

## *Computerized Diagnostic System for Brain Tumor Detection Using Artificial Intelligence*

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**Abstract--** Brain tumors are a significant health concern worldwide, and early detection plays a crucial role in improving patient outcomes. In this paper, we propose a computerized diagnostic system for brain tumor detection using artificial intelligence (AI) techniques. The aim is to develop an automated and accurate system that can assist medical professionals in the early diagnosis of brain tumors. The proposed system utilizes advanced AI algorithms, including machine learning and image processing, to analyze medical imaging data such as MRI scans. The system extracts relevant features from the images and employs a trained model to classify them as tumor or non-tumor regions. By leveraging the power of AI, the system can detect subtle abnormalities that may be indicative of a brain tumor, even at its early stages. To evaluate the performance of the system, we conducted experiments using a large dataset of brain MRI images. The results demonstrate the effectiveness and efficiency of the proposed computerized diagnostic system. Compared to traditional diagnostic approaches, our system achieves higher accuracy in detecting brain tumors, thereby aiding in timely intervention and treatment planning. The development of this computerized diagnostic system represents a significant advancement in the field of brain tumor detection. It has the potential to assist healthcare professionals in making faster and more accurate diagnoses, leading to improved patient care and outcomes. The integration of AI into medical diagnostics has immense potential in revolutionizing brain tumor detection and positively impacting the lives of patients around the world.

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## I. BACKGROUND OF STUDY

Brain tumors are abnormal growths of tissue in the brain that result from the uncontrolled multiplication of cells. These tumors not only increase pressure and size in the brain, but also cause abnormal neurological difficulties. The National Brain Tumor Foundation (NBTF) reports that over 300% of individuals with brain tumors in developed countries have died. Considering the high mortality rate in advanced regions with the best medical facilities, one can only imagine the devastating impact of this condition in developing and underdeveloped countries (NBTF, 2019).

Yazdani et al. (2015) classify brain tumors into two categories: metastatic or primary brain tumors. Primary tumors originate from brain cells, while metastatic tumors result from cells that have spread to the brain from another part of the body. Examples of brain tumors include glioblastoma, gliomas, pituitary adenoma, acoustic neuroma, and haemangioblastoma (Jayadevappa et al., 2011).

In recent years, there has been increased research attention on gliomas due to a rise in their incidence over the past decade (Abd-Ellah et al., 2016). Various approaches such as biopsy, spinal tap, MRI scan, neurologic exams, and angiogram have been used to diagnose brain tumors. However, the main challenge lies in detecting these tumors at an early stage. Early detection significantly improves the chances of survival. The conventional diagnostic approaches mentioned rely on specific input parameters such as tumor size, symptoms, serology tests, among others. However, there is a need for a system capable of detecting brain tumors at a very early stage and notifying experts promptly (Isin et al., 2016).

Among the available techniques, magnetic resonance imaging (MRI) is widely used in data collection and analysis for brain tumor detection. MRI is a non-invasive imaging method that utilizes radio frequency signals and advanced magnetic fields to generate internal images of target tissues. The information obtained from MRI scans provides valuable insights into the various modalities of brain cells, facilitating tumor segmentation and guiding future interventions for accurate diagnosis and treatment (Liu et al., 2019). However, the reliability of radiologists and other experts in analyzing and detecting tumors from MRI data remains a significant concern. The attributes of MRI results, such as size, shape, and other characteristics, contribute to the probability of false predictions by domain experts (Gordillo et al., 2013). To address these challenges, various approaches, including image processing techniques like segmentation, edge detection, and histogram equalization, have been employed to improve prediction performance. However, these techniques often lack a comprehensive understanding of the brain tumor problem and may suffer from poor accuracy, inconsistent results, and high costs (Yazdani et al., 2015).

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Recently, artificial neural networks have gained recognition for pattern recognition problems and have been applied to brain tumor classification. Different configurations, such as convolutional neural networks, recurrent neural networks, feed-forward neural networks, multilayer perceptron neural networks, and modular neural networks, have been utilized. Each neural network excels in addressing specific problem statements (Mohan et al., 2018).

Alternatively, clustering techniques have shown promising results in MRI imaging. By utilizing feature clusters extracted from MRI data, the clustering process can effectively learn and classify brain tumor results. This research aims to adopt the clustering technique to learn tumor clusters and utilize the obtained results for future predictions.

## II. REVIEW OF LITERATURES

In the early days, brain tumor was a severe disease with little or no remedy, thus resulting to death and was preceded by longstanding symptoms of coma, headaches and seizures. Physicians recognized that these symptoms were caused by increased intracranial pressure and developed skull trepanation to relieve it. Skull trepanation probably originated in ancient Africa and South America (Mauricio, 2016).



Figure 1: 3D view of Brain Tumor (Source: Image stack.com)

### A. Symptoms of brain tumor

Brain tumor symptoms are typically caused by increased pressure in the skull. This pressure can be a result of the tumor taking up too much space or blocking the flow of cerebrospinal fluid around the brain (Earnest et al., 2018). Common symptoms include headaches (worse upon waking), nausea and vomiting (worse in the morning or after changing position), confusion, blurred or double vision, seizures, weakness in body parts, and drowsiness (a later symptom).

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### ***B. Artificial Intelligence for Health Care***

Throughout history, humanity has faced the challenge of combating viral and infectious diseases through different tools, techniques, and methods. In ancient times, natural herbs were utilized by herbalists as local medicines, often through a trial and error approach without precise dosage measurement. However, with the advancement of western education and the application of scientific principles, these herbal medicines were modified and purified to enhance their effectiveness (Nwobodo, 2016).

Although significant progress has been made in the medical industry with the production of various forms of medicines, the rise of viral infections has posed a persistent problem. The proliferation of infectious diseases, coupled with the development of drug resistance, presents a serious challenge in the face of a growing global population. Efforts have been made to optimize the performance of the medical industry, such as the construction of more hospitals, increasing manpower, and employing various factors of production. However, the exponential rate of disease spread necessitates a new approach (Mardani et al., 2018).

In other sectors, such as manufacturing, artificial intelligence has been successfully applied to enhance performance and control responses. This same potential is believed to exist within the healthcare sector. Researchers, as documented in (Jiang et al., 2017), have employed machine learning techniques to address various pattern recognition problems, including the detection and prediction of diseases like diabetes and heart diseases with high accuracy and fast processing speed. It is therefore believed that these machine learning techniques can also contribute to addressing the diagnostic challenges associated with brain tumors in a precise manner.

Artificial intelligence is one of the methods for diagnosis of brain tumor. Other are also exist such as image processing, computer vision, Radiological imaging, and surgery.

### ***C. Deep learning in medical imaging***

Deep learning, an artificial intelligence technique, is widely utilized in the field of radiological image processing and analysis for the detection of anomalies in CT scans. Medical imaging, particularly in radiology, magnetic resonance imaging (MRI), theranostics, radiomics, radio oncology, end microscopy, and related areas, extensively employs deep learning for automated detection of intra-operative images (Chen et al., 2018).

Another significant application area, as highlighted by (Mardani et al., 2018), is advanced deformable image registration, which enables quantitative analysis across different physical imaging modalities and timeframes. For example, deformable registration is employed in the registration of three-dimensional MRI and trans-rectal

ultrasound to guide targeted prostate biopsy. In the case of brain MRI, a deep regression network learns the displacement vector associated with a pair of reference subject patches. Other applications include fast deformable image registration of brain MR image pairs using a diffeomorphic metric mapping model, unsupervised convolutional neural network-based algorithm for deformable image registration of cone beam CT to CT using a deep convolutional inverse graphics network, a deep learning-based 2D/3D registration framework for pre-operative 3D data and intra-operative 2D X-ray images in image-guided therapy, and real-time prostate segmentation during targeted prostate biopsy. Moreover, temporal information in a series of ultrasound images is utilized in various other applications (Mardani et al., 2018).

### III. REVIEW OF RELEVANT LITERATURE

A paper by Monica et al. (2019) discussed methods for detecting brain tumors in MRI images. They employed the pulse coupled Neural Network technique for enhancing brain MRI images and utilized back propagation training algorithms for classifying these images. The authors observed that image enhancement and segmentation using the pulse coupled Neural Network technique, along with the back propagation algorithm network, facilitated the detection of brain tumors in MRI images. However, they noted that the technique's design complexity and training time could be influenced by the number of hidden layers.

Danda et al. (2018) conducted research on the use of Naïve Bayes and decision tree algorithms for detecting and classifying brain tumors based on factors such as tumor origination, size, symptoms, treatment, and occurrence. The study found that the decision tree algorithm was simpler and more effective in predicting brain tumor treatment compared to the Naïve Bayes algorithm.

In their paper, Nikita and Naveen (2018) presented a novel approach for classifying brain tumor MRI images using the Hellinger decision method, HD Tree, and HD Forest algorithms. They applied this technique to classify 97 brain tumor images and achieved an accuracy of 96%. However, despite the success, the authors noted that the training data used in the study was relatively small. Sankari and Vigneshwari (2016) conducted a study on brain tumor classification using a CNN-based method. Their research focused on using a leaky rectifier linear unit (LReLU) as the non-linearity activation function in the CNN configuration for learning and classifying brain tumors. They emphasized the importance of basic features such as entropy, mean, and standard deviation of the images, and found that CNN performed well in representing complex features of brain tumor tissues.

Yuehao et al. (2017) utilized brain tumor MRI images to gather information for classifying tumor grading. They developed a brain tumor grading system using CNN algorithms. The CNN was configured with convolutional and fully connected layers and trained using the back propagation algorithm for tumor classification. The CNN showed an 18% increase in performance compared to the traditional artificial neural network (ANN) approach.

Vijay and Raju (2018) introduced an artificial neural network (ANN)-based early brain cancer detection system, comparing it with fuzzy logic techniques. The ANN-based system outperformed fuzzy logic in the classification of brain tumors.

Dena et al. (2015) conducted research on brain tumor prediction using a multi-layered perceptron and C4.5 classifier. The study found that the multi-layer perceptron achieved a higher accuracy rate of 95.2% compared to the 91.1% classification rate of the C4.5 classifier.

Eman et al. (2015) proposed a neuro-fuzzy approach for classifying brain tumor MRI images based on tumor shape and size. They reviewed various machine learning techniques and compared their performance. The study revealed that the Tree Augmented Naive Bayes Nearest Neighbor (TANNN) algorithm outperformed other algorithms, and the K-Nearest Neighbor algorithm had the minimum classification time rate.

Sunil et al. (2017) employed a Support Vector Machine (SVM) classifier for brain tumor tissues. They proposed an effective method for brain tumor classification using a combination of genetic algorithms and SVM. The genetic algorithm was used for feature extraction, and SVM was used for classification. The proposed system utilizes mean, mode, and median values of the tumor region to detect and classify the type of brain tumor in MRI images.

Vaishnavi et al. (2018) introduced a system for brain tumor detection using a CNN classifier and the Local Binary Patterns (LBP) feature extraction method. The CNN algorithm employed the ReLU activation function. The proposed method was tested on 100 images and achieved an accuracy of 86%.

Seetha and Selvakumar (2019) developed an automatic brain tumor detection model using the CNN classification algorithm. The model achieved a high accuracy of 97.5% in classifying tumor and non-tumor cases, surpassing the performance of SVM and DNN classification algorithms. Earnest (2018) presented a health and knowledge service support system that focuses on managing diverse knowledge from various sources. Their work also involved the creation of an ontology for organizing foods into 13 sections using a hierarchical structure. Haughton et al. (2018) designed a management system for hepatitis that monitors and controls blood glucose levels to prevent diabetic complications. They utilized artificial intelligence and applied supervised machine learning techniques, specifically support vector machines, to automatically detect and solve blood glucose control problems for individuals with type 1 hepatitis. Tokumaru et al. (2010) proposed an intelligent clinical decision system for hepatitis diagnosis, aiming to replace medical practitioners in the diagnosis of hepatitis and blood glucose monitoring. Their work employed a machine learning tool utilizing a decision tree model for classification and prediction after being trained on expert knowledge.



In Mosleley et al. (2019), a computerized diagnosis system is presented to assist radiologist multiclass classification to human brain. The work employs a hybrid machine learning technique based on generic algorithm and support vector machine for brain tumor classification.

In (Douk et al., 2019) the authors have employed three techniques namely: EM algorithm, H-means+ clustering and Genetic Algorithm (GA), for the classification of the diabetic patients. The performance for H-means+ proved to be better than others when all the similar symptoms were grouped into clusters using these algorithms. A study conducted in (Sankaranarayanan. 2014) intended to discover the hidden knowledge from a particular dataset to improve the quality of health care for diabetic patients. In (Mostafa, 2010) Fuzzy Ant Colony Optimization (ACO) was used on the Pima Indian Diabetes dataset to find set of rules for the hepatitis diagnosis.

Axel et al. (2018) research work was aimed at the employment of information and communication technology to design a web based fuzzy expert system for management of hypertension using the fuzzy logic technique. In this work, diastolic blood pressure, systolic blood pressure, age, and body mass index (BMI) were taken as input parameters to the fuzzy expert system and hypertension risk was the output parameter. Edelman et al. (2019) studied and reveal in his work that human disease diagnosis is a complex case and requires high level expertise. This work also aimed at the development of a web based clinical tool designed to facilitate the quality of exchange of electronic health record between patients and health care practitioners.

In Davis et al (2017), a case based medical expert system prototype that aids clinical diagnosis of four heart diseases was developed employing two different techniques induction and nearest neighbour (machine learning approach). The results indicate that the nearest neighbour is better than the induction strategy, where the retrieval accuracy were 100% and 53.8% respectively.

Atlas et al. (2017), proposed an intelligent system that help diabetes people monitor blood glucose level. The system queries for an input which is employed for training and then result based on fuzzy logic technique.

#### IV. DESIGN METHODOLOGY

To guide the development of the system, we opted for the iterative waterfall model as our system development life cycle (SDLC) approach. This model entails a sequence of stages, starting with requirement definition, followed by system and software design, implementation and unit testing, integration and system testing, and concluding with operational maintenance. In addition, we incorporated certain elements from other models, such as prototyping, to assist us in formulating system definitions and conducting analysis, including the creation of data flow diagrams. The Entity-Relationship Diagram (ERD) was employed to illustrate the relationships between entities, while Data Flow Diagrams served to depict the flow of data within the system.

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The Iterative waterfall model breaks down the system development lifecycle into phases, with each phase consisting of specific activities. For example, the Analysis stage focuses on understanding the functionality of dataflow in a complex system. This analysis is then used to design the software architecture, modules, and relationships among them.

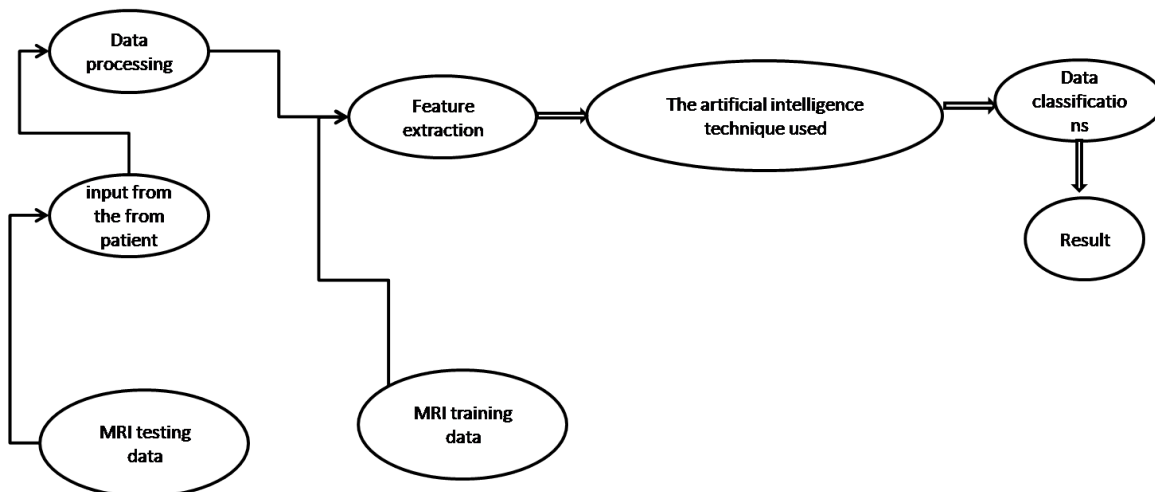


Figure 1.0: the data flow diagram

The data flow diagram shows the testing and the training dataset used to learn and test the artificial intelligence based diagnostic system as in figure 3.3; from the figure the training dataset was used to learn the artificial intelligence technique with the reference MRI images of brain cancer. Then the testing dataset was used to feed the system for checks and validation.

## A. Inputs to the system

This section presented the data which characterized the patient electronic health records and the biometric information of the parent alongside the MRI data collected from the radiology department.

Sample patient health records

FILENAME	TYPE	WIDTH	DEC
Patname	Character	11	0



Date	Character	10	0
Maresult	Character	7	0
Typesult	Character	13	0
TB result	Character	3	0
Peresult	Character	12	0
Diresult	Character	8	0
Hyresult	Character	12	0
Aneresult	Character	7	0

Number of past diagnosis

FIELD	TYPE	WIDTH	DEC
Pat-name	Character	11	0
Date	Character	10	0
Ailment	Character	15	0
MRI 1	Character	50	0

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MRI 2	Character	50	0
MRI 3	Character	50	0
MRI 4	character	53	0

The three file used for output are namely:- medical diagnosis, registration medical treatment, and symptom files respectively.

## V. PROCESSES AND PROCEDURE

This section describes a process for detecting epidemic diseases in scanned brain images. The steps include scanning the brain image, equalizing the histogram to remove background noise, detecting edges to simplify the image, segmenting the image into pixels with different thresholds, extracting geometric features for training purposes, normalizing the image by reducing light intensity, and training the dataset for future classification of brain tumors.

### A. Control Center

This is a high level center of the system showing the main menu and sub menu or the tumor detection system and the various contents and step to achieve the system operations. The diagram is presented below;

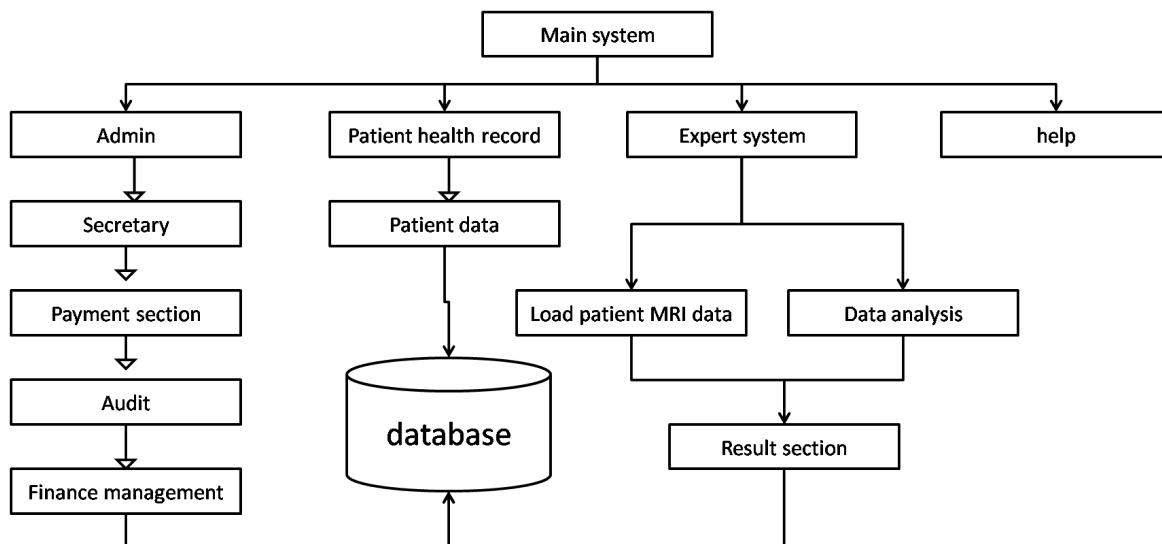


Figure 2.0: the control center diagram

## B. Input form design

This section presented the design of the input from for the user interface before implementation using the programming tool as show below;

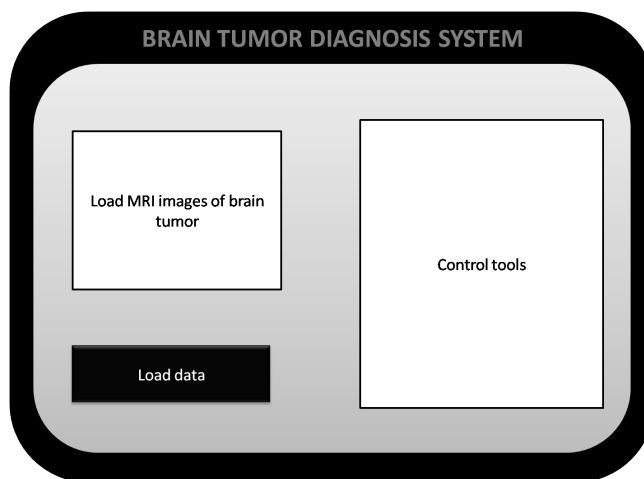


Figure 3.0: the input form design

The figure 3.0 presented the system input design form used for the development of the new system and the output when implemented is presented as shown below;

## C. Output design

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This section presented the system output when implemented using the high level programming language proposed for the system implementation. The system output is presented as shown below;

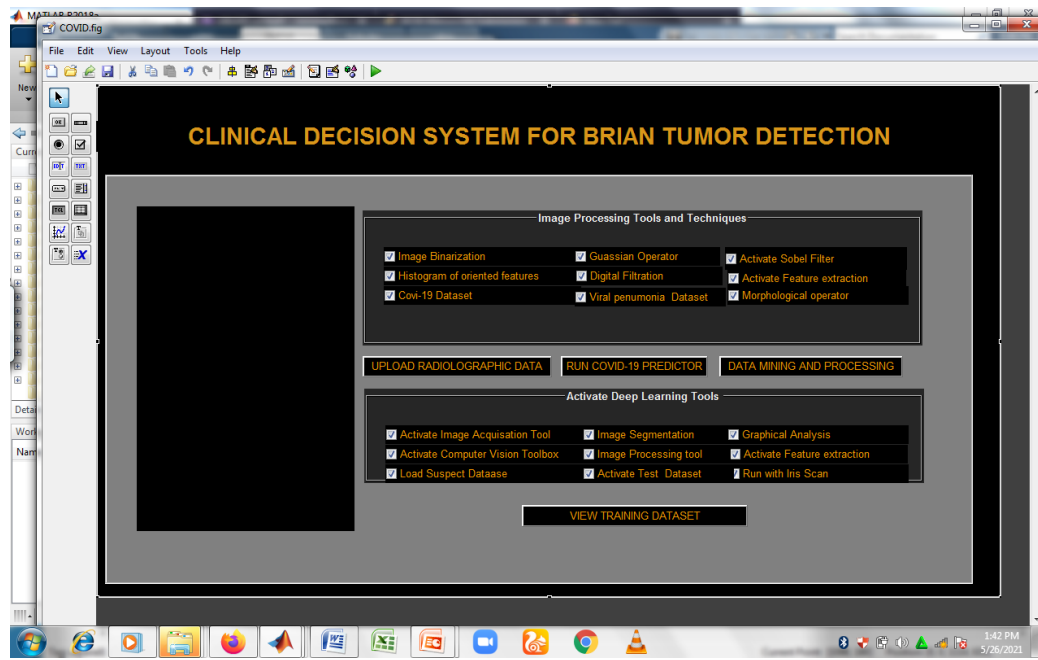


Figure 4.0: System output result

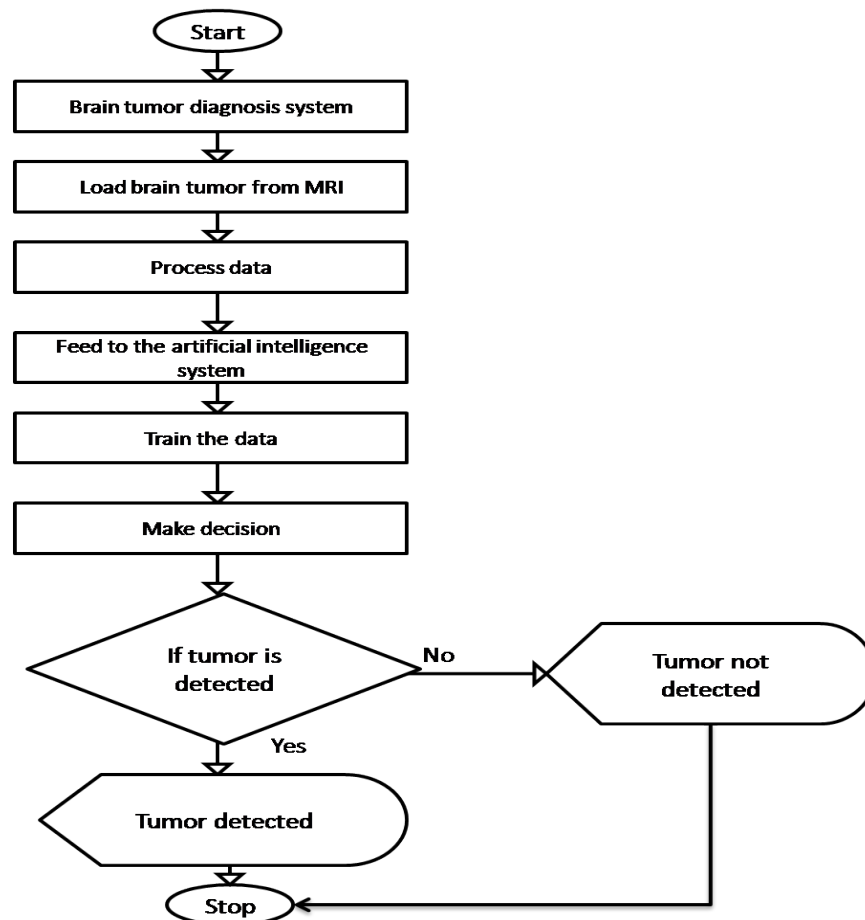


Figure 5.0: system flow chart

## VI. CONCLUSION

This research has identified brain tumors as a significant global health concern. The current approach to detect these tumors primarily involves the use of MRI scans in radiology departments. However, the analysis of the collected data heavily relies on human expertise, leading to a limitation where only developed tumors are typically detected, while smaller, early-stage tumors may go unnoticed. Given that early detection greatly improves the management of brain tumors, there is a pressing need to address this issue.

To tackle this challenge, the study has developed a clinical decision system utilizing artificial intelligence techniques. This system aims to intelligently detect brain tumors from MRI scans with a high level of accuracy, overcoming the limitations of human-based analysis. By leveraging advanced algorithms and machine learning,

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the proposed system enhances the detection capability, enabling the identification of tumors at the nursery stage. This technological advancement holds significant promise for improving the management and treatment outcomes of brain tumors.

The study used high level programming language to implement the system alongside data collected from MRI images of patients with brain tumor issues. The data was used to train the A.I system and then deployed as an expert system using the programming tool (MATLAB). Having successfully achieved the proposed system, the study was tested using various data such as MRI of many patients to test the system. The result showed that the tumor as successful detected with high level of accuracy.

## REFERENCE

- [1] Abd-Ellah MK, Awad AI, Khalaf AAM, Hamed HFA. Classification of brain tumor MRIs using a kernel support vector machine. Building Sustainable Health Ecosystems: 6th International Conference on Well-Being in the Information Society, WIS 2016, CCIS vol. 636. 2016. p. 151–60. [https://doi.org/10.1007/978-3-319-44672-1\\_13](https://doi.org/10.1007/978-3-319-44672-1_13).
- [2] Atlas SW, Grossman RI, Gomori JM, et al. Hemorrhagic intracranial malignant neoplasms: spin-echo MR imaging. Radiology 2017;164(1):71–77.
- [3] Axel L. Cerebral blood flow determination by rapid-sequence computed tomography: theoretical analysis. Radiology 2018;137(3):679–686.
- [4] Bauer S, Wiest R, Nolte LP, Reyes M. A survey of MRI-based medical image analysis for brain tumor studies. Phys. Med. Biol. 2013;58(13):R97. <https://doi.org/10.1088/0031-9155/58/13/R97>.
- [5] Brant-Zawadzki M, Badami JP, Mills CM, Norman D, Newton TH. Primary intracranial tumor imaging: a comparison of magnetic resonance and CT. Radiology 2018;150(2):435–440.
- [6] Chen N, Zhou M, Dong X, et al. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet. 2020 Jan 30. pii: S0140-6736(20)30211-7. doi:10.1016/S0140-6736(20)30211-7.
- [7] Chukwuemeka Odi A. A model of hybrid agent software system for combating indigeneous spam on GSM platform. February, 2016. International Journal of Computer Science and Engineering, vol. 9. Issue 4; pp 675-678;
- [8] Danda Shashank Reddy, Chinta Naga Harshitha, Carmel Mary Belinda,” Brain Tumor prediction using naïve Bayes classifier and decision tree algorithms”, International Journal of Engineering and Technology, 2018.
- [9] Davis PC, Friedman NC, Fry SM, Malko JA, Hoffmann JC Jr, Braun IF. Leptomeningeal metastasis: MR imaging. Radiology 2017;163(2):449–454.
- [10] Dean BL, Drayer BP, Bird CR, et al. Gliomas: classification with MR imaging. Radiology 2010;174(2):411–415.
- [11] Dena Nadir George, Hashem B. Jehlol, AnwerSubhi Abdul Hussein Oleiwi,” Brain Tumor Detection Using Shape Features and Machine Learning Algorithms”, International Journal of Scientific & Engineering Research, volume 6, issue 12, December-2015.

- [12] Douek P, Turner R, Pekar J, Patronas N, Le Bihan D. MR color mapping of myelin fiber orientation. *J Comput Assist Tomogr* 2019;15(6):923–929.
- [13] Earnest F 4th, Kelly PJ, Scheithauer BW, et al. Cerebral astrocytomas: histopathologic correlation of MR and CT contrast enhancement with stereotactic biopsy. *Radiology* 2018;166(3):823–827.
- [14] Edelman RR, Mattle HP, Atkinson DJ, et al. Cerebral blood flow: assessment with dynamic contrast-enhanced T2\* weighted MR imaging at 1.5 T. *Radiology* 2019;176(1):211–220.
- [15] El-Dahshan ESA, Mohsen HM, Revett K, Salem A-BM. Computer-aided diagnosis of human brain tumor through MRI: a survey and a new algorithm. *Expert Syst. Appl.* 2014;41(11):5526–45. <https://doi.org/10.1016/j.eswa.2014.01.021>.
- [16] Eman M. Ali, Ahmed F. Seddik, Mohamed H. Haggag, "Using Data Mining Techniques for Children Brain Tumors Classification Based on Magnetic Resonance Imaging", *International Journal of Computer Applications*, 2015.
- [17] R, Schörner W, Laniado M, et al. Brain tumors: MR imaging with gadolinium-DTPA. *Radiology* 2015;156(3):681– 688.
- [18] Goebell E, Paustenbach S, Vaeterlein O, et al. Low-grade and anaplastic gliomas: differences in architecture evaluated with diffusion-tensor MR imaging. *Radiology* 2016;239(1):217–222.
- [19] Goldsher D, Litt AW, Pinto RS, Bannon KR, Kricheff II. Dural "tail" associated with meningiomas on Gd-DTPA-enhanced MR images: characteristics, differential diagnostic value, and possible implications for treatment. *Radiology* 2010;176(2):447–450.
- [20] Gordillo N, Montseny E, Sobrevilla P. State of the art survey on MRI brain tumor segmentation. *Magn. Reson. Imaging* 2013;31(8):1426–38. <https://doi.org/10.1016/j.mri.2013.05.002>.
- [21] Guo AC, Cummings TJ, Dash RC, Provenzale JM. Lymphomas and high grade astrocytomas: comparison of water diffusibility and histologic characteristics. *Radiology* 2012;224(1):177–183.
- [22] HarshiniBadisa, Madhavi Polireddy, Aslam Mohammed, (2019). CNN Based Brain Tumor Detection. *International Journal of Engineering and Advanced Technology (IJEAT)* ISSN: 2249 – 8958, Volume-8 Issue-4, April 2019. Retrieval Number: D6681048419/19©BEIESP.
- [23] Haughton VM, Rimm AA, Czervionke LF, et al. Sensitivity of Gd-DTPA-enhanced MR imaging of benign extraaxial tumors. *Radiology* 2018;166(3):829–833.
- [24] Işin A, Direkoğlu C, Şah M. Review of MRI-based brain tumor image segmentation using deep learning methods. *Proc. Comput. Sci.* 2016;102(Supplement C):317–24. <https://doi.org/10.1016/j.procs.2016.09.407>. 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29- 30 August 2016, Vienna, Austria.
- [24] Jayadevappa D, Kumar SS, Murty DS. Medical image segmentation algorithms using deformable models: a review. *IETE Tech. Rev.* 2011;28(3):248–55. <https://doi.org/10.4103/0256-4602.81244>.
- [26] Kucharczyk W, Brant-Zawadzki M, Sobel D, et al. Central nervous system tumors in children: detection by magnetic resonance imaging. *Radiology* 2019;155(1): 131–136.
- [27] Liu J, Li M, Wang J, Wu F, Liu T. A survey of MRI-based brain tumor segmentation methods. *Tsinghua Sci. Technol.* 2019;19(6):578–95. <https://doi.org/10.1109/TST.2014.6961028>.
- [28] Logeswari T, Karnan M. An improved implementation of brain tumor detection using segmentation based on hierarchical self organizing map. *Int. J. Comput. Theory Eng.* 2010;2(4):591–8.
- [29] Lu S, Ahn D, Johnson G, Law M, Zagzag D, Grossman RI. Diffusion-tensor MR imaging of intracranial neoplasia and associated peritumoral edema: introduction of the tumor infiltration index. *Radiology* 2014;232(1):221–228.



- [30] Manasavi Sharma, Chetan Marwaha (2020). Brain Tumor Detection using Image Segmentation Techniques on MRI Images. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-4. Retrieval Number: D1689029420/2020©BEIESP DOI: 10.35940/ijitee.D1689.029420.
- [31] Mardani M, Gong E, J.Y. Cheng, S.S. Vasanawala, G. Zaharchuk, L. Xing”Deep generative adversarial neural networks for compressive sensing (GANCS) MRI” IEEE Trans Med. Imaging (2018)