Brain Tumor Detection in Magnetic Resonance Images Using Genetic Algorithms With Multiple Stages

[1]Ajay Vyas, [2]Vaishali Poriya*, [3]Sandeep Mathariya, [4]Nilesh Jain, [5*]Mahaveer Jain

[1,2,4,5] Institute of Computer Application, SAGE University, Indore, Madhya Pradesh 453331, India

[3]Department of Computer Science and Engineering, Medi-Caps University, Indore, Madhya Pradesh 453331, India

*profmahavir@gmail.com

Abstract. Biomedicine is still attempting to overcome one of the profession's most pressing problems: detecting brain tumors. Early detection of brain cancer is possible with advanced technology or instruments. Classifying brain cancer types utilizing patent brain images allows for automation in automated operations. Furthermore, the proposed new method is used to distinguish between brain tumors and other brain illnesses. To distinguish the cancer from the other parts of the brain, the input image is first pre-processed. Following that, the images are separated into different hues and levels before being processed using the Grey Level Co-Occurrence and SURF extraction methods to reveal crucial information in the photos. Genetic optimization reduces the size of the retrieved attributes. An advanced learning technique is utilized to train and validate tumor categorization based on cut-down characteristics. The technique's accuracy, error, sensitivity, and specificity are all compared to the present method. The approach has a 90%+ accuracy rate, with less than 2% inaccuracy for all types of cancer. Finally, the specificity and sensitivity are greater than 89% and 91%, respectively. Genetic algorithms are more efficient because the methods used are more accurate and specialized than the other ways.

Keywords: Genetic optimization, MRI, GLCM, brain tumor, SURF, advanced machine learning

1   INTRODUCTION

Central Nervous System (CNS) has a brain and spinal column. All the energetic functions such as thought, speech, vision, respiration, and movement of the body are controlled by CNS. When the abnormal cells grow in the CNS it can affect the person's thought and movement of the body. The spinal cord extends from the base of the brain to the lower back. Massages exchange to and from the brain to the rest of the body along the spine. The brain contains 50-100 billion neurons, many cells. Each cell in the brain performs specific functions. Because the brain is protected by the skull, it is extremely tedious to diagnose a brain tumor in its early stages, and the brain tumor exhibits no specific clinical signs. Generally, brain tumors are detected based on three symptoms [1]. The initial signs and symptoms are headache, vomiting, and altered consciousness brought on by an increase in intracranial pressure. [2-4]. The second indicator of brain malfunction is a shift in the affected person's personality or feelings. The final symptom is irritability, which includes absences. Seizures or exhaustion may also be seen. However, these symptoms alone are not sufficient to confirm brain tumor. Therefore, diagnosis of brain tumor is mainly based on imaging techniques. Based on origin, location, size of the tumor and biological

characteristics the brain tumors are classified. The early detection of brain cancer is one of the crucial issues. The World Health Organization (WHO) has classified brain tumors into 120 different categories, ranging from grade I to grade IV [5]. Based on the grade level the doctor can give the treatment to save the life of the patient [6]. In general, brain tumors are classified as primary or secondary. The original brain tumor originated in the brain. Initially brain tumors are classified as benign or malignant according to its spread. A benign tumor develops in the brain and does not spread to other parts of the body. This type of tumor is also called a non-cancerous tumor. Malignant brain tumors, also known as brain cancer, are aggressive tumors that invade surrounding tissues and may spread to other parts of the brain or spinal cord. Benign brain tumors are easier to cure than malignant brain tumors because extracellular development occurs only on the brain's perimeter. Benign brain tumor is treated through surgery it does not require Radiotherapy and Chemotherapy. Chemotherapy and radiation therapy are needed to treat a malignant brain tumor since the tumor develops quickly even after surgery and there is a probability it will return. The following sections explain the different detection methods for treating brain tumors, hybrid algorithm for detection of tumor in the brain.

2   RELATED WORKS

This section gives an overview of medical image analysis with respect to brain tumors. Medical technology uses various techniques for diagnosing cancer tissues in a human anatomy. Surgeons diagnose cancer cells based on family history and diagnostic reports from physical examinations such as MRI, biopsy, brain angiogram, computed axial tomography, magnetic resonance angiography, and electroencephalogram. Early discovery of a tumor improves the patient's survival rate [7]. To attain a proper prediction the analyzing of brain image is essential. By using efficient segmentation techniques, the brain image is analyzed, and doctors can plan the treatment. Radiologists need to spend a lot of time and effort segmenting tumors. Currently surgeons are using advanced noninvasive imaging techniques for analyzing cancer tissues. MRI (Magnetic Resonance Imaging) is one of the primary imaging modalities used for the detection, characterization, and monitoring of brain tumors but single MRI scan does not provide sufficient information for categorizing and segmenting the tissues for tumor identification, hence several MRI sequences are required. [8]. Many image segmentation methods are used to analyze the image easier. Watershed segmentation, edge detection, threshold level, intensity, and Markov Random model are a few segmentation techniques [9]. Now a days the brain aberrations are detected using Computer Aided Diagnosis (CAD) [10-16]. Using K-means clustering algorithm the location of tumor is detected from CAD [17]. They found this method avoids the misclustered region which is formed in MRI imaging technique. But this method gives dissimilar results for different clusters. Computer Aided Diagnostics scheme is developed from MRI technique for detecting brain tumor [18]. The active contour model improves the performance of CAD for investigating tumor location. Several techniques were utilized for segmentation, including Fuzzy Clustering using Level Set Method and Distance Regularized Level

Set Evolution for Medical Image Segmentation. [19]. The semi-automatic method was presented in [20] for analyzing dead cells in the brain. This technique involves user interaction and software steps. The surgeon needs a few input parameters and visualizes the data. This method is computationally effective to segment the brain tumor. In [21], structural MRI is offered as a method for detecting brain structure and investigating brain cell proliferation. Deep learning techniques like CNN can be used to extract features from image. The research paper [22] proposed a deep learning-based summary of brain tumor detection and cascaded architecture. Deep learning-based segmentation was proposed in [23]. In this paper they used supervised learning for detection of brain tumor. To get accuracy of result they need large amount of data. Hybrid abnormality detection algorithm was proposed in [24] which is used to find the dysfunction cells from MRI imaging using CAD. Authors in [25] presented the classification of images from MRI using self-organizing map artificial neural networks. The images are extracted after applying preprocessing like histogram equalization, filtering and edge detection.

3   METHODOLOGY

3.1   Dataset and Method

The identification of brain tumors directly improves the survival rate. A hybrid strategy based on deep learning and genetic algorithms is presented to address this issue. The suggested method's performance is confirmed with publicly available datasets from Brain Tumor Segmentation [26] and open access Series of Imaging Studies [27]. Each data set is composed of 985 MR images. These MR images are collected from 255 patients. These two data sets have images captured from various angles of the skull. By using modified deep learning and genetic algorithm the network is trained based on the MR images too their angles. In this proposed method out of 1970 images 394 images are used for validation and rest of the images used for the test purpose. Figure 1 shows the sample data sets for detecting brain tumor using Genetic algorithm and deep learning.
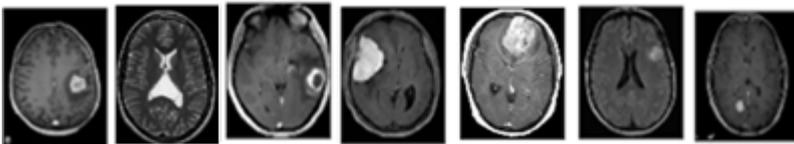

Fig. 1. Sample Dataset

3.2   Image Pre-processing

Image preprocessing is a fundamental step in image analysis pipelines, involving the manipulation and enhancement of raw image data to improve its quality, interpretability, and suitability for subsequent analysis tasks. In the context of medical imaging, such as MRI or CT scans, preprocessing plays a crucial role in ensuring

accurate and reliable results in tasks like tumor detection, segmentation, and classification. Figure 2 shows the methodology of the proposed work. It was observed that few MRI images in dataset are not clear due to presence of noise and low intensity. Brightness plays a vital role for analyzing an image to detect disease. Contrast level is an important property of an object that is used to separate another object from image.
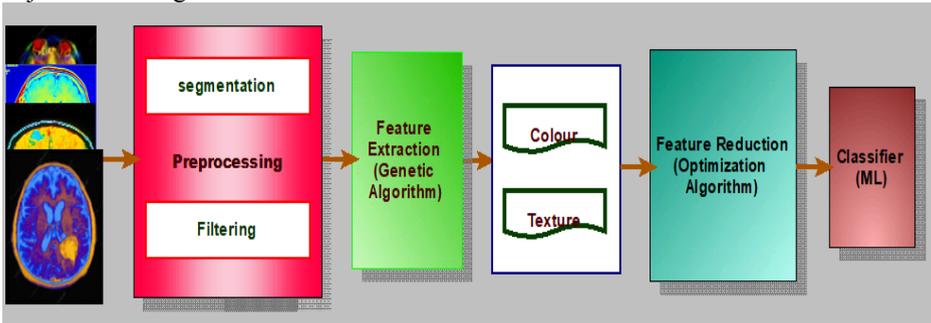

Fig 2. Methodology of Brain Tumor Detection

The mathematical expression for automatic brightness and contrast adjustment using power law transmission is given by expression (1) and (2).

$$s(x1, y1) = r(x1, y1) + k \tag{1}$$

$$s = kr^{\gamma} \tag{2}$$

where s and r represent grey colour levels of the pixels respectively in the input and output images and k is a constant. To get better quality of image the sample data should be pre-processed through filtering and segmentation. The main objective of this method is to enhance image quality so that the surgeon can figure out the tumor's location and grade. To improve the accuracy of the image the sample data should be resized by 256×256. The resized image is sent to the filter for removing the noise. After analyzing different filtering techniques, the median filter plays an important role in image pre-processing which is used to remove the noise and without altering the property of image. To separate the dysfunction cell or abnormal functions cell from the background the noise free image is applied to the clustering algorithm.

3.3   Extraction of Feature

This method is used to find the clinical features of tumor based on two aspects namely colour and texture. The colour variation directly reflects the grade level of the tumor. A group of colour variations of different grade levels of brain tumor is shown in Figure 3. The degree of colour variation is mainly focused on from grade level I to IV. Through quantitative analyses the first, second, third and fourth order of different colour variations is due to variation of hue and saturation level. Based on colour variation the image intensities t1, t2, tlc and flair are calculated.   Therefore, the

first-grade level S_i and second grade level σ_i of Hue and Saturation components can be obtained from equation (3) and (4)

$$S_i = \frac{1}{N} \sum_{j-1}^{N} R_{ij}$$

(3)

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j-1}^{N} \left(R_{ij} - S_i\right)^2}$$
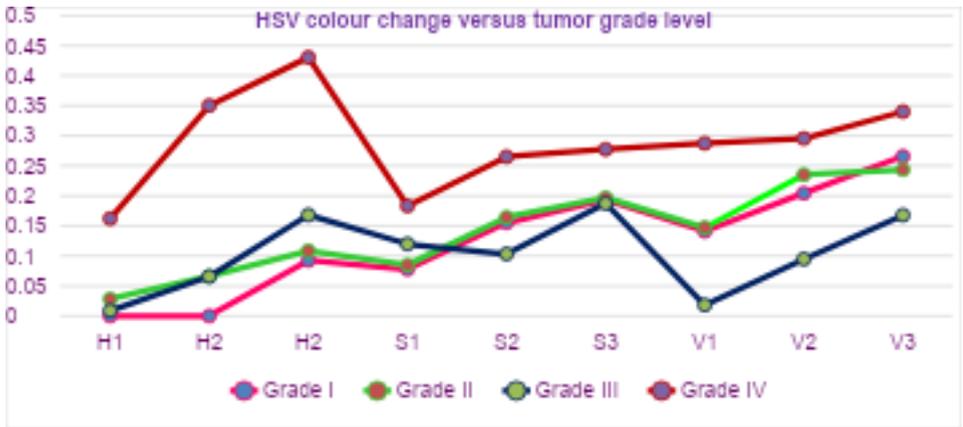
(4)

Fig. 3. Grading of Brain Tumor

3.4   Texture Feature Extraction

Apart from colour features the extraction of texture feature is also important for analyzing the images. Extraction of texture is obtained from integrating Gray Level Co-occurrence Matrix (GLCM) [28] and Speeded Up Robust Feature (SURF) [29]. The integrated algorithms are used to reduce the number of overlapping features. This method produces more accurate results compared to other texture extraction algorithms. This integrated algorithm detects all the matching features between the with and without brain tumor images. The Speed up robust feature extraction algorithm uses image convolution to find out the matching points between two images. This algorithm first calculates the surf using Haar Wavelet matrix. The orientation between the images is obtained from circular region around the key points which is calculated from H matrix. The GLCM algorithm is used to find out image angles and pixel distances. Using GLCM algorithm the main four texture features like distance, direction and gray values. Totally there are 161 features in this proposed work mainly concentrate on tumor shape.

$$Energy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} R^2\left(i, j; d, \theta\right)$$

(5)

$$Entropy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} R\left(i, j; d, \theta\right)\log R\left(i, j; d, \theta\right)$$

(6)

$$Moment\ of\ Inertia = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\left(i - j\right)^2 R\left(i, j; d, \theta\right)$$

(7)

$$Correlation = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ij\, R\left(i - j\right) - \mu_x \mu_y}{\sigma_x^2\, \sigma_y^2}$$

(8)

3.5   Image Optimization using Genetic Algorithm

The Advanced Machine Learning (AML) training model has a single hidden layer rather than several hidden layers. In contrast to the typical feed forward network training methodology, the hidden layer threshold value of hidden layer neurons and the connection weight between the input layer and the hidden layer are created at random.

Input, hidden and output layer neurons are represented by p, q and respectively. $a(x)$, b are the excitation function The training model of ALM can be expressed as,

$$\sum_{i=1}^{m}\alpha_i\, a\left(W_i\, x_i + b_i\right) = O_j\ ; j = 1,2,3,\dots\dots\dots N$$

(9)

Where $W_i = W_{1i}, W_{2i}, W_{3i}, \dots\dots\dots W_{mi}$ is the weight vector of input and hidden layer

$\alpha_i = \left[\alpha_{i1}, \alpha_{i2}\, \alpha_{i3}, \dots\dots\dots\alpha_{im}\right]^T$ is the weight vector of output and hidden layer

$O_i = \left[O_{i1}, O_{i2}\, O_{i3}, \dots\dots\dots O_{im}\right]^T$ denotes the network output value.

The performance of the training process is improved through adjusting the weights of input and hidden layers thresholds. By adjusting these values, the network performance is optimized. The following steps to be followed to optimize the performance of the learning processes.

Step I: Set the number of hidden layers.

Step II: Set and Initialize weights matrix of input and hidden layer.

Step III: Fit the object function using samples and apply heuristic search based on empirical principles to determine the next comparison point. To achieve crossover, determine the output error of the ALM using derivative-free optimization [30].

Step IV: Check to see if the maximum number of repetitions has been achieved and if there is no better alternative for subsequent samples.

Step V: Stop the algorithm.

4   Result and Discussion

This section addresses the type of tumor, its location, grade level, as well as the sensitivity and specificity of the ALM-analyzed tumors.

4.1   Analyzing Accuracy and Error

Images from 1970 are utilized to determine the tumor grade and location during simulation. Based on the hue, saturation, and value (HSV) colour feature the grade level the tumor is identified and with the help of integrated algorithm (SURF + GLCM) texture features are also identified. This texture feature will produce four different direction $0^{\circ}, 60^{\circ}, 120^{\circ} \text{ and } 180^{\circ}$. This integrated algorithm observes data in all the four directions and compared it with 394 validation data. The two colour and four texture features are combined to form a vector feature and used to identify the exact location and level of the tumor. Type of disease identification from different samples using different algorithms is compared. The proposed hybrid learning technique provides better performance compared to other algorithms. Figures 4 and 5 show the comparison result with respect to error and accuracy for each disease using different learning algorithms.
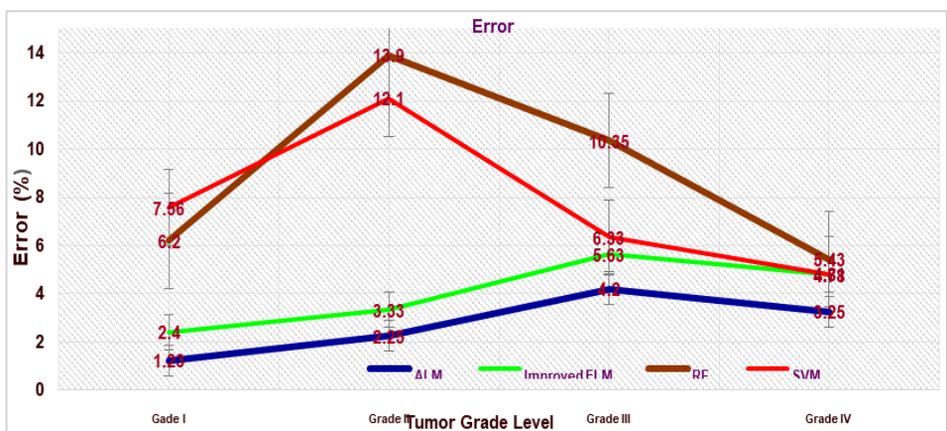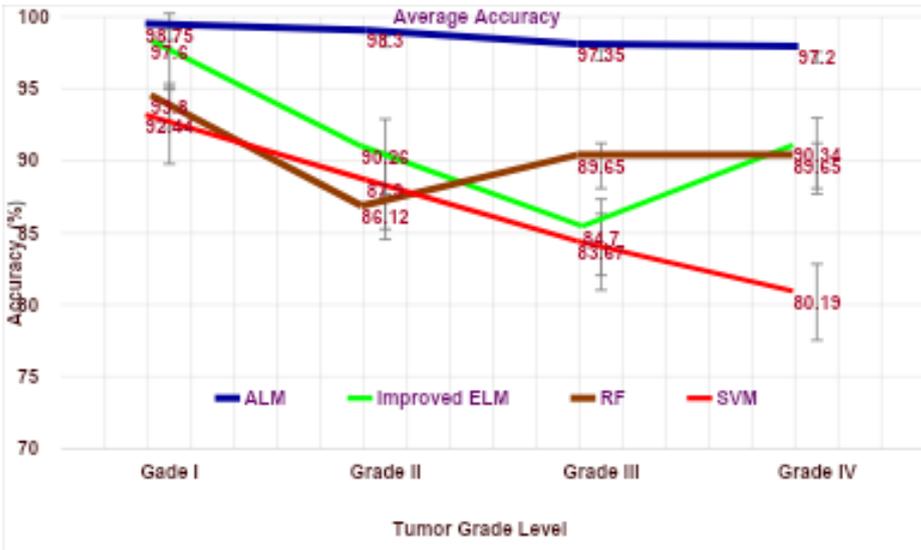

Fig. 4. Average Recognition Error

Fig. 5. Average Recognition Accuracy

4.2   Performance Analysis of Tumor Size

Figure 6 depicts the performance comparison of the proposed ALM method with the existing algorithm such as improved ELM, RF and SVM. The performance analysis of the proposed algorithm is high compared to existing algorithms. The performance analysis of Meningioma, Glioma and Pituitary tumor are 0.78, 0.59 and 0.49 respectively for the proposed ALM module.
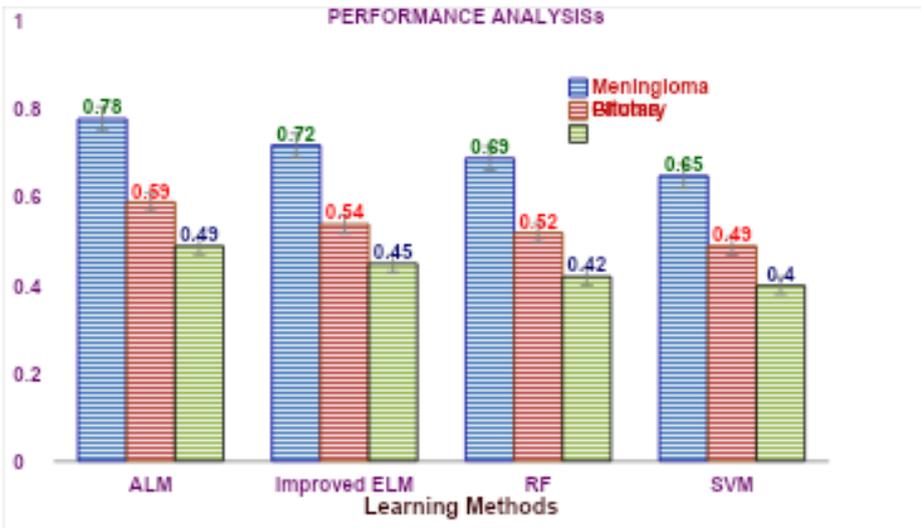

Fig. 6. Performance Analysis of Tumor size

4.3   Sensitivity

Figure 7 depicts sensitivity comparisons for the proposed ALM training module. The sensitivity of the proposed model is high for all the three brain tumors compared to the existing training modules. The sensitivity for Meningioma type of brain tumor is 0.68, Glioma is 0.59 and for Pituitary type of brain tumor is 0.44.
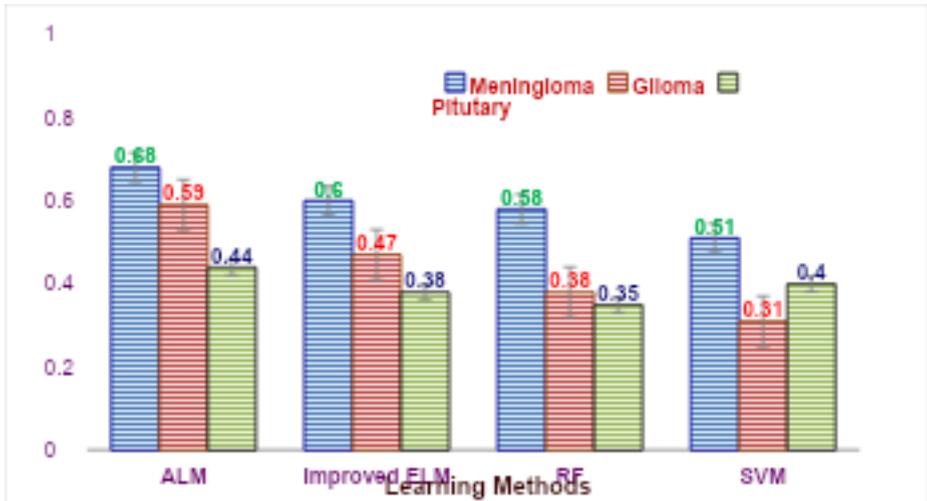

Fig. 7. Sensitivity

4.4   Specificity

The specificity of the proposed ALM training method is 0.96 for Meningioma type of tumor. The specificity for Meningioma and Pituitary type of tumor is same for improved ELM method is same for type of tumors. The proposed method has a higher specificity than the previous methods.
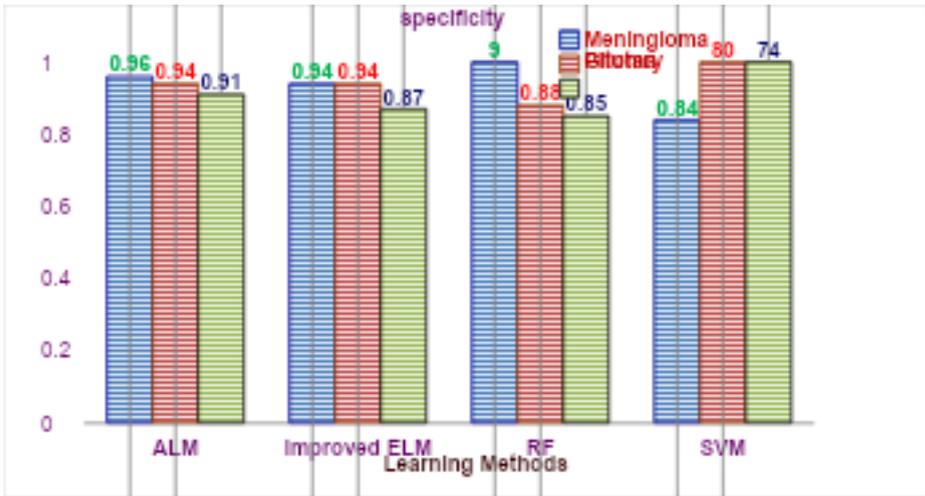
Fig. 8. Specificity

5   CONCLUSION

Detecting tumors in MRI images is a crucial task in medical diagnostics, with significant implications for patient care and treatment planning. Through advancements in imaging technology and machine learning algorithms, significant progress has been made in automating tumor detection processes, aiding radiologists in accurate diagnosis and early intervention. The use of deep learning techniques, notably convolutional neural networks (CNNs) and pre-trained models, have shown extraordinary performance in tumor diagnosis from MRI scans. These models can learn complicated patterns and features from enormous datasets, allowing them to distinguish between healthy tissue and tumor regions with great precision. An automatic technique for identifying brain tumors from MRI pictures is presented in this study. Image angles and pixel distances are calculated using the Integrated Grey Level Co-occurrence Matrix (GLCM) and Speeded up Robust Feature (SURF) techniques. Also, using the GLCM algorithm. The main four texture features like distance, direction, grade levels and gray values can be calculated. Using Advanced Learning Method (ALM), Genetic Algorithm and optimization technique type of brain tumor diseases, grade level of the tumor and location of the tumor are obtained. The simulation results show that the sensitivity and specificity of the tumors is more in the proposed method compared to the existing techniques.

References

1. Jan C. Buckner, Paul D. Brown, Brian P. O'neill, Fredric B. Meyer, "Central Nervous System Tumors", Symposium on Solid Tumors, Mayo Foundation for Medical Education and Research, 82(10):1271-86, (October 2007).
2. Sridhar, K. P., S. Baskar, P. M. Shakeel, and V. S. Dhulipala. Developing brain abnormality recognize system using multi-objective pattern producing neural network. J Ambient Intell Humaniz Comput: 1–9. 2018.
3. R. Anitha , D. Siva Sundhara Raja , Development of computer-aided approach for brain tumor detection using random forest classifier, Int. J. Imaging Syst. Technol. 28, pp. 48–53, (2018) .
4. R. Grant , Medical management of adult glioma, in: Management of Adult Glioma in Nursing Practice, Springer, pp. 61–80, (2019).
5. Johnson, Derek R., Julie B. Guerin, Caterina Giannini, Jonathan M. Morris, Lawrence J. Eckel, and Timothy J. Kaufmann. "2016 updates to the WHO brain tumor classification system: what the radiologist needs to know." Radiographics 37, no. 7 (2017): 2164-2180.
6. Wright, Erin, Ernest K. Amankwah, S. Parrish Winesett, Gerald F. Tuite, George Jallo, Carolyn Carey, Luis F. Rodriguez, and Stacie Stapleton. "Incidentally found brain tumors in the pediatric population: a case series and proposed treatment algorithm." Journal of neuro-oncology 141 (2019): 355-361.
7. S. Banerjee, S. Mitra, F. Masulli, and S. Rovetta, "Deep Radiomics for Brain Tumor Detection and Classification from Multi-Sequence MRI," arXiv preprint arXiv:1903.09240, (2019).
8. N. Nida , et al. , A framework for automatic colorization of medical imaging, IIOAB J. 7,pp. 202–209, (2019).
9. Amin, Javeria, Muhammad Sharif, Mussarat Yasmin, Tanzila Saba, and Mudassar Raza. "Use of machine intelligence to conduct analysis of human brain data for detection of abnormalities in its cognitive functions." Multimedia Tools and Applications 79 (2020): 10955-10973.
10. Naqi, S. M., Muhammad Sharif, Mussarat Yasmin, and Steven L. Fernandes. "Lung nodule detection using polygon approximation and hybrid features from CT images." Current Medical Imaging 14, no. 1 (2018): 108-117.
11. Liaqat, Amna, Muhammad Attique Khan, Jamal Hussain Shah, Muhammad Sharif, Mussarat Yasmin, and Steven Lawrence Fernandes. "Automated ulcer and bleeding classification from WCE images using multiple features fusion and selection." Journal of Mechanics in Medicine and Biology 18, no. 04 (2018): 1850038..
12. Sharif, Muhammad, Muhammad Attique Khan, Muhammad Faisal, Mussarat Yasmin, and Steven Lawrence Fernandes. "A framework for offline signature verification system: Best features selection approach." Pattern Recognition Letters 139 (2020): 50-59.
13. Shah, Jamal Hussain, Muhammad Sharif, Mussarat Yasmin, and Steven Lawrence Fernandes. "Facial expressions classification and false label reduction using LDA and threefold SVM." Pattern Recognition Letters 139 (2020): 166-173.
14. Raza, Mudassar, Muhammad Sharif, Mussarat Yasmin, Muhammad Attique Khan, Tanzila Saba, and Steven Lawrence Fernandes. "Appearance based pedestrians' gender recognition by employing stacked auto encoders in deep learning." Future Generation Computer Systems 88 (2018): 28-39.

15.   Ansari, Ghulam Jillani, Jamal Hussain Shah, Mussarat Yasmin, Muhammad Sharif, and Steven Lawrence Fernandes. "A novel machine learning approach for scene text extraction." Future Generation Computer Systems 87 (2018): 328-340.

16.   Sharif, Muhammad, Mudassar Raza, Jamal Hussain Shah, Mussarat Yasmin, and Steven Lawrence Fernandes. "An overview of biometrics methods." Handbook of multimedia information security: techniques and applications (2019): 15-35.

17.   Rohini Paul Joseph , C. Senthil Singh ,M.Manikandan, Brainătumor, "MRIimage segmentation and detection" images processing International Journal of Research inEngineering and Technology, Volume: 03 Special Issue: 01 | NC-WiCOMET-2014 |Mar-2014.

18.   R.Helenă andă N.Kamaraj,ă _CADă Scheme To Detect Brain Tumour In MR Images UsingActive Contour Models AndTree Classifiers", J Electr Eng Technol Vol. 10, No. 3: 742- 749, 2014

19.   C. Solomon and T. Breckon, Fundamental of Digital Image Processing: A Practical Approach with Examples in Matlab, Chichester, West Sussex: Wiley Blackwell, 2011.

20.   N. Sauwen, M. Acou, D. M. Sima, J. Veraart, F. Maes, U.Himmelreich, et al., "Semi-automated brain tumor segmentation on multi-parametric MRI using regularized non-negative matrixfactorization," BMC medical imaging, vol. 17, pp. 1-14, 2017.

21.   Dhanashri Joshi, Hemlata Channe, "A Survey On Brain Tumor Detection Based On Structural MRI Using Machine Learning And Deep Learning Techniques", International Journal Of Scientific & Technology Research Volume 9, Issue 04, April 2020.

22.   Havaei M, Guizard N, Larochelle H, Jodoin PM: BDeep Learning Trends for Focal Brain Pathology Segmentation in MRI,^ in Lecture Notes in Computer Science pp. 125–148, 2016.

23.   Akkus, Zeynettin, Alfiia Galimzianova, Assaf Hoogi, Daniel L. Rubin, and Bradley J. Erickson. "Deep learning for brain MRI segmentation: state of the art and future directions." Journal of digital imaging 30 (2017): 449-459.

24.   C. Lakshmi Devasena, M. Hemalatha, Efficient computer aided diagnosis of abnormal parts detection in magnetic resonance images using hybrid abnormality detection algorithm. Cent. Eur. J. Comput. Sci. 3(3), pp.117–128, 2013.

25.   S. Goswami, L. K. P. Bhaiya, in 2013 International Conference on Communication Systems and Network Technologies. Brain tumor detection using unsupervised learning based neural network,IEEE, Gwalior, pp. 573–577, 2013.

26.   Bakas, S., Reyes, M., Jakab, A., Bauer, S., Rempfler, M., Crimi, A., et al. "Identifying the best machine learning algorithms for brain tumor segmentation",progression assessment, and overall survival prediction in the brats challenge. arXiv Prepeint.arXiv:1811.02629, 2018.

27.   Marcus, D. S., Fotenos, A. F., Csernansky, J. G., Morris, J. C., and Buckner,R. L. Open access series of imaging studies: longitudinal MRI data innondemented and demented older adults. J. Cogn. Neurosci. 22, 2677–2684, 2010.doi: 10.1162/jocn.2009.21407

28.   Krithika, N.; Selvarani, A. G.: An individual grape leaf disease identification using leaf skeletons and KNN classification. International Conference on Innovations in Information, Embedded and Communication Systems, Coimbatore, pp. 1-5, 2017.
29.   Herbert Bay, Tinne Tuytelaars, and Luc Van Gool," SURF: Speeded Up Robust Features", European Conference on Computer Vision, 3951,pp 404-417, 2006.
30. A. S. Berahas, R. H. Byrd, and J. Nocedal, "Derivative-free optimization of noisy functions via quasi-newton methods," SIAM Journal on Optimization, vol. 29, pp. 965–993,2019.