed by Kasi Tenghongsakul et al., in [15] for the diagnosis of brain tumors using MRI data. The work focuses on deep transfer learning techniques for MRI image-based brain tumor detection. Pre-trained models like Inception ResNet-V2, ResNet50, MobileNet-V2, and VGG16 are compared, and their efficacy is assessed using a range of measures. According to the data, the most efficient method for detecting brain tumors using CLAHE MR images is VGG16 with RMSprop, which offers 100% accuracy, precision, recall, and F1-score.

III. DATASET DESCRIPTION

For those interested in machine learning and data science, Kaggle is an online community platform. Users can use GPU integrated notebooks, search and publish datasets, communicate with other users, and compete with other data scientists to solve data science challenges on Kaggle. Initially launching as a machine learning competition in 2010, Kaggle has since expanded to include a public data platform. a workstation for data science and artificial intelligence instruction that is cloud-based. Max Levchin succeeded Anthony

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Goldbloom as the original chair, and Goldbloom was one of its main individuals. 2011 saw the raising of equity valued at $25.2 million for the company. Google said on March 8, 2017, that they would be purchasing Kaggle.

IV. METHODOLOGY

The K-means clustering technique is used in the proposed RCS-BMIC system to dynamically identify centroids, which divides brain MRIs into two clusters.

Furthermore, it classifies brain MRIs into categories for tumors and non-tumors. There are several steps in this procedure, which include preprocessing the images, extracting edge features, clustering, and classifying the results.

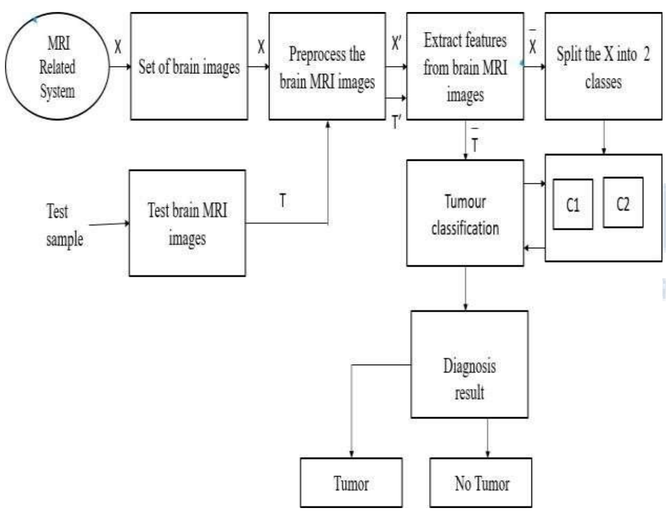

Fig. 1 System Architecture

A dataset of previous brain MRI images is gathered from the relevant medical system. A total of 253 photos—155 of which were tumor images and 98 of which were not—were gathered from a Kaggle platform. An RCS-BMIC system is used to deploy a collection of brain MRI images, denoted as X = Xifor, Xi = Xijr, j = 1,2,….,h, r = 1,2,….,w, where Xi represents the i th reference MRI from the image deposit X with n MRI image, Xijr is the j th height and r th width in the i th MRI image. Xi= Xijr where j=1, 2, 3,..,h ; r=1, 2, 3,..,w, and Xi = {$\boldsymbol{X}$1, $\boldsymbol{X}$2,....,$\boldsymbol{Xn}$ } where i=1,2, 3…, n Xi denotes a single brain MRI image inside the set, n is the total number of brain MRI images within the dataset, and X indicates a set that includes every brain MRI image in the dataset.

Preprocessing brain MRI images entails a number of processes to improve image quality. Resizing guarantees that you can change the image's dimensions without affecting the aspect ratio. This guarantees precise representation of brain structures and helps prevent distortion. A certain amount of random noise may be present in MRI pictures, which might make it difficult to understand key findings. One smoothing method that lessens this noise is Gaussian blur. At this stage, the proposed system is primarily concerned with employing convolution neural networks to extract edge characteristics from brain MRI images in order to find distinctive patterns that differentiate tumor regions from non-tumor areas. Feature extraction is a crucial stage in the use of convolutional neural networks (CNNs) for brain tumor identification.

Based on labeled data, a machine learning model learns in the training stage to discriminate between the extracted features of tumor and non-tumor images. This entails minimizing the discrepancy between the expected and actual classes by modifying the model's parameters. Tumor and nonthis pathway training or clustering to produce useful outputs for analytical or diagnostic uses.

Tumor images involves using K-Means techniques to classify or group these images into two classes, typically denoted as c1 (tumor) and c2 (no tumor). During training, a model learns patterns and features from labeled examples to distinguish between tumor and non-tumor images. Clustering, on the other hand, involves grouping images based on similarity without predefined labels

In the testing phase for brain MRI image analysis, let's denote the input image as T. This image undergoes preprocessing, resulting in T ′ .

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Mathematically, this can be represented as $T' = \text{Preprocess}(T)$. Next, T' serves as the input to a convolutional neural network (CNN) algorithm, which extracts features from the image. Let's represent the output features as $\bar{T}$ for $\bar{T}=\text{CNN}(T')$. These features capture important patterns and structures in the brain MRI image, allowing the model to make predictions or classifications. The testing phase involves feeding new images through

Machine learning techniques are commonly utilized for the classification of brain MRI images into tumor and non-tumor categories. The c1 and c2 clusters in this instance most likely allude to unique characteristics or patterns connected to the classes. Using characteristics from the c1 and c2 clusters, the system examines patterns in the MRI images to differentiate between instances with and without tumors. The objective of this technique is to accurately classify the photographs based on the patterns found in them.

V. RESULTS & ANALYSIS

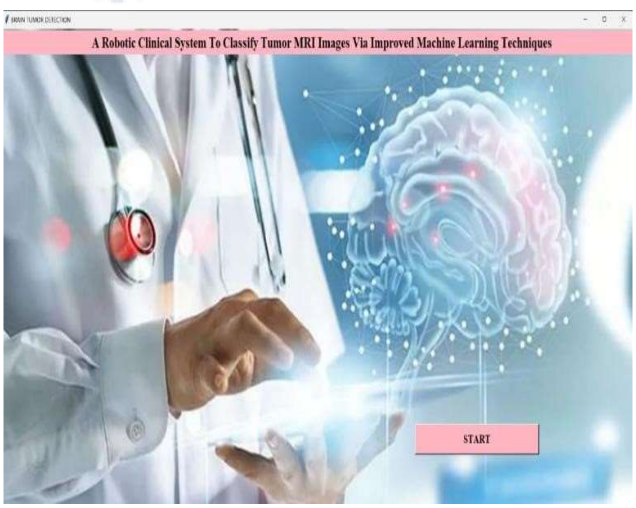

Fig.1 Home Page

Fig.1 shows the Front end or Home Page of the (RCS-BMIC) system

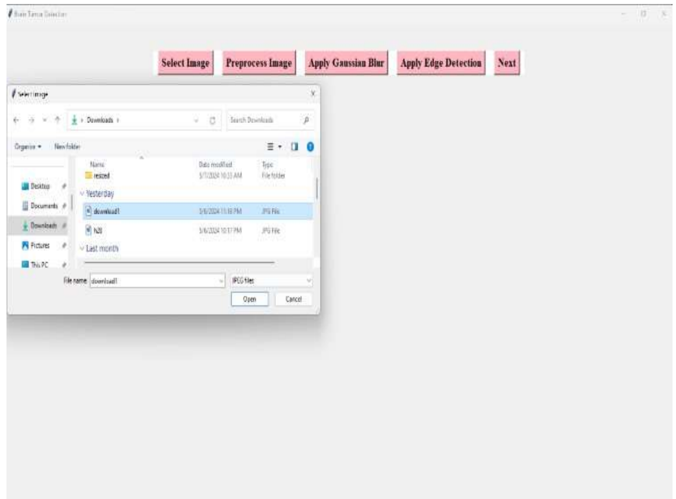

Fig.2 Select the Brain MRI Image

Fig.3 Display The Selected Image

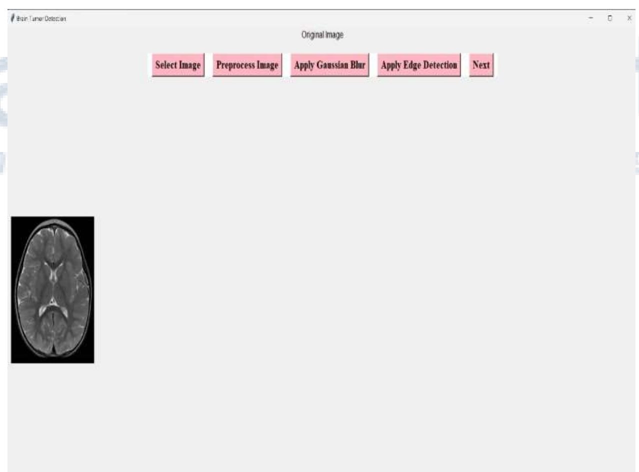

Fig.2 Shows the user to select the brain MRI Image from the file to be Diagnosis. Fig.3 Shows the user the selected MRI Image along with the size(height x width) of the Image.

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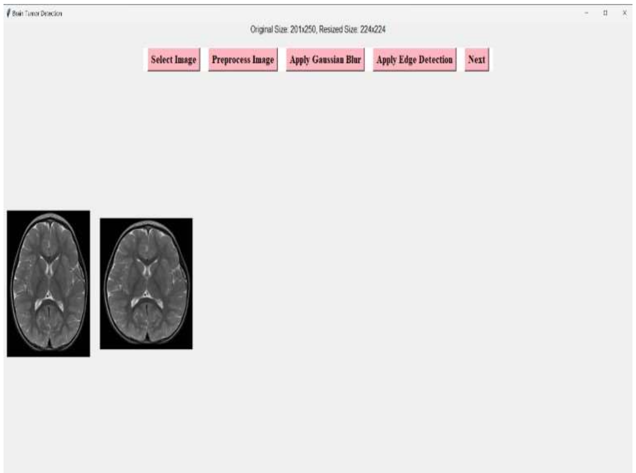

Fig 4 Preprocess the Image (Resizing)

Fig 4 Shows the user along with the original MRI image it also shows the resized Image (224x224)

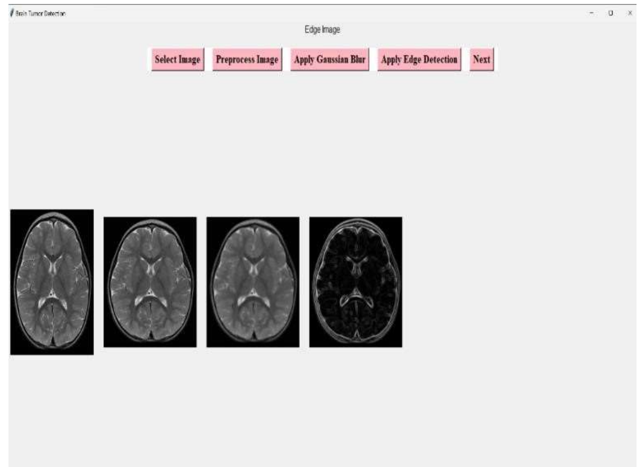

Fig 6 Extracting the Edge Feature

Fig 6 shows the user the edge feature extracted from the Brain MRI image using the Sobel Fliter

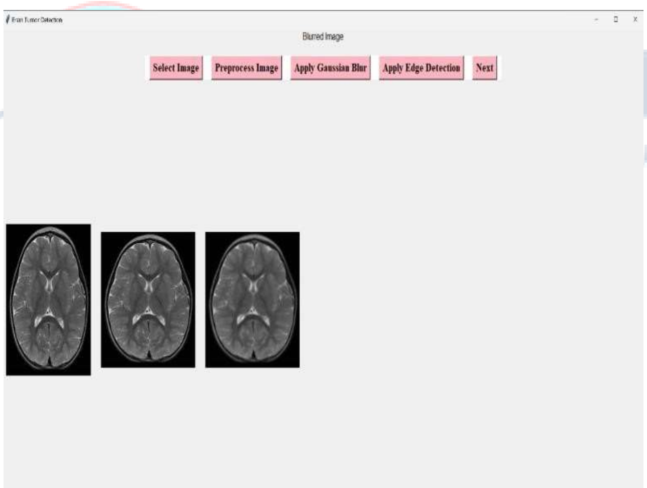

Fig.5 Preprocess the Image (Apply Gaussian Blur)

Fig 5 shows the user the noise reduction of MRI image by applying the gaussian blur technique.

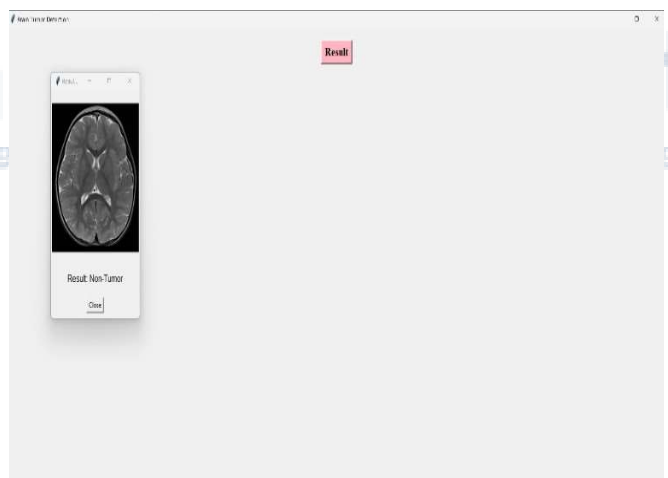

Fig.7 Diagnosis Result

Fig.7 shows the user whether the selected MRI image is tumor or no tumor Image.

A. References

The heading of the References section must not be numbered. All reference items must be in 8 pt font. Please use Regular and Italic styles to distinguish different fields as shown in the References section. Number the reference items consecutively in square brackets (e.g. [1]).

When referring to a reference item, please simply use the reference number, as in [2]. Do not use "Ref. [3]" or "Reference [3]" except at the beginning of a sentence, e.g. "Reference [3] shows …". Multiple references are each numbered with separate brackets (e.g. [2], [3], [4]–[6]).

Examples of reference items of different categories shown in the References section include:

- example of a book in [1]
- example of a book in a series in [2]
- example of a journal article in [3]
- example of a conference paper in [4]
- example of a patent in [5]
- example of a website in [6]
- example of a web page in [7]
- example of a databook as a manual in [8]
- example of a datasheet in [9]
- example of a master's thesis in [10]
- example of a technical report in [11]
- example of a standard in [12]

VI. CONCLUSIONS

The Introduction, Literature Survey, System Requirement Specification, and System Design have all been completed, marking the effective completion of the Phase-2 development of a Robotic Clinical System to Classify Brain MRI Images Via Improved Machine Learning Technique. The system's requirements have been successfully determined, and its design has been developed. The project's literature review offers a comprehensive summary of the machine learning methods currently in use and how they might be used to the classification of brain MRI images. Now that this project phase is over, the foundation for the system's development has been established. The system will be implemented in the following step, and then it will be tested and evaluated. Following satisfactory conclusion, it is anticipated

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The heading of the Acknowledgment section and the References section must not be numbered.
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