



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.

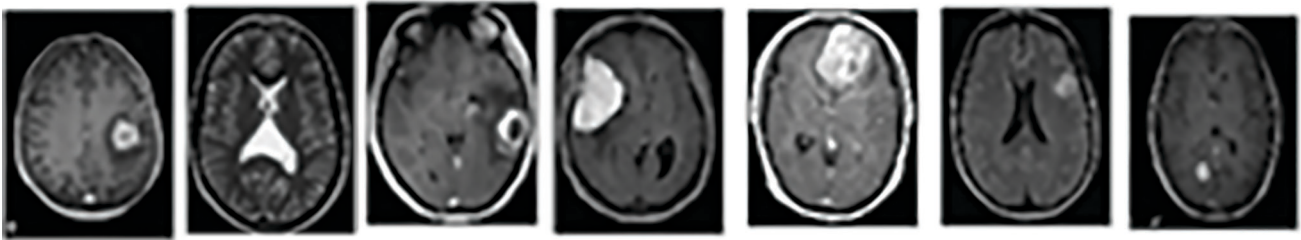


Fig. 1. Sample dataset

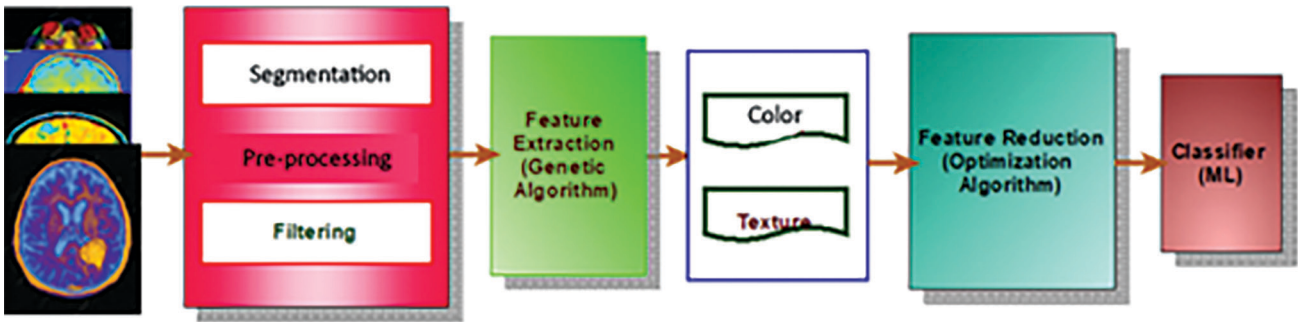


Fig. 2. Methodology of brain tumor detection

### 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).

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

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

### 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.

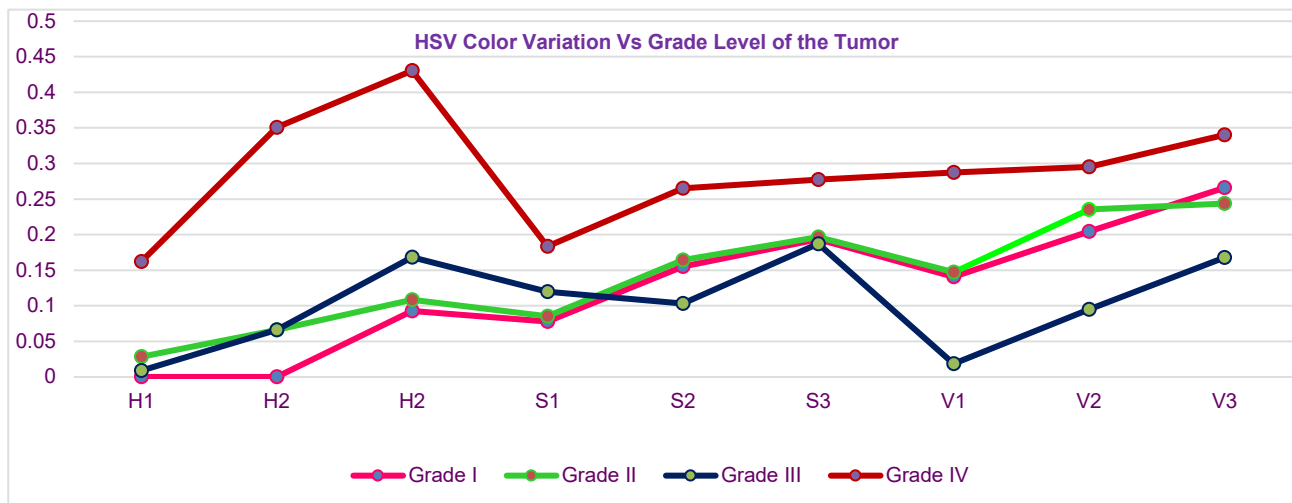


Fig. 3. Identification of grade level of the brain tumor

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.

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

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

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

$O_i = [O_{i1}, O_{i2}, O_{i3}, \dots, O_{im}]^T$  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.

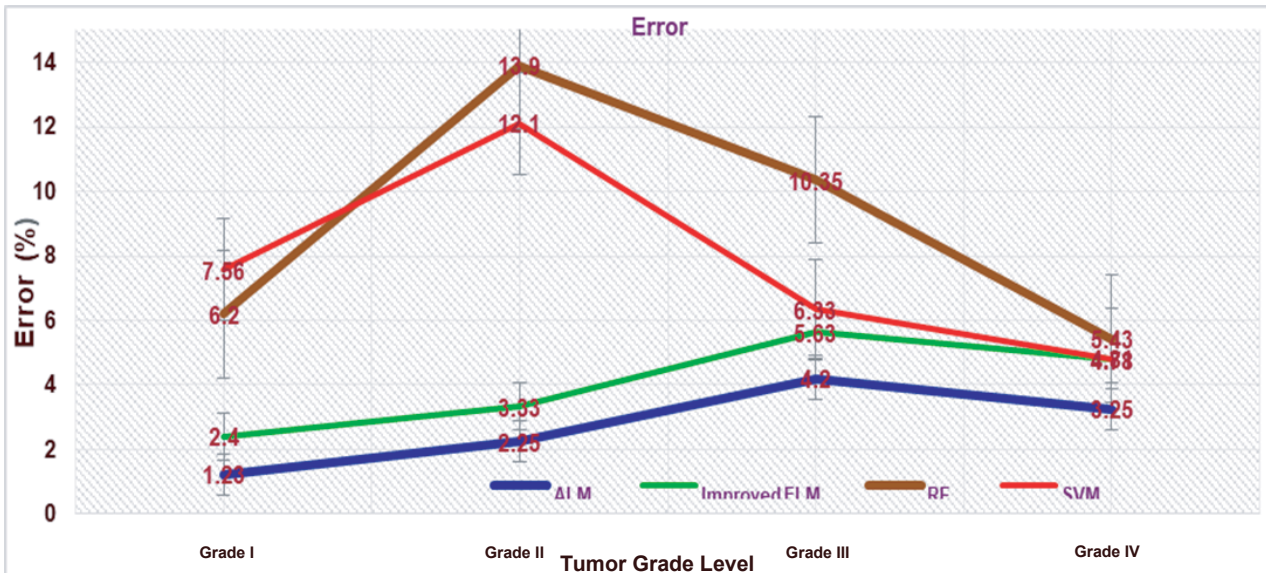


Fig. 4a. Average recognition error

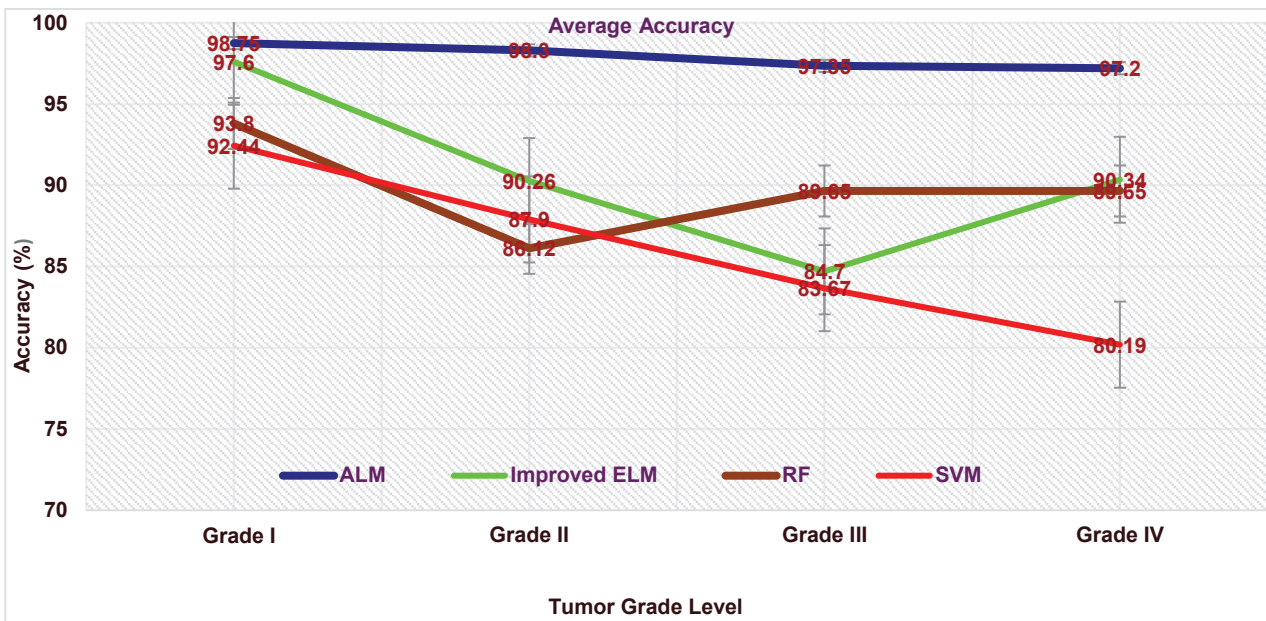


Fig. 4b. Average recognition accuracy performance analysis of size of the tumor

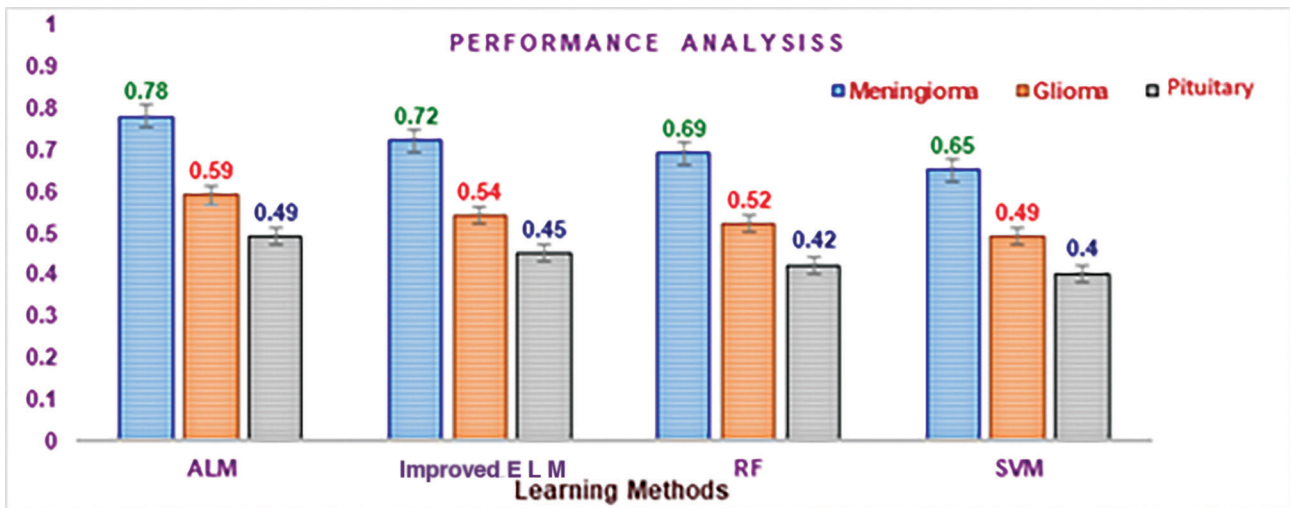


Fig. 5. Performance analysis of size of the tumor sensitivity

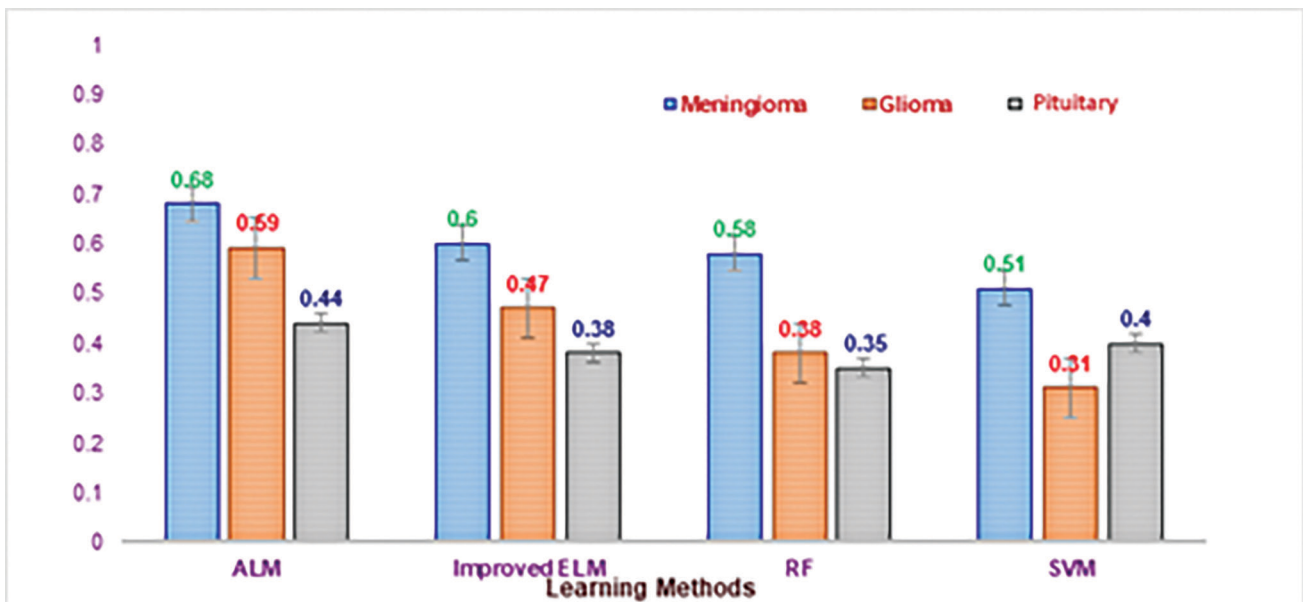


Fig. 6. Sensitivity specificity

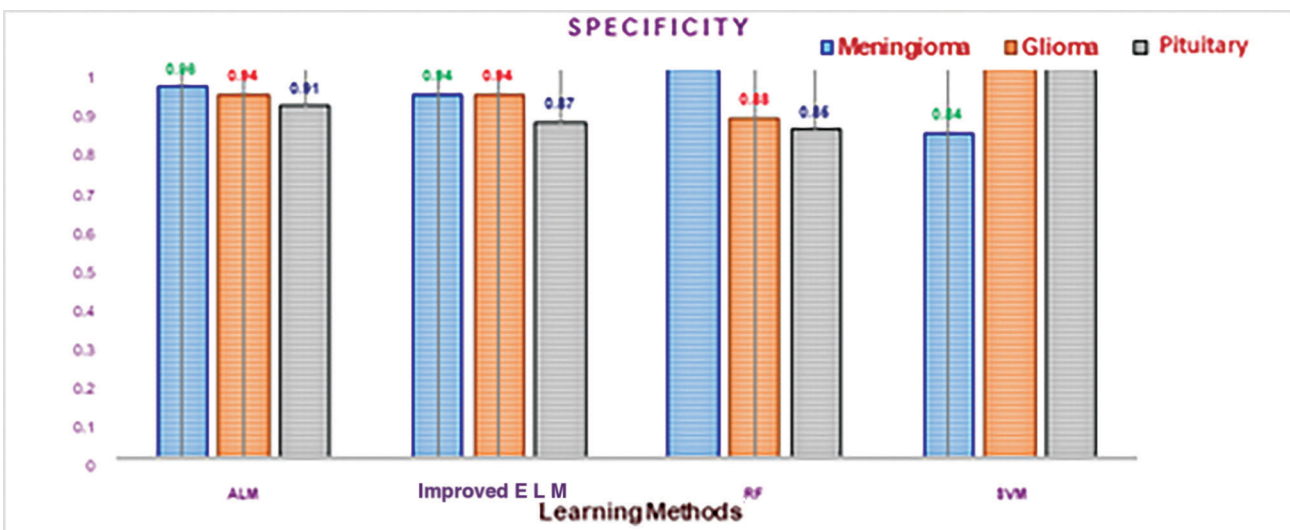


Fig. 7. Specificity

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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