International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Brain Tumor Classification, Segmentation, and Detection using Deep Learning - A Review

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Abstract— V.Vapnik in 1965 proposed Vector methods. Kimeldorf presented a technique for creating kernel space based on support vectors in 1971. Support Vector Machine (SVM) techniques were initially presented in the 1990s by V. Vapnik in the field of statistical learning. Since then, pattern recognition, natural language processing, image processing and other areas have seen extensive use of SVM. By converting non-linear sample space into linear space via a kernel approach, the algorithm's complexity is reduced. Image classification is a well-known issue in image processing. Predicting the input image categories using the features is the main objective of image classification. There are several different classifiers, including Artificial Neural Networks, Support Vector Machines, and Random Forests, Decision Forests, k-NNs (k Nearest Neighbors), and Adaptive Boost. SVM is one of the best techniques for categorizing any image or pattern. A common non-invasive technique used in the medical sector for the analysis, diagnosis, treatment of brain tissues is magnetic resonance imaging. When a brain tumor is discovered early, the patient's life can be saved by receiving the appropriate care. It becomes difficult to accurately identify tumors in the MRI slices, which requires fussy work..

Keywords- Brain Tumor, Segmentation, Classification, Magnetic Resonance Imaging

1. Introduction:

Support Vector Machines (SVM) find applications in various fields such as character recognition, text/image classification, biological sequence analysis, and data mining in biology. They are versatile tools for solving complex classification problems. The Generalized Portrait Method, a framework for pattern identification that was first suggested in 1962, contained the concepts of the support vector machine. The initial publication of this algorithm was in 1964. Support Vector Machines (SVM) can be informally described as a binary classifier. The learning technique aims to maximize the margin, as the model is based on a linear classifier with the best margin in the feature space. This optimization problem can be transformed into a convex quadratic programming problem [1].

SVM is mainly used for brain tumor classification and accurate detection. Segmenting, detecting, and extracting the tumor's infected area from magnetic resonance images is of the highest importance, but when we consider the diagnosis, it becomes time-consuming and subject to human error. To get over these restrictions, segmentation and classification are now done utilizing semi-automatic and automatic methods [2]. The main idea behind Support Vector Machines (SVM) is the use of decision boundaries defined by hyper planes to divide data points from various classifications. SVMs are capable of handling both linear and simple, classification tasks as well as nonlinear, more complex classification problems. Whether the data points are non separable or separable, SVMs can effectively handle both scenarios in both the linear and nonlinear cases [4]. SVMs use various techniques, such as kernel methods, to transform data into higher-dimensional spaces for effective classification. With their ability to handle a wide range of classification tasks, SVMs are versatile and powerful machine learning algorithms

Tumors are a pre-stage of cancer and have become a serious problem in today's era. Researchers are actively working to develop methods and treatments to combat them. Among the various types of tumors, brain tumors are particularly challenging as they involve abnormal cell growth within brain tissue. These tumors may not always be visible through conventional imaging techniques. One technique that plays a crucial role in visualizing and diagnosing brain tumors is Magnetic Resonance Imaging (MRI). MRI is a type of medical imaging that produces fine-grained images of the damaged area of the brain using radio waves and magnetic fields. By providing high-resolution images, MRI assists in the identification and characterization of brain tumors. Over 100 billion nerve cells make up the brain, one of the biggest and most intricate organs in the human body. These cells communicate with one another through billions of synapses. Unfortunately, it is susceptible to the development of tumors. An abnormal growth of tissue in the brain is referred to as a brain tumor.

Brain tumors are classified into different groups.

A. Benign and Malignant Brain Tumors: Benign tumors are generally less harmful and tend to grow slowly. On the other hand, malignant tumors contain cancerous cells and tend to grow rapidly.

B. Primary and Secondary Brain Tumors: Primary brain tumours develop from the brain's own cells. Secondary brain tumors, on the other hand, start in another area of the body before moving to the brain.

C. Naming and Grading Brain Tumors: The name of a brain tumor often indicates its origin and the type of cells it contains. Additionally, brain tumors are graded based on their level of malignancy, with higher grades indicating a more aggressive and invasive tumor. The grading system is established by organizations like the World Health Organization (WHO).

Understanding these classifications and characteristics of brain tumors is crucial for accurate diagnosis, treatment planning, and prognosis assessment.

According to the classification established by the World Health Organization (WHO), brain tumors are classified into four grades: I, II, III, and IV.

Grade I brain tumors are considered low-grade and cancerous. They exhibit slow growth and rarely spread into nearby tissues. Although these tumors grow slowly, they may infiltrate nearby tissue over time.

Grade II brain tumors are also cancerous but display a higher degree of aggressiveness compared to Grade I tumors. They grow at a moderate rate and have the potential to invade nearby tissues.

Grade III brain tumors, classified as high-grade cancerous tumors, grow rapidly and aggressively. These tumors exhibit significant infiltration into surrounding tissue. The cells of Grade III tumors appear highly abnormal compared to normal cells.

Grade IV brain tumors are the most severe and malignant. They grow and spread rapidly, infiltrating nearby tissues at an accelerated pace. The cells of Grade IV tumors appear highly abnormal and distinctly different from healthy cells.

Understanding the grading system helps medical professionals assess the aggressiveness and behavior of brain tumors, which in turn assists in treatment planning and determining the appropriate course of action for patients [6].

In recent times, SVM has emerged as one of the best techniques for efficient data classification. Its ability to create optimal decision boundaries makes SVM highly effective in classifying data [8]. SVM is a supervised learning method widely used for data analysis and classification tasks. It is considered a powerful tool in these domains. SVM classifiers demonstrate fast learning speed even with large datasets. They can be employed in two or more classification problems. Performance evaluation of SVM classifiers is based on various metrics such as Specificity, Sensitivity, Precision and Accuracy, Border error and Similarity. These metrics help assess the effectiveness and accuracy of the SVM model in classifying images. [10]

SVM is regarded as one of the best algorithms in the kernel algorithm family for pattern analysis in image processing. It offers mathematical tractability, high precision and better geometric explanations, making it a preferred classification technique. SVM performs well in a variety of applications, including network categorization and image processing. It also operates well with complex algorithms involving quadratic optimization and handles a wide range of features through kernel divisibility methods.

When it comes to classifying brain tumors (BT), Support Vector Machine is a motivated choice. The algorithm's performance can be evaluated based on metrics such as specificity, accuracy, and sensitivity. These metrics provide insights into the algorithm's ability to correctly classify different types of brain tumors and its overall performance in terms of precision and accuracy [13].

2. Literature Review:

Geetanjali et. al [2] proposed a method for segmentation using k-means clustering and Otsu thresholding. In this study, images are classified using a combination of support vector machine (SVM) and gray level occurrence matrix by extracting textural-based features. The input images are obtained from the publicly available TCIA Collections dataset, as well as from a regional diagnostic center comprising 20 patient samples. The experimental results demonstrate an impressive accuracy of 98.51% in distinguishing between malignant and benign cells using SVM, The SVM classifies the brain tumour in this study into normal and pathological tissues.

Arun et. al [3] in this study, MRI images with brain tumours were taken from an online database. A machine learning model was then created using the Particle Swarm Optimisation (PSO) algorithm for feature selection, The type of tumor in the examined brain MRI images was then identified using a Support Vector Machine (SVM) classifier..

From that region, a total of 14 features were retrieved, including the texture, shape and intensity feature classes. The PSO Algorithm is then used to choose only those features out of these 14 features that aid in categorization. In the provided dataset, there are two main types of tumours - benign and malignant.

If all 14 features are included, we discover that the PSO-SVM hybrid model's classification accuracy is 95.23%, outperforming the 86.82 percent accuracy of the basic SVM classifier. Likewise, sensitivity is 100 percent and specificity is 94.8 percent.

Rasel et. al [4] this research introduces a novel approach that combines Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for tumor classification. Through filtering and preprocessing methods, the brain MRI pictures, displaying both normal and pathological behavior, are first improved. Segmentation methods, notably the modified Fuzzy C-means (TKFCM) and temper based K-means clustering algorithms, are used to detect and categories brain tumors. A dataset of brain MRI images consisting of 37 images is collected from a publicly available online repository for the classification of benign and malignant tumor stages.

In the segmentation process of the brain MRI images, two types of features are extracted: statistical features and region property-based features. The statistical features, such as correlation, contrast, entropy, energy, homogeneity are specifically utilized for classifying whether the brain region is normal or tumorous. These extracted statistical features provide as input to a Support Vector Machine classifier, which is employed to classify and differentiate between normal and tumorous brain regions based on these features. The results of merging ANN with SVM are accuracy of 97.37%, 100% specificity, sensitivity of 98%, and BER of 0.0294.

Shanata et. al [5] proposed a system which relies on second-order texture features and a Support Vector Machine classifier. Specifically, features like Energy, Homogeneity, Correlation, Entropy are extracted to build the system. The workflow consists of several steps: feature extraction as part of the preprocessing, then training the MRI images with an SVM classifier based on the extracted features. Finally, the system is tested on the SVM classifier using different kernel functions to evaluate its performance and accuracy. A total of 50 images were obtained from the "Hubli Scan Centre," of which 20 were utilized for testing and 30 were used for training. 10 of the 20 images were benign, and the remaining 10 were malignant. The linear kernel had the maximum accuracy at 80%, and it also had the highest specificity and sensitivity at 90% and 80%, respectively. With a 60% lowest accuracy rate, the quadratic kernel has the specificity and sensitivity. These numbers are 60% and 90%, respectively.

D.Najrabi et. al [7] in this study tumors are divided using classifier techniques such Linear SVM, Non-Linear SVM, and LDA. Results and studies demonstrate that nonlinear SVM with a linear SVM and quadratic kernel are superior to other approaches for tumor type detection. In this research, a total of 30 features were extracted from MRI images. The dataset consisted of 243 patients, and each patient's data included these 30 features. In the first stage of the analysis, the data was normalized to ensure consistency and remove any potential bias caused by variations in feature scales. Subsequently, using Principal Component Analysis (PCA), the dataset's dimensionality was decreased, resulting in a reduction from 30 features to 29 features. The accuracy of different classifiers for the given dataset is as follows:

- Linear SVM: 87.7%
- Nonlinear SVM with Quadratic kernel: 88.5%
- Nonlinear SVM with Cubic kernel: 88.1%
- Linear Discriminant Analysis (LDA): 88.1%

Asmita et.al [9] by using significant information, segmentation based on SVM classifier and Particle Swarm Optimization (PSO), this study propose a model to categories the infected and non-infected brain. The PSO technique is employed to extract thirteen different characteristics from the brain MRI images using Discrete Wavelet Transform (DWT)-based features. RBF Kernel and Linear SVM are used to classify infected and non-infected MRI images. The suggested model is tested on a dataset of 50 MR images, including 8 normal brain images and 42 aberrant images that are tumor images. The linear SVM had the maximum accuracy at 63% while RBF SVM had 85% accuracy.

A.C Jinisha et. al [10] this article describes unique image processing methods for identifying brain tumors in MRI images. The Bag of Visual Words (BoVW) is a popular method for representing images as a collection of local features. It involves extracting and quantizing local features to form a visual vocabulary or codebook. The BoVW approach is widely utilized in computer vision tasks such as image classification and object recognition. The brain tumor is classified using Bag of Visual Words and SVM, and performance is monitored and improved; the overall accuracy is 96% and the sensitivity is 90%.

Tonmoy et. al [11] using the Fuzzy C-Means clustering algorithm, this study suggest a technique for extracting brain tumors from 2D Magnetic Resonance Brain Images (MRI). The clustering algorithm is applied to segment the tumor region, and subsequently, traditional classifiers and convolution neural networks are employed for further analysis and classification. A real-time dataset with various tumor forms, sizes, image intensities, locations was used for the experimental study. This study used scikit-learn's implementation of six conventional classifiers: Support Vector Machine (SVM), Multilayer Perceptron (MLP), Logistic Regression, K Nearest Neighbour (KNN), Random Forest and Naive Bayes. We used six classification techniques after segmenting the tumour and extracting its features. SVM yields the best results out of all of them, with an accuracy of 92.42%.

Xu Bi et. al [12] This paper focuses on using least absolute shrinkage and selection operator (LASSO) and information gain for feature selection in combination with an SVM classifier. The goal is to analyze the classification accuracy of the selected features. SVM classifiers are trained using the extracted features, and classification models are created to assess the accuracy of the features. The best feature subset was determined using decision tree, and the residue technique was utilized to create and assess the classification model of glioma. Proposed method SVM -Information gain (Selected Features) shows 91% accuracy and SVM-LASSO (Selected Features) 87% accuracy.

Rajat et. al [13] the focus of the paper is on enhancing the performance and reducing complexity through extraction of gray-level co-occurrence matrix (GLCM) based features, noise removal, extraction, and segmentation of brain tumors (BT) using Discrete Wavelet Transform (DWT). To eliminate the noise created by segmentation, morphological techniques are used. The accuracy of BT detection is examined using a classifier that is based on Support Vector Machines (SVM). According to experimental findings, the classification accuracy is 98.87%.

B. Devanathan et. al [14] in the suggested research, for the purpose of diagnosing brain tumor, the best multilevel thresholding based on segmentation and classification of model data has been developed. To improve the quality of the image, it first does three levels of preprocessing. Image

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segmentation is then done using the multi-level threshold holding with artificial bee colony (ABC) technique. After that, a usable collection of feature vectors is extracted using the Grey Level Co-occurrence Matrix (GLCM) approach as a feature extractor. Finally, a Support Vector Machine is used to do the classification procedure. The results show that the projected model has an effective performance with a accuracy 97.56%, sensitivity 97.90%, specificity 97.91%,

S. L. Jany Shabu et. al [15] this study suggests a novel method for segmenting and classification the brain tumor. It makes use of the S2LGSVM (Sparse Representation Segmentation with 2-Level GLCM and SVM) system. The scheme integrates sparse representation segmentation, GLCM, and SVM classification. The MRI images are first pre-processed utilizing enhancement and filtration methods. The enhanced MRI data is then segmented using Sparse Representation Based Segmentation (SRBS) technique. After segmentation resulting data is utilized to extract features. For describing the segmented data, a novel 2L-GLCM feature is proposed. At the end, the collected features are classified by a support vector machine (SVM) classifier in malignant and benign categories. The suggested S2LGSVM framework attained 96.92% accuracy, 95.82% precision, 97.93% specificity.

Saqlain et. al [16] an approach based on the Bag of Features (BoF) method for feature selection is introduced in this study. In the beginning, MRI pictures are used to extract hand crafted features. Following the extraction of texture features and shape metrics, the Flexible Wavelet Transform (FWT) approach is applied to convert the MRI data into a 2D spatial image. The AlexNet model is used to extract spatial characteristics from the MRI images after the Flexible Wavelet Transform (FWT) has been applied. These features are then combined to form a single combined feature vector table (CFV), consisting of four feature vectors. To further refine the feature set, feature selection is conducted using the Bag of Features (BoF) approach.
The histograms of the features are used to evaluate them,
allowing for the selection of the most relevant and discriminative features for subsequent analysis and classification tasks. The chosen features are passed to SVM and K-Nearest Neighbour (KNN) classifiers for classification, and SVM classifier achieves the maximum precision to recognize brain tumors. The results show that the quadratic SVM has an effective performance with accuracy of 93.6%

Ragib et. al [17] this study proposes an improved approach called Spatial Fuzzy C-Means (SFCM) for brain tumor segmentation. Additionally article presents the Quadratic Support Vector Machine (QSVM) for the categorization of tumour types, providing an effective and robust classification model for differentiating tumor types based on the segmented regions. The results show that the quadratic SVM has an effective performance with accuracy of 83.9%.

Sanjay et. al [18] The paper incorporates a feature extraction and selection process that utilizes statistical features from both unsegmented and segmented images. These features are combined to form a hybrid feature set, which encompasses the relevant characteristics from both types of images. These hybrid characteristics are used to construct the SVM classifier model. For classifying brain tumors into one of the two groups, benign and malignant, the SVM is represented as a non-linear classifier using several kernel functions, including linear, RBF, quadratic. 26 features, 13 of which are local and other 13 are recruited from GLCM and used in training. The approach produces a maximum accuracy of 95%, thus the experimental findings are very positive.

Ms. Swati Jayade et.al [19] based on MRI imaging, the research suggests categorizing tumors into two categories: malignant and benign. To extract pertinent characteristics from the data, the Grey Level Co-occurrence Matrix (GLCM) feature extraction approach is used. Using GLCM, the feature dataset is prepared, containing the extracted features that capture the relationships between pixel intensities in the image. Some issues with non-linear and complex applications are shown by SVM. In certain situations, the classification accuracy is poor, and selecting the best kernel function might be challenging. By merging SVM and the K-nearest neighbour (KNN) classifier, a variant of the SVM classifying approach is put forth to address these problems. The suggested hybrid classifier SVM-KNN performs well; its accuracy is 94.13%, which is higher than that of existing approaches.

Manu Gupta et.al [20] in this study, a new and innovative collection of features extracted from medical data without the need for invasive procedures is suggested for the diagnosis of brain tumors and the grading of those tumors using magnetic resonance imaging (MRI). A precise and efficient tumor diagnosis and classification based on tumor grades is made possible by the feature set, which is created to capture key properties from the MRI data. To differentiate between low-grade (LG) and high-grade (HG) brain tumors, texture features were extracted using segmentation-based fractal texture analysis (SFTA) and selected shape metrics from the segmented tumor volume. Support vector machine classifier is used to classify the tumor grade, and testing and training datasets are created using the k-fold cross-validation approach. By locating an ideal hyper-plane, the input data of an SVM classifier is divided into two distinct classes with accuracy, specificity, sensitivity of 87%, 88%, 86% respectively.

Ashfaq Hussain et.al [21] the approach for locating the tumor region employing morphological operation for watershed segmentation technique and skull stripping has been done in the suggested study. The four GLCM properties of these images— correlation, contrast, homogeneity, energy are then calculated. The support vector machine (SVM) classifier is then used to classify these images in the subsequent phase, with an average classification accuracy of 93.5 percent. All six support vector machine (SVM) classifiers were utilized in the suggested research.

Uswatun Hasanah et.al [22] the methodology includes the following steps: pre-processing, which involves applying median filters to the images to reduce noise, is followed by skull stripping, which clears non celebral tissues from MRI scans. In order to do image segmentation, threshold is used.

Statistical First order features taken from the histogram of the image are used to extract from the discovered tumor, and the GLCM is a statistical method that quantifies the relationship between pixel intensities at different spatial locations in an image used to extract second order features. The classification of brain images using SVM based algorithms is the focus of this study. The system classified pituitary, meningiomas, gliomas tumors with a accuracy, precision, sensitivity, specificity of 95,83%, 94,08%, 93,33%, 96,87% based on the results of tests conducted on 48 dates.

Hareem Kibriya et. al [23] this study investigates deep learning (DL) and machine learning (ML) approaches for multiclass brain tumor classification. Using end-to-end CNN models, notably ResNet-18 and GoogLeNet, brain MRI images are categorized in the first stage. Additionally, the deep features extracted from the CNN models (ResNet-18 and GoogLeNet) are further classified using a SVM. The proposed method is evaluated using three evaluation metrics: accuracy, sensitivity, and specificity. Among the CNN architectures tested, ResNet-18 achieved the highest accuracy of 97.8%. However, when combining the ResNet-18 with the SVM classifier, the accuracy improved to 98%.

Satti Harichandra et. al [24] In this study, we offer a machine learning technique for differentiating and classifying tumorous and non-tumorous regions in a cerebrum MRI dataset. The dynamic growth is then portioned using the chan-vese technique by picking an exact beginning position. The elements of the cancer area are extracted using the GLCM in the very next stage, and after that, key quantifiable highlights were chosen. The SVM is finally used to implement a two-class classifier, and KNN is used to approve its presentation. The recreation findings show that the suggested framework performs more accurately and efficiently than the present methodologies.

3. Conclusion:

Using supervised machine learning, Support Vector Machine (SVM) is a method for classifying data. It defines decision boundaries to separate data points of different classes. SVM can also be applied for image segmentation, where it separates regions of interest from the background based on specific features, enabling efficient and accurate image analysis. Brain tumor segmentation using SVM involves training the SVM classifier on labeled MRI images with tumor and non-tumor regions. The trained SVM model is then applied to new MRI scans to identify and delineate tumor regions from the rest of the brain, facilitating precise and automated tumor segmentation. Finally, we reviewed the paper using a number of segmentation and classification algorithms.

REFERENCE:

[1] Qiyu Wang, "Support Vector Machine Algorithm in Machine Learning", IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA-2022): 750-756

[2] GEETANJALI BIRARE; V. A CHAKKARWAR, "AUTOMATED DETECTION OF BRAIN TUMOR CELLS USING SUPPORT VECTOR MACHINE", 9TH INTERNATIONAL CONFERENCE ON COMPUTING, COMMUNICATION AND NETWORKING TECHNOLOGIES (ICCCNT-2018): 1-4

[3] Arun Kumar, Alaknanda Ashok, M.A.Ansari, "Brain Tumor Classification Using Hybrid Model Of PSO And SVM Classifier", International Conference on Advances in Computing, Communication Control and Networking (ICACCCN-2018): 1022-1026

[4] Rasel Ahmmed , Anirban Sen Swakshar, Md. Foisal Hossain, Md. Abdur Rafiq, "Classification of Tumors and It Stages in Brain MRI Using Support Vector Machine and Artificial Neural Network", International Conference on Electrical, Computer and Communication Engineering (ECCE), February 16-18, 2017: 229-234

[5] Shanata Giraddi, S V Vaishnavi, "Detection of Brain Tumor using Image Classification", International Conference on Current Trends in Computer, Electrical, Electronics and Communication (ICCTCEEC-2017): 640-644.

[6] M. H. O. Rashid, M. A. Mamun, M. A. Hossain and M. P. Uddin, "Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images", International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2) 2018: 1-4

[7] D.Najrabi, M.Hamghalam, A.Ayatollahi, "Diagnosis of Astrocytoma and Globalastom Using Machine Vision", Diagnosis of Astrocytoma and Globalastom Using Machine Vision – 2018: 152-155

[8] R.Vinoth, Chunchu Venkatesh, "Segmentation and Detection of Tumor in MRI images Using CNN and SVM Classification", Proc. IEEE Conference on Emerging Devices and Smart Systems (ICEDSS 2018): 21-25.

[9] Asmita Dixit, Aparajita Nanda, "Brain MR Image Classification via PSO based Segmentation", 2019 Twelfth International Conference on Contemporary Computing (IC3) - 2019: 1-5

[10] A.C Jinisha, Dr. T.S Siva Rani, "Brain Tumor Classification using SVM and Bag of Visual Word classifier", 2019 International Conference on Recent Advances in Energy-efficient Computing and Communication (ICRAECC) – 2019: 1-6

[11] Tonmoy Hossain, Fairuz Shadmani Shishir , Mohsena Ashraf, "Brain Tumor Detection Using Convolutional Neural Network", 1st International Conference on Advances in Science, Engineering and Robotics Technology 2019 (ICASERT) – 2019: 1-6

[12] Xu Bi, Jin Gen Liu, Ying Shan Cao, "Classification of Low-grade and High-grade Glioma using Multiparametric Radiomics Model", 2019 IEEE 3rd Information Technology, Networking, Electronic and

Automation Control Conference (ITNEC) – 2019: 574-577

[13] Rajat Mehrotra, M.A. Ansari, Rajeev Agrawal, "A Novel Scheme for Detection & Feature Extraction of Brain Tumor by Magnetic Resonance Modality Using DWT & SVM", 2020 International Conference on Contemporary Computing and Applications (IC3A) Dr. A.P.J. Abdul Kalam Technical University, Lucknow. Feb 05-07, 2020: 225-230

[14] B. Devanathan, Dr. K. Venkatachalapathy, "An Optimal Multilevel Thresholding based Segmentation and Classification Model for Brain Tumor Diagnosis", Fourth International Conference on Electronics, Communication and Aerospace Technology (ICECA-2020): 1133-1138

[15] S. L. Jany Shabu, Dr. C. Jayakuma, "Brain Tumor Classification with MRI Brain Images Using 2-Level GLCM Features and Sparse Representation based Segmentation", Third International Conference on Intelligent Sustainable Systems [ICISS 2020] IEEE Xplore Part Number: CFP20M19-ART; ISBN: 978-1-7281-7089-3: 794-799

[16] Saqlain Razzaq, Nimra Mubeen, Urwah Kiran, Muhammad Adeel Asghar, Fawad "Brain Tumor Detection from MRI Images Using Bag Of Features And Deep Neural Network", 2020 International Symposium on Recent Advances in Electrical Engineering & Computer Sciences (RAEE & CS): 1-6

[17] Ragib Shahariar Ayon, Jannatul Robaiat Mou, Sharafat Hossain Majed, Rathyatul Rifat, "Brain Tumor Segmentation and Classification usingSpatial Fuzzy C mean and Quadratic SupportVector Machine", 2019 3rd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE): 233-236.

[18] Sanjay Kumar C K, Dr. H. D. Phaneendra, "Categorization of Brain Tumors using SVM with Hybridized Local-Global Features", Fourth International Conference on Computing Methodologies and Communication (ICCMC 2020): 311-314.

[19] Ms. Swati Jayade, Dr. D. T. Ingole, Prof. Mrs Manik D. Ingole, "MRI Brain Tumor Classification using Hybrid Classifier", 2019 International Conference on Innovative Trends and Advances in Engineering and Technology (ICITAET): 201-205

[20] Manu Gupta, K.Sasidhar, "Non-invasive Brain Tumor Detection using Magnetic Resonance Imaging based Fractal Texture Features and Shape Measures", 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE2020), 07-08 February 2020: 93-97.

[21] Ashfaq Hussain, Ajay Khunteta, "Semantic Segmentation of Brain Tumor from MRI Images and SVM Classification using GLCM Features", Second International Conference on Inventive Research in Computing Applications (ICIRCA-2020): 38-43

[22] Uswatun Hasanah, Riyanto Sigit, Tri Harsono, "Classification of Brain Tumor on Magnetic Resonance Imaging Using Support Vector Machine", 2021 International Electronics Symposium (IES) | 978-1-6654-4346-3/21/$31.00 ©2021 IEEE | DOI: 10.1109/IES53407.2021.9594004: 257 - 262

[23] Hareem Kibriya , Momina Masood , Marriam Nawaz, Rimsha Rafique, Safia Rehman, "Multiclass Brain Tumor Classification Using Convolutional Neural Network and Support Vector Machine", 2021 Mohammad Ali Jinnah University International Conference on Computing (MAJICC) | 978-1-6654-2413-4/21/$31.00 ©2021 IEEE | DOI: 10.1109/MAJICC53071.2021.9526262: 1 – 4

[24] Satti Harichandra Prasad, Jyothirmai Gandeti, B.S.Sridevi, M.Neeladri, G. Ajay Sankar, K.Pavani, "Execution Analysis of Machine Learning Technique Based Detection and Classification of Brain Tumor from MRI images", 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) | 978-1-6654-3647-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICEEICT53079. 2022.976859: 1-4

Table 1: Tabulation of Literature review

Paper	Author	Year	Paper	Method	Parameters	Size of Sample
[2]	Geetanjali Birare; V. A Chakkarwar	2018	Automated Detection of Brain Tumor Cells Using Support Vector Machine	SVM	Accuracy	30 cancerous 30 non-cancerous tissues
[3]	Arun Kumar, Alaknanda Ashok, M.A.Ansari	2018	Brain Tumor Classification Using Hybrid Model Of PSO And SVM	Simple SVM and PSO-SVM	Accuracy, Specificity, Sensitivity	354 brain MRI images - online database BRATS-

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

			Classifier			2015
[4]	Ahmmed , Anirban Sen Swakshar, Md. Foisal Hossain, Md. Abdur Rafiq	2017	Classification of Tumors and It Stages in Brain MRI Using Support Vector Machine and Artificial Neural Network	ANN-SVM	Accuracy, Specificity, Sensitivity	46 images - tumor images are 37, normal brain images are 8 and 1 misclassified.
[5]	] Shanata Giraddi, S V Vaishnavi	2017	Detection of Brain Tumor using Image Classification	Linear kernel SVM	Accuracy, Specificity, Sensitivity	50 images were acquired, 30 images were used for training and 20 images for testing. In the 20 images,10 images were Benign and other 10 10 was Malignant.
[7]	D.Najrabi, M.Hamghalam, A.Ayatollahi	2018	Diagnosis of Astrocytoma and Globalastom Using Machine Vision	Linear SVM Quadratic SVM Cubic SVM LDA	Accuracy	27 patients belong to the TCIA center
[9]	Asmita Dixit, Aparajita Nanda	2019	Brain MR Image Classification via PSO based Segmentation	Linear SVM RBF SVM	Accuracy	The 50 brain MR images have 42 abnormal images that are tumor affected images and 8 normal brain images
[10]	A.C Jinisha, Dr. T.S Siva Rani	2019	Brain Tumor Classification using SVM and Bag of Visual Word classifier	SVM and Bag of Visual Word classifier	Accuracy, Specificity, Sensitivity	Data set consists of 80 set of images
[11]	Tonmoy Hossain, Fairuz Shadmani Shishir , Mohsena Ashraf	2019	Tumor Detection Using Convolutional Neural Network	Six classifiers - Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes and Random Forest which was implemented in scikit-learn.	Accuracy, Recall, Specificity, Precision, Dice score, Jaccard Index	187 and 30 MRI Images containing tumor and non-tumor respectively classified as class-1 and class-0

[12]	Xu Bi, Jin Gen Liu, Ying Shan Cao	2019	Classification of Low-grade and High-grade Glioma using Multiparametric Radiomics Model		AUC, Accuracy, Specificity, Sensitivity	60 patients, 27 low-grade gliomas, 33 high-grade gliomas.
[13]	Rajat Mehrotra, M.A. Ansari, Rajeev Agrawal	2020	A Novel Scheme for Detection & Feature Extraction of Brain Tumor by Magnetic Resonance Modality Using DWT & SVM	DWT +PCA + GLCM+ SVM	Accuracy	150 images
[14]	B. Devanathan, Dr. K. Venkatachalapathy	2020	An Optimal Multilevel Thresholding based Segmentation and Classification Model for Brain Tumor Diagnosis	ABC+GLCM+SVM	Accuracy, Specificity, Sensitivity	set of 98 normal class images and 155 tumor images
[15]	S. L. Jany Shabu, Dr. C. Jayakuma	2020	Brain Tumor Classification with MRI Brain Images Using 2-Level GLCM Features and Sparse Representation based Segmentation	S2LGSVM framework	Accuracy, Specificity, Precision	Open Access Series of Imaging Studies (OASIS) dataset that consists of 416 sample with ages varying from 18 to 96
[16]	Saqlain Razzaq, Nimra Mubeen, Urwah Kiran, Muhammad Adeel Asghar, Fawad	2020	Brain Tumor Detection From MRI Images Using Bag Of Features And Deep Neural Network	Quadratic SVM	Accuracy, Recall, Precision, F-score	2951 Images from Kaggle
[17]	Ragib Shahariar Ayon, Jannatul Robaiat Mou, Sharafat Hossain Majed, Rathyatul Rifat	2019	Brain Tumor Segmentation and Classification using Spatial Fuzzy C mean and Quadratic Support Vector Machine	Quadratic SVM	Accuracy	BraTS 2018 dataset – 20 images
[18]	Sanjay Kumar C K, Dr. H. D. Phaneendra	2020	Categorization of Brain Tumors using SVM with Hybridized Local-Global Features	Linear SVM Quadratic SVM RBF SVM Polynomial SVM	Accuracy	-
[19]	Ms. Swati Jayade, Dr. D. T. Ingole, Prof. Mrs Manik D. Ingole	2019	MRI Brain Tumor Classification using Hybrid Classifier	Hybrid classifier SVM-KNN	Accuracy	BRATS 2012 benchmark dataset

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

[20]	Manu Gupta, K.Sasidhar	2020	Non-invasive Brain Tumor Detection using Magnetic Resonance Imaging based Fractal Texture Features and Shape Measures	5-fold cross-validation SVM	Accuracy, Specificity, Sensitivity	15 brain tumor patients from MICCAI 2012 Challenge database
[21]	Ashfaq Hussain, Ajay Khunteta	2020	Semantic Segmentation of Brain Tumor from MRI Images and SVM Classification using GLCM Features	Linear SVM classification Quadratic SVM classification Cubic SVM classification Fine Gaussian SVM classification Medium Gaussian SVM classification Coarse Gaussian SVM classification	Accuracy	62 Images
[22]	Uswatun Hasanah, Riyanto Sigit, Tri Harsono	2021	Classification of Brain Tumor on Magnetic Resonance Imaging Using Support Vector Machine	GLCM with SVM	Accuracy, Specificity, Sensitivity, Precision	T1-weighted CE-MRI image obtained through an online dataset
[23]	Hareem Kibriya, Momina Masood, Marriam Nawaz, Rimsha Rafique, Safia Rehman	2021	Multiclass Brain Tumor Classification Using Convolutional Neural Network and Support Vector Machine	ResNet-18 + SVM, GoogLeNet + SVM	Accuracy, Precision, Recall	Figshare dataset that contains 3064 brain MRI images of 233 patients
[24]	Satti Harichandra Prasad, Jyothirmai Gandeti, B.S.Sridevi, M.Neeladri, G. Ajay Sankar, K.Pavani	2022	Execution Analysis of Machine Learning Technique Based Detection and Classification of Brain Tumor from MRI images	SVM	Accuracy, Specificity, Sensitivity, Precision	BRATS 2017 benchmark dataset

Table 2: Comparative Analysis of existing methods in terms of their Performance indicators

Paper	Method	Accuracy	Sensitivity/ Recall	Specificity	Precision	Dice score	Error rate	F1 score
[2]	SVM	98.51%	-	-	-	-	-	-
[3]	Simple SVM	86.82%	-	-	-	-	-	-
[3]	PSO-SVM	95.23%	100 %	94.8 %	-	-	-	-

[4]	ANN-SVM	97.37%	98%	100%	-	-	BER-0.0294	-
[5]	Linear kernel SVM	80%	80%	90%	-	-	-	-
[7]	Linear SVM	87.7	-	-	-	-	-	-
[7]	Quadratic SVM	88.5	-	-	-	-	-	-
[7]	Cubic SVM	88.1	-	-	-	-	-	-
[7]	LDA	88.1	-	-	-	-	-	-
[9]	Linear SVM	63%	-	-	-	-	-	-
[9]	RBF SVM	85%	-	-	-	-	-	-
[10]	SVM and Bag of Visual Word classifier	95%	90%	100%	-	-	-	-
[11]	SVM	92.42%	98.3%	42.8%	-	95.9%	-	-
[12]	SVM – All features	72.5%	80%	-	-	-	-	-
[12]	SVM - Information gain	91%	96%	85%	-	-	-	-
[12]	SVM-LASSO	87%	89%	90%	-	-	-	-
[13]	DWT +PCA + GLCM+ SVM	98.87%	-	-	-	-	-	-
[14]	SVM Classification	97.56%	97.90%	97.91%	-	-	-	-
[15]	S2LGSVM framework	96.92%	-	97.93%	95.82%	-	-	-
[16]	Quadratic SVM	93.6%	94%		91%			91%
[17]	Quadratic SVM	83.3%	-	-	-	-	-	-
[18]	Linear SVM	94%	-	-	-	-	-	-
[18]	Quadratic SVM	89%	-	-	-	-	-	-
[18]	RBF SVM	95%	-	-	-	-	-	-
[18]	Polynomial SVM	94%	-	-	-	-	-	-
[19]	Hybrid classifier SVM-KNN	94.13%	-	-	-	-	-	-
[20]	5-fold cross-validation SVM	87%	88%	86%	-	-	-	-
[21]	Linear SVM	97.2%	-	-	-	-	-	-
[21]	Quadratic SVM	97.2%	-	-	-	-	-	-

[21]	Cubic SVM	94.4%	-	-	-	-	-	-
[21]	Fine Gaussian SVM	86.1%	-	-	-	-	-	-
[21]	Medium Gaussian SVM	91.7%	-	-	-	-	-	-
[21]	Coarse Gaussian SVM	91.7%	-	-	-	-	-	-
[22]	GLCM with SVM	95.83%	93.33%	96.87%	94.03%			
[23]	ResNet-18 + SVM	98%	98%		98.3%			
[23]	GoogLeNet + SVM	97.6%	97.3%		97.3%			
[24]	SVM	98.43%	98.74%	87.52%	95.31%			