VOLUME 16, N° 4 2022
Journal of Automation, Mobile Robotics and Intelligent Systems

Automatic Detection of Brain Tumors Using Genetic Algorithms With Multiple Stages in Magnetic Resonance Images

Submitted: 1st September 2021; accepted 22nd August 2022

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DOI: 10.14313/JAMRIS/4-2022/31

Abstract:
The field of biomedicine is still working on a solution to the challenge of diagnosing brain tumors, which is now one of the most significant challenges facing the profession. The possibility of an early diagnosis of brain cancer depends on the development of new technologies or instruments. Automated processes can be made possible thanks to the classification of different types of brain tumors by utilizing patented brain images. In addition, the proposed novel approach may be used to differentiate between different types of brain disorders and tumors, such as those that affect the brain. The input image must first undergo pre-processing before the tumor and other brain regions can be separated. Following this step, the images are separated into their respective colors and levels, and then the Gray Level Co-Occurrence and SURF extraction methods are used to determine which aspects of the photographs contain the most significant information. Through the use of genetic optimization, the recovered features are reduced in size. The cut-down features are utilized in conjunction with an advanced learning approach for the purposes of training and evaluating the tumor categorization. Alongside the conventional approach, the accuracy, inaccuracy, sensitivity, and specificity of the methodology under consideration are all assessed. The approach offers an accuracy rate greater than 90%, with an error rate of less than 2% for every kind of cancer. Last but not least, the specificity and sensitivity of each kind are higher than 90% and 50%, respectively. The usage of a genetic algorithm to support the approach is more efficient than using the other ways since the method that the genetic algorithm utilizes has greater accuracy as well as higher specificity.

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

1. Introduction

The brain and spinal column are components of the central nervous system (CNS). The CNS is responsible for controlling all of the body's energizing processes, including cognition, speech, vision, breathing, and movement. When aberrant cells form in the CNS, it can have an effect on a person's thoughts as well as the way their body moves. The spinal cord extends all the way from the bottom of the brain down to the middle of the lower back. The spinal cord is the pathway via which messages go to and from the brain and the rest of the body. There are between 50 and 100 billion neurons in the brain, which is a very significant number of cells. The functions of the brain's individual cells may be broken down into categories. It is highly difficult to identify a brain tumor in its early stage since the brain is covered by the skull. Additionally, brain tumors do not display distinct clinical signs, making it even more difficult to diagnose. In most cases, the diagnosis of brain tumors is based on the presence of three symptoms [1]. Because of an increase in cranial pressure, the first symptom is a headache, along with vomiting and altered states of consciousness [2–4]. The second symptom is that the affected individual may experience changes in personality or emotions. This is caused by disorder in the brain. The final sign to look out for is irritability, which can also manifest as absences, weariness, or convulsions. However, brain tumors are not the only possible cause of these symptoms. Therefore, imaging techniques are the primary method utilized in the diagnosis of brain tumors. The features of the tumor, as well as its origin, location, and size, are taken into consideration when classifying brain tumors. The identification of brain cancer in its earlier stages is one of the most important issues in the field. According to the World Health Organization (WHO), there are 120 different forms of brain tumors. In addition, the WHO has rated the tumors from grade I to grade IV [5]. The doctor is able to provide the therapy necessary to preserve the patient's life depending on the grade level of the patient [6]. In most cases, there are two types of brain tumors: primary and secondary. Primary brain tumors are those in which the tumor first developed in the brain itself. The initial brain tumor might be classed as either benign or malignant depending on the degree to which it has spread. A brain tumor is considered benign if it does not spread to other regions of the body and begins there. A non-cancerous tumor is another name for this particular kind of growth. The malignant kind of tumor begins in the brain, but it can migrate to other regions of the body, such as the spine. Because the development of additional cells is confined to the periphery of the brain, benign brain tumors are far simpler to cure than their malignant counterparts. Surgery is the only treatment necessary for benign brain tumors; radiotherapy, chemotherapy, and other treatments are not necessary. Because a malignant brain tumor spreads quickly, even after surgery there is a potential for the tumor to reappear, the only way to effectively treat the tumor is with a combination of chemoradiotherapy and radiotherapy. In the next sections, an explanation of the many detection methods that may be used to treat brain tumors is provided, as well as a hybrid algorithm for detecting tumors in the brain.

2. Related Works

In this part, a general review of medical image analysis pertaining to brain tumors is provided. When attempting to diagnose cancerous tissues in a human body, medical technology employs a variety of diagnostic approaches. The cancer cells are diagnosed by a surgeon based on the patient's family history as well as the diagnostic report from the patient's physical examination, which include diagnostic procedures such as magnetic resonance imaging (MRI), computed axial tomography (CAT), biopsy, brain angiogram, magnetic resonance angiogram (MRA), and electroencephalogram. The discovery of the tumor at an earlier stage leads to an improvement in the patient's chance of survival [7]. It is necessary to do brain image analysis in order to arrive at an accurate prognosis. The picture of the brain is examined by a doctor using effective segmentation algorithms, which allows the doctor to arrange therapy. Radiologists have a very laborious and time-consuming task ahead of them when segmenting tumors. At the moment, surgeons are making use of cutting-edge, non-invasive imaging tools in order to conduct cancer tissue analysis. The MRI test is the gold standard non-invasive method for diagnosing brain tumors. However, a single MRI scan is not adequate for categorizing and segmenting the tissues for the purpose of detecting tumors; as a result, employing numerous MRI sequences is required [8]. In order to make the analysis of the picture simpler, many image segmentation methods are employed. Intensity, threshold level, edge detection, watershed segmentation, and Markov Random Field model are just a few of the several segmentation approaches that may be used [9]. These days, computer-aided diagnosis (CAD) is used to find out whether there are any abnormalities in the patient's brain [10–16]. The location of the tumor may be determined from CAD by using an algorithm called k-means clustering [17]. It was discovered that using this procedure prevented the formation of the misclustered area that occurs in the MRI technique. However, this strategy produces quite diverse findings depending on which cluster you look at. The MRI method of diagnosing brain tumors inspired the development of the CAD system [18]. The performance of CAD may be improved to better study the location of the tumor by making use of dynamic contour models. They utilize a number of techniques, including Distance Regularized Level Set Evolution (DRLSE) for medical image segmentation and fuzzy clustering using Level Set Method (LSM) in order to segment the images [19]. An approach that is only semi-automatic was described in Sauwen et al. for evaluating dead cells found in the brain [20]. The approach known as semi-automatic requires participation from the user as well as software stages. A surgeon requires a limited number of input parameters and then has to visualize the data. This procedure is efficient in terms of computing when it comes to dividing up the brain tumor. In Joshi and Channe [21], it is suggested that structural MRI might be utilized to identify the structure of the brain in order to investigate the proliferation of the cells in the brain. In order to determine the classification based on the segmentation of an image, machine learning techniques such as support vector machines and the random forest algorithm are utilized. An overview of brain tumor detection and cascaded architecture is provided in Havaei et al. [22], which made use of deep learning. An approach to segmentation based on deep learning was suggested in Akkus et al. [23]. In the article, supervised learning was employed to detect brain tumors. They require a vast quantity of data in order to provide accurate results. Using MRI imaging and CAD, a hybrid abnormality detection technique was published in Devasena and Hemalatha [24]. This approach is utilized to locate dysfunctional cells in the image data. Goswami and Bhaiya demonstrated a categorization of pictures obtained from an MRI using artificial neural networks that had a self-organizing map [25]. After doing some pre-processing on the photos, such as histogram equalization, filtering, and edge detection, the images are then retrieved.

3. Methodology

3.1 Datasets and Method

The diagnosis of a brain tumor increases the patient's chance of survival directly. A multi-phase automated brain tumor identification from MRI, which utilizes a hybrid approach based on genetic algorithm and deep learning techniques, has been offered as a solution to this problem. This solution is intended to address the issue. The performance of the proposed technique is confirmed by utilizing publicly accessible datasets, specifically Open Access Series of Imaging Studies (OASIS) [27] and Brain Tumor Segmentation datasets [26]. Nine hundred and eighty-five MRI scans are included in each of the datasets. MRI scans were taken from 255 different patients to create these photos. Both of these datasets contain photos of the skull taken from a variety of perspectives. The network is trained based on the MRI scans as well as their angles through the use of modified deep learning and genetic algorithms. In the approach that has been presented, there are 1970 photographs total, and out of them, 394 are utilized for validation while the remaining images are used for testing. The example datasets that were used in the detection of brain tumors using genetic algorithms and deep learning are presented in Figure 1.

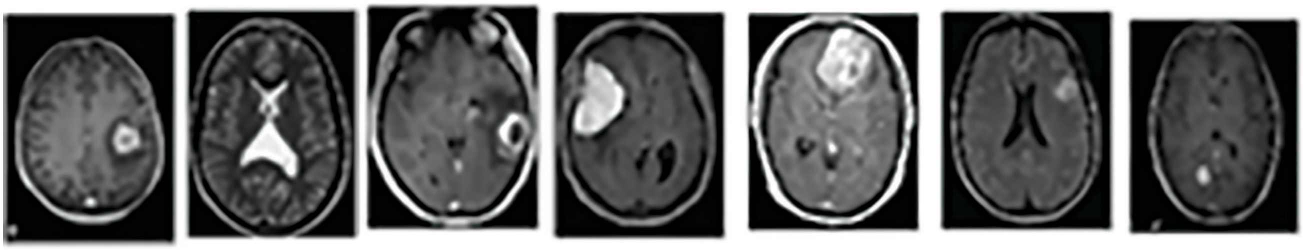

Fig. 1. Sample dataset

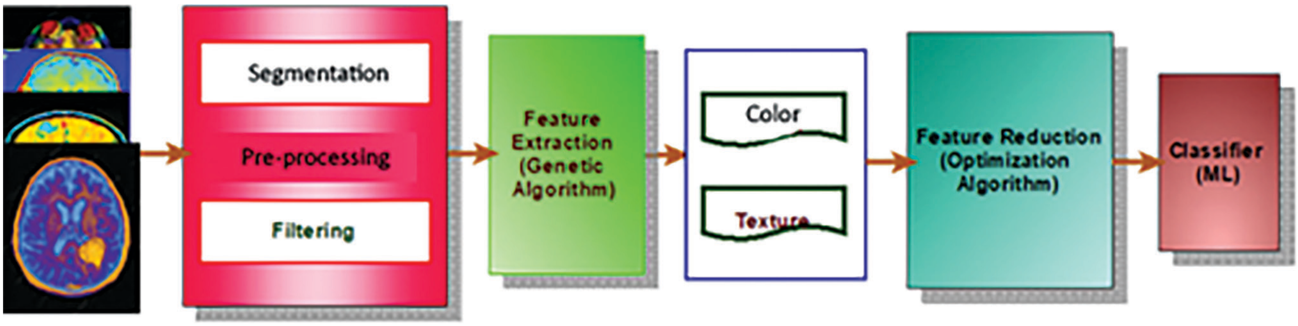

Fig. 2. Methodology of brain tumor detection

3.2 Image Pre-processing

Figure 2 below illustrates the methodology presented. It has been shown that the dataset's sample MRI scans do not produce a clear image due to noise and reduced intensity. The clarity of an image is crucial for analyzing it to detect sickness. In order to tell one thing from another in an image, contrast is a crucial characteristic to have.

Equation (1) is the mathematical expression for automatically adjusting the brightness and contrast of a scene based on a power law transmission, and expression (2) is the matching complement (2).

$$s(x,y) = r(x,y) + k \tag{1}$$

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

In this equation, s and r represent the gray levels of the pixels in the output picture and the input image, respectively, and k is a constant value. Filtration and segmentation are two forms of pre-processing that should be applied to the sample data in order to get a higher overall picture quality. The primary purpose of this procedure is to improve the picture quality so that the surgeon can pinpoint the precise site of the tumor and determine its grade. The sample data have to be enlarged in order to get a higher level of precision with the image. After being scaled, the picture is then sent through the filter to have the noise removed. Following an analysis of the various filtering methods, it was determined that the median filter plays a significant part in picture pre-processing. This filter is utilized to eliminate noise from an image without affecting its other properties. The clustering technique is performed to a noise-free picture in order to achieve the desired result of separating dysfunctional or abnormally functioning cells from the background.

3.3 Extraction of Feature

The color and the texture of the tumor are taken into consideration in this procedure, which is utilized to determine the clinical characteristics of the tumor. The color variation serves as an accurate reflection of the severity of the tumor's grade. In the figure, you can see a collection of color variants that each represent a distinct grade level of brain tumor. From level I all the way up to level IV, the degree of color variety is the primary focus of attention. Based on quantitative research, it has been shown that the first, second, third, and fourth orders of distinct color variations are caused by differences in hue and saturation level. Calculations of image intensities T1, T2, TLC, and FLAIR are performed on the basis of variations in color as shown in Figure 3. Therefore, the levels of hue and saturation that correspond to first grade and second grade may be derived from equation (3) and (4).

$$S_i = \frac{1}{N}\sum_{j-1}^{N} R_{ij} \tag{3}$$

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

3.4 Texture Feature Extraction

In addition to the color features, the extraction of the texture features is also an essential aspect of the analysis of the photographs. The Gray Level Co-occurrence Matrix (GLCM) [28] and the Speeded Up Robust Feature (SURF) [29] are both used in the process of texture extraction to provide the desired results. The integrated algorithms utilized in order to cut down on the quantity of overlapping characteristics. When compared to previous methods for the extraction of textures, this approach produces results that are more accurate.

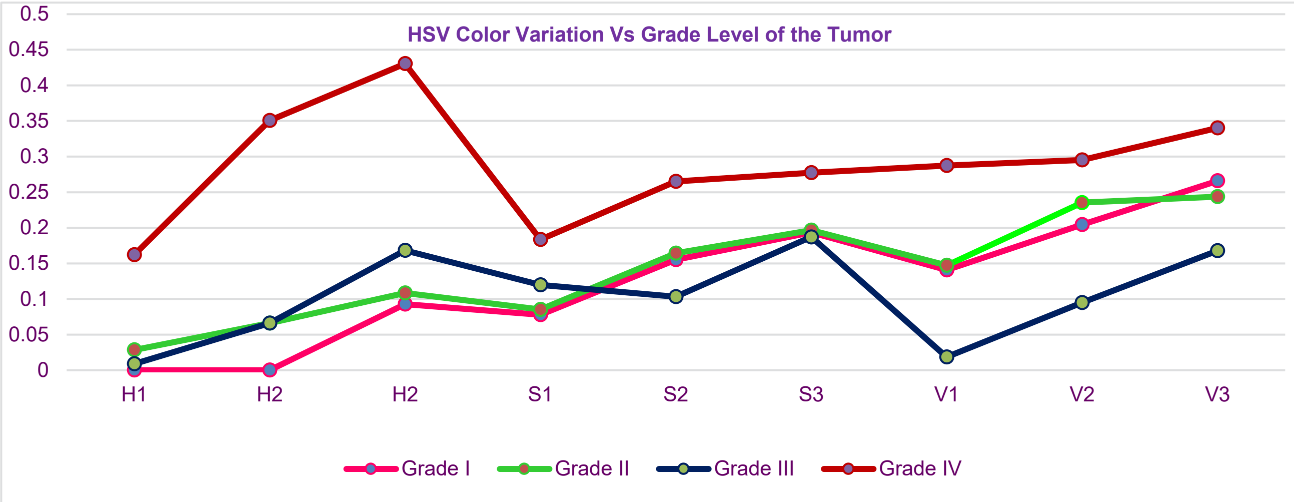

Fig. 3. Identification of grade level of the brain tumor

This integrated algorithm identifies all of the traits that are the same across photos of people with and without brain tumors. Image convolution is the method that the SURF extraction algorithm uses in order to locate the spots in two pictures that are identical to one another. The Haar Wavelet matrix is initially utilized in the calculation of the surf by this approach. The H matrix is used to compute the circular area surrounding the key points, which is then used to determine the orientation of the pictures relative to one another. Finding picture angles and pixel distances is accomplished with the help of the GLCM algorithm in equations 5 and 6. The GLCM method is used to determine the primary four properties of a texture, such as distance, direction, and gray value in equations 7 and 8. This suggested work includes a total of 161 characteristics, the majority of which center on tumor form.

$$Energy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} R^2(i,j;d,\theta) \tag{5}$$

$$Entropy = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} R(i,j;d,\theta)\log R(i,j;d,\theta) \tag{6}$$

$$Moment\ of\ Inertia = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} (i-j)^2 R(i,j;d,\theta) \tag{7}$$

$$Correlation = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} ijR(i-j)-\mu_x\mu_y}{\sigma_x^2\sigma_y^2} \tag{8}$$

3.5 Image Optimization Using Genetic Algorithm

The advanced learning machine (ALM) training model uses single hidden layer instead number of hidden layers. In this training model, the hidden layer threshold value of hidden layer neurons and connection weight between input layer and hidden layer are randomly generated without any adjustment compared to traditional feed forward network training models.

Where are number of neurons in the input layer, hidden and output layer respectively. , are the excitation function of neurons and the threshold value of neurons of the hidden layer respectively. The training model of ALM can be expressed as in equation 9.

$$\sum_{i=1}^{m} \alpha_i\, a(W_i\, x_i + b_i) = O_j\ ; j=1,2,3,..............N \tag{9}$$

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

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

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

As part of the simulation, the tumor's size and location are analyzed using photographs obtained in 1970. Researchers analyze the tumor's texture in terms of its hue, saturation, and value (HSV) colors to identify its grade using an integrated technique termed SURF + GLCM. Due to the one-of-a-kind landscape, four separate paths will be accessible. By collecting data in all four directions simultaneously, we are able to take a holistic strategy and then compare our results to 394 separate validation datasets. This strategy adopts a consistent methodology. There are two primary considerations and four distinct methods to implement to get the best data.

Step 1: Choose the number of hidden layers to develop an ALM brain tumor identification model.

Step 2: Initialize the weights of input and hidden layer threshold of the ALM model to get the optimal solution.

Step 3: By means of derivative-free optimization [30]to find out the output error of ALM to achieve crossover and selection to find next comparison point using heuristic search based on empirical rules and s fitting the objective function with samples.

Step 4: Check whether the maximum number of iterations is reached and also find out there is no better substitute for the next samples.

Step 5: Stop the algorithm to get an optimized image.

4. Results and Discussion

The following section explains the type of tumors, location of tumor, grade level, and sensitivity and specificity of the tumors is analyzed with the help of ALM technique.

4.1 Performance of Accuracy and Error

During the simulation, pictures from 1970 are analyzed to determine the tumor's grade and location. The hue, saturation, and value (HSV) color feature is used to detect the tumor grade and an integrated algorithm (SURF + GLCM) is used to identify the texture feature. Since this is a textured feature, it will provide four unique orientations. This holistic approach gathers data from all four axes, then compares it to 394 different validation sets. Using the vector feature formed by the two color and four texture qualities, we can locate the tumor and determine how far along its progression is. The algorithms used to determine the disease type from a collection of samples are compared and contrasted. The provided hybrid learning technique outperforms alternative learning algorithms in terms of performance. Figures 4a and 4b show the contrasting outcomes in terms of accuracy and error when applying different learning algorithms to each disease.

In Figure 5, we compare the effectiveness of the improved ELM algorithm, the RF method, and the SVM algorithm to that of the suggested ALM technique.

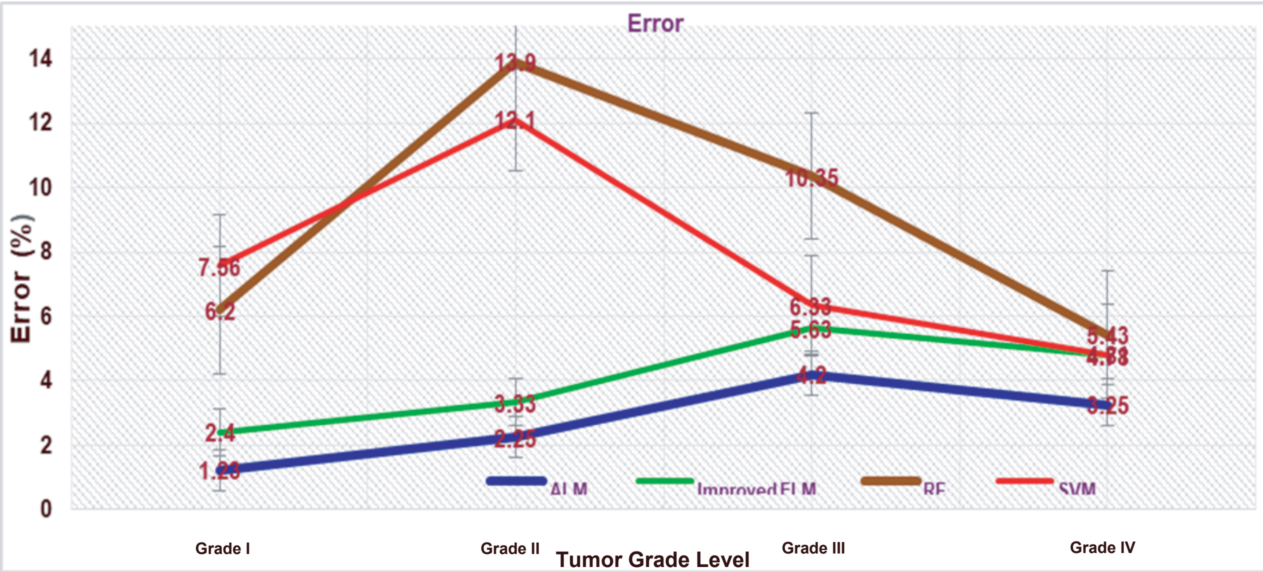

Fig. 4a. Average recognition error

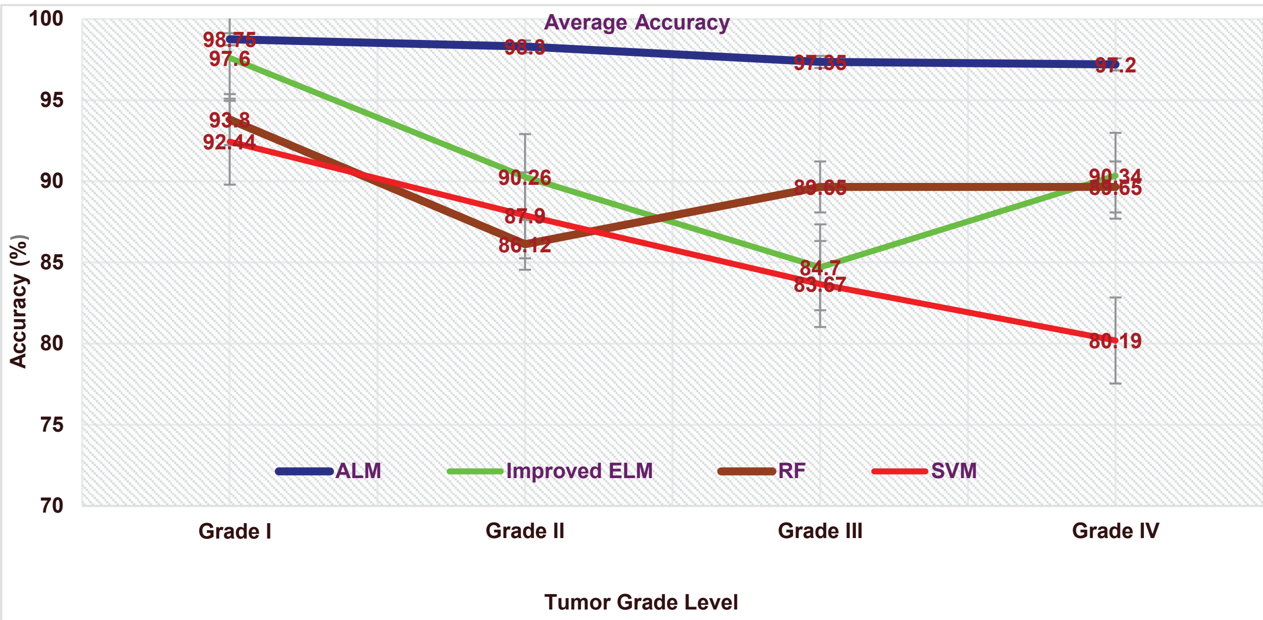

Fig. 4b. Average recognition accuracy performance analysis of size of the tumor

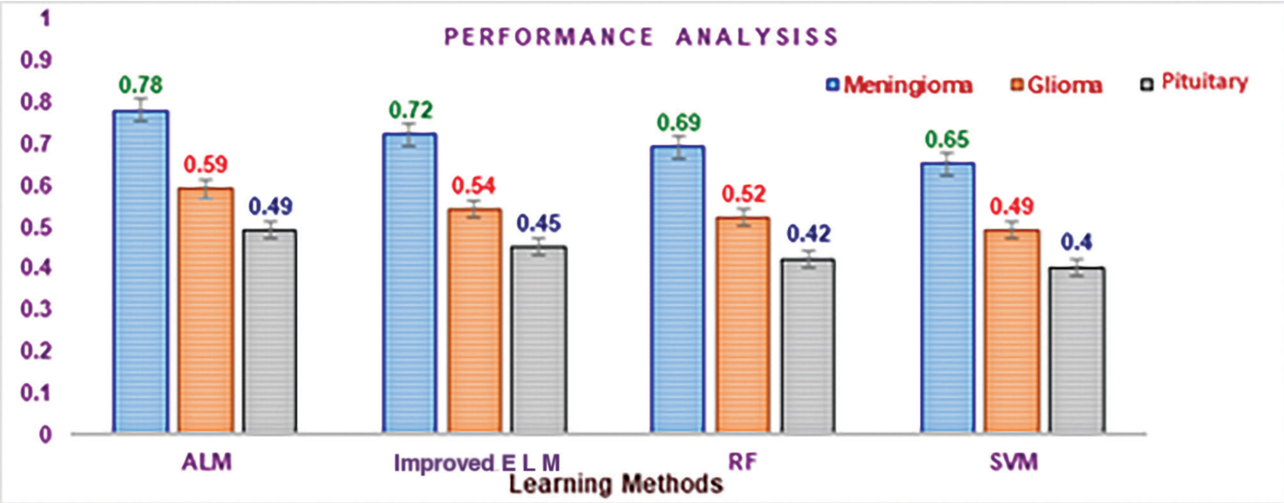

Fig. 5. Performance analysis of size of the tumor sensitivity

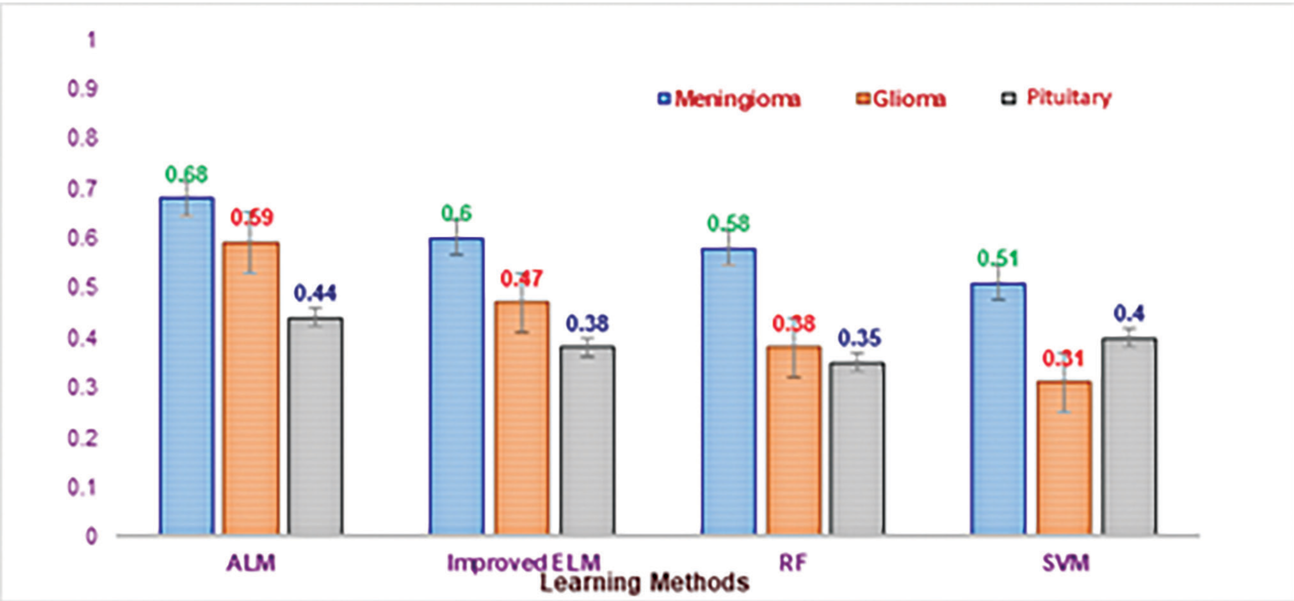

Fig. 6. Sensitivity specificity

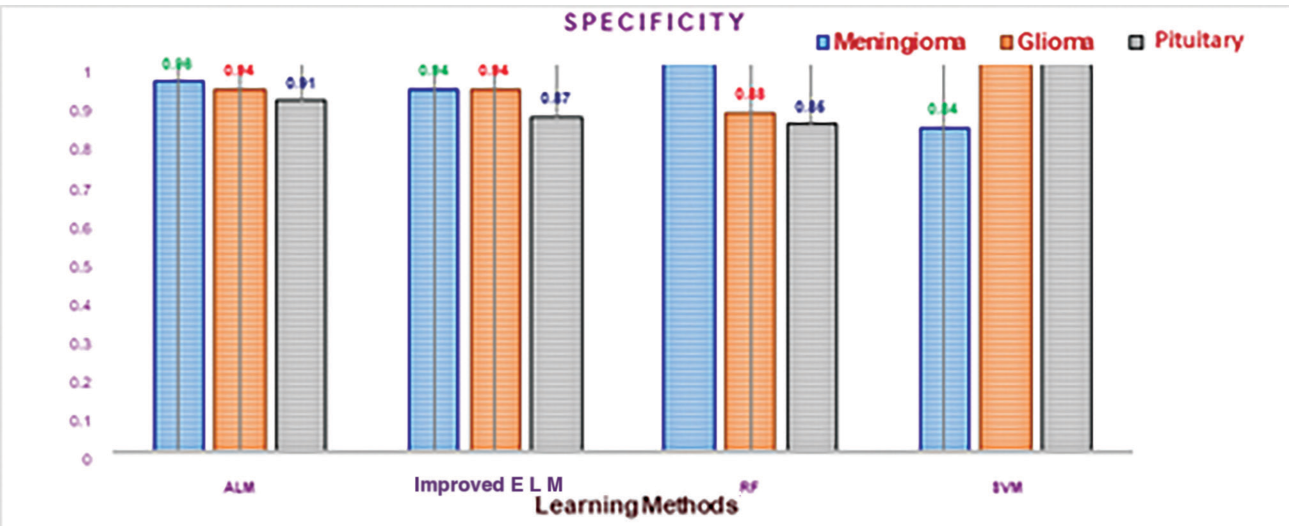

Fig. 7. Specificity

The recommended algorithm possesses higher performance metrics when contrasted with those of other algorithms. The performance analyses for the proposed ALM module show that meningiomas, gliomas, and pituitary tumors have respective values of 0.78, 0.59, and 0.49.

The suggested ALM training module's sensitivity comparison is depicted in Figure 6. When compared to the currently used learning modules, the suggested approach shows increased sensitivity for all three types of brain tumors. Sensitivity is 0.68 for detecting meningiomas, 0.59 for gliomas, and 0.44 for pituitary tumors.

The only form of tumor for which the recommended ALM training technique obtains a specificity of 0.96 is meningioma. The improved ELM approach has the same type-tumor specificity for meningiomas as it does for pituitary tumors. This is because both types of tumors originate in the pituitary gland. The technique that has been suggested is one that is more particular than the typical one.

5. Conclusion

In order to identify brain tumors mechanically, the authors of this study believe that MRI should be employed instead of conventional approaches. In order to estimate the angles and distances that exist between each pixel in a picture, one can use either the GLCM or SURF technique. Through the use of the GLCM technique, we are able to find the top four attributes of a texture. Distancing, orientation, gradient, and grayscale value are all examples of such factors. The kind of brain tumor illness, tumor grade, and tumor location may all be identified with the use of the ALM, the Genetic Algorithm, and an optimization method. Through computational modelling, we show that the suggested method outperforms the current standard of care for cancer detection in terms of both sensitivity and specificity.

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References

[1] C. Buckner, P.D. Brown, B.P. O'Neill, F.B. Meyer, "Central Nervous System Tumors", Symposium on Solid Tumors, Mayo Foundation for Medical Education and Research, vol. 82, no. 10, 2007, 1271–1286.

[2] K.P. Sridhar, S. Baskar, P.M. Shakeel, V.R.S. Dhulipala, "Developing brain abnormality recognize system using multi-objective pattern producing neural network," J Ambient Intell Humaniz Comput, vol. 10, no. 4, 2018, 1–8.

[3] R. Anitha and D.S.S. Raja, "Development of computer-aided approach for brain tumor detection using random forest classifier", Int J Imaging Syst Technol, vol. 28, 2018, 48–53.

[4] R. Grant, "Medical management of adult glioma", in: Management of Adult Glioma in Nursing Practice. London, UK: Springer, 2019, 61–80.

[5] D.R. Johnson, J.B. Guerin, C. Giannini, J.M. Morris, L.J. Eckel, and T.J. Kaufmann, "2016 updates to the WHO brain tumor classification system: what the radiologist needs to know", Radiographics, vol. 37, 2019, 2164–2180.

[6] Kalyani, G., Janakiramaiah, B., Prasad, L.V.N. et al. Efficient crowd counting model using feature pyramid network and ResNeXt. Soft Comput 25, 10497–10507 (2021). https://doi.org/10.1007/s00500-021-05993-x

[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, M. Sharif, M.U.G. Khan, M. Yasmin, S.L. Fernandes, "A framework for automatic colorization of medical imaging", IIOAB J, vol. 7, supp. 1, 2019, 202–209.

[9] J. Amin, M. Sharif, Y. Mussarat, T. Saba, M. Raza, "Use of machine intelligence to conduct analysis of human brain data for detection of abnormalities in its cognitive functions", Multimed Tools Appl, vol. 79, no. 3, 2019, 1–19.

[10] S. Naqi, M. Sharif, M. Yasmin, S.L. Fernandes, "Lung nodule detection using polygon approximation and hybrid features from CT images", Curr Med Imaging Rev, vol. 14, no. 1, 2018, 108–117.

[11] A. Liaqat, M.A. Khan, J.H. Shah, M. Sharif, Y. Mussarat, S.L. Fernandes, "Automated ulcer and bleeding classification from WCE images using multiple features fusion and selection", J Mech Med Biol, vol. 18, no. 4, 2018, 1850038.

[12] M. Sharif, M.A. Khan, M. Faisal, Y. Mussarat, S.L. Fernandes, "A framework for offline signature verification system: best features selection approach", Pattern Recognit Lett, vol. 139, 2018.

[13] Ramu, G. A secure cloud framework to share EHRs using modified CP-ABE and the attribute bloom filter. Educ Inf Technol 23, 2213–2233 (2018). https://doi.org/10.1007/s10639-018-9713-7

[14] M. Raza, M. Sharif, M. Yasmin, M.A. Khan, T. Saba, S.L. Fernandes, "Appearance based pedestrians' gender recognition by employing stacked auto encoders in deep learning", Future Gener Comput Syst, vol. 88, 2018, 28–39.

[15] G.J. Ansari, J.H. Shah, Y. Mussart, M. Sharif, S.L. Fernandes, "A novel machine learning approach for scene text extraction", Future Gener Comput Syst, vol. 87, no. 10, 2018, 328–340.

[16] M. Sharif, M. Raza, J.H. Shah, M. Yasmin, S.L. Fernandes, "An overview of biometrics methods", in: Handbook of Multimedia Information Security: Techniques and Applications. London, UK: Springer, 2019, 15–35.

[17] R.P. Joseph and C.S. Singh, "Brain tumor MRI image segmentation and detection in image processing", Int J Res Eng Technol, vol. 3, no. 13, 2014, 1–5.

[18] Kalyani, G., Janakiramaiah, B., Karuna, A. et al. Diabetic retinopathy detection and classification using capsule networks. Complex Intell. Syst. (2021). https://doi.org/10.1007/s40747-021-00318-9

[19] Solomon C. and Breckon T., Fundamental of digital image processing: a practical approach with examples in Matlab, Wiley Blackwell: Chichester, West Sussex, 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 matrix factorization", BMC Med Imaging, vol. 17, no. 1, 2017, 1–14.

[21] D. Joshi and H. Channe, "A survey on brain tumor detection based on structural mri using machine learning and deep learning techniques", Int J Sci Technol Res, vol. 9, no. 4, 2020.

[22] M. Havaei, N. Guizard, H. Larochelle, P.M. Jodoin, "Deep learning trends for focal brain pathology segmentation in MRI", in: Lecture Notes in Computer Science. London, UK: Springer, 2016, 125–148.

[23] B. Padmaja, P. V. Narasimha Rao, M. Madhu Bala and E. K. Rao Patro, "A Novel Design of Autonomous Cars using IoT and Visual Features," 2018 2nd International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), 2018 2nd International Conference on, Palladam, India, 2018, pp. 18-21, doi: 10.1109/I-SMAC.2018.8653736.

[24] C.L. Devasena and M. Hemalatha, "Efficient computer aided diagnosis of abnormal parts detection in magnetic resonance images using hybrid abnormality detection algorithm". Cent Eur J Comput Sci, vol. 3, no. 3, 2013, 117–128.

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

[26] S. Bakas, M. Reyes, A. Jakab, S. Bauer, M. Rempfler, A. Crimi, 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] D.S. Marcus, A.F. Fotenos, J.G. Csernansky, J.C. Morris, and R.L. Buckner, "Open access series of imaging studies: longitudinal MRI data in nondemented and demented older adults", J Cogn Neurosci, vol. 22, 2010, 2677–2684. DOI: 10.1162/jocn.2009.21407

[28] Dash, S.C.B., Mishra, S.R., Srujan Raju, K. et al. Human action recognition using a hybrid deep learning heuristic. Soft Comput 25, 13079–13092 (2021). https://doi.org/10.1007/s00500-021-06149-7

[29] H. Bay, T. Tuytelaars, and L. Van Gool, "SURF: Speeded Up Robust Features", European Conference on Computer Vision, vol. 3951, 2006, 404–417.

[30] A.S. Berahas, R.H. Byrd, and J. Nocedal, "Derivative-free optimization of noisy functions via quasi-newton methods," SIAM J Optimiz, vol. 29, 2019, 965–993.