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Research Article

A Review on Brain Tumor Classification in MRI Images

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Abstract: Classifying brain tumors using machine learning techniques have become an essential due to its importance in people life. The correct and fast diagnosis are the keys to reduce the percentage of deaths that have raised recently to significant numbers. The available techniques such as CT scan and MRI imaging are widely used nowadays and the latter is more common as it provides high resolution images from different angles for brain tissues. Determining the right type of brain tumor manually requires an expert who has a good knowledge in brain diseases. Also, it is time consuming and tedious for a lot of images. Moreover, human errors are possible and consequently false detection may cause a wrong procedure and treatment. Therefore, the scientists and researchers introduced different approaches for classifying tumor types automatically and efficiently without needing to human knowledge. This paper reviews these approaches, which includes traditional machine learning algorithms (MLs). These algorithms can be divided into two main parts, supervised and unsupervised. The most algorithms that are used and achieved high accuracy are SVM, KNN, and ANN. On the hand, today by enlarging the available data in this area and developing new ANN-based techniques, called deep learning, the performance of brain tumor classification is boosted. This family of techniques which can be used for both feature extraction and classification are also reviewed in this paper.

Keywords: MRI Image, Classification, Machine Learning, KNN, SVM**.**

1. Introduction

A brain is a central processing organ in a human body that controls most functions of the body such as thought, memory, vision as well as breathing. The brain consists of millions of cells that are stack in a rigid skull to protect this complex part from outside factors. However, diseases that happen inside brain due to abnormal proliferation of cells raised death to 787,000 in the end of 2020 according to National Brain Tumor Society [1]. This growth in abnormal cells could push normal ones and causes miss functionality for the brain [2, 3]. According to the World Health Organization (WHO), the brain tumors are classified into two types: Benign and Malignant. The former is harmless, non-cancerous and grows slowly, which is also called as low-grade (grade 1 and 2). In contrast, the latter has an aggressive state, characterizes as heterogeneous and spread in brain and other parts quickly. Therefore, it is classified as high grade (grade 3 and 4) and it is harmful and threaten patient's life [4]. For these reasons, early detection and treatment for tumors are vital to save lives and increase the ability of infected people to live longer [5]. Different techniques are used to diagnose brain tissues such as Computed tomography (CT) scan, Electroencephalography (EEG) and Magnetic Resonance Image (MRI). The later technique is more efficient and powerful that displays images for the internal organs of the human body based on magnetic field and radio waves. The images give valuable information regarding a structure of the brain tissues due to a high resolution provided by this technique. Research community, therefore; uses MRI technology to propose different approaches to determine precisely the location and degree of brain tumors automatically and without a need to human intervention [6, 7]. Although the MRI medical imaging technique shows the shape of the brain in 2D and 3D in accurate and clear manner, manually classification of MRI imaging are a challenge and cause errors in such complicated cases [8]. Different shapes for the brain tumors and types could be not an easy task even for experts to determine tumors and comparing its tissues with neighbouring healthy cells. Therefore, diagnosing based on human vision is tedious and time consuming. Moreover, human errors could be happened and lead to miss diagnostic that causes wrong treatment and wrong response [9]. On the other hand, the right and immediate response could save lives and increase the rate of survival. Accordingly, adopting automatic system that loads MRI medical images using computerised technology is urgent to obtain fast and accurate results with less time consuming. This system aims to help the doctors and radiologists in diagnosing and classifying tumors in the brain through designing innovative Computer Assisted Diagnosis (CAD) [10]. The CAD has become a hot area for researchers and developers in radiology diagnostic and medical imaging, particularly for classification cancer. In general, this system contains three stages: removing any noise in the image and segmenting the tumor region, features extraction from the segmented image based on statistical or mathematical analysis. Finally, setting a labelled MRI images during a learning process that are applied to a suitable classifier to predict any alteration in a tissue [11].

A classifier can be into divided into two main parts, supervised and unsupervised. Although they achieved high accuracy, a preparation for a dataset is a time consuming and needs more computational processing. Therefore, deep learning approach is proposed as an alternative solution, which removes steps of preparation and obtains high accuracy. The present study analyses the existing approaches that are utilized to classify brain tumor types based on MRI images. Many methods are proposed in the literature and surveys and they contained more information about pros and cons of these methods. However, there is still a need for a review to update the recent studies as a comparative analysis and list their contributions.

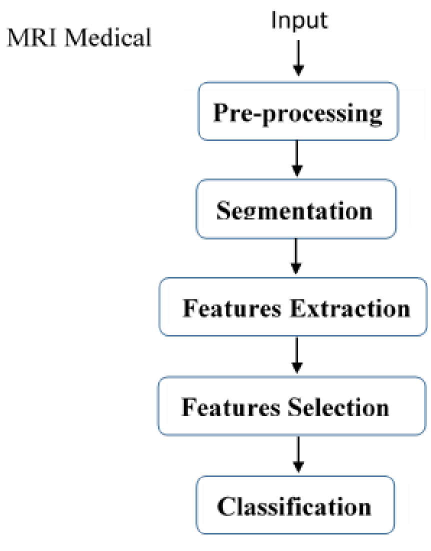
The contributions of this work are:

1. It presents a background about necessary steps to implement entire classification for brain tumors.
2. It introduces a survey about the existing methods regarding this field.
3. It shows readers developing directions of MLs for brain tumors classification.

2. Brain tumors classification

As mentioned earlier in the introduction that the brain tumor disease causes highly rate of death in the world. Therefore, segmenting and classifying brain tumors automatically have taken a lot of attention by researchers. Designing a system that is able to determine the tumor precisely and without human intervention is a challenge. The general block diagram of brain tumors classification presents in figure 1. The figure shows the main steps that are pre-processing and segmentation of the medical MRI images, extracting features and selecting the most relevant ones, and finally applying machine leaning algorithms [12]. The complete description of each step illustrates in the following subsections.

Figure 1. General block diagram of brain tumor classification



2.1 Data Acquisition

Medical imaging is related to components of human body such as water, bones, iodine, iron etc., characteristics of these components affect on a technology and principles of medical imaging [13]. There are various imaging modalities such as x-ray, positron emission tomography (PET), computed tomography (CT), and ultrasound and magnetic resonance imaging (MRI). The x-ray is emitting high level of radiation that is harmful to human body and could cause cancer or skin diseases. PET can display the functionality of some parts of human body rather than it shows a clear vision to these parts, however it is working by detection a radiation that is emoting from a radiotracer and should injected to the human's organ according. On the other hand, MRI technology that employs efficient magnets to generate a strong magnetic field to show an organ in precise details and from various angles. This device is working in two modes, the first mode uses high filed to produce images with high quality, while the second type or mode uses low filed for simple diagnosis. This tool is accurate to visualize abnormal tissues in the brain such as tumors, stroke, and haemorrhage.

2.2 Pre-processing

Image pre-processing is the first step of detection that a researcher or an inspector spend more time on dealing with as the following steps rely on it. The purpose of this step is to remove any noise or labels such as time and date, and enhance the quality of the image preparing for the next step of segmentation [14]. There are different techniques that are used to implement this process for example: cropping, image resizing, histogram equalization, filtering, and image normalization.

2.3 Segmentation

The next step of detection is a segmentation that represents the most essential part of image processing. This process contains a procedure to extract the area that is valuable in determining whether a region is infected or not. Segmenting brain tumor based on MRI images is facing several difficulties such as noise in the image, low contrast, loss boundaries, the changing in the intensities within tissues, and also the varying in tissue types [15]. The scholars such as [16, 17] classified segmentation into different approaches (i.e., threshold-based, region-based, boundary-based, and pixel classification techniques).

The former, which is a threshold-based assumes that pixels are classified to one class when they fall in a specific range [18]. Region-based approach supposes that the neighbouring pixels in a region have the same properties [19]. The third approach postulates that the characteristics of the pixels vary suddenly from region to region in the boundary line [20]. The latter one assumes that pixels are classified based on feature space, these features may depend on gray level, colour components, and local texture [21]. Combing two or more of the previous methods produces an approach called a hybrid [22-24].

2.4 Feature extraction techniques

Feature extraction is a process of reduction in number of features by creating new set of them that have the same information of the original ones, but they are completely different. The advantages of this technique are improving accuracy of the classifier, minimising risk of overfitting, ability to visualize data, and increasing the speed of training [25].

The authors Ziedan et al. [26] claimed that the popular approaches used for feature extraction are binary pattern (LBP), grey-level co-occurrence matrix (GLCM), Canny edge detection, and a bag of words (BoW). For instance a study [27] presented a scheme to classify brain tumors from MRI images the scheme consisted of the normal stages (i.e., pre-processing, segmentation, feature extraction, and classification). The authors proposed to use grey level matrix for feature extraction, the results showed high efficiency and accuracy. Other study [28] combined two technique to extract features DWT and Gray Level Co-occurrence Matrix. These techniques achieved promised accuracies for detection two types of brain tumor benign and malignant with 94.12% and 82.36% respectively. In contrast, a work [29] proposed to extract features in two stages, the first stage contained extracting statistical features and the second stage contained deriving features based on region property. The work used ANN classifier to detect brain tumors from a dataset that contained 39 images for benign and malignant with accuracy about 97.44%.

2.5 Feature selection techniques

This technique is also applied to minimize the volume of features in the dataset with keeping the same features. The technique is trying to order the features regarding their importance from top features to bottom features, the top ones are used mainly in the classification while removing or reducing the use of bottom ones. Similarly, this technique increases the speed the training stage and improves a precision of a classifier [30]. Practically, selecting the best features is done by employing supervised machine learning such as C5 algorithm. Examining the whole features and searching for the optimal ones manually is time consuming and prone to errors as each feature could affect with another one.

3. Classification

Classification methods can be classified into two main parts, supervised methods and unsupervised methods. The next sections show these parts in details with their algorithms.

3.1 Supervised methods

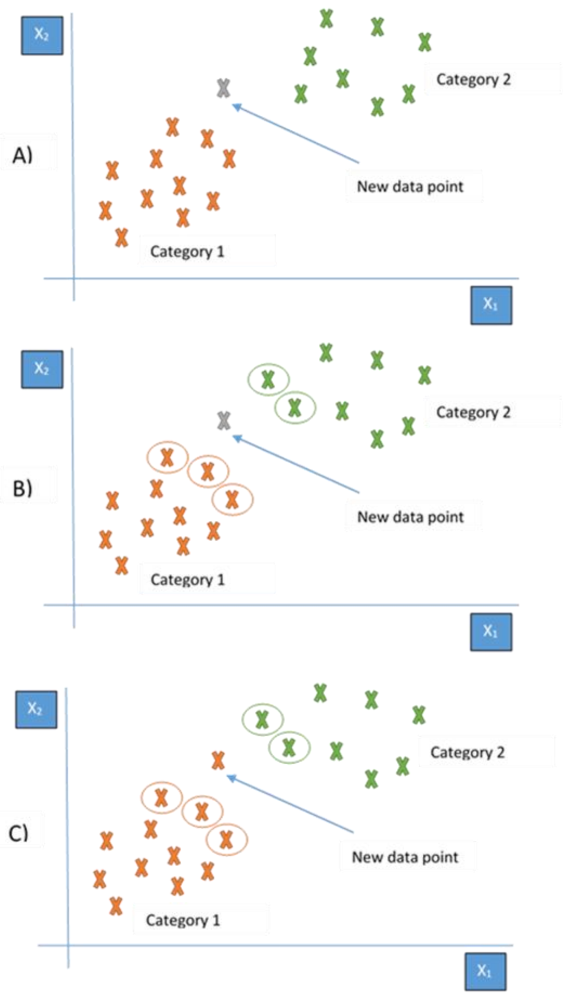
These methods consist of two phases (i.e., training and testing), in the training phase, the data are labelled accurately based on the extracted features. In this phase, the model firstly is built and then used to specify the classes that are unlabelled in the testing phase. The data are labelled manually, which requires human intervention, therefore, supervised classification surpasses unsupervised. Some classifiers are illustrated in the next subsections:

K-NN (Nearest Neighbour). The K-NN is simple and utilized in various applications such as healthcare, image and video recognition, finance, and handwriting. The mechanism of applying this algorithm is based on calculating nearest neighbour points, which are known and labelled, to unknown points. The algorithm calculates the distance through using one of the methods such as Hamming distance, Manhatten distance, Euclidean distance, and Minkowski distance, the method chosen based on problem domain. To explain the mechanism of this algorithm, a scenario is supposed that consists of two categories, category 1 in red colour, and category 2 in green colour as shown in figure 2. The scenario supposes also that a new data point, which is in gray colour, is added to the dataset. The question is how to classify this point? Is it belong to category 1 or category 2? According to KNN algorithm. There are number of steps that must follow to decide to which category the point belong:

- Choose the number K of neighbours, this number depends on number of extracted features and number of cases, by default k equal to 5 [31].
- Take the nearest neighbours of the new point according to algorithms, see figure 2, B.
- Among these neighbours, count the number of data points in each category.
- Assign the new data point to the category that has more neighbours, see figure 2, C.

Support vector machine (SVM). SVM algorithm can be used to solve problem in both classification and regression, but it is commonly used in classification tasks. In this algorithm, different n-spaces are created based on number of features to form a data point or sample, each feature represent a coordinate. Therefore, the goal of SVM algorithm is to find

Figure 2. K-NN algorithm [32]



out a boundary or line between n-dimensional space and this line called a hyperplane that segregates among classes. There are different possibility to draw various hyperplanes, but the best hyperplane is the one that has maximum margin. The maximum margin defines as a distance between extreme data points among classes, and these points called support vectors; thereby, new data point could be classified in more confidence [33, 34].

A study in [35] utilized SVM algorithm to classify brain tissues into three classes (i.e., normal, benign, and malignant). The study used spatial grey level dependence method for feature extraction and genetic algorithm (GA) to select the best feature to the classifier. Zhang et al. [36] proposed an algorithm for features selection by merging multi input data. However, this algorithm converts 3D MRI image pixels into 2D information that causes inability to validate this method in large datasets. In addition, this system requires more processing time to deal with linear and nonlinear problems as the data point is classified by SVM through segregating hyperplane proximately. In contrast, the authors in [37] presented an efficient approach to classify brain tumor called Diffusion Tensor Image Segmentation (D-SEG) by utilized both K-means and SVM. The K-means technique is used to determine a volume of interest of abnormality in the brain tissue, while the SVM is applied to delineate tumor types such as meningioma, metastases, and glioblastomas.

Artificial neural networks (ANNs). ANNs is the branch of artificial intelligence (AI) that back to 1940s, the first ANN model is developed by the scientists McCulloch and Pitts. It simulates the human brain and has the ability to learn just like natural neurons to obtain experience; this advantage is useful for different applications to build an automatic system. The ANN consists of number of inputs that move the signals to various hidden layers that are responsible of performing nonlinear transformations to produce results to the output layers. One of the ANNs classifier is Feed Forward Neural Network (FNN) that used by various studies [38-40], which is simple and the information flows in one direction from input layers to hidden layers and finally to output layers. FNN is trained by different algorithms such as Back propagation, Genetic, Particle Swarm Optimization, and Artificial Bee Colony. However, its limitations are computational cost, needing to optimize more parameters, and losing information of neighbouring. The authors in study [41] introduced an automatic system to detect brain tumor that was fast and robust. The study used feedback pulse-coupled neural network to segment MRI images, features are extracted by utilizing DWT, and the most important features are selected using PCA. Finally, classification process was applied using feed forward back propagation to determine whether the tissues are normal or not with accuracy approached to 99%. Also, a study [40] extracted features through utilizing Stationary Wavelet Transform (SWT) form MRI images that enhanced tumors detection. The authors used PCA also to minimize volume of features and consequently processing time. Three different algorithms are applied to train FNN (i.e., IABAP, ABC-SPSO and HPA), the latter showed high results in terms of accuracy, precision, sensitivity, and specificity.

Deep learning. Recently, various domains such as speech recognition, computer vision, robotics, and CAD have boosted with deep learning models that are able to feed with raw data and achieve high performance [41]. The advantages of using these models over traditional MLs are dealing directly with raw data (e.g., images), reducing in time consuming, less requiring to expert knowledge, and less effort to tune important features. Different architectures are introduced to represent deep learning models. Although there are various deep neural models such as recurrent neural networks (RNN) and transformers, the most common model for image processing is convolution neural network (CNN), which has been utilized in various applications as it can extract features and distinguish patterns in images successfully [42]. The architecture of CNN consists of three main layers which are convolutional, pooling and fully-connected layer. The first layer represents the main layer that can extract features from images such as boundaries and edges. This layer can learn a huge number of filters automatically in parallel for training dataset based on required predictive results. The second layer is responsible of data reduction which reduces the size of the features produced by the first layer and leads to less need to computational resources. The latter is a fully-connected layer that contains neurons and each one of them is linked to each neuron in the former layer. The layer is as a classifier to map the extracted feature vector from the previous layers into the categories [43]. CNN is similar to the operation of other neural networks that updates its weights regularly by taking an error from output and inserting it as output. The error back propagate to the network continuously to optimize filters and weights, moreover, the CNN normalized the output using a SoftMax function [44].

3.2 Unsupervised methods

In this type of methods, image pixels are classified automatically into different classes based on an algorithm without human intervention. In other words, in unsupervised methods, there is no need to train a model, the pixels are grouped together relying on common features. The following paragraphs present some of these methods.

K-means clustering. Clustering refers to a concept that partitions pixels or data points into clusters that have the same properties. There are two types of clustering (i.e., hard and soft clustering), the former means that the sample or pixel belongs to a cluster or not, therefore, no overlap in the clusters. In the contrast, the latter means that the sample or pixel must assign to a cluster, hence, the overlapping is possible. K-means is unsupervised clustering that is simple, but requires more processing time due to a large number of iterations. Choosing the right number of clusters (i.e., K) leads to accurate segmentation, otherwise, the results may be false. In real time clustering, the parameter K could be unknown and this needs to rerun the algorithm several times by choosing different value for the K. Moreover, in each iteration, the distance between data points and the nearest cluster is computed, therefore, this adds more computations and time. Several studies used K-means algorithm to separate brain tumor from the healthy ones. A study [45] used this approach on MRI images that are enhanced to obtain excellent features through converting these images to RGB images. Similarly, the authors in paper [46] utilized the same images and they achieved promising results.

Fuzzy C-means (FCM). FCM is an approach of clustering that may clusters share the same data points. This approach was developed in 1973 by the scientist Dunn and enhanced in 1981 by Besdek. It is commonly used to recognize patterns, and suitable for using in segmenting medical images [47]. The main drawbacks of this method are its sensitivity to noise and the errors that could happen in Euclidean distance. The first issue is solved by many studies such as [48-50] that proposed algorithms to count spatial information to reduce noise. The study in [48] incorporating spatial information with FCM algorithm called FCM_S. However, applying this approach consumed time due to a more computations at each iteration. This problem is dealt by modified FCM to FCM_S1 and FCM_S2 through using mean and median filtering in [49]. Similarly, the authors Benaichouche et al. in [50] used enhanced FCM that called EnFCM to reduce processing time. The study proposed to replace dealing with image pixel with gray level histogram. The latter issue regarding the Euclidian distance that was solved by studies [51, 52]. The studies proposed LP norms ($0 < p <= 1$) as a distance measures rather than Euclidian distance that minimized outliers.

3.3 Hybrid techniques

Hybrid techniques mean using more than one method or technique to obtain high accuracy, it focuses on advantages of these method and reduces their disadvantages. For instance, a study in [53] proposed to combine FCM and SVM to segment diseases related to the brain. The first approach utilized FCM to determine the infected area in the brain and used the second approach for classification, the authors extracted features by applying gray level length matrix. Researchers in study [54] claimed that the FCM technique can classify tumor tissues accurately more than K-means technique, while the latter can do the same task quickly. Therefore, the study used this merit in each classifier to carry out classification in less processing time with high outcomes. In other work [55], authors combined K-means and ANN to detect size of the brain tumors based on MRI images. The study utilized Gray-Level Co-Occurrence Matrix (GLCM) for feature extraction and thresholding for tumor detection. Other study [56] proposed an automatic approach to detect gliomas using MRI images, the study used two classification techniques Active Contour Models (ACM) and random forest (RF).

4. Literature review

Many studies have tried to propose an automatic scheme to classify brain tumors from medical MRI images. Machine learning (ML) have been utilized for this purpose starting with stages of cleaning data, extracting features, followed by selecting the most important of these features. Finally building a classifier based on labelled samples in the case of supervised learning and predicting inherent samples. ML can be classified into two main parts, supervised and unsupervised. The former uses labelled dataset to build a classifier by feeding input data to a model for tuning the model's weights properly. After that, new data are given to the model to test or predict a system, examples of these types of algorithms are Artificial Neural Network (ANN) [57], Support Vector Machine (SVM), and K-Nearest Neighbours (K-NN) [58]. In the contrast, unsupervised techniques use unlabelled datasets that find out the similarity and differences in the dataset and accordingly grouping the dataset without human intervention such as K-means, fuzzy c-means [59] and Self-Organization Map (SOM) [60].

A study in 2009 by Zacharaki et al. [61] introduced two approaches for classification. The first approach classified glioma type for various grades Grade1, Grade 2, and Grade 3, whereas the second one classified the grades for low and high. The study utilized SVM and KNN algorithms for classification and achieved accuracies 85% for multi-classification and 88% for binary classification. El-Dahshan et al. [62] used a Discrete wavelet transform (DWT) to extract features from 80 images of brain that contained normal and abnormal tissues. They utilized PCA for features reduction, and then the selected features are classified by using KNN and ANN with accuracies 98% and 97% respectively. Likewise, authors in [63] utilized MRI images for automatic brain tumors classification. The authors proposed Gaussian filter for pre-processing and region props algorithm for segmenting and localizing the tumor region. Followed by feature extraction with utilizing Multi-Texon histogram to prepare for classification. Finally, SVM algorithm was applied for diagnosing whether a tissue is cancerous or not with accuracy reached to 87%. The same authors on different work [64] proposed the same procedures that previously appointed, but they used different methods. An anisotropic filter was suggested as preliminary step to reduce any noise and increase the quality of the image. Skull-stripping process was applied that removes non-cerebral tissues like scalp and skull. Afterwards, the features are extracted through employing multi-texton structure descriptor and using statistical feature such as variance and mean instead of using multi-texton histogram in the previous work. Finally, a hybrid kernel based on SVM was used to detect the existing tumor with accuracy 93%. Other study [65] proposed an approach that contained firstly increasing a tumor region by expanding a tumor's image and then splitting a selected region into many parts. Three techniques extracted features from these regions which are Gray level Co-occurrence Matrix (GLCM), intensity histogram and BOW. Finally, classification is applied with accuracy reached to 91.28% through using ring form partition. Similarly, Alfone and Salem [66] utilized SVM classifier to build an automatic system to isolate brain tumor from MRI images. Fast Fourier transform (FFT) was used to extract features and Minimal redundancy Maximal Relevance (MRMR) technique to reduce number of features and to increase the classifier accuracy. The authors claimed that the system achieved high accuracy reached to 98.9%.

The authors in [67] suggested a methodology that detects and localizes MRI medical tumor images. The methodology consists of three main steps (i.e., pre-processing, segmentation and edge detection for the image, and finally classification). The study used k-means clustering algorithm to discover the infected region from the normal one. Another study [68] proposed an automatic system to determine brain tumors. Filters are utilized to enhance a quality of MRI images, then the segmentation process was applied to localize the region of the tumor. Followed by using Principal Component Analysis (PCA) for features extraction and finally the study relied on experts to identify tumor region from the segmented image with rate of accuracy 91.67%. Parasuraman et al. [69] proposed four stages, the first stage contained filters for pre-processing, and the second stage included image segmentation through using clustering technique. Afterward, gray-level co-occurrence matrix (GLCM) was used to extract features. Finally, ensemble classifiers are used to classify if the tumor is exist or not. The ensemble classifier consisted of feed forward artificial neural network (FNN), extreme machine learning and SVM. The proposed method achieved accuracy reached to 91.17%.

The initial steps for preparing a data are essential for applying a traditional machine learning algorithms, however, each step is a time consuming and also need more computational processing. Moreover, segmentation could be incorrect due to the variance in intensity and contrast of the image that lead to errors in classification. Likewise, for the features extraction that may be inconsistent as it depends on morphological features and causes errors in determining the type of tumor [70, 71]. Although these methods are achieved high accuracy in classifying different types of brain tumors, new approach has been a dominant for diagnosis called deep learning. This approach removes the initial steps of preparing data for the classifiers and increases the performance of prediction. Moreover, this technique has the ability to represent a complex relationship with minimum number of nodes [72].

A study [73] proposed using CNN algorithm to classify gliomas disease into two grades (low Grade or high Grade) and different grades (Grade 2, Grade 3, and Grade 4). The classifier was achieved accuracies 71% and 96% respectively. J.Seetha and Raja [74] suggested an automatic approach to classify brain tumors with low complexity and high performance. The Images are collected from different web sources based on Radiopaedia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 testing dataset [75]. CNN classifier was applied for classification by using Python script with training accuracy up to 97.5%. Other work [76] introduced CNN to determine three brain tumors (i.e., Meningioma, Glioma, and Pituitary). They achieved 98.51% accuracy for training the samples and 84.19 % for testing. Anaraki et al. [77] obtained higher accuracy to classify three grades of glioma reached to 90.09% by combing two ML algorithm, which are CNN and Genetic Algorithms (GA-CNN). Also, the authors Sultan et al. [78] suggested a CAD system based on CNN using MRI images to classify brain tumors into different types (meningioma, glioma, and pituitary) and glioma into three grades. The authors used 16 layers for CNN to process two publically datasets that contain 233 and 73 patients and 3064 and 516 as total images for each dataset. The authors utilized two dropout layers to avoid overfitting, softmax layer and fully connected layer for prediction results. Although the datasets are relatively small, the study proposed using data augmentation to obtain high results that reached to 96.13% and 98.7% for two datasets. Similarly the authors in study [79] classified MRI images using CNN method. The study used a technique called edge detection to capture regions of interest in the images and increased the size of training data by utilizing data augmentation technique. The proposed work applied to other models and the results found that this work need less computational power and achieved high accuracy 96%.

5. Discussion

Table 1 summarizes the recent studies regarding brain tumors classification. The table discusses two main approaches (traditional MLs and deep learning). The most algorithms that are used in the former and achieved high accuracy are SVM, KNN, and ANN. The authors in studies [62, 66] obtained very high accuracy through using these methods. The study [62] classified brain tumors into cancerous and not cancerous by utilizing KNN and ANN separately, also, the study relied on DWT and PCA for features extraction and selection respectively, which led to this result. Similarly, the study [66] obtained high accuracy by using SVM algorithm for classification brain tumors, and FFT and MRMR for features extraction and selection respectively. Although the previous studies succeeded in discriminating between effected cells and not effected, but they are not determine a type of diseases. A work [65] achieved a significant accuracy reached to 91% to classify three types of brain diseases, which are Meningioma, Glioma and Pituitary tumor. In the contrast, deep learning obtained very high accuracy to segregate different types of brain tumors through using CNN algorithm. The study [78] utilised two datasets, which contained 3064 and 516 images, with accuracies about 96.13%, 98.7% respectively. Compared to study [76] that used the same dataset and CNN algorithm, but it achieved low accuracy about 84%. The reason in this difference in their accuracies as the study [78] used 16 layers for CNN to process the datasets, the authors utilized two dropout layers to avoid overfitting, softmax layer and fully connected layers for prediction results.

6. Conclusions

This paper introduces a comprehensive study for recent methods for classification of brain tumors. The study explains also the main steps to analysis datasets starting with dealing MRI medical images that support a reader with information to develop this field and help for better diagnosis. Finally, it has been noticed from reviewing various methods that using K-NN, SVM, and CNN classifiers are achieved high results. Other studies proposed hybrid approaches to obtain high accuracy, nevertheless, these studies face complexity of analysis due utilizing more than one method.

Despite a traditional machine learning algorithms achieved high accuracy, each step is a time consuming and also need more computational processing. Moreover, segmentation could be incorrect due to the variance in intensity and contrast of the image that lead to errors in classification. Likewise, for the features extraction that may be inconsistent as it depends on morphological features and causes errors in determining the type of tumor [70, 71]. On the other hand, new approach has been a dominant to diagnosis brain tumors called deep learning. This approach removes the initial steps of preparing data for the classifiers and increases the performance of prediction. One of the most limitations of using deep learning technique is the lake in labelled data that are obtained from medical healthcare, the level of accuracy by using this technique increases with a big data [79].

Table 1. Overview of recent methods on the basis of features and classifiers.

Ref	Dataset	Features extraction technique	Features selection technique	Method	Classification type	Accuracy
[61]	MRI (102 images)	tumor shape and intensity characteristics and rotation invariant texture features	support vector machines with recursive feature elimination	Hybrid(SVM, KNN)	Multi & binary	85%, 88%
[62]	MRI (80 images)	Discrete wavelet transform (DWT)	PCA	KNN, ANN	Binary	98%, 97%
[63]	MRI(100 images)	Multi-Texon histogram	------	SVM	Binary	87%
[64]	MRI (100 images)	Multi-Texton structure descriptor and using statistical feature	-----	Hybrid kernel based on SVM	Binary	93%
[65]	MRI (3064 images for 233 patients)	Gray level Co-occurrence Matrix (GLCM), intensity histogram and BOW	------	Ring form partition	Multi	91.28%
[66]	MRI (100 images)	Fast Fourier transform (FFT)	Minimal redundancy Maximal Relevance (MRMR)	SVM	Binary	98.9%
[67]	The images is clustered directly using the k-means algorithm without using features extraction			K-means	Binary	------
[68]	6 images collected from the web	PCA	-------	Experts' Knowledge	Binary	91.67%

[69]	Few MRI images	gray-level co-occurrence matrix (GLCM)	---------	Ensemble classifier	Binary	91.17%
[73]	A lot of images	In deep learning technique, there is no need to extract and select features		DL (CNN)	Multi & binary	71%, 97%
[74]	Images are collected from different web resources			CNN	Binary	97.5%
[76]	MRI (3064 images)			DL (CNN)	Multi	84.19%
[77]	MRI (600 images for 130 patients)			GN, CNN	Multi	90.09%
[78]	Two MRI datasets (3064 for 233 patients & 516 for 73 patients)			CNN	Multi	96.13%, 98.7%
[79]	Images are collected from different web resources			CNN	Binary	96%

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