International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

A Survey on Brain Tumor Detection and Classification Methodologies in Medical Image Processing

[1]Benjamin, Olajide W., [2]Simon, I.O

[1,2]Department of Computer & Communication, Abubakar Tafawa Balewa University, Nigeria

***Abstract* - Aberrant tumors that develop in the brain are called tumors, and malignant tumors are called "cancer." CT scans, MRIs, or positron emission tomography (PET) scans are commonly used to identify malignant brain tissue. This study will focus on the different types of brain tumors, how they are detected, and how to help sufferers detect the cancer early. MRI and PET scans are used to diagnose brain tumors, and additional techniques such as molecular testing, lumbar puncture, and cerebral angiography are used to assess the stage of the disease. The objectives of this research investigation are to (i) identify abnormal photographs; (ii) segment the tumor regions; and (iii) determine the stage of the cancer. This investigation will be used to determine the appropriate methodology for brain tumor detection.**

Keywords: Brain Tumor, MRI, PET scan, Medical Image Processing, Artificial Neural Network, Tumour segmentation.

I. INTRODUCTION

The brain or cerebrum of an individual governs or controls every function of their body and its organs. It can also be thought of as a central control system that regulates the several fundamental acts, such as memory, pain, and emotions. Via various nerve connections, each of these bodily organs is directly linked to the brain, where effective communication occurs. Of these, only a small number of organs are directly integrated with the spinal cord and are connected to the brain system that controls the organs.

Many nerves that have been linked together and have the ability to communicate when a single point of contact is formed are referred to as synapses. To explain the brain's fundamental structure by observing how it perceives and perhaps previews a larger image. The cortex is a cumulative group of nerves and their surrounding tissue. These groups are divided by small valleys known as fissures, and gyrus separates them. Here, the brain's vast valley and central regions are utilised to divide it into distinct hemispheres, such as the left and right sides. As seen in Figure 1, the limbic system refers to the central region of the brain that is directly below the corpus callosum.

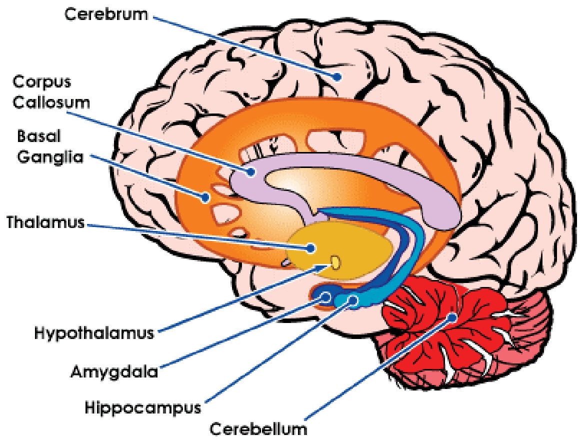

Figure 1: Internal structures of human brain

The human brain is said to be the most developed, intricate, and functional organ in the human body. It is made up of three main structures:

Cerebrum

Known as the cerebral hemispheres, it is divided into the left and right halves and may be regarded as the largest portion of the brain. Its surface vents also appear to be narrow cuts and ridges.

Cerebellum

It is located directly below the bigger part of the cerebrum and is known as a smaller region of the human brain. Furthermore, it features massive grooves rather than convolutions. It is composed of grey matter and is the outermost cortex. On the other hand, the middle part of it might have white materials, giving it a tree-like appearance.

Thalamus

The thalamus develops from the immature diencephalon, with distinct progenitor spaces, including the caudal and rostral areas, influencing its development. The thalamic reticular core is structured by inhibitory Gamma-Aminobutyric Acid (GABA) neurons, which are propelled forward by the rostral begetter space.

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

Pituitary Gland

Located at the base of the cerebrum, the pituitary is a pea-sized organ enclosed inside a hard framework. The pituitary is protected by the sellaturcica, which allows for very little growth. The pituitary is sometimes referred to as the "ace organ" because it regulates the function of the majority of other endocrine organs.

Hypothalamus

It is a region of the brain that forms the third cerebral ventricle's space and is located beneath the thalamus. One essential component of the cerebrum is the nerve centre. It is a little structure that resembles a cone that extends downward from the brain and ends with the infundibular pituitary tail and a cylindrical attachment to the pituitary organ. Because of its brain-pituitary organ collaboration, the nerve centre affects the endocrine system and contains a control community for certain aspects of the autonomic sensory system.

Medulla Oblongata

The base side of the skull contains the brain's lowest partition, known as the Medulla Oblongata. The spinal cord encircles the back of the Medulla Oblongata, which has a roughly triangular form. The layer of tissue known as the meninges envelops the brain and spinal cord and is linked to conscious thought, feelings, and growth.

Cerebro Spinal Fluid (CSF)

Salts, white blood cells, carbohydrates, and proteins make up the CSF. This guarantees that the brain and spinal cord won't get hurt. This is to be circulated in conjunction with the spinal cord and brain system's ventricles, or channels. There are two types of soft brain tissues: White Matters and Grey Matters. The exterior bone structure closely binds several types of brain tissues together. However, another name for these grey matter structures is called neuroglia. Because of this, it should be regarded as a neuronal component, and brain activity is controllable. White matter is formed of axons that are disposed of there.

II. BRAIN TUMOR – TYPES AND STAGES

Benign Brain Tumour

Benign brain tumours make up 50% of primary brain tumours. These are tumours that grow slowly, with a specific shape and defined border. Benign tumour cells have a normal appearance and do not spread to other bodily regions or brain structures. It may be fatal if it develops in the brain's important regions. One useful treatment for benign brain tumours is surgery. The following characteristics serve as examples of the benign type.

- It stays out of the tissues that surround it.
- It progresses really slowly.
- Localised: The tumours that are localised are limited to a certain region.
- Typically, it is not malignant.

Malignant Brain tumour

Brain tumours that are malignant are cancerous. They are rapidly growing tumours that invade other parts of the brain before moving to other parts of the body. A malignant tumor's chance of survival is extremely poor. These tumours have the ability to move from the brain to the spinal cord through cerebrospinal fluid. Their shape is irregular and they lack defined borders. The malignant sort is characterised by the following traits. It has the ability to use force to enter the next cell, and even after therapy, it could come back.

- It has a malignant quality.
- Invasive: They have a tendency to spread out into the surrounding area, and they are quite challenging to eradicate entirely.
- It develops really quickly.

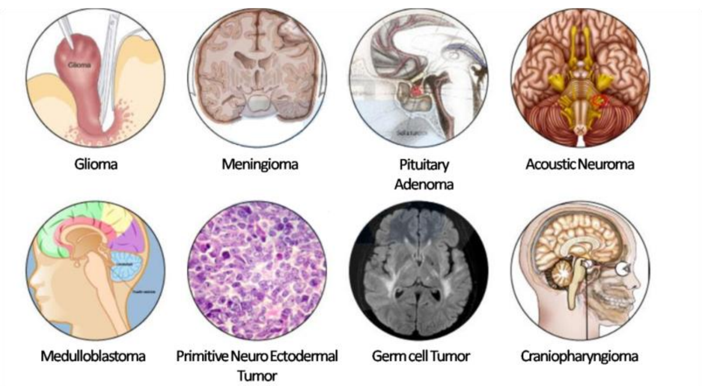

Figure 2: Different types of tumor

MRI for the Identification of Brain Tumours

Through the utilisation of magnetic flux density and its properties with applications to the human tissue capuring process, it can offer detailed images of the human brain. As an alternative to a Computed Tomography (CT) scan, an MRI scan uses no radiation.

An MRI scan can identify a variety of brain ailments, including tumours, cysts, edoema, haemorrhage, anomalies in growth and structure, pathological conditions, illnesses, or blood vessel problems. When a brain injury or stroke can

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

cause damage to a region is determined by operating on the affected brain region.

Brain MRI scans are particularly useful in evaluating problems such as chronic weakness, headaches, blurred vision, and fainting. This testing procedure also helps to discover specific persistent with a CT scan, X-ray, or ultrasound, making it particularly useful for identifying issues with the pituitary and brain stem. Figure 3 shows an MRI of the relevant brain region.

In general, magnetic resonance imaging (MRI) scans may provide very high-quality images of the brain, and they are considered the most effective way to detect brain tumours. Generally speaking, these brain MRI pictures are more detailed than CT scans. Nevertheless, they are unable to obtain CT scans or images of the skull bones, therefore they are unable to show how tumours affect the human skull. The MRI scans have taken advantage of radio waves and powerful magnets to capture images of the brain. In order to help with detail observation, contrast agents, also referred to as gadolinium, might to used on the vein to capture the images.

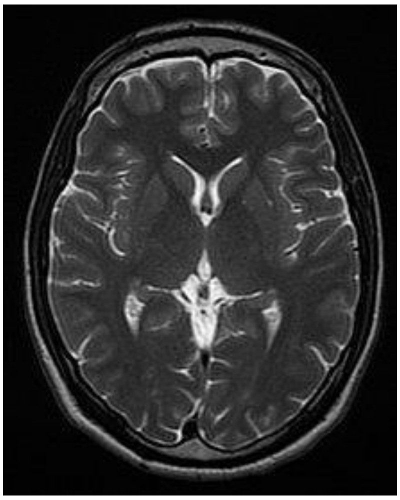

Figure 3: MRI image for Brain

MRI Image for Brain Tumor Detection

The MRI can be used to estimate the size of brain tumours. In order to provide the best image possible, a specific stain known as a contrast standard is administered prior to the test. The patient has either had this stain injected into a vein or has been given fluids to consume. When compared to a standard scan, MRI can produce more detailed images of the brain, making it the preferred tool for identifying brain tumours. The results of a neurotest have been carried out by internists or neurologists who assist in determining which type of MRI to use. Figure 4 shows the established brain tumour detection MRI image.

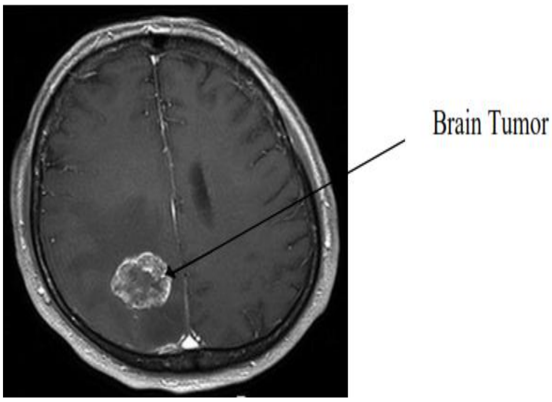

Figure 4: MRI image

MRI is significant and practical ways to assess people's health. Whether the mass is inside or outside the internal organs, it is found utilising image processing techniques that have been improved. Computer Aided Detection Techniques are techniques that can carry out this operation. Medical imaging procedures can be made more successful with the use of CAD technologies. The basic idea behind CAD techniques is to improve the precision of diagnoses, detect abnormal formations that could be tumours in the brain or any other area of human body.

A number of processes are included in the Computer-Aided Design (CAD) technique. The end of the process is the categorization step, which is depicted in Figure 4. These high-quality photographs can be utilised by the technologies that are used for recognition. The possibility of higher detection and access rate is directly addressed by this significant idea, which is both crucial and relevant. During the pre-processing stage, the primary objective may be to produce an MRI image of the brain that is of a high quality. The following are the two primary contrast based non-linear pixel enhancement property methodology to acquire high clarity of MRI.

III. DETAILED LITERATURE SURVEY

Suvashisa Dash et al. (2024) used fuzzy factor logic improvement algorithm for selecting the non-linear pixel points in the image to identify the non-linear pixel regions to differntiate with the other pattern tissue regions in the MRI. The structure of these non-linear regions and its selection points were optimized through the certainity algorithms. They obtained 99.23%, 99.12%senstivity, and 98.78%ccuracy, respectively.

Abdusalomov et al. (2023) used a sizable collection of brain tumour images to tackle the difficult problem of brain tumour detection in MRI scans. They showed how applying transfer learning to fine-tune Promising findings were obtained when their deep learning model correctly detected

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

the existence and exact location of brain tumours in MRI scans. With a 99.5% accuracy, their suggested strategy outperformed conventional techniques in terms of accuracy.

In biological applications, image processing is essential, according to Rina Bopche et al. (2018). An MRI cannot pinpoint the exact location of the tumour because it is an abnormal tissue formation. Therefore, up until now, doctors have been treating it based only on conjecture. To provide comprehensive information about brain tumours, picture segmentation is being used for analysis. Included are morphological processes, grayscale and thresholding, histogram equalisation, K-means clustering, and noise removal (median filter).

Abbasi et al. (2017) used the legendre polynomial to estimate and eliminate bias fields. Histogram matching was used to bring all of the photos in the experiment's intensity levels into balance.

A brain tumour partition and revelation framework was set up by Swe Zin et al. (2016). Every image is analysed in accordance with their methodology, which may guarantee the tumour territory's vicinity in the MRI brain image in various potential scenarios. At this point, the precise system is completed. In order to improve the image for future planning, the underlying stages involve clearing noise using standard channels. But in order to eliminate the tissues in the skull region, morphological movement is required, which is directly dependent on restricted respect. Subsequently, the water division process is managed by the partition marker. The development project for the affected division zone is isolated from the first pixel control evaluation. Lastly, the tumour area is identified through the application of morphological operations.

Clinical picture edge disclosure was reported by Leela et al. (2014). A particular advancement in clinical picture separation and 3D augmentation is called "clinical image pre-handling." In clinical images, salt and pepper noise were gradually regularised. The conventional methods for filtering salt and pepper noise are not considered optimal. To eliminate the noise of salt and pepper, morphological deterioration is used as a route. The analysis's findings for image de-noising in the medical field were dynamically demonstrated.

According to Aslam et al. (2015), the technique for the precise division is dependent on the surface component. The authors have integrated the final results of GLCM with Ada Boost classifier to achieve accurate brain tumour disclosure and partitioning. With the use of Ada Boost computation, tumours and non-tumor pixels were arranged according to criteria such as energy, contrast, entropy, homogeneity, and correlation. The component vector, which measures the spatial association between two adjacent pixels using GLCM, was chosen.

IV. BRAIN TUMOR SEGMENTATION METHODS

According to Mukhiddinov et al. (2023), data augmentation is gaining popularity in a number of study fields, with the applications of imaging logics with lot of pixel fusion efficiencies. A dataset can be purposefully made larger by using techniques like noise addition, scaling, and data rotation. A few of the changes that can be done to images include zooming in to make them larger, flipping them vertically or horizontally by specific degrees, and adjusting the brightness. These methods are used in data augmentation to successfully expand the dimensionality of the training set, improving the resilience and performance of ML and DL models.

Using the enhanced YOLOv7 model, Asad et al. (2023) had great success in identifying brain tumours in a range of circumstances. We employed images of both large and small tumours to verify that our procedure was consistent. Early detection is critical for successful brain cancer prevention and treatment. Their technique found small tumour spots in images with excellent accuracy while successfully reducing false positives.

A variety of machine learning techniques based on soft computing were examined by Mansi Lather et al. (2020) for the purpose of tumour picture detection. An optimum path snake technique was created by Filho et al. (2019) to find optimal pointing pixels in brain imaging and identify aberrant regions impacted by tumours. Key segmentation index attributes were evaluated between the new methodology and standard segmentation techniques.

A deep cascaded neural network was utilised by Cui et al. (2018) in order to demonstrate the autonomous segmentation of brain gliomas in vivo. The intra-tumor classification network and the tumour localization network are the two subnetworks that make up this network. This strategy gives findings that are pretty fair.

Pham et al. (2018) state that noise density and initial clustering centroid dependency are the main problems that fuzzy clustering-based MRI image segmentation attempts to solve. Using knowledge of local spatial information, a novel kernelized fuzzy clustering technique based on kernel entropy is employed to denoise the image. This is a substitute for hard C, a clustering technique that reduces processing effort while denoising the image. The kernel settings govern the algorithm's performance. A population-based image

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

optimisation technique called enhanced particle swarm optimisation is used to segment the MRI image using new fitness functions. The ability of the particle swarm optimisation to find global optima and the rate of convergence are used to evaluate its performance.

Ganesh et al. (2017) stated that MRI images need to be updated before they can be used for reliable and efficient feature extraction. Features are used to find abnormalities in images. The three main regions of MRI brain images are classified using the improved Fuzzy K Means (FKM) adaptive clustering algorithm. The three regions are the cerebrospinal fluid (CFS), gray matter (GM), and white matter (WM) spaces. For the pathological analysis to be accurate, these regions need to be segmented effectively. The technique utilizes the watershed algorithm after opening and closing reconstruction to segment the images.

This work presents a new approach for tumor diagnosis based on MRI imaging by integrating the combined approaches that provide advantages to the proposed system. Determine the tumor area and isolate the tumor spot accurately. By comparing the results with the ground truth (GT) of the processed image, the accuracy was determined.

Using k-means, Asmaa et al. (2017) developed two connectivity prediction methods based on spectral clustering. The network nodes were clustered using the k-means algorithm based on the eigenvectors of the normalized Laplacian matrix. Then, the original data points were characterized as linear integrations of the subset of data points selected as reference points.

Kong et al. (2015) reported a strong discriminant segmentation method based on information theoretic analysis. The known goal of this technique was to reduce the uncertainty associated with supervoxel assignment while selecting the advantageous feature for the discriminant procedure for brain tissue segmentation. Also, a modified AdaBoost pixel-level classification approach to describe mining data at nearby sites is described.

Cerebrospinal fluid, gray matter, and white matter were the abnormal brain tissues that Saritha et al. (2016) are different from normal brain tissue (necrotic core, edema and active cells). This is due to the closer examination and increased contrast of the soft tissue images obtained with the MRI modality. This work uses fully automated and semi-automated segmentation algorithms. The main goal of this work is to provide a detailed nonlinear description of MRI data centers using several systematic techniques.

Chaddad et al. (2016) developed an adaptive morphological method to extract brain regions from MRI. The mathematical morphological techniques used to obtain reliable and accurate results using the denuded skull were dilation and erosion. In skull ablation, the technique works well and is sensitive in different MRI modalities. The most perceived disadvantage of this technology is the longer calculation times.

V. FEATURE ENHANCEMENT METHODS

The elliptical component is calculated from the MR picture, and Farah et al. (2021) recognised and removed the anomalies of the skull region from the scanned output of the MRI image. Tumours in brain regions are being treated with this learned algorithm. Here, the trained algorithm known as k-fold examines the image dataset and different simulation results.

Rehman et al. (2020) suggested a model for intricate calculations, without involving healthy participants, the techniques and methodologies detailed in this work have been elloborated with lot of validation and synthesis techniques.

According to Rajagopal et al. (2019), weighted random forest characterisation techniques have been used to detect glioma tumours. Portion partition and hub arrangement for parents and children served as the foundation for this tactic. Each parent hub featured a 3*3 sub mask window for its central pixel, and its power was divided into two subsequent child hubs. We discussed these clustered child hubs as both a glioma case and a non-glioma scenario. Using a k-fold characterization testing procedure, this technique was attempted and the large dataset of MR images provided a 0.4% failure rate.

Shree et al. (2018) used Probabilistic Neural Network (PNN) and DWT to extract and categorise information from brain imaging. Utilising DWT characteristics improved classification accuracy, according to the results.

Agnieszka et al. (2018) looked into combining grouping with other similar patterns that enhance the effectiveness of statistical analysis. Reversed related features were selected as cluster analysis characteristics from a set of attributes that were employed in the clustering process. By finding new relationships between elements, the medical diagnostic was enhanced and made possible to draw conclusions from statistics. Hybrid methods did not, however, lead to more accurate medical diagnosis.

Fadoua Badaoui et al. (2017) looked into a processing method based on feature extraction and selection. Correlation and rank analysis served as the foundation for the feature

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

extraction, which assisted in lowering the number of variables. Feature selection also helped eliminate unimportant variables with the aid of specifically designed discriminant analysis techniques. With the least amount of computation and processing time, the prediction outcomes were improved. Still, there is no solution to the problems posed by space's complexity.

The Chi-square test was first used to examine descriptive symptoms and characteristics linked to cancer in order to identify the important contributing factors in the recommended method. A feature adaptive enhanced decision tree was created by sorting and processing the selected characteristics.

Convolutional neural networks (CNNs) were used by Anitha et al. (2017) to classify glioma cerebrum tumours based on standard brain MRI scans. The results showed sensitivity of 96.1%, specificity of 97.2%, and accuracy of 98.1%. This calculation failed to identify the number of pattern tumours in various cerebrum MR images and may not have been able to extract the immediate and aberrant list of capabilities from the original brain MR image. This technique may not be appropriate for low-level brain MR imaging and is meant to reduce the tumour arrangement rate.

According to Kumar et al. (2015), the field of brain tumours depended on dimensionality reduction features and the use of several classifiers. Their strategy's feature assurance possessed an entropy quality, and it was a quick way to handle different subsets of paranormal frequencies. The ability choices were autonomous and utilised during the classifier's planning phase. Using an image from the bootstrap trial method, they computed different classifiers. After that, the classifiers are used to select the best features, which leads to the models being requested. A large amount of classifier assurance was completed for each classification. They used an iterative process to maintain a model for their assessment.

VI. DEEP LEARNING ALGORITHMS

Using brain magnetic resonance imaging, Khaliki et al. (2024) classified brain tumors, including gliomas, meningiomas, and pituitary tumors. Convolutional neural networks (CNN) and transfer learning techniques based on CNN Inception-V3, EfficientNetB4, and VGG19 were used for classification. Precision, footprint, recall, and F-score were used to evaluate these models. The transfer learning model with the highest precision result, VGG16, has the following values: 98% for recall, 98% for precision, 97% for F-score, and 99% for area under the curve (AUC).

The main goal of Saeedi et al. (2023) was to develop two different techniques for pixel and texture classification using their region-based algorithm. KNN, RF, and SVM achieved the highest accuracy rates of 86%, 82%, and 80%, respectively.

Heba Mohsen et al. (2018) presented a powerful technique that fused deep neural network (DNN) and discrete wavelet transform (DWT) to classify brain MRI images into three categories: normal and three types of malignant brain tumors including glioblastoma, sarcoma, and metastatic brain tumors. Full convolutional networks (FCNs) were mainly used, and CNNs were effectively employed for brain tumor segmentation. A set of voxels with a linear spatial relationship between the feature maps (FMs) at a given location and the corresponding categorized voxels were segmented into FCNs to create new FMs; the FMs were merged in the convolutional layer; therefore, channel mixing can be crucial. On the other hand, no FM has the same relevance to a particular class.

To create increasingly difficult features for the semantic segmentation process, Sergio Pereira et al. (2016) introduced feature recombination using linear expansion and compression. In addition, a SegSE (Segmentation SE) block was introduced for feature recalibration, which collected contextual information while maintaining spatial significance. Finally, these approaches were approached using the available data in brain tumor segmentation.

The deep learning process was defined by Charron et al. (2018), who found it in the broader context of the machine learning process. Standard architectures were proposed with a clearer focus on CNNs. A study was then conducted on specific research papers on deep learning techniques for radiotherapy. These were divided into seven sections related to patient workflow and some suggestions for possible future uses were given. This study involved the deep learning and radiotherapy communities and aimed to increase the number of enthusiastic applications of radiotherapy through new partnerships between these two fields.

The architecture of CNN deep learning algorithm was proposed by Mengqiao et al. (2017) for the brain tumor segmentation procedure. This approach integrates global and local features as structural elements, which can play an important role in developing brain tumor segmentation in brain MRI images.

According to Lakshmi et al. (2018), classification plays a key role in predicting the affected area. Pointing Kernel Classifier (PKC) and Support Vector Machine are used to identify the abnormal degree of image segmentation from the given input image. This approach is similar to comparing

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

sensitivity, specificity, and accuracy measures with those of current systems. As a result, stable operation in PKC up to the maximum value was recommended. Therefore, the improved result shows how well the proposed PKC works.

VII. CONCLUSION

This research focused on various brain tumor classification and segmentation techniques to address the previously discussed problem of tumor segmentation process in medical applications. However, many approaches have only been tested on a small number of datasets with very different parameters because it can be difficult to find a typical medical imaging dataset to test a method. As a result, previous techniques were less advantageous and less data dependent. These aforementioned challenges make comparison between the described approaches and with manually segmented medical image data impossible. According to the survey study, further advances in brain tumor segmentation are needed to detect brain tumors early. It was concluded that the best techniques to separate brain tumors from MRI images by improving the quality are artificial neural networks, K-means clustering and FCM, SVM deep learning algorithm and CNN.

REFERENCES

[1] Caponetti, L, Castellano G & Corsini, V, 'MR brain image segmentation: A framework to compare different clustering techniques', Information, vol. 8, no. 4, pp. 130-138, 2017.

[2] Chaddad Ahmad & Camel Tanougast, 'Quantitative evaluation of robust skull stripping and tumor detection applied to axial MR images', Brain Informatics, vol. 3, no. 1, pp. 53-61, 2016.

[3] Cui, S, Mao, L, Jiang, J & Xiong, S, 'Automatic semantic segmentation of brain gliomas from MRI images using a deep cascaded neural network', Hindawi Journal of Healthcare Engineering, pp. 1-20, 2018.

[4] Despotovic, I, Goossens, B & Philips, W, 'MRI segmentation of the human brain: Challenges, methods, and applications', Computational and Mathematical Methods in Medicine', pp. 1-20, 2015.

[5] Fadoua Badaoui, Amine Amar, Laila Ait Hassou, Abdelhak Zoglat & Cyrille Guei Okou, 'Dimensionality reduction and class prediction algorithm with application to microarray Big Data', Journal of Big Data, Springer, vol. 4, no. 32, pp. 1-11, 2017.

[6] Farah, M., Sternberg, S., Nichols, T., Duda, J., Lohrenz, T., Luo, Y., & Ramey, C. "Randomized manipulation of early cognitive experience impacts adult brain structure," Journal of Cognitive Neuroscience, vol. 33, pp. 1197-1209, 2021.

[7] Filho PR, Da AC, Silva Barros JS, Almeida JPC, Rodrigues VHC & De Albuquerque 2019, 'A New Effective and Powerful Medical Image Segmentation Algorithm Based on Optimum Path Snakes', Applied Soft Computing Journal, vol. 76, pp. 649-670.

[8] Ganesh M, Naresh M & Arvind C, 'MRI brain image segmentation using enhanced adaptive fuzzy K-means algorithm', Intelligent Automation & Soft Computing an International Journal, vol. 23, no. 2, pp.325-330, 2017.

[9] Khaliki, M.Z., Başarslan, M.S. Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. Sci Rep vol. 14, no. 2664, 2024.

[10] Kong Y, Deng Y, Dai Q, "Discriminative Clustering and Feature Selection for Brain MRI Segmentation," IEEE Signal Processing Letters, vol. 22, no. 5, 2015.

[11] Kumar, P & Vijayakumar, B, 'Brain tumor MR image segmentation and classification using by PCA and RBF kernel based support vector machine', Middle-East Journal of Scientific Research, vol. 23, no. 9, pp. 2106-2116, 2015.

[12] Lakshmi, A., Arivoli, T. & Pallikonda Rajasekaran, M. "A Novel M-ACA-Based Tumor Segmentation and DAPP Feature Extraction with PPCSO-PKC-Based MRI Classification," Arab J Sci Eng., vol. 43, pp. 7095–7111, 2018.

[13] Saeedi, S., Rezayi, S., Keshavarz, H. et al. MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Med Inform Decis Mak., vol. 23, no. 16, 2023.

[14] Saritha, S & Amutha Prabha, N, 'A comprehensive review: Segmentation of MRI images—brain tumor', International Journal of Imaging Systems and Technology, vol. 26, no. 4, pp. 295-304, 2016.

[15] Shree, NV & Kumar, TNR, 'Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network', Brain Informatics, pp. 1-8, 2018.

[16] Sung, H, Ferlay, J, Siegel, RL, Laversanne, M, Soerjomataram, I, Jemal, A & Bray, F, 'Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries', CA Cancer J Clin., vol. 71, pp. 209-249, 2021.

[17] Huang M, Yang W, Wu Y, Jiang J, Chen W, Feng Q, "Brain Tumor Segmentation Based on Local Independent Projection-Based Classification," IEEE

International Current Journal of Engineering and Science (ICJES)
Volume 3, Issue 12, pp 5-12, December-2024
Article DOI: https://doi.org/10.47001/ICJES/2024.312002
ISSN (Online): 2583-7257

transactions on Bio-Medical Engineering, vol. 61, pp. 2633-2645, 2014.
[18] Juneja, K & Rana, C, ‘An improved weighted decision tree approach for breast cancer prediction’, International Journal of Information Technology, pp. 1-8, 2018.

Citation of this Article:

Benjamin, Olajide W., & Simon, I.O. (2024). A Survey on Brain Tumor Detection and Classification Methodologies in Medical Image Processing. *International Current Journal of Engineering and Science - ICJES*, 3(12), 5-12. Article DOI: https://doi.org/10.47001/ICJES/2024.312002

****