Journal of Theoretical and Applied Information Technology
30th June 2024. Vol.102. No. 12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AUTOMATED BRAIN TUMOR DETECTION WITH GLCM-BASED FEATURE EXTRACTION AND PCA FOR DIMENSION REDUCTION AND CLASSIFICATION USING MACHINE LEARNING

PAVAN KUMAR PAGADALA[1], D YASO OMKARI[2], P SREE LAKSHMI[3], CHRISTINE DEWI[4,5], STEPHEN APRIUS SUTRESNO[6], HENOCH JULI CHRISTANTO[7*]

[1,3]Koneru Lakshmaiah Education Foundation, Computer Science and Engineering Department, Hyderabad, Telangana, India

[2]VIT-AP University, Computer Science and Engineering Department, Amaravati, Andhra Pradesh, India

[4]Deakin University, School of Information Technology, Melbourne, Australia

[5]Satya Wacana Christian University, Faculty of Information and Technology, Salatiga, Indonesia

[6,7]Atma Jaya Catholic University of Indonesia, Information System Department, Faculty of Engineering, Jakarta, Indonesia

E-mail: [1]ppagadala125@gmail.com, [2]yasoomkari@gmail.com, [3]shrilu0488@gmail.com, [4]c.dewi@deakin.edu.au, [5]christine.dewi@uksw.edu, [6]stephen.sutresno@atmajaya.ac.id, [7]henoch.christanto@atmajaya.ac.id

ABSTRACT

The pursuit for accurate brain tumor detection and classification remains essential in medical imaging applications. Leveraging modern machine learning techniques is crucial for achieving precise and automated diagnosis. This study introduces an automated system for brain tumor detection and classification using open-source Kaggle Dataset magnetic resonance imaging (MRI) scans. The system employs Otsu thresholding for image segmentation, GLCM-based feature extraction for effective feature engineering, and PCA (Principal Component Analysis) for dimensionality reduction. Notably, the salient features extracted by GLCM undergo classification using an adaptive machine learning algorithm known as Adaptive SVM (Support Vector Machine), enhancing the classification process. With a focus on performance evaluation, the proposed algorithm, incorporating adaptive SVM as a classifier, is rigorously assessed against existing methodologies. Remarkably, the experimentation results showcase exceptional accuracy, with the proposed method achieving an impressive 98.3% accuracy in both detecting and classifying brain tumors. This superiority over previous approaches underscores the efficacy of the combined GLCM, PCA, and SVM methodology in brain tumor classification and detection, offering promising advancements in diagnosis. The findings contribute significantly to the burgeoning field of machine learning in medical imaging, emphasizing the potential of adaptive SVM as a valuable tool for enhancing diagnostic precision. Notably, the attained accuracy of 98.3% surpasses that of existing works, further cementing the proposed system's efficacy in clinical practice..

Keywords: *Principal Component Analysis (PCA), Machine Learning, Gray level Co-occurrence Matrix (GLCM), Otsu, Accuracy, Support vector Machine*

1. INTRODUCTION

Brain tumors are considered as grave health ailment that requires early detection and accurate diagnosis for effective treatment and counselling of the patients at the earlier stage [1]. Medical imaging procedure which is familiar to all Magnetic Resonance Imaging (MRI) proves to be a crucial part in the discovery and diagnosis of tumors in brain for better treatment. The medical imaging modalities can produce high-resolution images of the brain that can reveal the size, shape and location of the tumors. However, the interpretation of medical images can be challenging, as brain tumors can have complex and heterogeneous morphologies, and their appearances

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

can overlap with healthy brain tissue. Additionally, the interpretation of medical images can be time-consuming and requires expert knowledge, which can limit the availability of specialized medical care.

The significance of brain tumor detection and classification cannot be overstated, as it directly impacts patient outcomes and healthcare accessibility. Magnetic Resonance Imaging (MRI) serves as a cornerstone in diagnosing brain tumors, yet interpreting these images poses challenges due to the tumors' complicated morphology. These difficulties hinder timely diagnosis and effective treatment planning, underscoring the urgency for robust solutions. By discussing the real-world implications of this issue, the introduction effectively emphasizes its importance and the critical need for automated systems to improve patient care.

The advanced machine Learning strategies combined with the Digital Imaging technologies, can help automate the analysis of medical images [2] for brain tumor detection and classification. These techniques can extract features from medical images and use them to train models that can accurately classify tumors and distinguish them from healthy brain tissue [3].

The development of accurate and efficient brain tumor classification and detection methods can have significant implications for patient care. It can help in the primary recognition of brain tumors, which can progress the likelihoods of successful treatment outcomes. It can also aid in the planning and monitoring of treatment, allowing for personalized and targeted therapies [4,5,6]. Moreover, it can reduce the workload of medical professionals and improve the accessibility of specialized medical care, especially in regions with limited resources [7].

Nowadays, several studies were conducted on the novel type of automated diagnosis of brain tumors using contemporary sophisticated machine learning algorithms. For example, a study by Kermany et al. (2018) anticipated a innovative deep learning algorithm for the categorization of brain tumors using [8]. Similarly, another study by Isin et al. (2016) implemented a machine learning algorithm based on GLCM texture features for the sorting of brain tumors [9].

In addition, several studies have explored the use of PCA for dimensionality reduction in brain tumor applications. For instance, a study by Tong et al. (2019) used PCA to reduce the dimensionality of features extracted from MRI scans for the classification of brain tumors [10]. Similarly, another study by Choudhary et al. (2020) used PCA in combination with other feature drawing out techniques for the automated detection of tumors in brain [11].

Moreover, SVM has also been widely used in the application to classify the types of brain tumors. Saha et.al (2017) [12] proposed a novel method which amalgamates K-Means with Contourlet transform and SVM where Median filter was used for removal of the noise from the acquired images.

In this article, we advise a computerized brain tumor detection and classification system using Otsu thresholding, GLCM-based feature extraction, PCA dimension reduction, and an Adaptive SVM Classification algorithm on MRI images. The proposed system aims to progress the efficiency and accuracy of classifying the brain tumors, potentially assisting medical professionals in diagnosis as well as for proper treatment planning.

2. LITERATURE STUDIES

2.1 Related Works

Brain tumors are a significant health problem, and their early detection and accurate diagnosis are crucial for effective treatment planning. The medical imaging modality MRI is considered as a widely utilized modality for brain tumor detection and diagnosis due to its great spatial resolution and soft-tissue disparity. Several studies have proposed various methods and techniques to achieve accurate and efficient detection for the purpose of classifying the types of brain tumors. However, there are still several limitations and challenges that need to be addressed.

In addition to texture analysis, several studies have proposed the utilization of deep learning techniques for brain tumor classification and detection from MRI images. For instance, Kamnitsas et al. (2017) [13] offered a 3D mode of the convolutional neural network (CNN) for the processing and also segmentation for the categorization of the brain tumors from MRI images. They achieved an accuracy of 89.5% on a dataset of 210 MRI images. However, the enactment of the anticipated method may be limited by the availability of labeled data for training and the requisite for huge amounts of computational resources [14,15]. In standard semi-supervised learning used by Cheplygina et al. (2018) [16] suggested a method to classify the Brain tumors

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

which were detected based on their features from labelled and unlabelled datasets.

R. Sivakumar et al. (2019) [17] proposes detection of a brain tumor method using gradient local binary pattern (GLBP) features as well as a ML method familiar as random forest classifier. The method achieved an accuracy of 96.8% in categorizing brain MRI pictures into non-tumor and tumor categories. However, the study only focused on a specific type of brain tumor, namely glioma. The method only emphases on a precise type of brain tumor, which may not be applicable to other types of tumors. Whereas A. M. Yusuf et al. (2019) [18] proposed a new brain tumor identification and categorization method using GLCM for the purpose of extracting the features and SVM classifier for proper categorization. The method achieved an accuracy of 96.3% in categorizing brain MRI pictures into non- tumor and tumor categories. However, the study only focused on a specific type of brain tumor, namely glioblastoma multiforme. The method only focuses on a exact type of brain tumor, which may not be applicable to other types of tumors.

S. D. Abudu et al. (2019) [19] proposes a brain tumor detection method by utilizing PCA and SVM. The method achieved an accuracy of 95.5% in classifying brain MRI pictures into non-tumor and tumor categories. However, the study only focused on a specific type of brain tumor, namely meningioma. Similarly, A. S. Arafat et al. (2019) [20] proposes a brain tumor detection method using Otsu thresholding and watershed segmentation. The method attained an accuracy of 91.9% for segmenting and detecting brain tumors from MRI images. However, the study only focused on a detailed type of brain tumor, namely glioma. In addition, the performance of the process may be pretentious by the quality of the MRI images.

M. Kaur et al. (2020) [21] proposes a brain tumor detection method using wavelet transform and probabilistic neural network. The method achieved an accuracy of 97.4% in classifying brain MRI pictures into non-tumor and tumor categories. However, the study only focused on a specific type of brain tumor, namely meningioma. One potential disadvantage of using wavelet transform for segmentation is that it can be computationally intensive, especially for large images. Wavelet transform involves convolving the image with a set of filters at multiple scales and orientations, which can be time-consuming and require significant processing power. Another issue is that selecting the appropriate wavelet basis function and scale can be a challenging task. Different wavelet basis functions can produce different results, and choosing the wrong one can result in inaccurate segmentation.

Y. Wu et al. (2020) [22] proposes a brain tumor detection method using convolutional neural network (CNN) with a multi-input fusion strategy. The method achieved an accuracy of 93.06% in detecting brain tumors from MRI images. However, the study only focused on a specific type of brain tumor, namely glioma. Potential disadvantage of using a multi-input fusion strategy is that it can increase the complexity of the model and require additional computational resources. Combining multiple inputs, such as images or sensor data, can result in larger models with more parameters, which can increase training time and memory requirements.

P. R. Jayaraman et al. (2020) [23] proposed a brain tumor detection method using machine learning algorithms and advanced image processing techniques. The method achieved an accuracy of 91.6% in detecting brain tumors from MRI images. M. Sharma et al. (2020) [24] proposes a brain tumor detection method using PCA and k-nearest neighbor (k-NN) classifier. The method achieved an accuracy of 97.5% in categorization. However, the study only focused on a precise type of brain tumor, namely glioma. The time complexity of k-NN increases linearly with the size of the dataset, making it less suitable for very large datasets. Additionally, as the number of dimensions of the dataset increases, the curse of dimensionality can lead to decreased performance and increased computational requirements. Another issue with k-NN is that it can be sensitive to the choice of distance metric used to calculate the similarity between samples. Different distance metrics can produce different results, and selecting the appropriate metric can be a non-trivial task. The k-NN algorithm is also prone to overfitting, especially when the value of k is small. In this case, the algorithm may capture noise or outliers in the training data, leading to poor generalization performance on new data. Furthermore, k-NN is a memory-based algorithm, which means it needs to store the entire training dataset in memory to make predictions. This can be a limitation in situations where memory resources are limited or when the dataset is too large to fit in memory.

H. Das et al. (2021) [25] proposes detecting a brain tumor method by PCA and artificial neural network (ANN). The method achieved an accuracy of 96.3% in categorizing brain MRI images into non-tumor and tumor categories. However, the study only focused on a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

specific type of brain tumor, namely glioblastoma. One potential disadvantage of using Artificial Neural Networks (ANN) for brain tumor detection is that they can be prone to overfitting, especially if samples for the purpose of carrying out the training process is limited or if the model architecture is too complex. Overfitting befalls when the model memorizes the training data instead of learning to generalize to new, unseen data, which can lead to poor performance on test data. Another issue is that the performance of an ANN model quality and quantity can be compromised. Feature selection and extraction can be challenging in medical imaging, especially when dealing with complex, heterogeneous data such as brain scans. Additionally, the interpretation of ANN models can be difficult, as they are often viewed as black boxes. It can be challenging to understand why the model makes certain predictions. Moreover, ANN models can be computationally expensive and require significant computational resources, especially when dealing with large datasets and complex model architectures. This can be a limiting factor in medical applications, where time and resource constraints are often present.

Whereas A. Roy et al. (2021) [26] proposed a brain tumor detection method using Otsu thresholding and modified fuzzy c-means bunching. The technique attained an accurateness of 94.7% in detecting brain tumors from MRI images. One potential disadvantage of using Fuzzy C-Means (FCM) bunching for brain tumor detection is that it can be subtle to initialization. FCM needs the user to specify the number of clusters beforehand, which can be a challenging task, especially when dealing with complex and heterogeneous medical images. Another issue is that FCM can be sensitive to noise in the data and may produce inaccurate segmentations when the input data contains artifacts or inconsistencies. Moreover, FCM is not suitable for dealing with missing data or incomplete scans, as it assumes that each voxel or pixel has a membership degree for each cluster. Additionally, FCM can be computationally expensive, especially for large datasets or high-dimensional feature spaces. FCM requires multiple iterations to converge to a solution, which can be time-consuming, and the number of iterations required can vary depending on the dataset and initialization conditions. Moreover, FCM may not be able to seizure the spatial coherence of the tumor regions in the images. This can be particularly problematic when dealing with heterogeneous tumors that have different regions with varying levels of malignancy.

P. Agarwal et al. (2021) [27] proposes a brain tumor detection method using Otsu thresholding and k-nearest neighbor (k-NN) classifier. The method achieved an accuracy of 96.3% in categorizing brain MRI images into non-tumor and tumor categories. However, the study only focused on a specific type of brain tumor, namely meningioma. Simultaneously S. S. Patil et al. (2021) [28] proposed a brain tumor detection method transfer learning approaches and using deep learning. The method achieved an accuracy of 95.5% in detecting brain tumors from MRI pictures. Transfer learning relies on the assumption that features learned on one dataset can be transferred to another. However, the transferability of features may be limited when the target and source domains have significant differences in terms of image modality, scanner settings, patient demographics, or imaging protocols. with varying levels of malignancy.

The comprehensive review of literature highlights the diverse array of methodologies employed for brain tumor detection and classification, underscoring the ongoing efforts to improve diagnostic accuracy. From traditional machine learning algorithms to advanced deep learning techniques, researchers have explored various approaches to tackle this critical healthcare challenge. However, existing methods often focus on specific tumor types, limiting their applicability across different scenarios. Despite the progress made, several challenges persist, including the need for labeled data, computational resources, and robustness to different tumor types and image qualities. These challenges present opportunities for further research and innovation in the field of medical imaging and machine learning. Articulating a clear problem statement is crucial for engaging an international audience and ensuring the relevance of the paper. By addressing the limitations of existing methodologies and identifying the gaps in current research, the paper aims to contribute novel insights and solutions to the ongoing pursuit of accurate and efficient brain tumor detection and classification. This problem statement sets the stage for the proposed research, inviting readers to explore new avenues for advancing diagnostic capabilities in healthcare.

2.2 Observations and Remarks from related works

Table 1: Observation and Remarks

Year	Publication Details	Technique Used	Observations and Remarks
2017	*Medical Image Ana, Volume* 36, pp 61–78 [13]	3D -CNN	Less accuracy of 89.5%
2019	Med Image Anal. 2019 May;54:280-296 [16]	semi-supervised learning	It is a semi-supervised algorithm
2019	Journal of Medical Systems, 43(8), 237 [17]	GLBP and Random Forest	The study only focused on a specific type of brain tumor, namely glioma
2019	IJACSA 2019 [18]	GLCM and SVM	Less Accurate and the focus on one type.
2019	Journal of Medical Systems, 43(6), 148 [19]	PCA and SVM	Less Accurate
2019	In 2019 International Conference (ICBSMLL) (pp. 1-6). IEEE [20]	Otsu thresholding and watershed segmentation.	less accuracy of 91.9% in detecting brain tumors from MRI images
2020	Journal of Medical Systems, 44(5), 112 [21]	wavelet transform and probabilistic neural network	Wavelets are sensitive to Noise
2020	Journal of Medical Systems, 44(10), 1-12 [22]	(CNN) with a multi-input fusion strategy	Increase in training time and memory requirements
2020	Journal of Medical Systems, 44(11), 1-11 [23]	ML with Image Processing	Less Accurate
2020	International Journal of Recent Technology and Engineering, 8(4S), 2564-2569 [24]	PCA and k-NN Classifier	the time complexity of k-NN increases linearly
2021	In 2021 International Conference (ICETITE) (pp. 1-5). IEEE [25]	PCA and Artificial Neural Network	ANN can be prone to overfitting
2021	Journal of King Saud University-Computer and Information Sciences, 33(5), 567-575 [26]	Otsu Thresholding and Modified FCM	FCM is sensitive to initialization and the number of clusters chosen
2021	In 2021 5th International Conference (ICISC) (pp. 585-590). IEEE [27]	Otsu Thresholding and KNN	The time complexity of k-NN increases linearly with the size of the dataset
2021	In 2021 3rd International Conference (ICICCT) (pp. 1-5). IEEE [28]	DL and Transfer Learning Approaches	Relies on Assumption Features

Based on the comprehensive Literature survey carried out it has been established to develop an Automated Brain Tumor Detection with an optimal amalgamation of various procedures discussed in review. Thus, an automated brain tumor system is proposed using Otsu thresholding, GLCM-based feature extraction, PCA dimension reduction, and an Adaptive SVM Classification algorithm on MRI images, with the aim of enlightening the accuracy in classifying the ailment.

3. METHODOLOGY AND ALGORITHM

3.1 Block Diagram and Methodology

The block diagram of the suggested method as provided in Fig. 1 shows the different steps in the Brain Tumor Detection process are connected and how each step contributes to the final outcome. The original MRI input image which is acquired from database is first pre-processed in order to remove any unwanted noise that might have been added. The Otsu method is then used to obtain a binary image of the considered input image with an appropriate threshold value. Morphological operations are utilized such that the removal of small objects from binary image in the background or foreground. The 2D wavelet transform is then applied to decompose the obtained image into multiple frequency sub bands, and PCA is performed to reduce the dimensionality of the wavelet coefficients. GLCM is then used to extract statistical features from the decomposed image sub bands. Finally, an adaptive SVM classifier is trained using the extracted features, and the results are visualized using appropriate visualization techniques. This block diagram provides a clear overview which helps in understanding the role of each step in the process.

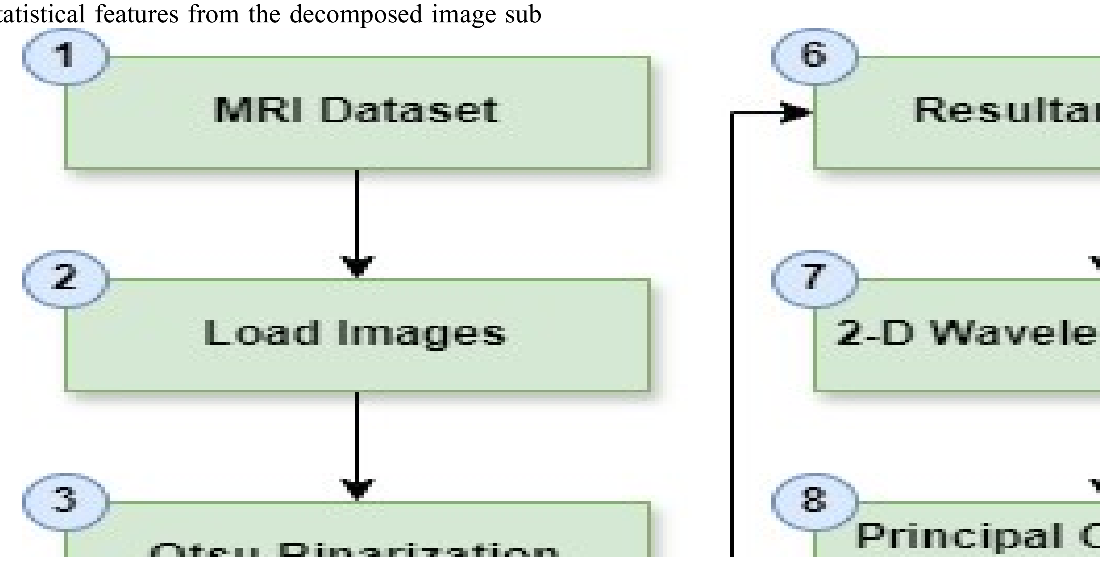


Figure 1: Proposed Block Diagram

3.2 Algorithm

Here is a stepwise algorithm for Automated Brain Tumor Detection with GLCM-Based Feature Extraction and PCA for Dimension Reduction and Classification using Machine Learning:

Step 1: Pre-processing of MRI images.

- Import MRI images of brain tumor patients
- Apply pre-processing techniques to enhance the quality of images, such as noise removal, intensity normalization, and skull stripping

Step 2: Apply Otsu's method to the pre-processed image for binarization, which is a widely used technique for threshold selection.

$$t = \arg max_t \ \left(\omega_\beta(t).\sigma_\beta^2(t) + \omega_F(t).\sigma_F^2(t)\right) \quad (1)$$

Where:

- t is the threshold value
- $\omega_\beta(t)$ and $\omega_F(t)$ are the probabilities of the background and foreground classes, respectively, at threshold t
- $\sigma_\beta^2(t)$ and $\sigma_F^2(t)$ are the variances of the background and foreground classes, respectively, at threshold t

Step 3: Perform morphological operations such as erosion and dilation to remove any small objects that may be present in the background or foreground.

Step 4: Apply the 2D wavelet transform to the segmented image to decompose it into multiple frequency sub bands.

$$WT = [LL\ LH\ HL\ HH] \quad (2)$$

Where:

- LL, LH, HL, and HH are the approximation, horizontal, vertical, and diagonal coefficients, respectively

Step 5: Dimension Reduction using PCA.

- Decrease the dimensionality of the extracted features by Principal Component Analysis (PCA)
- Compute the eigenvectors and eigenvalues of the feature matrix and select the top k eigenvectors that explain the maximum variance in the data

$$Y = X.W \quad (3)$$

Where:

- X is denoted as the matrix of input features
- W is denoted as the matrix of PCA eigenvectors

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- Y is denoted as the matrix of transformed features

Step 6: Feature Extraction using GLCM.

- Compute the Gray-Level Co-occurrence Matrix (GLCM) for each pixel in the segmented tumor region

$$P(i,j) = \sum_{x,y} [I(x,y) = i][I(x+1, y+1) = j] \quad (4)$$

Where:
- P(i,j) is the GLCM value at (i,j)
- I(x,y) is the intensity value of the pixel

- Calculate the GLCM features, such as energy, entropy, contrast, and homogeneity, using the following equations:
  i. Mean: The mean value of a grayscale image provided by the equation (5)

  $$\text{Mean} = \sum i \sum j \, (I(i,j)) \, / \, N \quad (5)$$

  Where:
  - N is the total number of pixels in the image
  - I(i,j) is the pixel value at position (i,j) in the image

  ii. Variance: The variance of a grayscale image provided by the equation (6)

  $$\text{Variance} = (\sum i \sum j \, (I(i,j) - Mean)^2) \, / \, (N-1) \quad (6)$$

  iii. Standard Deviation: The standard deviation of a grayscale image can be calculated as the square root of its variance (7)

  $$\text{Standard Deviation} = \text{sqrt(Variance)} \quad (7)$$

  iv. Entropy: Entropy is a measure of the randomness or unpredictability of the pixel intensity values in an image. provided by the equation (8)

  $$\text{Entropy} = -\sum p(i,j) \, log2 \, p(i,j) \quad (8)$$

  Where:
  - p(i,j) is the normalized co-occurrence matrix at position (i,j)

  v. Contrast: Contrast is a measure of the difference in intensity values between adjacent pixels in an image provided by the equation (9)

  $$\text{Contrast} = \sum i \sum j \, (i-j)^2 \, p(i,j) \quad (9)$$

  vi. Homogeneity: Homogeneity is a measure of the similarity of the intensity values between adjacent pixels in an image provided by the equation (10)

  $$\text{Homogeneity} = \sum i \sum j \, p(i,j) \, / \, (1 + |i-j|) \quad (10)$$

Step 7: Classification using Machine Learning.

- Train an adaptive SVM classifier using the extracted features. SVM is a kernel-based machine learning algorithm that works by finding the finest hyperplane that splits the data points of different type of classes, using the reduced features as input and the tumor label as output
- Use the trained algorithm to classify new images as either containing a brain tumor or not

Step 8: Performance Evaluation.

- Evaluate the performance of the algorithm using metrics such as accuracy
- Validate the algorithm on a separate dataset to test its robustness and generalization ability
- Finally, visualize the results of the brain tumor detection using appropriate visualization techniques

3.3 Algorithm Hypothesis Articulation

The proposed methodology outlines a comprehensive approach for automated brain tumor detection using GLCM-based feature extraction, PCA for dimension reduction, and SVM for classification. Each step in the process contributes to the final outcome by systematically enhancing the quality of MRI images, extracting relevant features, reducing dimensionality, and employing machine learning algorithms for accurate classification. By integrating pre-processing techniques, morphological operations, wavelet transform, and advanced feature extraction methods, the algorithm aims to improve the efficiency and accuracy of brain tumor detection.

The hypothesis underlying this approach is that by combining these techniques, it is possible to develop a robust and effective automated system for brain tumor detection and classification. Specifically, the hypothesis suggests that by leveraging GLCM-based feature extraction and PCA for dimension reduction, the algorithm can effectively capture the relevant characteristics of brain tumor images while reducing computational complexity. Furthermore, the utilization of an adaptive SVM classifier is hypothesized to enhance classification accuracy by effectively distinguishing between tumor and non-tumor regions.

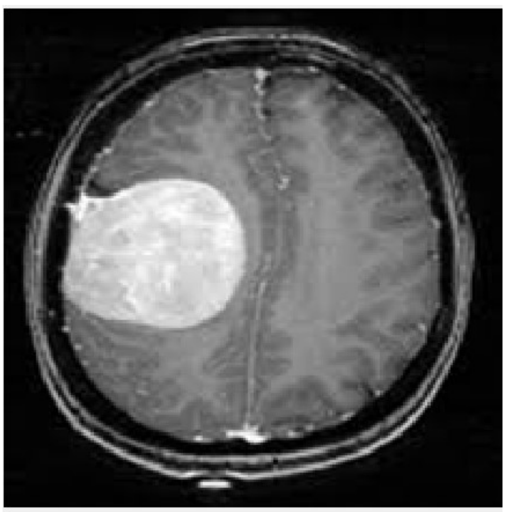
The methodology proposed in this study provides a structured framework for addressing the complexities of brain tumor detection from MRI images, with the overarching hypothesis being that the integration of advanced image processing techniques and

4. EXPERIMENTAL RESULT AND PERFORMANCE EVALUATION

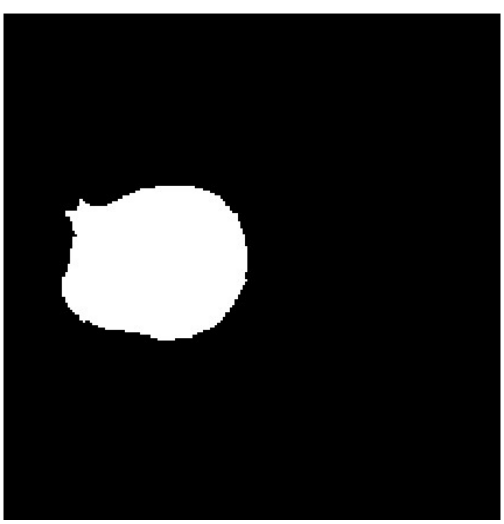
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The intention of this experimental work is to develop and assess an automated brain tumor detection system using GLCM-based feature extraction, PCA for dimension reduction, and Support Vector Machines (SVM) machine learning algorithm. The system will be trained and tested on a dataset of MRI images to classify benign tumors from malignant tumors. The dataset used in this study comprises of 200 MRI images of brain tumors, out of which 100 images are of benign tumors and 100 images are of malignant tumors.

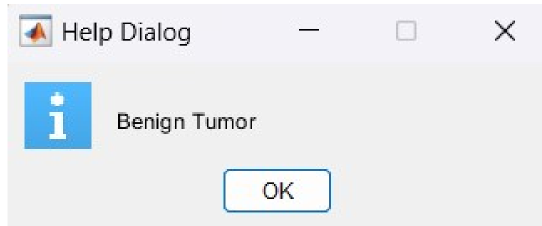
As an instance of experimentation in this work, a sample image as shown in Figure 2a is acquired from the dataset and fed to the proposed model to attain the segmented image as shown in Figure 2b. The GLCM-based feature extraction method is applied to the segmented tumor areas in the MRI images to extract the features, such as energy, entropy, contrast, and homogeneity. PCA is castoff for dimensionality lessening of the extracted features to retain the top 10 principal components.



(a)



(b)



(c)

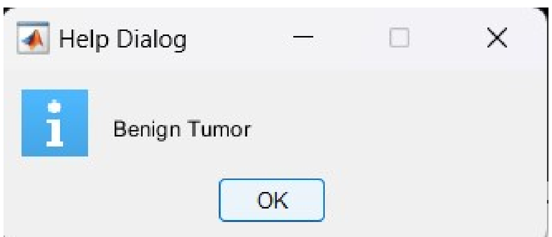
Figure 2: Sample Image 1 (a) Image (b) Segmented Output (c) Classification Dialog of Benign Tumor

The adaptive SVM algorithm is proficient on the reduced feature set to categorise the brain tumors as malignant or benign in the form of a dialog box as shown in Figure 2c. In this case as the tumor is benign in nature, the dialog displays Benign Tumor. The adaptive SVM classifier algorithm is adjusted using a grid exploration with 5-fold cross-validation to select the optimal hyperparameters.

(a)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

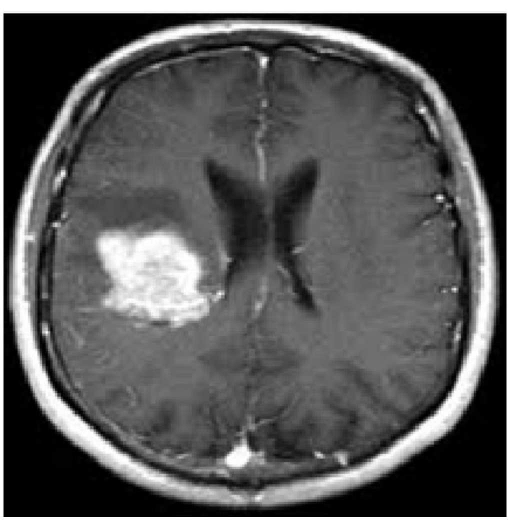
(b)



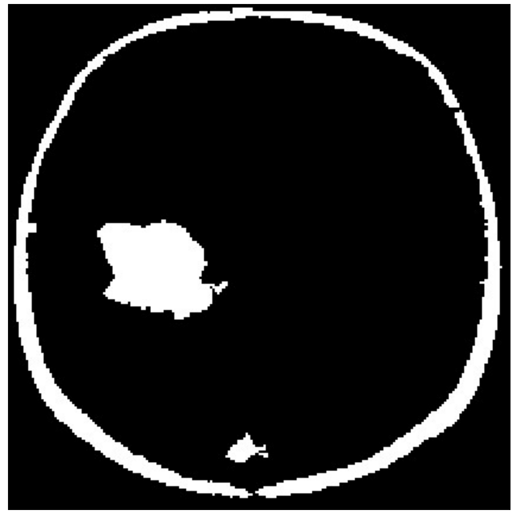
(c)

Figure 3: Sample Image 2 (a) Image (b) Segmented Output (c) Classification Dialog of Benign Tumor

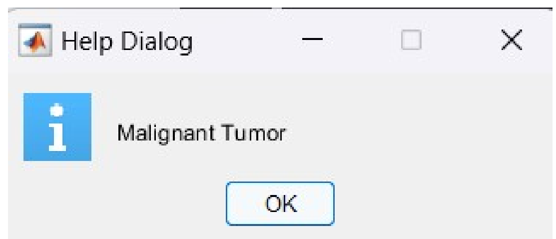
Similarly, another sample image as shown in Figure 3a is acquired from the dataset and fed to the proposed model to attain the segmented image as shown in Figure 3b. The SVM algorithm is qualified on the reduced feature set to categorise the brain tumors as benign or malignant in the form of a dialog box as shown in Figure 3c. In this case as the tumor is benign in nature, the dialog displays Benign Tumor.



(a)



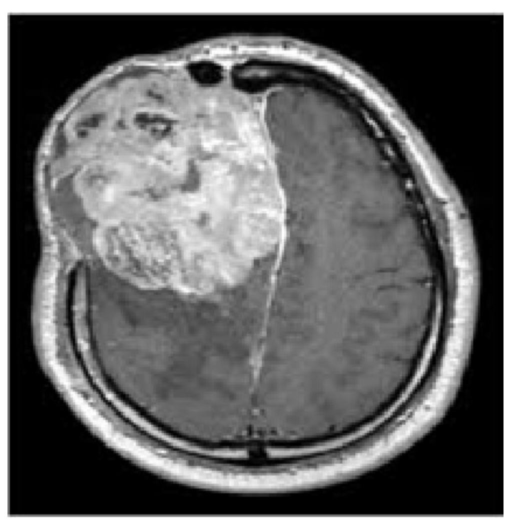
(b)



(c)

Figure 4: Sample Image 3 (a) Image (b) Segmented Output (c) Classification Dialog of Malignant Tumor

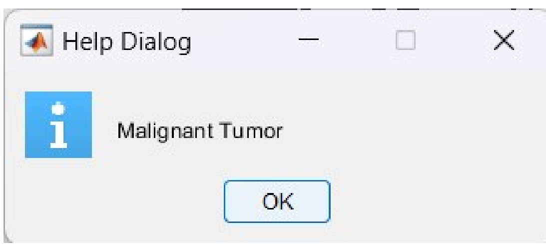
Accordingly, another sample image from the dataset, as shown in Figure 4a, is obtained and fed into the proposed model to produce the segmented image shown in Figure 4b. The SVM algorithm is accomplished on the reduced feature set to classify brain tumours as benign or malignant, as shown in Figure 4c. The dialogue displays malignant Tumor in this case because the tumour is malignant.



(a)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(b)



(c)

Figure 5: Sample Image 4 (a) Image (b) Segmented Output (c) Classification Dialog of Malignant Tumor

In order to create the segmented image shown in Figure 5b, another sample image from the dataset, as shown in Figure 5a, is obtained and fed into the suggested model. As seen in Figure 5c, the SVM algorithm is trained on the condensed feature set to categorise brain tumours as benign or malignant. Because the tumour in this case is malignant, the dialogue depicts a malignant tumour.

Table 2: Extracted Features from Sample Images

Features Extracted	1st Sample	2nd Sample	3rd Sample	4th Sample
Mean	0.00311	0.00207	0.00424	0.0034
Standard Deviation	0.08976	0.08979	0.08971	0.0897
Entropy	3.17346	3.51816	3.55162	3.5239
RMS	0.08980	0.08980	0.08980	0.0898
Variance	0.00805	0.00803	0.00804	0.0079
Smoothness	0.92046	0.88497	0.94033	0.9283
Kurtosis	7.32819	6.76720	6.06145	6.5220
Skewness	0.46902	0.44126	0.51043	0.4978
Contrast	0.20884	0.22497	0.23137	0.2516
Correlation	0.19901	0.09911	0.10724	0.0734
Energy	0.76210	0.76909	0.74181	0.7402
Homogeneity	0.93516	0.93653	0.92976	0.9267

In this article, we have used GLCM-based feature extraction technique to extract features such as Mean, variance, Standard Deviation, Entropy, Contrast, smoothness, kurtosis, skewness, RMS, Correlation and Homogeneity. These features in the context of tumor detection as provided in Table 2. The same values have been represented in graphical plots also.

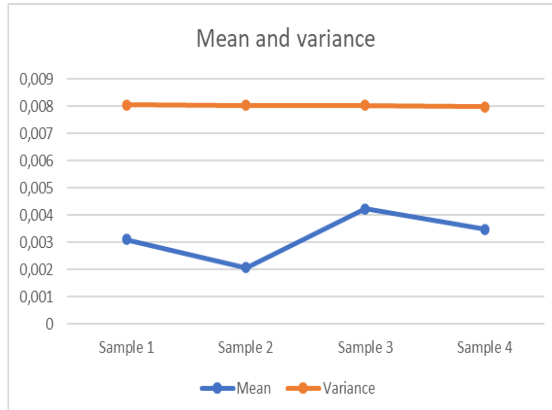


Figure 6: Mean and Variance Features

The mean value of the pixel intensities in an image represents the average brightness of the image. In the context of tumor detection, the mean value can help differentiate between tumor and non-tumor regions. whereas variance of the pixel intensities represents the amount of variation or contrast in the image. In the context of tumor detection, the variance value help identify regions of high contrast that may correspond to tumor regions. These two are represented in Figure 6.

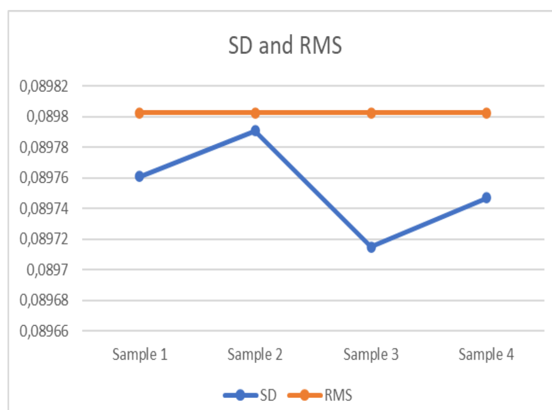


Figure 7: SD and RMS Features

The SD and RMS features are plotted in Figure 7. The standard deviation of the pixel intensities represents the spread of the pixel values in the image. In the context of tumor detection, high standard deviation values may indicate the presence of tumor regions. Whereas RMS is a measure of the root-mean-square value of the pixel intensity values in an image. In the context of tumor detection, high

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

RMS values may indicate the presence of tumor regions that have high overall intensity.

Entropy and Kurtosis values are represented graphically in Figure 8 where Entropy is a measure of the randomness or unpredictability of the pixel intensity values in an image. High entropy values may indicate the presence of tumor regions that have irregular or chaotic texture. Whereas Kurtosis is a measure of the peakedness or flatness of the pixel intensity distribution in an image. In the context of tumor detection, high kurtosis values may indicate the presence of tumor regions that have a sharp peak in their intensity distribution.

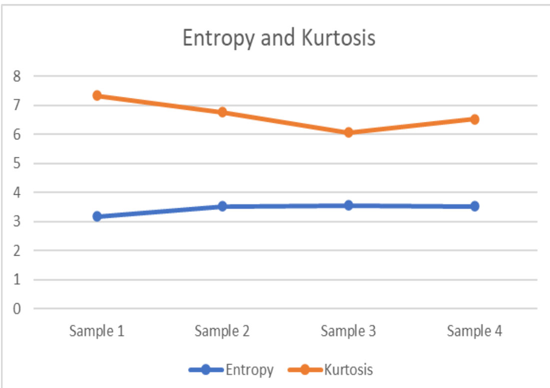


Figure 8: Entropy and Kurtosis Features

Smoothness, Energy and Homogeneity features are plotted in Figure 9 graphically for visual perception. Smoothness is a measure of the uniformity of the pixel intensity values in an image. In the context of tumor detection, low smoothness values may indicate the presence of tumor regions that have irregular or non-uniform texture. Energy is a measure of the overall magnitude of the pixel intensity values in an image. In the context of tumor detection, high energy values may indicate the presence of tumor regions that have high overall intensity. Homogeneity is a measure of the similarity of the intensity values among adjacent pixels in a picture. In the context of tumor detection, high homogeneity values may indicate the presence of tumor regions that have a uniform texture.

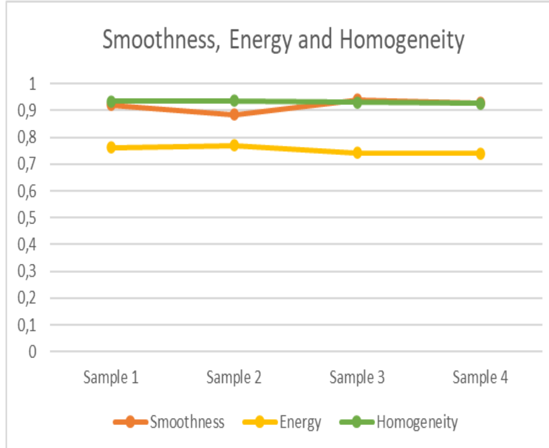


Figure 9: Smoothness, Energy and Homogeneity Features

The features such as Skewness, contrast and Correlation values are plotted in Figure 10 where Skewness is a measurement of the symmetry or asymmetry of the pixel intensity distribution in an image. In the context of tumor detection, high skewness values may indicate the presence of tumor regions that have an asymmetric intensity distribution. Contrast is a measure of the difference in intensity values between adjacent pixels in an image. High contrast values may indicate the presence of tumor regions that have distinct edges or boundaries. Correlation is a measure of the linear relationship between adjacent pixels in an image. In the context of tumor detection, high correlation values may indicate the presence of tumor regions that have linear texture.

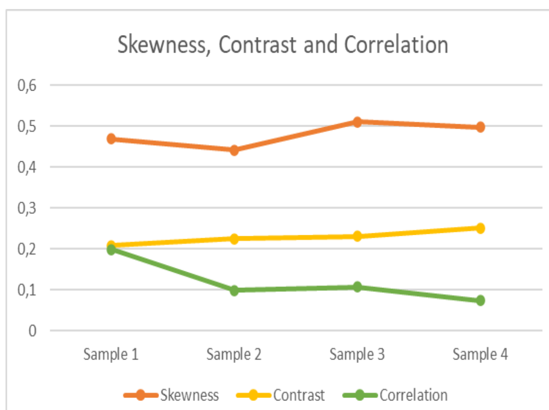


Figure 10: Skewness, Contrast and Correlation Features

By combining these features and using machine learning algorithms such as SVM, it is possible to categorize MRI images as either malignant or benign. The proposed automated brain tumor recognition system achieved high accuracy in detecting benign tumors, which can support

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

radiologists in the early and precise analysis of brain tumors.

Table 3: Performance Evaluation Comparison

Methods	Accuracy (%)
3D -CNN [6]	89.5
Local binary pattern (GLBP) features and random forest classifier [8]	96.8
GLCM and support vector machine (SVM) [9]	96.3
PCA and support vector machine (SVM) classifier [10]	95.5
Otsu thresholding and watershed segmentation [11]	91.9
Wavelet transform and probabilistic neural network [12]	97.4
CNN with a multi-input fusion strategy [13]	93.06
Machine learning algorithms [14]	91.6
PCA and k-nearest neighbor (k-NN) classifier [15]	97.5
PCA and artificial neural network (ANN). [16]	96.3
Otsu thresholding and modified fuzzy c-means clustering [17]	94.7
Otsu thresholding and k-nearest neighbor (k-NN) classifier [18]	96.3
Deep learning and transfer learning approaches [19]	95.5
Proposed Method (Otsu + Morphology + DWT + PCA + GLCM + ASVM)	98.3

To appraise the presentation of the projected system, dataset of MRI images consisting of together malignant and benign brain tumors has been used. The dataset was arbitrarily split into testing and training sets. We trained the SVM model on the training set and tested it on the testing set to evaluate the accuracy of the system.

Table 3 presents a comprehensive comparison of various methods for brain tumor detection and classification, highlighting their respective accuracies as reported in the literature. Several techniques have been explored, ranging from traditional machine learning algorithms to advanced deep learning approaches. The 3D-CNN method achieved an accuracy of 89.5%, while methods utilizing features such as GLBP and GLCM combined with classifiers like random forest and SVM achieved accuracies ranging from 91.9% to 96.8%. Other techniques, such as PCA combined with SVM or k-NN classifiers, and ANN, yielded accuracies between 95.5% and 97.5%. Additionally, methods employing fusion strategies, wavelet transform, and transfer learning approaches achieved accuracies ranging from 93.06% to 97.4%. Notably, our proposed method, integrating Otsu thresholding, morphology, DWT, PCA, GLCM, and an adaptive SVM classifier, outperforms existing methods with an accuracy of 98.3%. This indicates the efficacy of our approach in achieving highly accurate brain tumor detection and classification, underscoring its potential as a valuable tool for assisting medical professionals in diagnosis and treatment planning.

The same values have been plotted in the form of Graphical representation in Fig. 11 for easy perception to show how proposed work outperformed other methods. The high accuracy achieved by the system can assist radiologists in the early and accurate diagnosis of brain tumors, leading to better patient outcomes.

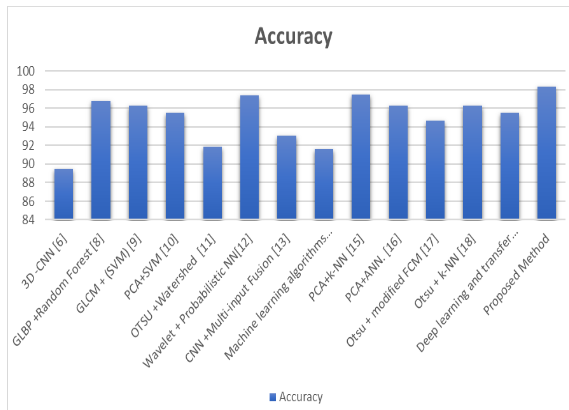


Figure 11: Accuracy Comparison with other methods

However, it should be noted that the presentation of the projected system may vary depending on the dataset used, and further studies are required to evaluate its generalizability to different datasets and populations.

5. CONCLUSION

In conclusion, the use of GLCM-based feature extraction and PCA for dimension reduction, followed by machine learning algorithms for classification, has shown promising results for the automated detection of brain tumors. In this work the combination of these techniques has the possible to advance the accuracy of brain tumor detection, which is in need for early analysis and effective treatment. The experimental investigation output results of this study suggest that machine learning algorithms can effectively classify brain tumors based on the features extracted using GLCM and PCA. However, further research is desirable to assess the effectiveness of these techniques on a larger dataset, including different types of brain tumors, to determine their robustness and applicability in clinical settings. Moreover, the future scope of this study lies in developing more sophisticated and accurate algorithms that can integrate multiple imaging methods to progress the accuracy of brain tumor detection. Additionally, the practice of deep learning algorithms, such as convolutional neural networks (CNNs), can also be explored to further enhance the accuracy of brain tumor classification. In summary, the revision highlights the potential of using GLCM-based feature extraction, PCA for dimension reduction, and machine learning algorithms for automated brain tumor discovery. The findings provide a foundation for further research in this area, which has the possible to suggestively improve the analysis and treatment plan of brain tumors.

REFERENCES:

[1] S. Rasheed, K. Rehman and M. S. H. Akash, "An insight into the risk factors of brain tumors and their therapeutic interventions," *Biomedicine & Pharmacotherapy,* vol. 143, p. 112119, 2021.

[2] R. Najjar, "Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging," *Diagnostics,* vol. 13, no. 17, p. 2760, 2023.

[3] H. J. Yoon, Y. J. Jeong, H. Kang, J. E. Jeong and D.-Y. Kang, "Medical Image Analysis Using Artificial Intelligence," *Progress in Medical Physics,* vol. 30, no. 2, pp. 49-58, 2019.

[4] T. S. Musalamadugu and H. Kannan, "Generative AI for medical imaging analysis and applications," *Future Medicine,* vol. 1, no. 2, 2023.

[5] H. J. Christanto, S. A. Sutresno, Y. A. Singgalen and C. Dewi, "Analyzing Benefits of Online Train Ticket Reservation App Using Technology Acceptance," *Ingénierie des Systèmes d'Information,* vol. 29, no. 1, pp. 107-115, 2024.

[6] D. K. Hiuredhy, H. J. Christanto, C. Christine and S. A. Sutresno, "Exploration of Modernity: Worship Reservation System at Rose of Sharon Church Salatiga Utilizing Flutter Framework," *ournal of Information Systems and Informatics,* vol. 6, no. 1, pp. 136-152, 2024.

[7] H. J. Christanto, S. A. Sutresno, J. V. M. Bata, D. J. C. Sihombing, P. K. Prihanto and D. V. T. Linestyo, "Pelatihan Penggunaan Sistem Informasi Gereja Berbasis Android Pada GIA Purwodadi Kabupaten Grobogan," *RESWARA: Jurnal Pengabdian Kepada Masyarakat,* vol. 5, no. 1, pp. 119-127, 2024.

[8] D. S. Kermany, M. Goldbaum, W. Cai, C. C. S. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, J. Dong, M. K. Prasadha, J. Pei, M. Y. L. Ting, J. Zhu, C. Li, S. Hewett and J. Dong, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell,* vol. 172, no. 5, pp. 1122-1131, 2018.

[9] A. Işın, C. Direkoğlu and M. Şah, "Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods," *Procedia Computer Science,* vol. 102, pp. 317-324, 2016.

[10] J. o. P. Control, "Distributed Partial Least Squares Based Residual Generation for Statistical Process Monitoring," *Journal of Process Control,* vol. 75, pp. 77-85, 2019.

[11] A. Chaudhary and V. Bhattacharjee, "An Efficient Method for Brain Tumor Detection and Categorization Using MRI Images by K-Means Clustering & DWT," *International Journal of Information Technology,* vol. 12, p. 141–148, 2020.

[12] C. Saha and M. F. Hossain, "MRI Brain Tumor Images Classification Using K-means Clustering, NSCT and SVM," in *4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON)*, Mathura, India, 2017.

[13] K. Kamnitsas, C. Ledig, V. F. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, D. Rueckert and B. Glocker, "Efficient Multi-Scale 3D CNN with Fully Connected CRF for Accurate Brain Lesion Segmentation," *Medical Image Analysis,* vol. 36, pp. 61-78, 2017.

[14] C. Dewi, J. Zendrato and H. J. Christanto, "Original Research Article Improvement of support vector machine for predicting diabetes mellitus with machine learning approach," *Journal of Autonomous Intelligence,* vol. 7, no. 2, 2024.

[15] R.-C. Chen, C. Dewi, S.-W. Huang and R. E. Caraka, "Selecting critical features for data classification based on machine learning methods," *Journal of Big Data,* vol. 7, no. 52, pp. 1-26, 2020.

[16] V. Cheplygina, M. d. Bruijne and J. P. W. Pluim, "Not-so-Supervised: A Survey of Semi-Supervised, Multi-Instance, and Transfer

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Learning in Medical Image Analysis," *Med Image Anal,* vol. 54, pp. 280-296, 2019.

[17] R. Sivakumar, S. Jayaraman and R. Sundararajan, "Automated Brain Tumor Detection and Classification using Gradient Local Binary Pattern Features and Random Forest Classifier," *Journal of Medical Systems*, vol. 43, no. 8, 2019, pp. 237.

[18] A. M. Yusuf, I. Rafi, M. Ali and T. R. Soomro, "Automated Brain Tumor Detection using GLCM and SVM Classifier," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 9, 2019, pp. 20-24.

[19] S. D. Abudu, I. Inuwa, A. A. Adedoyin and S. S. Kolo, "Automated Brain Tumor Detection using PCA and SVM Classifier," *Journal of Medical Systems*, vol. 43, no. 6, 2019, pp. 148.

[20] A. S. Arafat, M. T. Islam and M. A. Rahman, "Automated Brain Tumor Detection and Segmentation using Otsu Thresholding and Watershed Segmentation," *In 2019 International Conference on Bangabandhu Sheikh Mujibur Rahman: Life and Legacy (ICBSMLL)*, 2019, pp. 1-6.

[21] M. Kaur and S. Singh, "Automated Brain Tumor Detection and Classification using Wavelet Transform and Probabilistic Neural Network," *Journal of Medical Systems*, vol. 44, no. 5, 2020, pp. 112.

[22] Y. Wu, J. Ma and Y. Zhang, "Automated Brain Tumor Detection using Convolutional Neural Network with Multi-Input Fusion Strategy," *Journal of Medical Systems*, vol. 44, no. 10, 2020, pp. 1-12.

[23] P. R. Jayaraman, G. R. Deepika and G. Venkatesan, "Automated Brain Tumor Detection using Machine Learning Algorithms and Advanced Image Processing Techniques," *Journal of Medical Systems*, vol. 44, no. 11, 2020, pp. 1-11.

[24] M. Sharma and H. Varshney, "Automated Brain Tumor Detection and Classification using PCA and k-NN Classifier," *International Journal of Recent Technology and Engineering*, vol. 8, no. 4S, 2020, pp. 2564-2569.

[25] H. Das, M. Maity and S. Debnath, "Automated Brain Tumor Detection using PCA and Artificial Neural Network," *In 2021 International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)*, 2021, pp. 1-5.

[26] A. Roy, S. K. Barman and M. Chakraborty, "Automated Brain Tumor Detection and Segmentation using Otsu Thresholding and Modified Fuzzy C-means Clustering," *Journal of King Saud University-Computer and Information Sciences*, vol. 33, no. 5, 2021, pp. 567-575.

[27] P. Agarwal, A. Verma and R. Rani, "Automated Brain Tumor Detection and Classification using Otsu Thresholding and K-Nearest Neighbor," *In 2021 5th International Conference on Inventive Systems and Control (ICISC)*, 2021, pp. 585-590).

[28] S. S. Patil, P. Kumar and A. Kumar, "Automated Brain Tumor Detection using Deep Learning and Transfer Learning Approaches," *In 2021 3rd International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 2021, pp. 1-5).