Evolution in diagnosis and detection of brain tumor – review

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Abstract: Diagnosis of Brain tumor at an early stage has became an important topic of research in recent time. Detection of tumor at an early stage for primary treatment increases the patient’s survival rate. Processing of Magnetic resonance image (MRI) for an early tumor detection face the challenge of high processing overhead due to large volume of image input to the processing system. This result to large delay and decrease in system efficiency. Hence, the need of an enhanced detection system for accurate segmentation and representation for a faster and accurate processing has evolved in recent past. Development of new approaches based on improved learning and processing for brain tumor detection has been proposed in recent literatures. This paper outlines a brief review on the developments made in the area of MRI processing for an early diagnosis and detection of brain tumor for segmentation, representation and applying new machine learning (ML) methods in decision making. The learning ability and fine processing of Machine learning algorithms has shown an improvement in the current automation systems for faster and more accurate processing for brain tumor detection. The current trends in the automation of brain tumor detection, advantages, limitations and the future perspective of existing methods for computer aided diagnosis in brain tumor detection is outlined.

Key words: Brain Tumor Detection, Intelligent approach, diagnosis and analysis

1. Introduction

Various algorithms and architectures have been proposed for development of precise and more effective categorization of brain tumors for an early prediction. Cancers develop as an unrestrained and abnormal expansion of cells in certain part of the body. The growth of glaucoma cells in the brain cause brain tumors. Among different types of cancer, brain tumors are the most important. It is defined as a primary or metastatic tumor based on the origin of the tumor. The initial tumor develop from cell tissue, metastatic
cells develop at different parts of the body and expand into the body area. Chemotherapy and radiotherapy are used in the treatment of cancer. Current development in machine learning outcome as a evolving approach in detection and prevention of primary cancer. Machine learning methods are developed for faster processing and higher detection rate. In a machine learning system, multiple-level were processed for detection of feature vectors and decision making. The representing feature vectors are large in count and results in a high processing overhead. This restricts usage of ML system and effects the detection rate of decision approach. Existing processing methods introduce distortions in MRI samples that need to be removed for precise operating. The inconsistency of distortion property constraint existing filtration to remove different interferences observed due to varying processing environment. Digital MRI processing has outcome to be a cheapest and fastest option for the diagnosis of brain tumors at an early stage. Recent research focuses on algorithms for analyzing and diagnosing the presence of brain tumor, under the supervision of MRI reading from the benchmark database and the theoretical supervision of expert radiologists. The automated system were developed for denoising, segmentation feature extraction and classification subjected to process of training and classifying the sample using computer-based coding and manually-identified MRI results. The computer aided diagnosis (CAD) systems are evolving for automated decision in early prediction of brain tumors.

2. Brain Tumor Diagnosis

Brain is a vital organ of all living beings. It is a centralized processing unit in human which sense, control and operates all part of our body [1]. Brain constitutes of 3 main parts;

1. Fore Brain: This part of brain is formed by cerebrum, thalamus and hypothalamus which are responsible for thought, memory and information exchange.
2. Mid Brain: This part of the brain is formed of tectum and tegmentum. They are responsible for long term memory forming.
3. Hind Brain: This is consisting of pons and medulla oblongata which helps in controlling of motions, heart movement, breathing operation etc.

The functional region of a human brain is illustrated in figure 1.

![Functional regions of a human brain](image)
Brain consists of two types of cells namely, Neuron and Galilean cells. An unusual expansion of brain cell in brain is called Brain tumor. Brain tumors could be cancerous or non-cancerous in nature. The analysis of tumor in detection of cancerous characteristic is a difficult task due to varying nature of the tumor and a co-resembling nature with other region of brain. The cases of brain tumor has rapidly raised in recent past. The fast changing of living life style and the environmental condition has given a raise to such effect [2]. An early detection of this effect has a high chance of recovery compared to a late stage. However, in present scenario a major of tumor are diagnosed at late stage. Early stage detection is hence a primal need. The large volume of data diagnosis and the specialization of radiologist define the accuracy and time of processing.

2.1. Types of Brain Tumors
Brain tumors are majorly of two types [1,3]:

1. Primary brain tumor: This tumor grows with the brain regions and does not spread out. these type of tumor can be benign or malignant.
   a) Benign: This type of tumor has a slow growth and defined by distinct boundaries.
   b) Malignant: This type tumor has a rapid growth and has an irregular boundary. It spreads to nearby brain region within the brain.
   c) An illustration of Benign and malignant brain tumor is shown in figure 2.

![Figure 2. (a) Benign brain tumor, (b) Malignant Brain tumor [1].](image)

2. Metastatic brain tumor: This tumor evolves at other part of body and spread to the brain region. This type of effect is developed by the carrying of cancerous cell by the blood stream to brain. The most commonly observed cancer type is the lung and breast cancer.

There are above 120 types of brain tumor of which the commonly observed are;

Gliomas: A brain tumor which is developed from the glial cells which are present at the surrounding of a neuron [4]. The major type of Glioma type cancer is the astrocytoma [5,6]. The astrocytoma is presented into 4 grades as per world health organization (WHO) [7] is listed as;

1) Pilocytic Astrocytoma - Grade I
2) Low-Grade Astrocytoma – Grade II
3) Anaplastic Astrocytoma – Grade III
4) Glioblastoma Multiforme - Grade IV
Based on the characteristic of the brain tumor, WHO has defined a grade scale for brain tumor as [7,8];

| Tumor Grade | Tumor characteristic |
|-------------|----------------------|
| I           | Survive longer       |
|             | Basically normal in appearance |
|             | Low in malignant     |
|             | Grow at a slow rate  |
|             | Appear abnormal in view |
| II          | Spread to side by tissues |
|             | It can recur for a higher grade |
|             | Slower in growth     |
|             | Recur to a higher grade effect |
| III         | Abnormal in view     |
|             | Diffuse to side tissues |
|             | Reproduce as an abnormal cell |
|             | Very abnormal in view |
| IV          | Reproduce at a higher rate |
|             | Appear around dead cells |
|             | Generate new vessels for growth |

### 2.2. Brain Imaging
Various brain imaging approach were used in diagnosis of brain tumor. Method such as positron emission tomography (PET), single-photon emission computed tomography (SPECT), computed tomography (CT), magnetic resonance imaging (MRI), Functional MRI (FMRI) and magnetic resonance spectroscopy (MRS) were used for the localization of brain tumor for its size, location, shape etc [9-12]. The scanning operation is developed as a contrast agent based, where the variation of normal and effected tissues were observed by the variation of dye absorption [13]. In the scanning process, a dye is injected into vain which is passed to brain tissues. The commonly used scanning methods are MRI, CT, or PET. The Magnetic Resonance Imaging (MRI) is developed using magnetic field and computer to capture brain scan image into film. Computer tomography (CT) is developed by combining complex X-Ray and computer device. It can be used in developing a combined observation of tissues, blood vessels and bones and are also used in detection of few tumor cases. Positron Emission Tomography (PET) is used in monitoring of brain activities in a live view. This method is developed by observing the absorption rate of glucose by a tumor. A radioactive marked deoxyglucose is injected to patient and the scanning observes the activity of brain based on the processing of glucose by the tumor. Among these methods MRI based imaging is mostly used in the diagnosis of brain tumor. MRI is non-invasive approaches which is used for derving a good contrast to soft tissue and are found in many diagnosis clinics. MRI in combination with CT and PET is used in making decision for tumor structure, activity and metabolism. MRI provides a robust imaging of
different tissues contrast in brain tumor diagnosis by varying excitation and repetition. Multiple MRI sequences are captured for the diagnosis of brain tumor. Different sequences captured in the MRI are T1-weighted (T1), T1-weighted with contrast enhancement (T1c), T2-weighted (T2) and T2-weighted with fluid attenuated inversion recovery (T2FLAIR). The most used sequence is the T1 sequence for diagnosis. In the T1c imaging the borders are highlighted due to the accumulation of contrast agents. A MRI sample of different imaging is shown in figure 3 [10].

![MRI images](image)

**Figure 3.** (a) T1-weighted MRI, (b) T1c MRI, (c) T2 weighted image, (d) T2FLAIR- weighted MRI [10]

Among all imaging approach, MRI provides a significant contrast for varying image tissues. It is very effective in processing for segmentation and tumor detection. The advantage of MRI in its representation makes the MRI imaging most suitable in tumor diagnosis.

3. Analysis

The evolution of brain tumor detection has outcome with various means of diagnosis and new technologies are evolving in improving the estimation performance more accurate. The objective of automation in brain tumor detection needs an analysis of the recent development in the brain tumor diagnosis for a region to present an accurate decision. The recent analysis developed for a past 4 years in an Indian region [14] revealed that a majority of brain tumor cases is observed for Meningioma. The observations for different brain tumor observed for a period of 4 year is given and a graphical representation is shown in figure 4.

| Type             | Observed cases (%) |
|------------------|--------------------|
| Meningioma       | 48                 |
| Astrocytoma      | 41                 |
| Pituitary adenoma| 6                  |
| Schwannoma       | 5                  |
| Ependymoma       | 4                  |
| Metastatic tumor | 4                  |
Figure 4. Percentage density of brain tumor cases.

The cases observed at a lower rate of occurrence are listed in table 3.

Table 3. Low frequent cases observed for brain tumor [13].

| Type                     | Observed cases (%) |
|--------------------------|--------------------|
| Oligodendrogioma         | 2                  |
| Lymphoma                 | 2                  |
| Oligoastrocytoma         | 1                  |
| Medulloblastoma          | 1                  |
| Hemangioblastoma         | 1                  |
| Choroid plexus papilloma | 1                  |
| Central neurocytoma      | 1                  |

Table 4. Gender based case analysis for High frequent Brain Tumor [14].

| Type                  | Male | Female |
|-----------------------|------|--------|
| Meningioma            | 28   | 20     |
| Astrocytoma           | 22   | 19     |
| Pituitary adenoma     | 2    | 4      |

Table 5. Gender based analysis for Low frequent Brain Tumor cases [14].

| Type                     | Male | Female |
|--------------------------|------|--------|
| Schwannoma               | 1    | 4      |
| Ependymoma               | 3    | 1      |
| Metastatic tumors        | 3    | 1      |
| Oligodendrogioma         | 2    | 0      |
| Lymphoma                 | 0    | 2      |
| Oligoastrocytoma         | 1    | 0      |
| Medulloblastoma          | 1    | 0      |
| Hemangioblastoma         | 1    | 0      |
| Choroid plexus papilloma | 1    | 0      |
The observation of Brain tumor analysis were evaluated for gender variation. The case analysis revealed a higher rate of infection for male compared to female cases. The count of brain tumor cases observed for high frequent and low frequent cases on gender base is listed in table 4 and 5 respectively [14]. Of the total 117 observations for brain tumor cases monitored for 4 year, 65 male and 52 female cases were observed. The observation developed for varying ages for the observing period reveals a age group of 41-60 years patients were more effected. Variation of different types of brain tumor cases under different gender is shown in figure 5.

![Table 6. Observation for Age wise cases of brain tumors [14].](image)

| Type              | Lower age group 0-20 | Young Age Group 21-40 | Average Age Group 40-60 | Higher Age group 61-90 | Total |
|-------------------|----------------------|-----------------------|-------------------------|------------------------|-------|
| Meningioma        | 2                    | 10                    | 29                      | 7                      | 48    |
| Astrocytoma       | 4                    | 16                    | 17                      | 4                      | 41    |
| Pituitary adenoma | -                    | 3                     | 2                       | 1                      | 06    |
| Schwannoma        | -                    | 3                     | 2                       | -                      | 05    |
| Ependymoma        | 4                    | -                     | -                       | -                      | 04    |
| Metastasis        | -                    | 1                     | -                       | -                      | 04    |
| Oligodendroglioma | -                    | 1                     | 1                       | 3                      | 02    |
| Lymphoma          | -                    | -                     | 2                       | -                      | 02    |
| Oligoastrocytoma  | -                    | -                     | 1                       | -                      | 01    |
| Medulloblastoma   | -                    | 1                     | -                       | -                      | 01    |
| Hemangioblastoma  | -                    | 1                     | -                       | -                      | 01    |
| Choroid plexus papilloma | - | 1 | - | - | 01 |
| Total             | 10                   | 38                    | 54                      | 15                     | 117   |
The meningioma case and Astrocytoma cases with 48 and 41 total counts is observed to be dominant for infection case. The case analysis of brain tumor cases in reference to age group variation is listed in table 6 [14]and plotted in figure 6 below.

![Figure 6. Brain tumor statistic on Age reference](image)

4. Computer Aided Diagnosis (CAD) System

The process of MRI diagnosis based on technicians is a slow process, and has manual errors. Computer based automation processing is an appropriate technique to automate tumor detection for brain cancer detection and classification. Analysis of various medical images in the diagnosis such as computed tomography (CT), single-photon emission computed tomography (SP), magnetic resonance spectroscopy (MRS), positron emission tomography (PET), and SP Predictors were used in the analysis of early detection of brain tumors. Various computer-aided diagnostic (CAD) methods were introduced for the automatic processing of such scan images [15, 16]. In developing CAD system in [17] an Integrated estimation approach using learning approach to detect primary brain cancer is presented. The scan images were processed using spectral levels which leads to more effective representation of processing sample in frequency domain for brain cancer detection. In [18] an analysis for the study of brain anatomy and cancer detection is presented. This method provides a comprehensive study of brain structure, cancer character analysis, and the anatomical study for cancer diagnosis. Over the past 10 years, there has been a dramatic change in imaging and radiotherapy in cancer treatment [19].

In order to analyze the automated detection of brain tumors using magnetic resonance imaging (MRI), different Computer processing approaches were presented in [20,21,22]. The brain images were processed for classification where a single measurement or multiple computing was proposed using learning networks to identify the primary brain tumors. In [23] a combined modeling of EEG signal with MRI sample for brain tumor detection is presented. This process develops EEG analysis-based tumor detection with MRI scan images of brain samples processed using Matlab tool. The presented approach is process to extract the actual area of the brain tumor region and train for extracted feature vectors. [24] Presented an approach to Pre-Processing and Post-Processing Steps for Brain Cancer, where six different methods of processing are presented for a large area of MRI sample processing. The diagnosis of MRI sample is
developed using four major processing namely, filtration, segmentation, feature extraction and classification. Each of this stage has an impact on the processing accuracy.

4.1. Distortion Minimization and Effect in MRI Processing

Wherein efforts on noise elimination are resolved through in-depth filtration methods, descriptive features are highly susceptible to interference observed in the computation process. Wherein the test sample image is processed for the entire region, feature count is large resulting in a high processing overhead. The classification operation processing on the extracted feature yields into the processing overhead issue [25]. To obtain a accurate descriptive feature, images need to be noise free. Preprocessing is an important process in brain tumor detection. The effect of distortion is very important factor in making decision. To achieve high-quality accuracy, the complexity in image filtration for representation and classification needs to be reduced. In the early stage of processing, Captured MRI sample are pre-processed to remove the distortions acquired by processing system in improving the quality of image content for processing. Figure 7 shows a noise effect on the processing MRI sample.

![Figure 7](image)

**Figure 7.** Original and Noise effected sample in MRI processing [26].

In processing image the use of pre-processing and post-processing measures for the optimal elimination of noise for brain tumor filtration is presented in [26]. Images are processed using Mean filtration and median filtration for noise reduction [27]. However, the static nature of the filtration leads to constraint this filtration to a specified region only. A wavelet based filtration is presented in [28] where the images are processed in spectral domain. The processing coefficients of spectral bands are however overhead to the filtration process. In [29] a integer-to-integer coding for noise elimination for MRI image processing is presented. A reversible filtration process for noise minimization is presented in [30]. In [31] a multi resolution coding using multi wavelet transformation is present; this filtration offers a good visual of noise suppression, however with the constraint of large processing coefficients. The filtration process is very critical as the later processes are fully dependent on the accuracy of the image sample passed. Hence, filtration process needs an improvement in terms of accuracy and processing complexity. The filtered images are then processed for segmentation. Approaches for image segmentation are briefed in next section.

4.2. Region Detection and Segmentation in MRI Processing

Detection of region of interest in a MRI sample is a challenging task in automated tumor detection. This approach process on MRI sample in prediction of tumor area and extracting from the MRI sample for feature computing [32-35]. In recent past a watershed segmentation method for tumor area segmentation is outlined in [36]. This method demonstrates the ability to segment areas of tumor and non-essential areas in MRI based on pixel-based coding. In [37] graph-based method for region identification is outlined. The outlined method provides a method for the learning based approach using combination of regional coding
and the registration process. A markovian approach for tumor region segmentation in outlined in [38]. This approach performs a probability based region scan to the isolation of region of interest in MRI sample. A curvature based segmentation following the edge geometry is outlined in [39]. This approach computes the distinct bounding region to represent the region of interest. Morphological methods were developed in [40,41] over binarized sample in segmentation process. The low complex processing is however limited with the accuracy of binary interpolation. A process of segmentation representation is illustrated in figure 8 below.

![Figure 8](image)

**Figure 8.** (a) MRI sample with tumor region, (b) region marked, (c) segmented region [40].

Various past methods were developed with the objective a segmentation process. A summary of the past segmentation approach with their performance in listed in table 7 below.

| Index | Approach                                      | Segmentation accuracy (%) |
|-------|-----------------------------------------------|---------------------------|
|       |                                               | Complete area | Suspicious area | Non suspicious area |
| [42]  | Time domain features                          | 88            | 75             | 75             |
| [43]  | Tangential operator                           | 82            | 72             | 61             |
| [44]  | Interlinked method with a non-linear operation| 87            | 77             | 72             |
| [45]  | Non linear approach                           | 89            | 82             | 71             |
| [46]  | Local feature vector                          | 81            | 77             | 76             |

Segmented region are processed for feature vector in classification. Representation of accurate featured is hence a primal need in detection accuracy and delay performance. Past developments in the area of feature vector representation is outlined in following section.
4.3. Descriptive Feature Representation of MRI Sample
Feature representation has a significant impact on classifier performance; in [47] a partial feature representation for MRI sample is presented. This approach process on the time domain feature vector using shape and area of suspected reign. In [48,49] a registration based image processing using spatial feature is presented. This approach process on a 3D representation of MRI sample in extracting spatial feature. In [50] a frequency domain feature is represented. This approach computes the feature using discrete wavelet transformation. The spectral domain extraction for wavelet band is outlined in [51]. The spectral domain processing has a significance of energy based coding, however the accuracy of feature representation is based in the selection criterion been applied. An advance learning approach using convolution neural network for feature extraction is presented in [52], where multiple layers of MRI spectral are used for feature representation. Most dominantly GLCM feature are used as descriptive feature [53-57]. These features are represented by the content of the image and defined by multiple Harlick features. The computation is simpler however the accuracy of thee features is dependent on the content of processing sample accuracy. A summary of developed feature extraction method is outlined in table 8.

| Index | Descriptive feature | Classification approach | System Accuracy (%) |
|-------|---------------------|-------------------------|---------------------|
| [58]  | Histogram feature   | Support vector Machine  | 88                  |
| [59]  | Gabor feature       | Support vector Machine  | 91                  |
| [60]  | GLCM feature        | MP-Neural network       | 95                  |
| [61]  | GLCM feature        | Probabilistic neutral network | 82          |
| [62]  | Selective feature   | Convolutional Neural Network | 81          |
| [63]  | GLCM feature        | Convolutional Neural Network | 86          |
| [64]  | Fisher feature      | Caps Network            | 88                  |

4.4. Machine Learning and Classification Approaches
In [65] an extensive literature has been presented based on the process of advanced medical processing for cancer detection and current approach for its treatment. The new method of analyzing cancer cells using an image processing approach is described in [66]. A hybrid method of cancer detection has been described in [67] for accurate identification of malignant region in brain tumor analysis. The proposed method achieves higher accuracy for trained data under noise-free condition. Classifier models were developed with a variety of learning methods such as artificial neural networks (ANNs) [68], nonlinear classifier [69], or linear classifiers [70] model. In [71] a artificial neural network (ANN) is used by the Back Propagation Network (BNN) to identify Tumor areas in MRI sample.

[72,73,74] present a deep learning method for 3D sample processed using convolutional neural network method for MRI processing in recognition of tumor class is described in [75]. This method presented a mean to provide large local feature vectors for processing based on neural network and analysis of the classification system. Analysis on BRATS dataset illustrated a score of 87%, 77% and 73% for entire region, core region and active tumor region respectively. [76] Described the interpolation
method of huge count of information for the selection of the feature to vector to solve the neural network processing problem with brain tumor segmentation and low complication. Presented approach applies a hyperbolic tangent function as a non-linear operator in classification. An observation of 83%, 73% and 69% for entire, core and active tumor region is observed respectively. Two methods for machine learning applied to tumor detection is described in a Cascaded manner in [77]. This method used two phases of training to avoid class imbalances in the training process. Maxout operator is used for post processing with an accuracy of 88%, 79% and 73% obtained on different sample of BRATS dataset. New intelligent systems were developed in recent past in tumor detection. Brain imaging and diagnosis for automated tumor detection is outlined in [78-80]. The evaluation of accuracy and limitations of existing cancer detection systems were described in [81,82]. The described method explains the possibility of existing methods for tumor detection using semi supervised learning. The special feature of the brain tumor in spatial domain is outlined in [84]. [85] Presents a reciprocal information for the calculation of local features and classification. Locally similar features for 3-D MRI samples are outlined and the procedure of extracting and registering the image feature is described. The development in the area of deep learning has tremendous in tumor detection. In [74, 4] a extensive survey in the evolution of deep learning presenting the approaches of different methods for classification is presented. In [29] deep learning approach using convolution neural network is presented for glioma detection in brain image. In [32] brain tumor diagnosis based on deep learning approach is presented. The learning is developed based on the type of specified sorting of images. In [37] a deep learning approach using Wavelet transform and convolutional neural network is presented. In advanced concept of deep learning, a 3D convolution network for tumor detection is outlined in [56, 80]. A high range of context coding in 2D is used for 3D processing. Deep learning method using a multi scale patch is presented in [61]. Multi scale illustrates a higher accuracy in classification operation. Concatenation based diagnosis of brain tumor using deep learning is outlined in [65, 73]. The outlined approach mere the feature details in processing for classification. A deep learning approach using machine convolution neural network with a SVM model is outlined in [81]. Under a semi supervised model for brain tumor a deep learning semi supervised is presented in [82]. The learning overhead and slower convergence limits the performance of the classifier model following deep learning approach. An outline to the classification model in MRI processing is summarized in table 9.

With past literatures the developed filtration approach is constraint with the localization of filtration and measuring of filtering coefficients which misclassify filtering for multiple image samples. Filtration process should hence be developed with a global approach for filter coefficient considering local variation and mapping with past observations in developing filtration. The segmentation approaches are limited to region using content details. The variations in the content and finer regions with diffusion lead to a non localization of segmentation to region of interest. As the MRI sample has finer details at edge regions, a more precise region marking and segmentation approach under low variations are needed. Representations of features are developed based on the segmented regions, where shape, size and texture details outline the feature of the segmented region. The details are limited to the pixel magnitude. The variations in content would lead to the deviations in magnitude which result in false descriptive features.
Table 9. Analysis of tumor detection for different segmentation method with varying control.

| Index | Method                                      | Control                        | Fully segmented | Partial segmented | Low segmented |
|-------|---------------------------------------------|--------------------------------|-----------------|-------------------|---------------|
| [76]  | Expert feedback                             | Manual                         | 82              | 73                | 64            |
| [77]  | Learning with CNN approach                  | Complete processing            | 86              | 78                | 67            |
| [78]  | Registration with segmentation approach     | Partial processing             | 88              | 71                | 62            |
| [79]  | Merging feature vectors                      | Complete processing            | 89              | 72                | 63            |
| [80]  | CNN approach in 3D sample                   | Complete processing            | 88              | 78                | 65            |
| [81]  | Support vector machine                      | Partial processing             | 87              | 71                | 63            |
| [82]  | K-mean approach                             | Complete processing            | 86              | 73                | 67            |
| [83]  | CNN based approach                          | Complete processing            | 88              | 77                | 62            |
| [84]  | Automation in state modeling                | Partial processing             | 83              | 73                | 66            |
| [85]  | Varying CNN feature                         | Complete processing            | 72              | 57                | 53            |

5. Conclusion

A comprehensive literature survey is conducted on the developed methods for the proposed work of brain tumor detection. The automation of the brain tumor is important task because of its volumetric data presentation, fine-grained features, and complexity in decision-making. In which, the accuracy of the decision and the use of the source in the calculation are important in the automated system. The processing speed, complexity in calculation is also important in system performance. Improving operational efficiency, recent developments have tend to include new machine learning systems that have expanded the use of machine learning methods in MRI diagnosis. The paper described recent advances in the process of automated brain tumor detection, Segmentation, feature presentation, and classification models. The past developed approaches are observed to be complex in computation. Intelligent approach to machine learning methods such as the neural network (NN) provided an advantage in processing and classification of tumors and non-tumorous region in the sample. Machine learning methods have given an
opportunity to develop new approaches to improve automated performance with faster speeds and better accuracy.

In future to improve the performance of brain tumor detection, a new filtration approach with adaptive measure of filtering parameters based on dynamic windowing and recurrent mapping is focused. An improvement in segmentation based on multiple scaling with advanced feature extraction and classification is focused. The learning overhead and classification limitation in terms of accuracy and processing time will be addressed.

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