International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7459
***Article Received**: 22 May 2023 **Revised:** 12 July 2023 **Accepted:** 02 August 2023*

Brain Tumor Prediction using Adaptive Connected Component based GLCM and SVM Method

A. Srinivasa Reddy[1], R. Raja[2], N. Satheesh[3], R. Muruganantham[4]
[1]Associate Professor
Department of CSIT
CVR College of Engineering
Hyderabad, India
srinivas.asr@gmail.com
[2]Associate Professor
Department of CSE (Cyber Security)
CVR College of Engineering
Hyderabad, India
nsraja1984@gmail.com
[3]Professor
Department of CSE (AI)
SET, Jain Global Campus
Jain University, Bangalore, India
nsatheesh1983@gmail.com
[4]Professor
Department of IT
TKR College of Engineering and Technology
Hyderabad, India
muruganantham1979@gmail.com

Abstract— A crucial stage in the diagnosis of brain disorders using magnetic resonance images is feature extraction. The feature extraction procedure is used to reduce the amount of the picture data by removing the necessary information from the segmented image. The segmentation strategy and features that are extracted have an impact on the classification algorithm's dependability. With the aid of a Support Vector Machine, texture features are retrieved in this study using a Grey Level Co-occurrence Matrix, while form features are extracted using connected areas. Images of benign tumours, malignant tumours, and a normal brain all exhibit distinctive features. The classification of MR images can benefit from this change in feature values. A SVM classifier will receive the features that were thusly obtained for training and testing and further able to classify the abnormalities in brain images.

Keywords- Brain tumor, Support Vector Machine, Grey Level Co-occurrence Matrix, Clssification, Benign, Malignant.

I. INTRODUCTION

The brain, which is regarded as a complex structure, is an essential component of the body. The cranium that the intellect is naturally enclosed in prevents an examination of its potential. The cerebellum, brain stem, and cerebrum make up most of the brain. The cerebrum, which consists of the left and right half of the globe separated by a split, is the most important and prominent part of the brain. It is in the front area of the skull. It controls the body's sophisticated tactile and neurological capacities as well as the initiation and coordination of intentional action. An abnormal mass of cells growing inside or outside of your brain is called a Brain tumour. Brain tumour can develop in brain cells, but it can also start elsewhere and travel to the brain. As the tumour enlarges, it puts pressure on the surrounding brain tissue and alters its functionality. A radiologist examines the images from an MRI scanner to look for anomalies. The manual classification of MR images is time-consuming and challenging. The computer-aided detection of brain illnesses involves several crucial phases, including pre-processing, segmentation, feature extraction, and classification. The features of the segmented regions are examined once the tumour regions from the MRI have been divided up. Features are the characteristics that describe the entirety of the image. The original MRI data set is broken down into several features during the feature extraction process. The term "feature vector" also applies to this feature collection. The fundamental components of every classification method are these feature vectors. Tumours are divided into benign and malignant categories according to their degree of severity. Slow-growing and less dangerous tumours are known as benign tumours. Fast-growing malignant tumours can harm nearby tissues. These tumours have specific characteristics that

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help with categorization. Magnetic resonance imaging (MRI) is one way to find malignancies in any part of the body. One of the main reasons of death for many people today is a brain tumour. Since brain tumours are among the worst tumours, it's critical to diagnose them immediately and administer the appropriate treatment to prevent death. The detection of these cells is a difficult problem because of the development of cancer cells. It is critical to compare MRI therapies for brain tumours. It is quite difficult to see the abnormal brain regions when using simple imaging techniques. Through the cranial nerves, the brain stem provides the basic power and actual innervations to the face and neck. Despite its little size, the brain stem plays a crucial role in the transmission of nerve signals from the main portion of the brain to the remaining portions of the body. The corticospinal tract (motor), the back segment average lemniscus pathway (fine touch, vibration, and sensation), and the turn thalamic tract (pain, temperature, tingle, and rough touch) are all joined by this. Additionally, the cerebrum stem plays a crucial role in the regulation of the respiratory and circulatory systems. It is important for maintaining cognition, regulating the sleep cycle, and controlling the focused sensory system. The most intricate component of the human body is the skull.

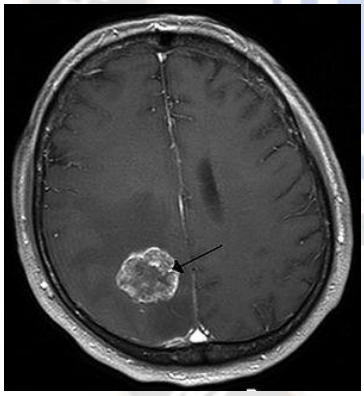

Figure 1. Brain Tumor image

For investigators to investigate and ascertain its function, there are significant barriers. The brain tumour is created by the uncontrolled cell proliferation in this intricate region. Usually, the central spinal canal is where it develops. Brain tumour imaging can find brain tumours. Brain tumour identification and therapy are greatly aided by imaging, and tumour size has become a crucial diagnostic signal in treatment planning and result evaluation.

Essential brain tumours are those that originate in the cerebrum, while optional or metastatic cerebrum tumours are those that originate in other regions of the body and spread to the brain. The main goal of brain tumour imaging research is to distinguish between the patient's clear clinical data and their suggestive highlights. This information is integrated into the multidimensional image data and subsequently supports and screens interventions following disease identification, enabling the expert radiologists to treat the infection with an accurate diagnosis and legal medication.

Any group of pixels that are not divided by a boundary are referred to as linked. A connected component is a largest region of connected pixels. An image is divided into segments by the group of linked components. In many applications of image processing, picture segmentation is a helpful operation. To find connected pixel regions—that is, areas of adjacent pixels that have the same set of intensity values—connected component labelling scans a picture pixel-by-pixel (from top to bottom and left to right).

II. LITERATURE STUDY

A.Suresh et al. [1] presented "revolutionary Grey Level Cooccurrence Matrix (GLCM)-based texture classification algorithm. By extracting the spatial relationship of each pixel in the GLCM, the texture categorization is accomplished. The original texture image is used as the input for the proposed approach, which calculates GLCM using the differences along the input texture image's first non-singleton dimension. Then, using data from both GLCM, the statistical features contrast, correlation, energy, and homogeneity are determined. To classify data, the collected characteristics are fed into the K Nearest Neighbour (K-NN) algorithm. Using the Brodatz database, the suggested system's performance is assessed and contrasted with that of PSWT, TSWT, the Gabor transform, and the linear regression model."

Shijin Kumar P.S et al. [7] stated that "Feature extraction is a crucial step in the computer assisted diagnosis of abnormalities in magnetic resonance images (MRI) of the brain. The procedure of feature extraction reduces the size of image data by removing the crucial information from the segmented image. This technique can be used to capture visual data from a segmented image. From the returned features, it is possible to differentiate between healthy and diseased brain MRI. The segmentation strategy and features that are extracted have an impact on the classification algorithm's dependability. In this study, form characteristics are recovered using connected areas, while texture features are extracted using the Grey Level Co-occurrence Matrix (GLCM). Images of benign tumours, malignant tumours, and a normal brain all exhibit distinctive features. The classification of MR images can benefit from this change in feature values."

A.Srinivasa Reddy [13] proposed that "Magnetic resonance imaging (MRI) is one way to find malignancies in any part of the body. One of the main reasons of death for many people today is a brain tumour. Since brain tumours are among the worst tumours, it's critical to diagnose them immediately and administer the appropriate treatment to prevent death. Finding these cells can be difficult due to the growth of cancer cells. It is

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critical to compare MRI therapies for brain tumours. It is quite difficult to see the abnormal brain regions when using simple imaging techniques. In this paper, automated methods for brain tumour classification and detection are proposed. The five steps that make up the suggested task are preprocessing, segmentation, feature extraction, feature selection, and classification. Following manual skull stripping preprocessing to obtain the region of interest (ROI), noise effects are subsequently removed with the median filter. The second stage then involves segmenting the tumour using the updated modified region growth algorithm (MRG), which contains both orientation limitations and intensity limits. Extraction of GLCM-based texture features is the third step. The best features are then selected using the grasshopper optimization algorithm (GOA). The next step is to classify various cancer types using the adaptive support vector machine (ASVM). Data from experiments are analyzed using a variety of measures. The suggested technique correctly separates and classifies the brain tumour in MR images, as shown by experiments and results."

P.C. Reddy [15] presented that "One of the challenging, infrequent jobs in medical image processing is the removal and analysis of brain tumours. Segmentation is also important for the administration of medical images. For instance, the cancer portion of MRI scans of a brain tumour are successfully separated from the original MRI images. In this paper, the performance is assessed utilising our newly proposed algorithm, Modified Region Growing (MRG), where the entire anticipated approach is implemented in the MATLAB platform and the outcome analysis is carried out. Using several parameters, including PSNR, MSE, and SSIM, our new approach is contrasted with the prevailing K-Means and FCM techniques."

B.Jagadeesh et al. [16] stated that "This study provides a reliable and blind watermarking method based on support vector machines (SVMs) for the discrete wavelet transform domain copyright protection of photos. The relationship between the coefficients in different subbands of the discrete wavelet transform decomposition is the foundation of this approach. The proposed approach is very secure and immune to a wide range of attacks, including Low pass filtering, Salt & Pepper noise, Gamma correction, JPEG compression, Row-Column Copying, Row-Column Blanking, Bit plane removal, Cropping, Resize, and Histogram Equalization, among others. Experimental results show that the proposed system outperforms a method proposed by Li et al. in terms of Normalised Cross Correlation (NC) and Peak Signal to Noise Ratio (PSNR) in terms of both robustness and imperceptibility."

Hareem Kibriya et al. [18] experimented that "Brain tumours are among the most serious forms of cancer brought on by the unchecked growth of brain cells inside the skull. Therefore, a quick and reliable tumour identification technique is essential for the patient's wellbeing. Recently, numerous automated artificial intelligence (AI) techniques for tumour diagnosis have been created. These methods, however, produce subpar results; as a result, a reliable method for making accurate diagnoses is required. This study proposes a unique method for detecting brain tumours using a collection of deep and custom feature vectors (FV). The unique FV is a combination of intricate features based on VGG16 and hand-crafted features based on the GLCM (grey level co-occurrence matrix). The innovative FV has more robust properties than independent vectors, which boosts the suggested method's ability to discriminate. The outcomes demonstrate the resilience of the suggested approach, which may be used to precisely identify brain tumours from MRI scans in the real world. Additionally, cross-tabulated data were used to validate the efficacy of our model."

III. SUPPORT VECTOR MACHINE

Support Vector Machine, or SVM, is one of the most used supervised learning approaches, and it is used to tackle problems with classification and regression. The SVM method seeks to identify the best line or decision boundary that may divide n-dimensional space into classes to quickly categorise fresh data points in the future. This optimal decision boundary is known as a hyperplane. SVM is used to choose the extreme vectors and points that contribute to the hyperplane. Support vectors, which are used to represent these extreme scenarios, are the foundation of the SVM technique.

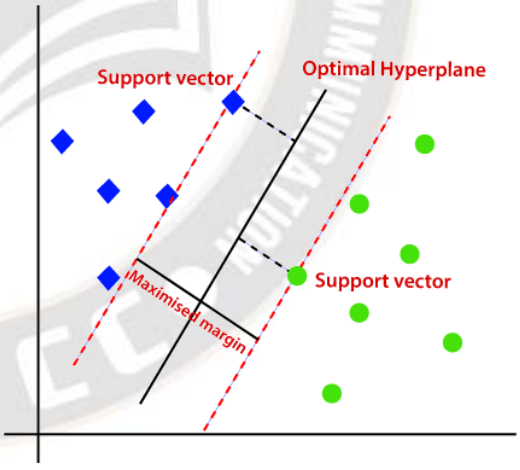

Figure 2. Support Vector Machine

SVM is available in two forms: Data that can be separated into two classes by a single straight line are used for linear SVM. The classifier used is referred to as a Linear SVM classifier, and this type of data is known as linearly separable data. For non-linearly separated data, non-linear SVM is utilised. Non-linear data is a dataset that cannot be classified using a straight line, and the classifier used is referred to as a Non-linear SVM classifier.

The data points or vectors that are closest to the hyperplane and have the biggest impact on where the hyperplane is situated

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are called support vectors. There may be multiple lines or decision boundaries used to divide the classes in n-dimensional space, but we must find the best decision boundary to help classify the data points. This ideal boundary is known as the SVM hyperplane. The SVM approach helps to locate the proper decision boundary or region, also referred to as a hyperplane. The nearest line from each class is identified by the SVM algorithm. These points are referred to as support vectors. The margin is the separation between the vectors and the hyperplane. SVM aims to increase this margin.

IV. CONNECTED COMPONENTS

A group of neighboring pixels in a binary image is referred to as a connected component. The definition of pixel connection determines whether pixels are adjacent. Any group of pixels that are not divided by a boundary are referred to as linked. A connected component is the largest region of connected pixels. An image is divided into segments by the group of linked components. Image segmentation is a helpful technique in many image processing applications. picture segmentation is the set of related components that divide a picture into segments.

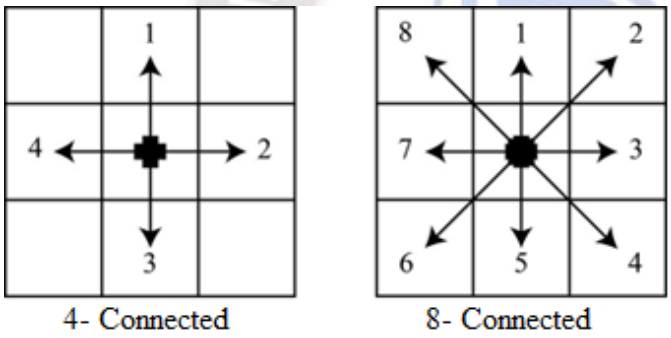

Figure 3. 4 and 8 connected components

4-connectivity: Two pixels are joined if their edges come into touch. A single object is created when two pixels are joined in either the horizontal or vertical direction and are both on.

8-connectivity: The edges or corners of two pixels come together to form a connection. Two neighboring pixels are one object if they are both on and related to one another in the horizontal, vertical, or diagonal planes.

V. GREY LEVEL CO-OCCURRENCE MATRIX

By calculating how frequently a pair of pixels with specific values and spatial relationships appear in an image, the GLCM function describes the texture of an image. GLCM is a statistical method for analysing texture that takes the spatial connection between pixels in images into account. The variation in intensity at the intriguing pixel is determined by the GLCM, which is mostly employed in pattern recognition. The reference and neighbour pixels are the connections that the GLCM surface considers at any given time. In terms of homogeneity, consistency, and other factors, the GLCM set of highlights can be used to reflect the overall norm for the degree of connection between groups of pixels from different perspectives. The distance between pixels is one of the key elements that affects how well GLCM separates images. When you use the separation 1, it encourages you to reflect the degree of connection between adjacent pixels (also known as a short-range neighborhood network). While increasing the spacing esteem causes the degree of association between distant pixels to be reflected.

A co-occurrence matrix, sometimes called a co-occurrence distribution, refers to the separation and precise spatial association throughout a certain size picture sub-area. It also describes the delivery of co-happening values at a given balance. The GLCM is implemented on a dim scale image. A dim dimension (grayscale force or Tone) esteem i pixel's frequency in a horizontal plane, vertical space, or corner to corner to adjacent pixels is determined by the GLCM. Where i and j represent the image's dark dimension values (tone). Since regular surfaces are made up of instances of sporadic sub-components, a factual methodology views a picture surface as a quantitative proportion of the plan of powers in an area. The co-event framework uses spatial relationships of similar dim tones to capture the numerical highlights of a surface.

For each element (i, j), the final GLCM simply adds the number of times the input image's pixel with value i occurred in the necessary spatial relationship to a pixel with value j. The number of grey levels in the image determines the size of the GLCM.

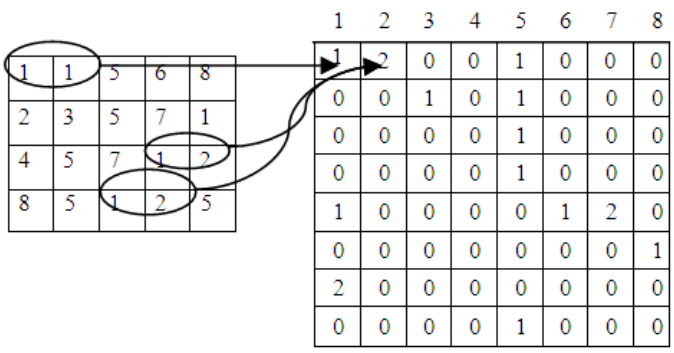

Figure 4. GLCM matrix for 8 gray values

The GLCM is a summary of how frequently various pixel brightness value combinations (also known as grey levels) appear in an image. It tabulates the instances in which a pixel with value X is near a pixel with value Y in a particular direction and distance before using the results to derive statistics. The GLCM functions calculate the frequency of pairs of pixels with values and in a specific spatial relationship to generate a GLCM and then extract statistical metrics to describe the texture of an image from this matrix. The GLCM features include Contrast, Dissimilarity, Entropy, Mean, Variance, Homogeneity, Energy, Correlation.

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A. Contrast

Contrast is used to measure the local fluctuations of the gray-level co-occurrence matrix.

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij} * (i-j)^2 \quad (1)$$

B. Dissimilarity

A linear measure of local changes in an image is called dissimilarity.

$$Dissimilarity = \sum_{i,j=0}^{N-1} P_{ij} * |i-j| \quad (2)$$

C. Entropy

The highest value of entropy, a measure of unpredictability, is achieved when all the elements of the set are equal.

$$Entropy = -\sum_{i,j=0}^{N-1} P_{ij} * ln(P_{ij}) \quad (3)$$

D. Mean

The mean value is obtained by dividing the sum of the pixel values by the total number of pixel values.

$$Mean\ \mu_i = \sum_{i,j=0}^{N-1} i(P_{ij}) \quad (4)$$

E. Variance

The variance reveals the distribution of the pixel values.

$$Variance\ \sigma_i^2 = \sum_{i,j=0}^{N-1} P_{ij} * (i-\mu_i)^2 \quad (5)$$

F. Homogeneity

The homogeneity value of each pixel in the image is calculated. A values matrix is produced after the homogeneity values have been computed.

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+|i-j|^2} \quad (6)$$

G. Energy

Energy function returns the squared sum of its constituents. Range = [0 1] Energy for a steady picture is 1.

$$Energy = \sum_{i,j=0}^{N-1} P_{ij}^2 \quad (7)$$

H. Correlation

The joint likelihood of the chosen pixel pairings occurring is measured via correlation.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} * \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{\sigma_i^2 * \sigma_j^2}}\right] \quad (8)$$

VI. PROPOSED METHOD

The two steps of the proposed system are mainly composed of the feature extraction stage and the classification stage. Feature extraction is a critical pre-processing step for pattern recognition and machine learning problems.

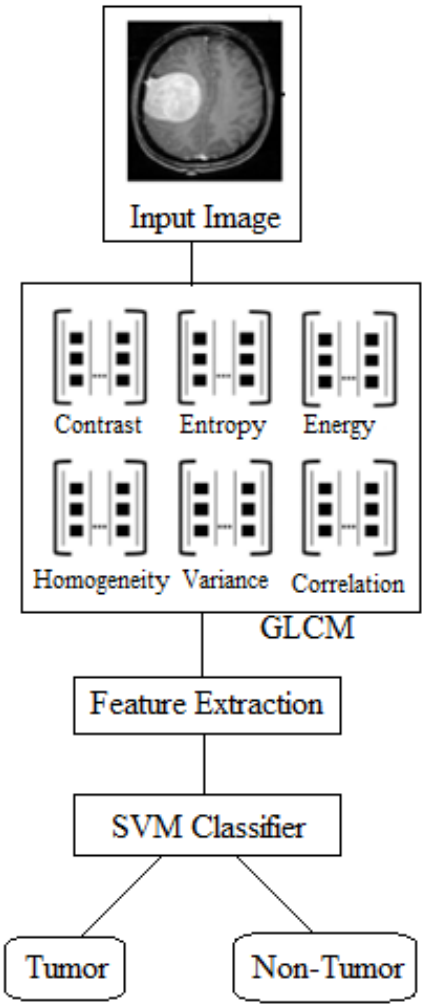

Figure 5. Proposed Algorithm

The GLCM features generated from the original texture image and the identical GLCM features derived from the difference image are merged and used as features in the proposed approach to classify the digital texture pictures. The GLCM is normalized such that the product of all of its components is 1. The joint chance of pixel pairs with a known spatial relationship and grey level values i and j occurring is represented by each element (i,j) in the normalized GLCM. Let's assume that p represents the input texture image's normalized GLCM.

The two GLCM that are created from the given unknown texture picture and the differences computed along the first non-

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singleton dimension of the unknown texture image are used in the classification phase. Both GLCMs are used to determine the feature vector of the unidentified texture image. The features in the database created during the feature extraction stage are then used to process this vector. The textures were classified using an SVM classifier, and the distance between the features and their database counterparts was determined using the Euclidean distance. The percentage of test set photographs correctly classified into the appropriate texture class serves as a measure of classification performance.

VII. RESULT ANALYSIS

This study utilised the publicly available Kaggle dataset of brain MR images for brain cancer classification. There are MRIs of tumours and normal tissue in both datasets. 30% of the MRI samples were used for validation, while the remaining 70% were used to train the models.

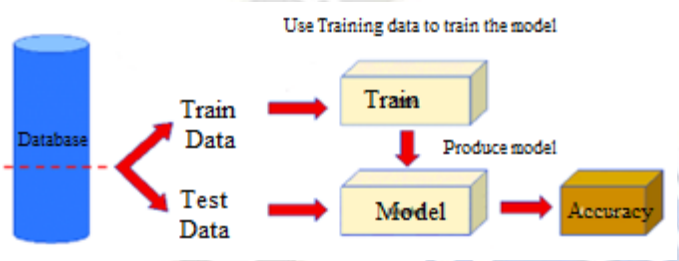

Figure 6. Training and testing the model

The most widely used method for assessing classification models is the confusion matrix (CM), a straightforward cross-tabulation of the real and categorized data for each class. In this work, the performance of the model was assessed using a number of classification measures based on the CM, including accuracy, F1-score, recall, and precision. The F1-score is a valuable tool for combining precision and recall into a single benchmark that combines elements of both criteria. It is often used in situations where there is an imbalance in the data.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (9)$$

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (12)$$

We have considered 540 images for our analysis which is mixture of both Tumor and Non-tumor brain images. We have applied existing SVM and proposed Adaptive GLCM-SVM approach on these datasets. We have tabulated the values for Accuracy, Precision, and Recall for existing and proposed methods.

TABLE 1: Confusion Matrix

	Accuracy	Precision	Recall
SVM	87	85	91
Adaptive GLCM-SVM	92.5	89	93.5

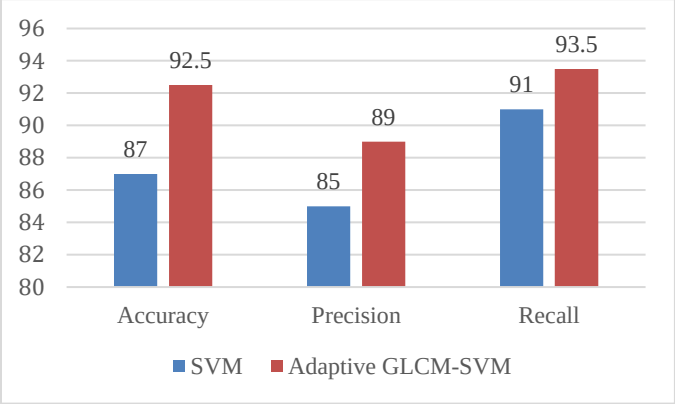

Figure 7. Comparison results

CONCLUSION

This study suggests a unique ensemble learning approach for the detection and classification of brain tumours that incorporates both GCLM and SVM features as well as the connected component attributes. On a dataset of 540 brain images from the Kaggle competition, our technique was individually trained and tested, and it achieved a maximum accuracy of 92.5%. We also validated across datasets and compared the proposed approach to the existing systems. The results show the robustness of the proposed method, which may be applied to accurately detect brain cancers from MRI scans in the real world. To improve the system, we will eventually collect medical images from other modalities and use different CNN designs. Additionally, we are willing to try the recommended technique by categorizing brain MRI scans in order to pinpoint the particular type of cancers.

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