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Brief Review for Multi-Class Brain Tumor Diseases Schemes Using Machine Learning Techniques

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Keywords: Tumor Diseases, Feature Extraction, Machine Learning.

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Abstract:

Brain tumor diseases have had a considerable impact worldwide, affecting millions of individuals of different age groups, including both children and adults above 20 years old. Because they are more needed in people's lives, using the method-based classifying of brain tumors by machine learning schemes has become necessary. However, healthcare applications face challenges in identifying the most suitable classification-based metric, such as accuracy, due to the utilization of recent datasets. This study omits the aim to provide a thorough evaluation of computational intelligence strategies used in tumor diagnosis. Several successful data mining techniques have been implemented, including wavelet analysis and spatial pixel modulation techniques. Furthermore, feature extraction and reduction techniques, such as the Grey Level Co-occurrence Matrix (GLCM), have been used to prepare the features for classification. Magnetic resonance imaging scan (MRI) is frequently utilized for the diagnosis of brain tumor diseases which is highly applied for classification-based machine learning. The review paper was focused on gliomas, meningiomas, and pituitary adenoma diseases. Technically, the usage of kernel principal component KPCA analysis with the proposed adaptive back propagation neural network scheme produced better performance-based classification metrics, (i.e:99.84%) for the accuracy metric. The aforementioned review articles have demonstrated that usage of the machine learning-based health care applications (brain diseases) classification widely assists the patient's outcome and operations inside the hospitals. In summary, the paper has highlighted the importance of machine learning schemes for brain tumor detection and classification, and it also provided a comprehensive analysis and comparison of the state-of-the-art to show the methods such as ;(feature extraction, feature reduction), pros, cons, and the contributions for each of them. The paper's results are considered an advantageous starting point for future works.

Keywords: Tumor Diseases, Feature Extraction, Machine Learning.

مراجعة مختصرة لأنظمة أمراض الأورام الدماغية متعددة الفئات باستخدام تقنيات التعلم الآلي

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الخلاصة:

تُعتبر أمراض الأورام الدماغية من الأمراض التي لها تأثير كبير على مستوى العالم، حيث تؤثر على ملايين الأفراد من مختلف الفئات العمرية، بما في ذلك الأطفال والبالغين فوق سن العشرين. نظرًا لأهميتها البالغة في حياة الناس، أصبح استخدام طرق التصنيف بواسطة تقنيات التعلم الآلي ضروريًا. ومع ذلك، تواجه التطبيقات الصحية تحديات في تحديد المقياس المناسب للتصنيف، مثل الدقة، بسبب استخدام مجموعات بيانات حديثة. تهدف هذه الورقة البحثية إلى تقديم تقييم شامل لاستراتيجيات الذكاء الحسابي المستخدمة في تشخيص الأورام. تم تنفيذ عدة تقنيات تعدين بيانات ناجحة، بما في ذلك تحليل المويجات وتقنيات تعديل بكسل المكاني. علاوة على ذلك، تم استخدام تقنيات استخراج وتقليص السمات، مثل مصفوفة التواجد المستوى الرمادي (*GLCM*)، لإعداد السمات للتصنيف. تُستخدم صور الرنين المغناطيسي (*MRI*) بشكل متكرر لتشخيص أمراض الأورام الدماغية والتي يتم تطبيقها بشكل كبير للتصنيف القائم على التعلم الآلي. ركزت الورقة الاستعراضية على أمراض الأورام الدبقية والأورام السحائية والأورام النخامية. من الناحية التقنية، أدى استخدام تحليل المكون الرئيسي بالنواة *KPCA* مع مخطط شبكة العصبونات الارتجاعية التكيفية المقترح إلى إنتاج أداء أفضل لمقاييس التصنيف، (أي: ٩٩,٨٤٪) لمقياس الدقة. أظهرت المقالات الاستعراضية المذكورة أن استخدام تطبيقات الرعاية الصحية المستندة إلى التعلم الآلي (أمراض الدماغ) يساعد على نطاق واسع في نتائج وعمليات المرضى داخل المستشفيات. وباختصار، أبرزت الورقة أهمية أنظمة التعلم الآلي للكشف عن الأورام الدماغية وتصنيفها، وقدمت أيضًا تحليلاً شاملاً ومقارنة لأحدث الطرق لعرض الأساليب مثل؛ (استخراج السمات، تقليص السمات)، والمزايا والعيوب والمساهمات لكل منها. تُعتبر نتائج الورقة نقطة انطلاق مفيدة للأعمال المستقبلية.

الكلمات المفتاحية: أمراض الأورام الدماغية، استخراج الميزات، التعلم الآلي.

1. Introduction:

Imaging technology is used by the medical specialty of radiology for both diagnostic and interventional procedures [1]. Glial cells, which surround and support the brain's neurons, are the source of gliomas, a particular kind of tumor. The meninges, which are the membranes that wrap the outer regions of the brain and spinal cord, are the source of meningioma, a tumor that arises from them [2]. Tumors can differ in kind and size, and their location frequently reveals information about their form and rate of growth. Visual diagnosis of brain tumors and associated disorders such as blood channel abnormalities, stroke, brain traumas, aberrant brain development, and brain hemorrhage is greatly aided by medical imaging techniques. Common types of brain scans include computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission (SPECT) scans [3,4,5,6,7,8,9,10].

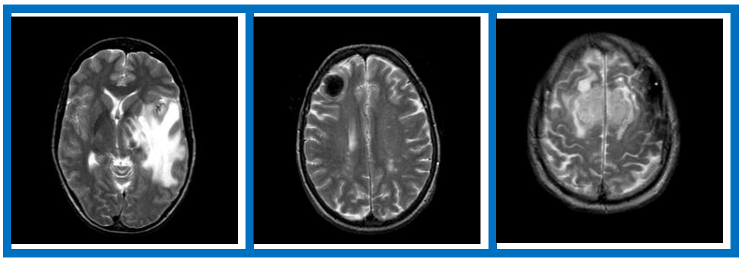

Figure 1: Examples of MRI human brain diseases [40].

MRI scan images have been used for the classification of different human brain diseases such as stroke, tumors, and precision. The paper has used the tumor classification based on different tumor types such as benign, malignant, and grade. Different methods have been introduced earlier such as in [12]. The segmentation-based spatial domain was used before to segment the MRI scan and identify the types of diseases. For the process of classification-based brain disease schemes, segmentation is not usually mandatory.

Table 1: Comparison of imaging techniques CT, MRI, PET, and SPECT in the human brain diseases

Modalities	Mechanism	Spatial Resolution (mm)	Function	Imaging period (min)	Diseases
MRI	Magnetism	0.1	Anatomical details: Tissues details: Dead vs risk tissues	60	Stroke, tumor, depression, and AD
CT	Radiation dose	0.05	Anatomical details: Boundary: Cortex	10-15	Stroke, depression, and schizophrenia
PET	Nuclear medicine tools: Radioisotopes: Using the positrons Injected	1-2	Show physiological processes.: Glucose metabolism and blood-flow	20-60	Transition from MCI to AD, depression, and schizophrenia
SPECT	Nuclear medicine tools: Radioisotopes injected: Using gamma-ray	0.5-2	Show physiological processes.: Blood flow	30-90	Transition from MCI to AD, depression, and schizophrenia

So, segmentation is considered today as a pre-processing stage before going to the current technology of artificial intelligence methods such as machine learning, transfer learning, and deep learning schemes. **Figures 1** and **2** explore the brain tumor classification which is divided into three stages.

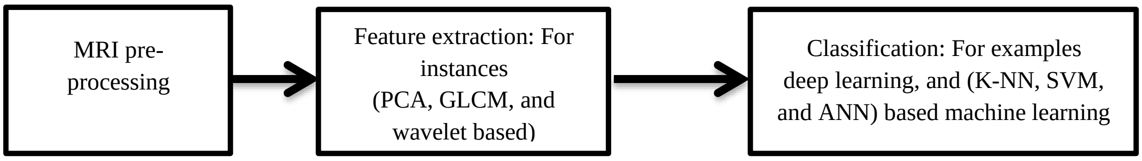

Figure 2. Overall block diagram of brain tumor classification [14].

Before the feature extraction phase, image preprocessing is conducted to enhance the quality of the image through techniques like filtration and resolution enhancement **[13]**. In the context of brain MR image classification, the preprocessing step may or may not include a segmentation phase **[14]**. Feature extraction included stages of reducing the size of the dimensionality of the data by using the extraction of important features such as shape, texture, intensity, and statistics. However, processing the entire image data for classification can be computationally intensive and time-consuming **[14]**.

Therefore, feature selection, also known as dimension reduction, is employed to further reduce the dimensionality of the feature vector. PCA and LDA have been used to reduce the dimension in the classification of brain tumors **[23,24]**. To highly provide the minimizing of the feature vectors with improved classification accuracy, a proposed SVM-based recursive feature extraction of important, modified genetic scheme (GA), and the simulated annealing scheme (SA) are also proposed in **[17,22,27,28]**. According to the science of image processing and computer vision based using machine learning, the usage of MRI scan has been used to better decide the typical diseases in the brain MRI from the normal to fatal cases **[24,28]**, which the most common machine learning schemes such as SVM, Random forest RF, neural network NN, and K-nearest neighbor KNN **[31]**.

The self-organizing map neural network, or SOM-NN, is a clustering-based unsupervised classification method. **[11, 16, 17, 21, 23, 23]**. Add to that, artificial neural networks ANN and KNN schemes have been proposed using the MRI scan which used the supervised techniques to classify the MRI into various classes that used the modified hyperplanes and binary classification while the kernel-based Gaussian has been used for complex datasets for more than one class **[11,12,30,31]**. For the classification of brain tumors, ensemble classifiers built on SVM can also be used **[34]**.

1.1 Research Limitations: Different scholars have tried to provide the optimal approaches for image classification of brain tumors. Based on current papers, it is evident that machine learning-based feature extraction and reduction models exhibit acceptable outcomes. However, it should be recorded that there are different issues to perform better results in both AI-based-research and clinical issues such as:

1- The visual quality of medical imaging: for instance, the low contrast of MRI images may lead to a struggle classification of the tumor location and the normal brain tissue [23].

2- Boundary location of tumor diseases [3].

3- Imbalance problem: for instance; The big region of interest (ROI) of a large tumor may have a full impact on the retrieved characteristics, and that affects data-driven-based ML methods [9].

1.2 Research Questions: The best way to the most essential parts of a review paper is to propose various research questions. This is due to the questions can assist and estimate the accurate scope of the literature review. We can summarize various research questions as follows:

RQ1: Currently, which schemes are currently thought to be the most effective for classifying brain tumors?

RQ2: What is the relation between feature extraction, and reduction methods and performance-based classification metrics such as accuracy?

RQ3: How can the machine learning model improve diagnostic processes, which leads to more preserving imaging details?

RQ4: Does the number of samples affect the classification outcome?

The objective of the paper is to provide a comprehensive comparison to review various classification methods for multi-class tumor brain disease-based machine learning schemes. The comparison involves different feature extraction and selection techniques along with classifier tools such as SVM, Import Vector Machine, KNN, and Random Forest. The main metrics for comparison among recent papers are classification accuracy, f1- score, true positive, and true negative. The paper is organized as follows: Section 2 discusses related works, Section 3 explains the proposed methodology, and Section 4 provides a detailed analysis and discussion. The conclusion and future works of the paper are presented in the final section.

2. Literature Review

2.1. Scope of this Review: In this paper, the review's findings from various scholarly articles have been summarized from good scientific databases like Springer, IEEE Digital Library, Elsevier, and Wiley. To ensure the preservation of good research results in human brain-based medical imaging, the paper reviewed the proceedings as well of best reputation conferences from different raspatories.

2.2 Review the Recent Studies: Recent studies have focused on tumor classification in image and computer vision applications. Several methodologies have been proposed for brain tumor detection and classification using various techniques [9].

In one study [36], a multi-stage approach was introduced for tumor detection. The method involved glioma and meningioma classification, followed by segmentation. The brain MRI classification process uses KNN, a straightforward supervised learning algorithm, which operates on the tenet that related objects are closer to one another [30] [33]. For binary classification, supervised SVM is frequently utilized by creating hyperplanes; for more complicated datasets, kernel approaches such as the Gaussian kernel are used [11] [12]. SVM-based ensemble classifiers can also be used to classify brain tumors [34].

An automated technique for identifying brain tumors in MRI images was published in a different study [37]. The technique used a gray-level co-occurrence matrix (GLCM) for feature extraction and mean filtering for image improvement. Referring to the process of selection of the important features, probabilistic NN (PNN), and KNN schemes have been suggested while the classification-based modified GA is used. In [38], the article has produced a novel scheme that uses the spatial fuzzy c-mean FCM and the modified morphological operation for furthered noise reduction, while the PCA for feature extraction and reduction is applied. For classification, a non-linear kernel support vector machine (SVM) was used.

In [39], an ensemble learning technique for classifying brain tumors was presented. Pre-processing, feature extraction, feature selection, and classification were all part of the procedure. During the pre-processing stage, methods for normalization and quantization were applied, as well as the region of interest (ROI) of the lesion and tumor. The majority voting method was used for prediction, and the basis learner was a support vector machine (SVM) classifier.

For the classification of stroke diseases, a unique plan known as the Pathological Stroke Classification System (PSCS) was presented in [40]. Weighted local energy-based principal component analysis (WLEPCA) was utilized for feature reduction and selection, while non-subsampled shear let transform (NSST) was utilized for feature extraction. KNN, RF, and SVM classifiers were used for the classification; RF achieved the highest accuracy of 96.10%. Several local binary patterns (LBP) techniques were applied in [41] to classify typical forms of brain tumors. Three types of local binary patterns were used: classical LBP, local binary patterns between relations between neighbors (n LBP), and local binary patterns based on angles (α LBP). KNN, ANN, RF, A1DE, and LDA methods were used to do the classification; the n LBP d=1 feature extraction approach and KNN model achieved the greatest success rate of 95.56%. According to the article proposed in **[42]**, the ant colony and thresholding for feature extraction and modified SVM performed higher accuracy compared to the state of arts (i.e. accuracy=97.7%) for brain tumor classification. Also, in **[43]**, the modified SVM for brain tumor classification is introduced. The contribution of the paper is to reduce the number of feature vectors used to feed to the classifier, the role given to the GA for the feature selection process, and the number of vectors used.

In **[44]**, the dataset with MRI-T1 has been used, and the GLCM, intensity histogram (IH), and a bag of word schemes are introduced for feature extraction. The feature selection-based linear discriminant analysis LDA. The method outperforms the previous works with (accuracy =91.14%) by SVM classification of brain tumors. While in **[45]**, the author has recorded good classification-based metric (i.e; accuracy=85.70%) using the SVM scheme, the proposed method segmented the MRI images to level 3 wavelet (using DWT) for feature extraction, while localized region-active contour LRBAC for feature selection.

In **[46]**, the article has shown better performance-based accuracy metric (i.e., accuracy =95.65%), the method used the GLCM feature extraction using MRI-T2 dataset, the SVM and RF-based kernel are used as classifiers to classify the brain tumors.

A method to detect brain tumors and extract features from MRI pictures was introduced in **[47]**. Anisotropic diffusion filtering and greyscale conversion were two pre-processing procedures. The Chan-Vese algorithm and multi-level thresholding were used for tumor segmentation. A genetic algorithm (GA) was used to pick characteristics after a variety of texture, statistical, and wavelet features were measured. The classification accuracy of an artificial neural network (ANN) was 98.3%.

Differentiating benign and malignant brain tumors was addressed in **[48]**. DWT was used for the process of the extraction of important features, a genetic algorithm for the process of the reduction of unnecessary features, and SVM for classification. The method achieved high accuracy, although the root mean square error (RMS) was noted as a limitation.

Table 2: The recent works of multi-class brain diseases

Author	Modality	Brian disease	Feature extraction	Feature selection& reduction	Classification Based-methods	Accuracy (%)
G. B. et al. [36]	MRI	Normal , glioma, meningioma	GLCM, GLRLM	NA	RF	87.62%
Azawi et al. [37]	MRI	Normal, Lymphoma, Cystic oligodendro glioma, Glioblastoma multiform, Meningioma, Ependymoma, and Anaplastic astrocytoma	GLCM	K-NN, GA	PNNA	100% when 45^0 97.14% when 90^0 98.57% when $135^0, 0^0$
Devkota et al. [38]	MRI	Normal ,glioma, metastatic adenocarcinoma, meningioma and Sarcoma	GLCM	PCA	SVM	92%
Shafi et al. [39]	MRI	Normal, glioma, meningioma, pituitary adenoma multiple sclerosis	GLCM, GLIRM, GLSZM and NGTDM.	Relevance measures based on information gain. The concept of entropy is used in information gain to rank the feature.	SVM	97.95%
Yousif et al. [40]	Fused images (CT/MRI)	(1) Acute stroke (speech arrest), (2) acute stroke (writes, but cannot read, alexia without agraphia), (3) acute stroke (trouble speaking), (4) fatal stroke, (5) hypertensive encephalopathy, and (6) multiple embolic infarctions.	NSST	WLEPCA	KNN, SVM, and RF.	96.10%
Kaplan et al. [41]	MRI	Normal, glioma, meningioma, and pituitary	nLBP, αLBP, LBP	correlation-based method	KNN	95.56%.
Hussain et al. [42]	MRI	Normal, malignant, and benign	LBP, HOG,SFTA	PCA	SVM	94.7٠%
Tajik et al. [43]	MRI	Normal, glioma, visual agnosia and meningioma	GLCM+DWT	GA	SVM, K-NN	96.67%
Chang et al. [44]	T1-weighted MRI.	meningioma, glioma, and pituitary	GLCM, and BOW	LDA	SVM	91.28%
Zia et al. [45]	MRI	Normal, Grade II glioma Grade III glioma Grade IV glioma	DWT	PCA	SVM	88.26%
Kharrat et al. [46]	T2-weighted MRI	Normal, malignant, and benign	2D Wavelet Transform and spatial gray level dependence matrix (DWT-SGLDM)	SA	GA-SVM	95.65%
Kabir et al. [47]	MRI T1,T2	Normal, malignant, and benign	Texture, statical, and wavelet Feature.	GA	ANN	98.3%
Kumar et al. [48]	MRI	Normal, malignant, and benign	DWT+GA	PCA	Kernel SVM	Varies from 80% to 90%
Sharif et al. [49]		Normal, malignant, and benign	GLCM	GA	SVM	99.69%
Gudigar et al. [50]	MRI	Normal, malignant, and benign	DWT for image decomposition.	PSO	SVM	97.38%
Deepa et al. [51]	MRI T1,T2	Normal, malignant and benign	Gabor wavelet	KPCA	AFBPNN	99.84%
Hasan et al. [52]	MRI	Normal, Lymphoma, Glioblastoma multiform, Cystic oligodendroglioma, Ependymoma, Meningioma and Anaplastic astrocytoma	first-order statics (FOS) and second-order statics (SOS)	DMWT	PNN	97%

3. Research Methodology

Artificial intelligence (AI) has provided a good analysis of medical imaging which caused more computational, complexity and medical data availability in the last decades. Although many applications for using AI classification in the imaging of brain tumors have been presented before, their clinical impact is still to be studied. A systematic review was performed to study the multi-class brain tumor in the analysis of classification brain tumor imaging in various diseases. We performed a brief review and meta-data analysis was achieved by the good reporting for systematic reviews and meta-analyses for better guidelines for future studies in the field of using the various machine learning schemes to classify human brain tumor diseases. This brief literature review (BLR) shows the proposed review steps used to explore the classified approaches of the tumor as outlined in **Figure 3**.

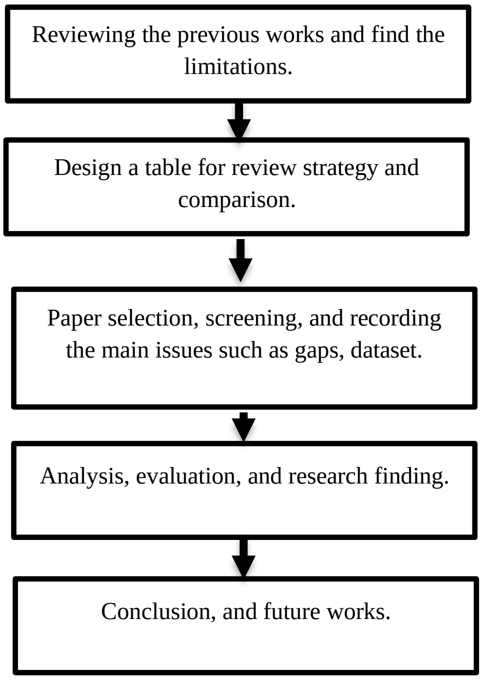

Figure 3: Proposed steps for a brief review of our paper.

4. Result and Discussion

This section provides a deep concise summary of each paper and analysis of its pros and cons. A review of each paper is also provided to help the reader quickly understand the most essential parts of each paper. The analysis of different schemes for brain tumor classification is as follows :For example, in the studies **[36,37,38]**, the accuracy achieved for tumor brain classification was moderate, not exceeding 90%. This accuracy is lower compared to other existing works such as **[45]**. However, when **[45]** was used with different schemes of gray-level co-occurrence matrix (GLCM), it failed to achieve high accuracy. On the other hand, in **[51]**, the use of Gabor wavelet for feature extraction resulted in an accuracy of 99.87%. In [42,45,48,50], the classification of brain diseases using local binary patterns (LBP) with different approaches aimed to increase accuracy. The K-nearest neighbors (KNN) algorithm showed better performance when 4 or 7 features were selected, but it failed to maintain high accuracy when 256 features were used. In [40], a novel stroke classification system was developed, achieving a 96.10% accuracy by capturing 15 features from the proposed feature reduction stage.

Overall, various methods for feature extraction and reduction were explored, and the best methods were evaluated based on accuracy. The approach in [51], which combined the AFBPNN decision with kernel-based principal component analysis (PCA) for feature extraction and selection, achieved the greatest accuracy of 99.84%. The second-highest accuracy of 97.9% was achieved in [39] when feature extraction was carried out using GLCM-based entropy. When using PCA and GLCM for feature extraction, other techniques like [42, 45, 36] also produced acceptable classification results with accuracies of 94.7%, 85.7%, and 87.62%, respectively. As a result, this study assesses a suggested model's classification performance using a variety of feature extraction and reduction techniques in conjunction with machine learning. Using an adaptive firefly backpropagation neural network (AFBPNN) and cross-validation with a 10-fold increase, the classification accuracy was 99.84%. The need for brain tumor classification tools in clinical practice must contain accurate validation, ongoing development, and use the ethical policies. As a result, there are many exciting schemes, involving medical imaging data integration, using AI with personalized medicine, and data extraction for the imaging diagnostic.

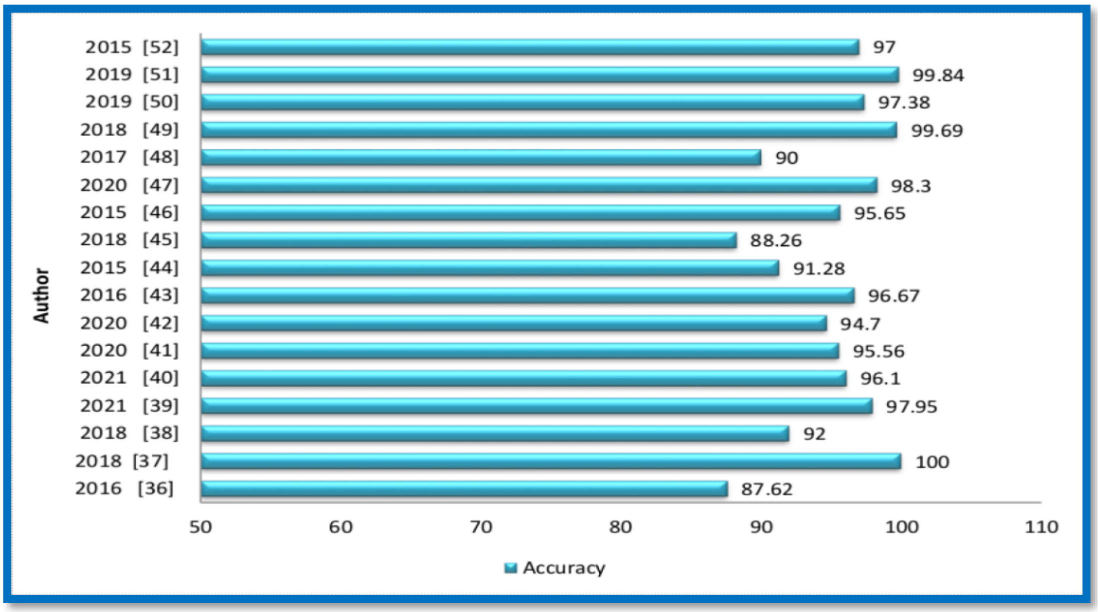

Figure 4: The comparison of various proposed methods using classification-based accuracy metric.

5. Conclusion :

This paper focuses on the review of the current development of intelligent multi-class multi-level (MCML) classification schemes for brain tumor disease classification. This research aims to provide an early assessment of tumors to aid users and clinicians. The proposed algorithms utilize traditional machine learning approaches, involving pre-processing, segmentation, feature extraction, and classification steps. In the pre-processing step, noise and contrast illumination are eliminated, while a hybrid technique is employed for region of interest extraction during segmentation. Color and texture features based on gray-level co-occurrence matrix (GLCM) are extracted and selected in the feature extraction and selection steps, followed by classification.

The study presented that the paper **[51]** has achieved a high accuracy of 99.84% by applying kernel-based principal component analysis (KPCA) with a firefly backpropagation neural network (FBPNN). Lastly, the scheme outperforms better compared to other methods in the classification of MRI scan images to different stages such as Normal case, abnormal, malignant or benign, and low grade or high grade. The future trend for this field still opens problems, especially in terms of the increased number of datasets, and for designing FPGA-based classification hardware more memory occupancy is still needed.

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