Enhanced deep auto encoder technique for brain tumor classification and detection

Syed Jahangir Badashah[1], Kavita Moholkar[2], Sunil L. Bangare[3], Gaurav Gupta[4], Devi T.[5], Sammy Francis[6], Venkatesan Hariram[7], Batyrkhan Omarov[8], Kantilal Pitambar Rane[9], Abhishek Raghuvanshi[10]

[1]Department of Electronics and Communication Engineering, Sreenidhi Institute of Science and Technology, Yamnampet, India
[2]Department of Computer Science and Business Systems Engineering, JSPM'S Rajarshi Shahu College of Engineering, Savitribai Phule Pune University, Pune, India
[3]Department of Information Technology, Savitribai Phule Pune University, Sinhgad Academy of Engineering, Pune, India
[4]Department of Computer Science and Engineering, G. L. Bajaj Institute of Technology and Management, Greater Noida, India
[5]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India
[6]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[7]Department of Practice of Medicine, Vinayaka Mission's Homoeopathic Medical College and Hospital, Vinayaka Mission's Research Foundation Deemed to be University, Salem, India
[8]Department of Information Systems, Al-Farabi Kazakh National University, Almaty, Kazakhstan
[9]Department of Electronics and Telecommunications Engineering, BharatiVidyapeeth College of Engineering, Navi Mumbai, India
[10]Department of Computer Science Engineering, Mahakal Institute of Technology, Ujjain, India

Article Info

Article history:

Received Apr 12, 2024
Revised Jan 14, 2025
Accepted Feb 28, 2025

Keywords:

Accuracy
Adaptive wiener filter
Brain tumor
Classification
Deep auto encoder
Fuzzy C means clustering
Prediction

ABSTRACT

A brain tumor can develop due to uncontrolled proliferation of aberrant cells in brain tissue. Malignant tumor can influence the nearby brain tissues, potentially resulting in the person's death. Early diagnosis of a brain tumor is crucial for ensuring the survival of patients. This article introduces an improved method using a deep auto encoder for the classification and detection of brain tumor. Magnetic resonance imaging (MRI) images are obtained from the BraTS data sets. The images undergo preprocessing using an adaptive Wiener filter. Image preprocessing is essential for eliminating noise from the input MRI pictures, hence enhancing the accuracy of MRI image classification. The fuzzy C-means technique is used to accomplish image segmentation. The classification model comprises deep auto encoder, convolution neural network (CNN), and K-nearest neighbor techniques. The classification model is developed and evaluated using MRI image slices from the BraTS dataset. Accuracy of deep auto encoder is 98.81%. Accuracy of CNN is 95.50 and accuracy of K-nearest neighbor (KNN) technique is 91.30%.

Corresponding Author:

Abhishek Raghuvanshi
Department of computer Science Engineering, Mahakal Institute of Technology
Ujjain, India
Email: abhishek14482@gmail.com

1. INTRODUCTION

A brain tumor is usually an anomalous proliferation of brain cells. While certain brain tumors are noncancerous, others can be cancerous. A "primary brain tumor" refers to tumors that originate from brain tissue. Metastasis is the process by which a malignant tumor moves from a different location in the body to the brain. The selection of treatment options can differ based on the specific type, location, and size of the tumor. Treatment aims to mitigate symptoms or achieve therapeutic objectives. Intermittent headaches and migraines may indicate the presence of a tumor. It has the potential to cause blindness. Our current understanding of the genesis and cause of this aberrant tumor growth is limited, preventing us from making definitive conclusions [1].

Tumors can be classified based on their potential for malignancy and their site of origin. A tumor that is not malignant and does not metastasize to other organs is classified as a benign tumor [2]. These entities are readily noticeable and exhibit a moderate pace of expansion. Malignant brain tumors originating from cancer have the ability to metastasize to different regions of the brain. These tumors exhibit a high level of aggressiveness and pose a significant challenge in terms of detection [3]. When searching for a tumor, doctors employ either X-rays or magnetic resonance imaging (MRI). An MRI scan is indicated when all other tests have proven inadequate in yielding satisfactory outcomes. MRI scans utilize radio waves and magnets to generate perfect images [4].

Primary brain tumors are uncommon neoplasms that typically originate in the brain and do not metastasize to other regions of the body. Primary brain tumors can be either benign or malignant. The growth of a benign brain tumor is characterized by its slow pace, well-defined boundaries, and infrequent dissemination. Although the cells in benign tumors are not malignant, they can nevertheless represent a significant health risk if they infiltrate a critical region. Malignant brain tumors exhibit rapid growth, possess poorly defined boundaries, and ultimately metastasize to other areas of the brain. Contrary to its widespread label, malignant brain tumors do not fulfill the diagnostic criteria for cancer since they do not undergo metastasis, which is the spreading of cancer to other areas of the body beyond the brain and spinal cord [5].

MRI utilizes the combination of radio waves and magnetic fields to provide harmless and painless images of the brain. MRI distinguishes itself from computed tomography (CT) by not utilizing radiation waves. Typically, an MRI scanner will include a large toroidal magnetic field with a central aperture. As part of the procedure, each patient will recline on a table that smoothly moves into the testing channel. Individuals afflicted with claustrophobia might seek solace in the numerous medical facilities equipped with MRI machines that include advanced opening technology. Medical facilities and imaging institutes utilize MRI machines to conduct brain examinations [6]. A high-powered antenna can precisely determine the precise position of an individual's atoms within the body by utilizing radio waves, which are subsequently sent to a computer for examination. Computers have the ability to do millions of calculations, resulting in the generation of high-resolution images of the human body [7].

MRI can detect brain tumors, cysts, swelling, bleeding, irregularities in expansion and structures, inflammatory conditions, diseases, and blood vessel abnormalities. Following a brain injury or stroke, a determination is made regarding the optimal timing for surgical intervention to identify the specific region that has been impacted. MRI scans of the brain are valuable for detecting disorders such as multiple sclerosis, chronic fatigue syndrome (CFS), headaches, blurred vision, and other related problems. An MRI scan is crucial for diagnosing problems with the pituitary gland and brain stem, as it offers precise images of the brain structures that cannot be seen using CT, X-ray, or ultrasound [8]. The MRI image of brain part has been illustrated in Figure 1. The MRI image of brain tumor detection has been established in Figure 2.

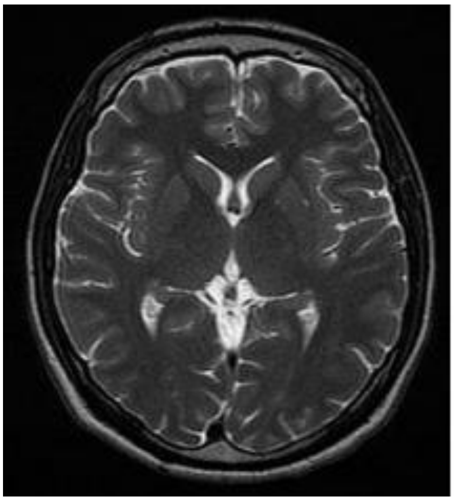

Figure 1. MRI image for brain

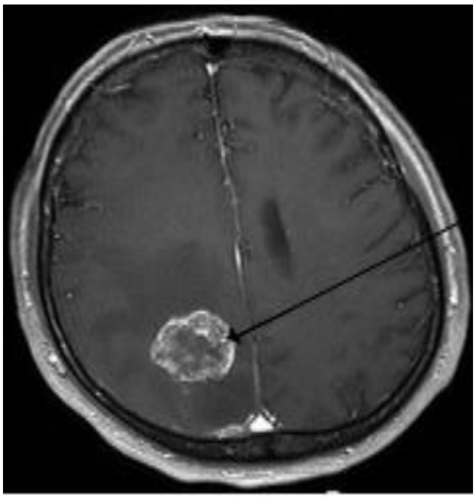

Figure 2. MRI image for brain tumor detection

In the field of medicine, digital image processing has the capacity to significantly assist in the identification of diseases and tumors. Every pixel in a digital image possesses a distinct intensity value and specific position, constituting a defined quantity of elements. MRI is particularly valuable in the field of medicine for obtaining a deep understanding of the internal processes of the body [9]. The main purpose of this is to uncover discrepancies in bodily tissues that can be assessed utilizing an enhanced technique as opposed to approximated tomography. Consequently, this technique is employed as a unique method, particularly for cancer imaging and the identification of brain tumors. MRI pictures are divided into multiple pieces using a technique called image segmentation. This approach generates numerous sets of pixels within a single image. Image segmentation can simplify the process by doing in-depth analysis and collecting pertinent data. Another interpretation is the dissemination of equivalent distinctiveness by assigning a label to each pixel in a brain image. The outcomes from the pixel analysis will be often utilized for asset distribution [10].

2. RELATED WORK

2.1. Segmentation techniques for brain tumors

An essential stage in computer-aided diagnostic techniques is the identification and subsequent division of brain tumors; this stage encompasses a multitude of contributions. Authors introduced a novel approach utilizing deep neural networks to accurately separate brain images from 2D MRI data. The model includes an encoder and decoder that can recognize cancers often identified by medical professionals. Additionally, a specific data augmentation technique is used. Low-grade glioma is considered more challenging to treat compared to other forms of malignant or tumorous cells due to the relatively challenging nature of tumor detection using standard procedures. The model was facilitated by automated approaches for detecting and localizing low-grade gliomas, as stated by the authors. The methodology was validated using the pixel accuracy method, which was implemented with the Znet framework, a deep learning architecture. A semantic segmentation method was devised to address the issue of class imbalance. This approach depended on acquiring the true values from the background elements, which often replaced with very high pixel values that could be misleading [11].

Authors provided a description of a method for segmenting brain tumors using MRI data. Both the training MRI pictures and the assessment inference were included in the strategy. The lack of effectiveness of current cutting-edge techniques in providing accurate results in real-time situations led to the development of a cross-modal distillation strategy. To overcome the constraints of the single sequence CNN model, it was imperative to develop an enhanced CNN architecture capable of effectively analyzing the MRI images, which commonly consist of many sequences of data. During the evaluation of the models using the BRATS 2018 dataset, researchers discovered that cross-distillation yielded superior results in terms of segmentation quality compared to a single sequence CNN model. Cross-distillation was shown to enhance the operational model of a single sequence CNN when exposed to multiple sequential MRI image data [12].

In their study, researchers introduced a multitasking approach that considers the presence of many modalities in MRI data. The approach was described as an automated procedure using segmentation fusion, in which a variational encoder was employed to combine many characteristics and rebuild the images. A regularization technique was employed to achieve segmentation fusion, aiming to extract features from many modalities. The objective of the fusion was to enhance feature engineering by acquiring a more comprehensive understanding of the several characteristics present in the input photos. The model incorporated an uncertainty-based approach into its multi-tasking framework, resulting in decreased weight during the training process. The model underwent testing with real-time scenarios utilizing the benchmark dataset, BRATS 2020. The results indicate that the multi-tasking model outperforms the variational autoencoder (VAE) model in terms of both computational efficiency and accuracy in segmenting [13].

Research work employed a learning and branching strategy to create an HMRNet method that integrates a multiscaling feature. This method is specifically developed to process photographs that have a high level of detail and clarity. The objective of the model was to accurately identify and separate the clinical target volume by analyzing and dividing images of the anatomical brain barriers to cancer. Our primary emphasis was on the scales, while also ensuring the accurate retrieval and preservation of the anatomical characteristics of the human brain as contextual information. The bidirectional feature calibration was established as a means to turn the features into spatial attention maps, with the goal of enhancing the features and facilitating improved segmentation. Segmenting the brain is difficult due of the diverse sizes and shapes of the known barriers. The described approach boosted both bidirectional and monodirectional capabilities by extending the attention span, while high-resolution images enhanced the structural information. This model is dependent on exclusively ABC data obtained from the MICCAI dataset [14].

Inventors demonstrated the validity of the concept of many modalities by employing a streamlined approach, namely the ELU-Net with an enhanced structure. The model utilized a complex skip connection structure to investigate the linkages that arose from the semantic associations of the characteristics. The thick and layered links generated aggregated feature maps that specifically targeted tumors. An enhancement was implemented to the loss functions to enable their specific utilization for the entire tumor, the central region of the tumor, and the expanded tumor. The findings demonstrated that the model had superior performance compared to the conventional U-Net and U-Net++ architectures when evaluated on the BRATS 2018 dataset [15].

2.2. Deep learning algorithms

Deep neural networks have proven to be highly valuable for medical image segmentation in the context of computer-aided diagnosis. In their study, researchers combined deep neural networks with discrete wavelet transform to develop a model that can accurately divide brain tumors into segments. The model categorized brain tumors into three classes: sarcoma, metastatic, and glioblastoma, employing a unique methodology to address the problem statement. Consequently, the model only presented the classification results for the malignant brain tumor variations. As previously stated, CNNs have demonstrated exceptional performance in the areas of feature engineering, extraction, and particularly brain tumor segmentation. In the future, it is anticipated that these networks will transition to being fully convolutional networks [16].

Researchers conducted a comprehensive analysis to evaluate the benefits of deep learning models. They compared the performance of these models to that of machine learning algorithms introduced within the past decade. CNNs will be used to segment, extract, and map boundaries from input images that have been prepared for various properties. Several models combine radiation and deep learning techniques to demonstrate the various processes a patient would undergo. The roadmap is seen as a crucial instrument for future planning, contingent upon the duration of the procedure. To foster eager collaboration in relation to comprehensive applications, forthcoming models will possess a broader perspective.

In 2017, this research work created a segmentation technique using CNNs. This technique considers both the local and global properties of deep learning frameworks. The presence of brain tumors was detected through a thorough examination of the image, focusing on intricate local and global characteristics. The understanding of the necessity of segmentation and the optimization methods for it were enhanced due to the variations seen among the attributes [17].

A group of researchers conducted a comprehensive analysis of different deep learning strategies to determine their effectiveness. We conducted a comprehensive analysis and documentation of many computer-aided diagnosis models that employ deep learning techniques. These models encompass a wide range of applications, such as detecting lesions, analyzing cellular and tissue organization, examining brain hemispheres, performing segmentation, and classifying tumors, among others. The challenges of deep learning strategies and the methods to overcome them were detailed in order to provide guidance for future developments [18].

Research work [19] proposed a strategy that integrated classification and segmentation to predict the regions affected by tumors in the given brain images. The input photos were analyzed using support vector machine and pointing kernel classifier to determine the specific regions of the brain impacted by tumor cells. In order to assess the performance of the model indicated above, we evaluated its sensitivity, specificity, and accuracy. The pointing kernel classifier demonstrated superior performance in segmentation compared to the support vector machine.

3. PROPOSED METHOD

This section presents an enhanced deep auto encoder technique for brain tumor classification and detection as shown in Figure 3. MRI images are acquired from BraTS data sets. Images are preprocessed by adaptive wiener filter. This image preprocessing is necessary to remove noise from the input MRI images and results in improving accuracy of MRI image classification. Image segmentation is performed by fuzzy C means algorithm. Classification model consists of deep auto encoder, CNN and KNN algorithms. Classification model is trained and tested using BraTS data set MRI image slices.

The fundamental objective of image preprocessing in MRI is to enhance image quality for following tasks by removing extraneous and unrelated features from the background. Therefore, MRI brain pictures can be improved using image preprocessing techniques that remove artifacts, boost the picture quality, and enable more precise tumor segmentation. During picture preprocessing, masks are constructed to identify pixels with maximum intensity, aiming to minimize distortion. An adaptive wiener filter (AWF) is a type of filter that operates in the frequency domain. The AWF can dynamically modify its operation by taking into account the mathematical singularity of the medical MRI image within the 14-area filter. This filter is specifically designed for processing MRI images in gray-scale format. Transformation applying filtering techniques to remove noise [20]. Image enhancement partitioning by use the outermost rectangular frame. Adaptive filter presentations can be superior when compared to non-adaptive counterparts. Adaptive filters will facilitate the estimate of two crucial mathematical variables: mean and variance. The WF employs a pixel-wise adaptive

Wiener method, which relies on statistics derived from the neighboring pixels in an MRI image. This filter use pixel-wise adaptive Wiener filtering to conduct a local assessment of mean and standard deviation on an MRI image. It leverages neighborhoods of dimensions M by N.

Clustering algorithms can be employed as an unsupervised segmentation strategy to divide an MRI image into many groups of pixels with comparable brightness, without the need for training images. During the training process, clustering-based segmentation approaches utilize the existing image data. The segmentation algorithms employ a two-step process, consisting of data clustering and evaluation of individual brain tissue classes, to perform segmentation and training simultaneously. The most commonly employed algorithms for photo segmentation problems are K-means clustering and fuzzy C-means clustering. The input data can be partitioned into K clusters using the K-means clustering method [21]. The mean intensity of each class is repeatedly assessed, and the image is segmented by classifying all pixels in that class based on the centroid in their surroundings. In the context of brain pictures, this procedure is iterated. K-means clustering is considered a tough classification approach since it assigns each pixel in an input image to a single class in each iteration. The fuzzy C-means clustering algorithm, also known as the soft categorization technique, is another clustering approach that is based on fuzzy set theory. Fuzzy C-means allows for the classification of each pixel into many groups based on a predetermined membership value, which can be seen as a potential simplification of K-means clustering [22].

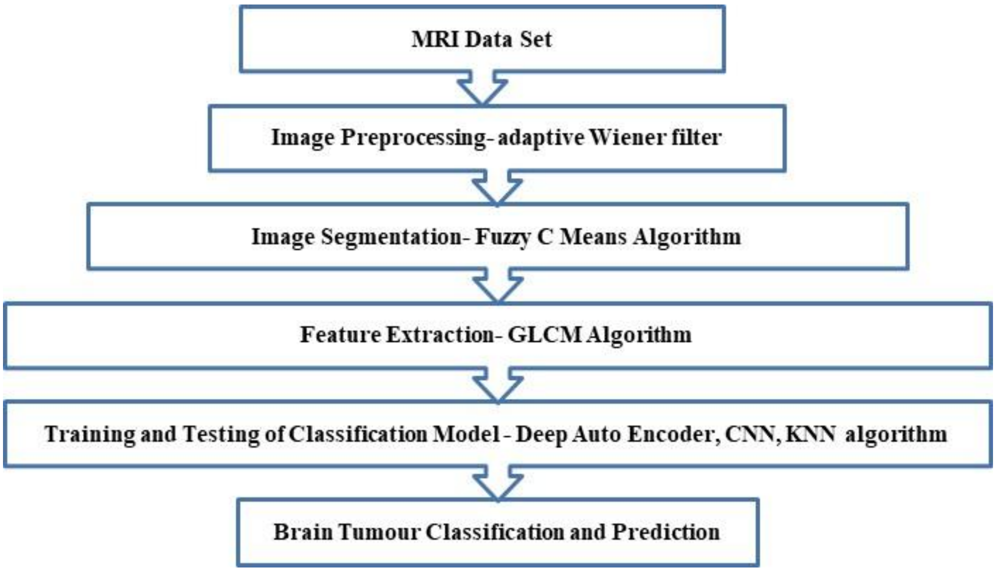

Figure 3. Enhanced auto encoder enabled deep learning for brain tumor classification and detection

From a medical perspective, medical images can be classified based on their distinctive features utilizing the image classification method. This picture classification method utilizes spectral foundation or spectrally distinct characteristics, such as brain density, texture, and feature space. Research has demonstrated that image classification techniques can employ decision rules to partition the feature space into many classes. In the medical domain, rapid computer systems, supported by mathematical algorithms and effective classification approaches, have successfully achieved picture categorization. The following are the standard procedures for categorizing MRI images to identify tumors.

DAE, a type of deep learning technique, employs greedy preparameter optimization training of an unsupervised layer to extract the layered distinctiveness of high-dimensional input data from medical images. The approach utilizes a neural network architecture and a multilayer nonlinear network. Data analysis and exploration (DAE) utilizes this characteristic, and the distinctive attribute of scattered data is already accessible. The hidden layer process, encoder, and decoder are all contained within the DAE. The architecture and training techniques of the initial automatic encoder were enhanced to construct the DAE. Various DAEs are founded on distinct theories within the realm of deep learning, such as arithmetic theory, sparse hypothesis, convolution theory, and robust theory. The construction and implementation of DAE will result in a decrease in the original input dimensions. By analyzing the fundamental characteristics of the input image data from underrepresented class typical examples and various non-class benchmark datasets, the efficiency of feature extraction is enhanced [23].

A CNN, derived from the analysis of the visual system's structure, is a highly efficient method for training a multilayer network. This technique employs spatial links to minimize the amount of factors required to enhance the training performance. A CNN can be understood as a neural network with several layers, where each layer consists of two-dimensional planes and each plane is characterized by a set of individual neurons. An example of how CNN can be used is for the detection of handwritten characters. CNNs are mostly effective in detecting displacement, scaling, and other forms of deformation invariance in two-dimensional pictures. This solution avoids the explicit feature sampling method by directly examining the training data. CNNs can generate outcomes that vary significantly from other neural network classifiers due to their construction through parallel research. This parallel approach has the potential to produce superior results compared to networks composed of interconnected neurons. CNNs offer distinct benefits for image processing and segmentation, and their ability to extract valuable features has resulted in highly effective outcomes. Every neuron in a CNN possesses a hierarchical local association structure and necessitates a minuscule input. This takes the computational model of biological neural networks closer to the definitive neural network. This technique will be employed for immediately processing medical photos using the categorization process. It specifically focuses on gray level images [24].

KNN is a straightforward and efficient non-parametric technique used to categorize data records. It works by identifying the KNN to a given data point, which are then used to create a neighborhood around that point. Usually, when determining how to classify t, whether or not distance-based weighting is taken into account, the most common choice is to rely on the majority vote of neighboring data entries. The efficacy of the classification hinges on the selection rate, so the accurate determination of the value for k is crucial when employing KNN. The KNN technique exhibits bias by a factor of k. When dealing with fundamental algorithms, there are numerous methods available to select the most efficient execution for various values of k. KNN is a case-based learning algorithm that keeps all training data for grouping. Its slow learning methodology disqualifies it from numerous possible applications, such as real-time web scraping for a large-scale shop. An approach to enhance the identification of representatives for communication with all of the training classification data, namely. Utilize the dataset to train and classify by implementing an inductive learning technique. Several algorithms, such as decision trees and neural networks, were initially created to design a system capable of achieving this goal, and their individual standard performances have been thoroughly documented. The KNN model is valuable for classifying newswire stories and influencing readers because of its simplicity and effectiveness. The Reuters corpus is used to classify context, which helps in creating a KNN model to improve efficiency without compromising classification accuracy [25]

4. RESULTS ANALYSIS AND DISCUSSION

This experiment data set contains MRI slices from BraTS12 to BraTS18 and 3,064 MRI slices from 233 patients [26]. Total of 5063 MRI samples and each of these images may contains one of the three types of brain tumors: meningioma, glioma, or pituitary tumor. The images have an in-plane resolution of 512×512 pixels with a pixel size of 0.49×0.49 mm^2. The thickness of the slices is 6 mm, and the gap between them is 1 mm. The images are preprocessed using an adaptive wiener filter. This image preprocessing is required to eliminate noise from input MRI pictures, which improves the accuracy of MRI image classification. Fuzzy C means method is used for image segmentation. The deep auto encoder, the CNN, and the KNN algorithms make up the classification model.

The efficacy of the used approach is assessed using metrics like accuracy, sensitivity, specificity, and precision. Accuracy metrics are intended to assess the precision of a method's predictions. The proportion of brain malignancies accurately identified relative to the overall count of brain tumors is termed classification accuracy. A sensitivity analysis is performed to evaluate the influence of fluctuating values and parameters of a model on the final result. The capacity of the data classification metric to precisely identify actual positive values is essential. The specificity of a data categorization measure denotes its capacity to reliably identify real negative values. Precision is measured by the number of correctly anticipated positive results. The results are shown in Table 1 and Figure 4. The accuracy of the deep auto encoder is 98.81%. The accuracy of the CNN is 95.50%, whereas the accuracy of the KNN approach is 91.30%.

Table 1. Results of deep auto encoder for brain tumor detection

	Accuracy	Precision	Specificity	Sensitivity
KNN	91.3	92.31	91.91	92.66
CNN	95.5	94.71	95.34	94.56
Deep auto encoder	98.81	97.53	98.28	96.37

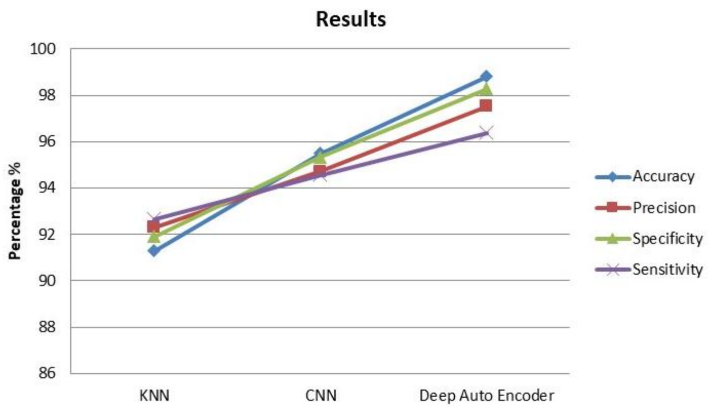

Figure 4. Results of deep auto encoder, CNN and KNN techniques for brain tumor detection

5. CONCLUSION AND FUTURE WORK

In this research work, an improved deep auto-encoder technique for brain tumor classification and detection. MRI images are obtained using BraTS datasets. MRI pictures may show one of three forms of brain tumors: meningioma, glioma, or pituitary tumor. The photos are preprocessed with an adaptive wiener filter. This image preprocessing is required to remove noise from input MRI images, hence improving the accuracy of MRI image classification. The fuzzy C means approach is used for image segmentation. The classification model is made up of three algorithms: deep auto encoder, CNN, and KNN. Accuracy of deep auto encoder is 98.81%. Accuracy of CNN is 95.50 and accuracy of KNN technique is 91.30%. In future, this proposed method can be extended to work in real time brain tumor detection and on colored images.

ACKNOWLEDGEMENTS

We are deeply thankful to our institutions for providing the necessary resources and facilities that enabled the successful completion of this research.

FUNDING INFORMATION

No funding received for this research work.

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Syed Jahangir Badashah		✓	✓	✓	✓	✓		✓	✓	✓			✓	
Kavita Moholkar		✓				✓		✓	✓	✓	✓	✓		
Sunil L. Bangare		✓	✓		✓	✓		✓	✓	✓			✓	
Gaurav Gupta	✓		✓	✓	✓	✓		✓	✓	✓			✓	
Devi T.		✓				✓		✓		✓	✓	✓		
Sammy Francis			✓				✓			✓	✓		✓	✓
Venkatesan Hariram		✓	✓	✓	✓	✓		✓	✓	✓			✓	
Batyrkhan Omarov	✓			✓	✓									
Kantilal Pitambar Rane	✓	✓		✓	✓	✓		✓	✓	✓			✓	
Abhishek Raghuvanshi	✓	✓		✓										

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

Ethical approval was not required for this study, as it did not involve human or animal subjects.

DATA AVAILABILITY

Data used in the paper is available at https://www.med.upenn.edu/sbia/brats2018/data.html.

REFERENCES

[1] M. J. Lakshmi and S. N. Rao, "Brain tumor magnetic resonance image classification: a deep learning approach," *Soft Computing*, vol. 26, no. 13, pp. 6245–6253, Jul. 2022, doi: 10.1007/s00500-022-07163-z.

[2] W. Jun and Z. Liyuan, "Brain tumor classification based on attention guided deep learning model," *International Journal of Computational Intelligence Systems,* vol. 15, no. 1, p. 35, Dec. 2022, doi: 10.1007/s44196-022-00090-9.

[3] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, "A deep learning-based framework for automatic brain tumors classification using transfer learning," *Circuits, Systems, and Signal Processing,* vol. 39, no. 2, pp. 757–775, Feb. 2020, doi: 10.1007/s00034-019-01246-3.

[4] T. Fernando, H. Gammulle, S. Denman, S. Sridharan, and C. Fookes, "Deep learning for medical anomaly detection—a survey," *ACM Computing Surveys*, vol. 54, no. 7, pp. 1–37, Sep. 2022, doi: 10.1145/3464423.

[5] S. Bonte, I. Goethals, and R. Van Holen, "Machine learning based brain tumour segmentation on limited data using local texture and abnormality," *Computers in Biology and Medicine*, vol. 98, pp. 39–47, Jul. 2018, doi: 10.1016/j.compbiomed.2018.05.005.

[6] Y. Jiang, J. Hou, X. Xiao, and H. Deng, "A brain tumor segmentation new method based on statistical thresholding and multiscale CNN," *Intelligent Computing Methodologies*, vol. 2, no. 3, pp. 235–245, 2019, doi: 10.1007/978-3-319-95957-3_26.

[7] M. W. Nadeem, M. A. A. Ghamdi, M. Hussain, M. A. Khan, K. M. Khan, S. H. Almotiri, and S. A. Butt, "Brain tumor analysis empowered with deep learning: a review, taxonomy, and future challenges," *Brain Sciences,* vol. 10, no. 2, pp. 118–151, 2020, doi: 10.3390/brainsci10020118.

[8] Z. Huang, X. Du, L. Chen, Y. Li, M. Liu, Y. Chou, and L. Jin, "Convolutional neural network based on complex networks for brain tumor image classification with a modified activation function," *IEEE Access,* vol. 8, pp. 89281–89290, 2020, doi: 10.1109/ACCESS.2020.2993618.

[9] B. Amarapur, "Computer-aided diagnosis applied to MRI images of brain tumor using cognition based modified level set and optimized ANN classifier," *Multimedia Tools and Applications,* vol. 3601, pp. 3571–3599, Feb. 2020, doi: 10.1007/s11042-018-6308-7.

[10] H. M. Rai and K. Chatterjee, "2D MRI image analysis and brain tumor detection using deep learning CNN model LeU-Net," *Multimedia Tools and Applications*, vol. 80, nos. 28–29, pp. 36111–36141, Nov. 2021, doi: 10.1007/s11042-021-11504-9.

[11] M. A. Ottom, H. A. Rahman, and I. D. Dinov, "Znet: deep learning approach for 2D MRI brain tumor segmentation," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 10, pp. 1–8, 2022, doi: 10.1109/jtehm.2022.3176737.

[12] M. Rahimpour *et al*., "Cross-modal distillation to improve MRI-based brain tumor segmentation with missing MRI sequences," *IEEE Transactions on Biomedical Engineering,* vol. 69, no. 7, pp. 2153–2164, Jul. 2022, doi: 10.1109/tbme.2021.3137561.

[13] Y. Liu, F. Mu, Y. Shi, and X. Chen, "SF-Net: a multi-task model for brain tumor segmentation in multimodal MRI via image fusion," *IEEE Signal Processing Letters,* vol. 29, pp. 1799–1803, 2022, doi: 10.1109/LSP.2022.3198594.

[14] H. Fu et al., "HMRNet: high and multi-resolution network with bidirectional feature calibration for brain structure segmentation in radiotherapy," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 9, pp. 4519–4529, Sep. 2022, doi: 10.1109/jbhi.2022.3181462.

[15] Y. Deng, Y. Hou, J. Yan, and D. Zeng, "ELU-Net: an efficient and lightweight U-Net for medical image segmentation," *IEEE Access,* vol. 10, pp. 35932–35941, 2022, doi: 10.1109/ACCESS.2022.3163711.

[16] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, and A.-B. M. Salem, "Classification using deep learning neural networks for brain tumors," *Future Computing and Informatics Journal,* vol. 3, no. 1, pp. 68–71, Jun. 2018, doi: 10.1016/j.fcij.2017.12.001.

[17] P. Meyer, V. Noblet, C. Mazzara, and A. Lallement, "Survey on deep learning for radiotherapy," *Computers in Biology and Medicine,* vol. 98, pp. 126–146, Jul. 2018, doi: 10.1016/j.compbiomed.2018.05.018.

[18] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, "Deep learning for brain MRI segmentation: state of the art and future directions," *Journal of Digital Imaging*, vol. 30, no. 4, pp. 449–459, Jun. 2017, doi: 10.1007/s10278-017-9983-4.

[19] S. Chidambaram, E. L. Goh, and M. A. Khan, "A meta-analysis of the efficacy of whole-body computed tomography imaging in the management of trauma and injury," *Injury,* vol. 48, no. 8, pp. 1784–1793, Aug. 2017, doi: 10.1016/j.injury.2017.06.003.

[20] M. Rasheed *et al.,* "Recognizing brain tumors using adaptive noise filtering and statistical features," *Diagnostics,* vol. 13, no. 8, pp. 1451–1451, Apr. 2023, doi: 10.3390/diagnostics13081451.

[21] R. Khilkhal and M. Ismael, "Brain tumor segmentation utilizing thresholding and K-means clustering," *2022 Muthanna International Conference on Engineering Science and Technology (MICEST)*, Samawah, Iraq, 2022, pp. 43-48, doi: 10.1109/MICEST54286.2022.9790103.

[22] M. Bhardwaj, N. U. Khan, V. Baghel, S. K. Vishwakarma, and A. Bashar, "Brain tumor image segmentation using K-means and fuzzy C-means clustering," *Elsevier eBooks*, pp. 293–316, Jan. 2023, doi: 10.1016/b978-0-32-398370-9.00020-2.

[23] D. R. Nayak, N. Padhy, P. K. Mallick, and A. Singh, "A deep autoencoder approach for detection of brain tumor images," *Computers and Electrical Engineering*, vol. 102, p. 108238, Sep. 2022, doi: 10.1016/j.compeleceng.2022.108238.

[24] A. Chattopadhyay and M. Maitra, "MRI-based brain tumour image detection using CNN based deep learning method," *Neuroscience Informatics*, vol. 2, no. 4, p. 100060, Dec. 2022, doi: 10.1016/j.neuri.2022.100060.

[25] K. V. Archana and G. Komarasamy, “A novel deep learning-based brain tumor detection using the Bagging ensemble with K-nearest neighbor,” *Journal of Intelligent Systems*, vol. 32, no. 1, Jan. 2023, doi: https://doi.org/10.1515/jisys-2022-0206.
[26] “MICCAI BraTS 2018: Data | Section for Biomedical Image Analysis (SBIA) | Perelman School of Medicine at the University of Pennsylvania,” *University of Pennsylvania*, 2018. Available: https://www.med.upenn.edu/sbia/brats2018/data.html.

BIOGRAPHIES OF AUTHORS

Dr. Syed Jahangir Badashah is professor, Department of Electronics and Communication Engineering, Sreenidhi Institute of Science and Technology, Yamnampet, Hyderabad, India. He can be contacted at email: syd_jahangir@yahoo.co.in.

Dr. Kavita Moholkar is working as Associate professor, Department of Computer Science and Business Systems Engineering, JSPM'S Rajarshi Shahu College of Engineering, Savitribai Phule Pune University, Pune, India. He can be contacted at email: kavita.moholkar@gmail.com.

Dr. Sunil L. Bangare working as an associate professor in the Department of Information Technology at Sinhgad Academy of Engineering, Pune, India. He graduated in Bachelor of Engineering in Electronics and Telecommunication at Amravati University (SGBAU), Amravati, Maharashtra, India. He secured master of technology in information technology at Bharati Vidyapeeth Deemed University, Pune, India. He completed Ph.D. in the field of computer science and engineering at Koneru Lakshmaiah Education Foundation (K. L. University), Vaddeswaram, India. He completed his PGD C-DAC. He is a Fellow (FIE)-The Institution of Engineers (India). He is in teaching profession for more than 16 years and have 1.6 years of industrial experience. He can be contacted at email: sunil.bangare@gmail.com.

Gaurav Gupta is an assistant professor from 2013 in the Department of Computer Science and Engineering in G.L. Bajaj Institute of Technology and Management, Greater Noida. He has done his MCA from Ajay Kumar Garg Engineering College, Ghaziabad & M.Tech from Monad University, Hapur. He can be contacted at email: gaurav.mintu@gmail.com.

Dr. Devi T. is professor in Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India. She can be contacted at email: devi.janu@gmail.com.

Dr. Sammy Francis is assistant professor in Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India. She can be contacted at email: sammy@kluniversity.in.

Dr. Venkatesan Hariram is professor and head in Department of Practice of Medicine, Vinayaka Mission's Homoeopathic Medical College and Hospital, Vinayaka Mission's Research Foundation Deemed to be University, Salem, Tamilnadu, India. He can be contacted at email: venkathompath@gmail.com.

Batyrkhan Omarov received his bachelor's and master's degrees from Al-Farabi Kazakh National University, Almaty, Kazakhstan in 2008 and 2010, respectively. In 2019, he received his Ph.D. from Tenaga National University, Kuala Lumpur, Malaysia. His research interests include machine learning, deep learning, data science, image processing, medical image analysis, and artificial intelligence in medicine. He can be contacted at email: batyahan@gmail.com.

Dr. Kantilal Pitambar Rane received B.E degree in electronics and telecommunication engineering from North Maharashtra University, Jalgaon in 1996. M.E Degree in Electronics Engineering from Shivaji University, Kolhapur in 2005. PhD Degree in Electronics Engineering from North Maharashtra University, Jalgaon in 2013. He is currently working as professor at Bharati Vidyapeeth College of Engineering Navi Mumbai, India. His research interests include image processing, IoT, AI, and machine learning. He can be contacted at email: kantiprane@rediffmail.com.

Dr. Abhishek Raghuvanshi is working as Dean Academics and Professor of Computer Science and Engineering in Mahakal Institute of Technology in Ujjain in India. He is having teaching experience of 19 years, research experience of 15 years and administrative experience of 11 years. His research areas include- machine learning, internet of things security, health care analytics. He is having many publications in SCI and Scopus indexed journals. He has also worked on many governments of India funded research projects. He can be contacted at email: abhishek14482@gmail.com.