Analysis of Various Brain Tumour Detection Techniques

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***Abstract*—Medical image processing is one of the most commonly used technology in the healthcare domain. Detecting the presence of tumour in the internal organs is one of the major application of digital image processing in the medical field. This task is generally accomplished through CAD (Computer-Aided Detection). In image processing, the detection of tumour in the brain relies upon the analysis of the imaging data of brain tumour images. The first step in brain tumour detection is determining the status of the patient by analysing the images of the brain tumour accurately. The overall process of tumour detection in the brain involves several stages such as taking image data as the input, pre-processing the input data, segmentation, extracting relevant features and classification. A brief analysis of several brain tumour detection techniques with regard to certain metrics is provided in this paper**.

Keywords—Brain Tumour, Feature Extraction, Classification, Machine Learning

I. INTRODUCTION

The human brain is an important and the most complex part of the body in which 50–100 billion neurons are present. An enormous number of cells have formed it and every cell plays a particular function. Several cells that are produced in the body are split for creating new cells so that the human body can function efficiently. The death of aged or damaged cells leads to the formation of new cells, and thus in this way new cells are formed [1], [2]. Sometimes, the generation of new cells occurred in the body when these are actually not required. Furthermore, aged or damaged cells are not dying appropriately in the way they should. Thus extra cells are developed in the body due to which a lump of tissues called a tumour is grown. The sensitive functioning of the body gets affected when a tumour has occurred in the brain. The treatment of this tumour is a costly, complicated and painful process. The reason behind this is the location and spreading capability of tumour [3], [4]. Brain tumours are of two kinds namely benign tumour and malignant tumour. In benign tumours, the non-cancerous cells are comprised and malignant ones are the ones comprising of cancerous cells.

Digital image processing (DIP) is the approach in which information from digital images stored as pixels are processed. Medical image processing is the branch of digital image processing in which medical information from Magnetic Resonance Imaging (MRI) images, Computed tomography scans are processed. It is the most efficient approach for observing the health status of the people. Thus, for research on medical diagnostic image data has taken into consideration. The brain tumour has been presented as a major topic of research in the medical sector because tumour disease is very complex and occurs naturally. Advanced image processing methods are implemented to detect whether the tumour has occurred in internal organs or not. The CAD system is utilized to execute this process. The initial phase in determining the condition of the patient is to analyse the images of the brain tumour accurately. But, personal medical knowledge of doctor and differences in experience levels have a great influence on the accurate analysis of image results. Thus, the accurate detection of images of brain tumour is essential. The MR images are useful to get the desired information regarding the shape, size and position of human tissues and organs. The images provided through MRI are clear and precise. By the use of MRI, the diagnostic efficiency has enhanced and a fine guide is offered to localize the tumour and to provide surgical treatment [5], [6]. Brain tumour MRI makes the utilization of 3-D multi-band imaging technology and chest X-ray scanning, etc. Unlike the 2-D images, 3-D multiband MRI is capable of providing the coordinate position of the tumour part so that the doctor can be assisted in exactly locating the tumour region [7], [8]. Fig. 1 represents General Brain Tumour Detection System.

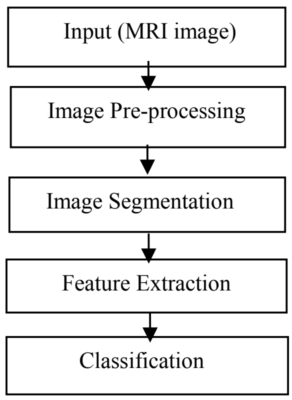

Fig. 1. General Brain Tumour Detection System

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Four phases included in an image processing system are Pre-processing of the input image, Segmentation, Extraction of relevant features and Classification. Medical image processing ensures a high success rate by utilizing images of high quality in the detection system. Thus, the initial process of the pre-processing phase is focused on enhancing the quality of input images [9], [10]. Histogram Equalisation (HE) is an extensive method that is implemented to maximize the quality of digital medical images by changing their pixels intensity. This makes the image stronger. The histogram is used to make the image different under the image processing and is utilised to deal with the pixel distribution problem.

In the second phase, the digital image is split into numerous segments [11], [12]. Efficient segmentation is necessary to identify an abnormality in the brain and to offer an alternative representation of an image whose analysis is easier [13], [14]. In digital image processing, Otsu's thresholding technique is used to compute threshold value based on clustering or the grey-level image can be converted to a binary image. It is assumed through the algorithm that two classes of pixels are comprised in the image subsequent to a bimodal histogram. Afterwards, these two classes are separated to compute the optimum threshold so that there is minimum intra-class variance and their interclass variance is maximum. Among all clustering algorithms, the K-means algorithm is generally used. The essence of this algorithm is to collect the patterns from different clusters based on their distance from the cluster [15], [16]. This algorithm is beneficial because this is fast, simple, highly efficient and scalable for big data sets. In addition to this, the time complexity of this algorithm is close to linear and appropriate for mining extensive data sets.

In the feature extraction process, the information of higher-level related to an image including shape, texture, colour and contrast is gathered. The essential parameter of the Machine Learning system is to analyse the texture [17], [18]. The considerable attributes are chosen to improve the efficiency of the diagnosis system. Grey-Level Co-occurrence Matrix (GLCM) is an excellent statistical approach that is useful to express the spatial relationships among each pixel and its neighbouring pixels. This technique is often implemented to carry out the texture analysis. Some statistical values whose extraction is done from the co-occurrence matrix are homogeneity, energy, correlation, and contrast. A practical example of GLCM is represented in Fig. 2.

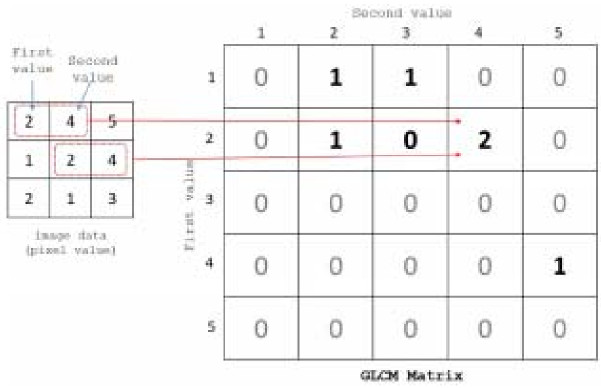

Fig. 2. Example of GLCM with (0, 1) offset

The given Equation shows the mathematical expression of GLCM.

$$G_{\Delta x,\Delta y}(i,j) = \sum_{x=1}^{n}\sum_{y=1}^{m}\begin{cases}1, & if I(x,y) = i \text{ and } I(x+\Delta x, y+\Delta y) = j\\ 0, & otherwise\end{cases} \tag{1}$$

In (1), the indexes of elements are denoted using i and j in the output matrix. Moreover, x and y are employed to denote the pixel location of the target digital image. The spatial relationship parameters are defined using Δx and Δy. Diverse outcomes are obtained when GLCM of the same target image I is carried out with various offset parameters [19], [20]. This method consists of two phases in order to bring out the important attributes from the medical images. The initial phase is the evaluation of GLCM and the second phase consists of the computation of GLCM based texture features. It is difficult to classify brain tumours as the shape, size, location and contrast of tumour tissue cells are varied. Existing Deep Learning (DL) methods are helpful in categorizing diverse kinds of brain tumours.

Support Vector Machine (SVM) is a supervised learning model that is used to solve both the problems of classification and regression. The unique property of this technique is that it enhances the geometric margin in a synchronous manner. A former knowledge is not needed even in the case of higher input space dimension [21], [22]. Thus, SVM becomes a fine classification model. This technique focuses on distinguishing the data points of given classes in the training data set. The data set given as input is visualized as two sets of vectors in n-dimensional space using SVM. A hyperplane is developed separating the two classes and that can increase the margin between the given classes. The margin is computed on both sides of the separating hyperplane, using two parallel hyperplanes. The generalization error will be lower in case of a larger margin.

The separating hyperplane assists in viewing the training data as:

$$u.z + c = 0 \quad (2)$$

Here, u signifies the m-dimensional vector and c is utilized to show the scalar.

A vector u is perpendicular to the hyperplane and the parameter c which is a scalar quantity is used for maximizing the margin. When c is absent, the hyperplane passes through the origin [23], [24]. The margin is maximized using the parallel hyper-planes. The given equation defines these parallel hyperplanes as:

$$u.z + c = 1 \quad (3)$$

$$u.z + c = -1 \quad (4)$$

The parallel hyper-plane is selected in case of division of training data linearly. Geometrically, the distance among the hyper planes is measured as 2/|u|. The equation is expressed as:

$$u.z_j - c \geq 1 \quad (5)$$

$$or$$

$$u.z_j - c < -1 \quad (6)$$

A hyper plane is described formally using the given notation:

$$L(z) = \alpha_o + \alpha^c z \quad (7)$$

In which α weight denotes the vector and α_o is the bias.

The α and α_o are scaled to depict the optimal hyperplane. The selection of one representation is done from diverse possible representations of hyperplane as [25], [26]:

$$|\alpha_o + \alpha^c z| = 1 \quad (8)$$

z is used to represent the support vectors which are the training data points found closer to the hyperplane

The distance from the support vector z to a hyperplane is represented with the expressed equation as:

$$(\alpha_o, \alpha): Distance = \frac{|\alpha_o + \alpha^c z|}{\alpha} \quad (9)$$

However, for canonical hyperplane, the numerator equates to one and distance between hyperplane and the support vector is defined as [27], [28]:

$$Distance_{support\ vector\ machine} = \frac{|\alpha_o + \alpha^c z|}{\alpha} = \frac{1}{\alpha} \quad (10)$$

K-means clustering is an unsupervised learning algorithm that is implemented to split the objects into k groups according to the attributes. This algorithm is concentrated on generating the close-fitting cluster and suits appropriately to low dimensional data [29], [30]. Each cluster representative is called a centroid. The traditional algorithm employs the Euclidean distance to quantify the distortion so that the clustering process focuses on reducing the SSE (sum-of-squared error) amid the objects and cluster centroids [31], [32].

Naïve Bayes is a supervised learning algorithm in machine learning. It can be used to solve the problem of classification. It is based on the Bayes theorem and is generally used in text classification problems. It takes the decision on the basis of probability. So, The NB (Naive Bayesian) is a simple Bayesian network whose formation is done using Directed Acyclic Graphs (DAGs) that have only one parent and a number of children. It is assumed that the child nodes are independent of their parent node [33], [34].

A decision tree is another supervised learning method in which decisions are taken based on the features of the given dataset. It is mostly preferred to solve classification problem though it can be used for both classification and regression problems. It starts with a root node, tests the feature specified by this node and then expands further like a tree structure [35].

II. LITERATURE REVIEW

A. Brain tumour detection using Deep Learning

Sangeetha et al. (2020) discussed that the experts had implemented several algorithms to detect the brain tumour automatically based on DL algorithms [36]. The planning of these algorithms was done for training and tuning numerous images in a short period. Moreover, various kinds of classification algorithms were suggested along with several iterations on the basis of Convolution Neural Networks models namely VggNet, GoogleNet and ResNet 50. At last, it was indicated that a higher accuracy was acquired using ResNet 50 that was computed 96.50% in comparison with the other models. Moreover, this model had a lower execution time.

Gore and Deshpande (2020) analysed that the major task was to detect the brain tumour [37]. The detection of tumour from the image was challenging. A review was put forward that was conducted on detecting brain tumour based on Deep learning (DL) methods. The existing techniques were analysed and their comparison was also performed. In the end, the investigation and comparison study carried out of novel studies had described. The results from the presented review depicted the recognition of several research gaps.

Raut et al. (2020) intended a Convolution Neural Networks (CNN) algorithm for detecting the brain tumour [38]. First of all, the essential data was created by enhancing the Magnetic Resonance Imaging (MRI) images. Thereafter, the pre-processing of images was executed for eliminating the noise. These pre-processed images which determined whether the input image having a tumour or not were utilized to train the intended algorithm. The error rate was mitigated and outcomes were obtained with higher accuracy using Back Propagation (BP) in the training phase. Autoencoders were employed on the generated image for eliminating the irrelevant attributes. At last, the K-Means algorithm was applied for segmenting the tumour area.

Çinar and Yildirim (2020) used CNN models for diagnosing the brain tumour through MRI images. The use of these models was quite popular during the diagnostic process [39]. This work used Resnet50 architecture, a type of CNN, as the base model. In this work, eight new layers were added in the Resnet50 architecture by removing its last five layers. This model attained an accuracy rate of 97.2%. In the results, the devised technique was proved efficient and worthy to be used in CAD frameworks for the detection of brain tumour. The main focus of this work was to combine different architectures and use them as hybrid frameworks for tumour detection.

Maharjan et al. (2019) proposed a new framework that consisted of a CNN with some modification in loss function and regularization parameter [40]. This work measure the processing time and the classification accuracy for a variety of tumours. According to results, the proposed approach outperformed other approaches by obtaining 2% more accuracy and a lesser processing time of 40~50 ms.

B. Brain tumour detection using machine Learning

Hemanth et al. (2019) suggested an automatic segmentation technique that was planned on the basis of CNN [41]. This single method was incorporated to segment and classify the image. The suggested technique had different phases in which data was gathered, pre-processing was done; average filtering and segmentation were carried out; attributes were extracted and the image was classified and recognized using Convolutional Neural Network (CNN). The Data Mining (DM) methods were implemented to extract the considerable relations and patterns from the data. The brain tumour can be detected and prevented in initial phases using Machine Learning methods.

Abbas et al. (2019) recommended a technique named Local Independent Projection-based Classification (LIPC) to detect and segment the brain tumour [42]. At first, the noise was eliminated and the image was enhanced using image processing methods. Thereafter, Principal component analysis (PCA) was applied to evaluate distinct textural attributes so that a superior score was attained in classification. The MICCAI 2013 dataset which comprised tumour of high grade and low grade had been used. A Dice Score obtained from the recommended approach was found 0.95 for a complete tumour in comparison with other techniques.

TABLE I. DEEP LEARNING TECHNIQUES

Author	Year	Advantages	Disadvantages
R. Sangeetha, A. Mohanarathinam, G. Aravindh, S. Jayachitra, M. Bhuvaneswari	2020	The accuracy of ResNet 50 was computed 96.50% in comparison with the other models.	The recall obtained from these algorithms was found lower.
Deipali Vikram Gore, Vivek Deshpande	2020	The recognition of several research gaps was done from the presented review.	This review had not proved efficient as advancement was required in Deep Neural Network (DNN).
Gajendra Raut, Aditya Raut, Jeevan Bhagade, Jyoti Bhagade, Sachin Gavhane	2020	The error rate was mitigated and outcomes were obtained with higher accuracy using BP in the training phase.	The irrelevant attributes were generated using this approach.
Ahmet Çinar, Muhammed Yildirim	2020	This model attained an accuracy rate of 97.2%. In the results, the devised technique proved efficient and worthy for using in CAD frameworks for the detection of brain tumour.	The loss values are so small that for every model it needs to be multiplied by 100.
Sunil Maharjan, Abeer Alsadoon, P. W. C. Prasad, T. A. Dalain, Omar Hisham Alsadoon	2020	According to results, the proposed approach outperformed other approaches by obtaining 2% more accuracy and a lesser execution time of 40~50 ms.	In this work, small datasets were used in the proposed deep learning model.

Manogaran et al. (2019) focused on deploying an enhanced ML technique based on orthogonal gamma distribution for analysing all the segments of brain tumour regions so that the abnormalities were detected in the region of interest in an automatic way [43]. The machine-learning algorithm was utilized to quantify the sensitivity and selectivity of the proposed model. The efficacy of optimal automatic detection was authenticating by gathering and analysing the benchmark dataset. The outcomes obtained in experimentation revealed that the presented technique provided an accuracy of around 99.55% to detect brain tumours. This approach was useful in the sector of detecting and analysing brain abnormality with no human intervention in the health care sector.

Zaw et al. (2019) used a Naïve Bayes classifier for identifying the correct location of the tumour where all cancerous tissues were present [44]. The major concern of this approach was the detection of the cancerous region using a number of brain MRI scans and to predict that whether the detected region was cancerous or not. Unlike other exiting techniques, this technique was capable of detecting the tumour present in different brain parts. For this purpose, this approach used 50 brain MRI scans and obtained a detection rate of 81.25% and 100% for tumour images and non-tumour images respectively with 94% of total accuracy.

Divyamary et al. (2020) developed an effective technique known as NB (Naive Bayes) for detecting the brain tumour in the initial phase [45]. First of all, the image was obtained from the patient. The noise was eliminated, segmentation of the image was done using morphological operation and relevant attributes were extracted from the segmented image. At last, the classification was performed. The results demonstrated that the developed technique provided an accuracy rate of 84% as compared to traditional techniques. In addition, the developed technique was capable of detecting the brain tumour and obtained a higher success rate.

C. Brain tumour detection using Optimization algorithms

Sharif et al. (2019) investigated Brain Surface Extraction (BSE) technique to eliminate the skull from the image at first [46]. The particle swarm optimization (PSO) algorithm had employed this image for acquiring superior segmentation. Subsequently, the extraction of Local Binary Patterns (LBP) and deep attributes was done. The attributes were selected using genetic algorithm (GA). At last, the tumour grades were classified with the help of the Artificial Neural Network (ANN) and other classification methods. The investigated technique was quantified on public datasets. This technique provided an accuracy of up to 99%. The outcomes revealed that the investigated technique was efficient and unique as compared to state-of-art schemes. The presented technique was unable to detect the substructures of tumour such as solid, necrotic, enhancing component.

Vijay et al. (2016) designed an algorithm recognized as Enhanced Darwinian Particle Swarm Optimization (EDPSO) to segment the tumour automatically and to tackle the limitations of the PSO algorithm [47]. There were four phases in this algorithm. The pre-processing phase utilized the tracking algorithm to eliminate the undesired areas of MRI images. After that, the Gaussian filter was utilized to remove the noises and high-frequency element.

TABLE 2: MACHINE LEARNING TECHNIQUES

Author	**Year**	**Advantages**	**Disadvantages**
G. Hemanth, M. Janardhan, L. Sujihelen	2019	The brain tumour can be detected and prevented in initial phases using Machine Learning methods.	Its accuracy was depending upon the processing of every phase.
Khizar Abbas, Prince Waqas Khan, Khan Talha Ahmed, Wang-Cheoul Song	2019	A Dice Score obtained from the recommended approach was found 0.95.	This technique was unable to deal with the issue of segmenting the brain tumour automatically.
Gunasekaran Manogaran, P. Mohamed Shakeel, Azza S. Hassanein, Priyan Malarvizhi Kumar, Gokulnath Chandra Babu	2019	The presented technique provided an accuracy of around 99.55% in detecting brain tumours.	The recall was found lower and execution time was found higher.
Hein Tun Zaw, Noppadol Maneerat, KhinYadanar Win	2019	This approach used 50 MRI scans and obtained detection rate of 81.25% and 100% for tumour images and non-tumour images respectively with 94% of total accuracy.	It was quite challenging for the naïve bayes classifier to detect the tumours located in the middle part of the brain because of the false positive result of the eyes.
D. Divyamary, S. Gopika, S. Pradeeba, M. Bhuvaneswari	2020	The results demonstrated that the developed technique provided the accuracy rate of 84% as compared to traditional techniques. In addition, the developed technique was capable of detecting brain tumour and obtained a higher success rate.	The overall accuracy of the naïve Bayes classifier is not satisfactory.

The next phase implemented Darwinian Particle Swarm Optimization (DPSO) to segment the brain images. In the last phase, Adaptive Neuro-Fuzzy Inference System (ANFIS) was executed for classifying the images. The MRI images of the brain were applied to compute the performance of the designed technique. The results depicted that the designed algorithm provided a superior quality rate. The performance of the algorithm was not efficient in terms of robustness.

Rammurthy and Mahesh (2020) intended an optimization-driven method known as Whale Harris Hawks optimization (WHHO) to detect the brain tumour with the Magnetic Resonance Imaging (MRI) images [48]. The extraction of attributes was done from the segments. Moreover, Deep CNN (DCNN) algorithm was deployed to detect the brain abnormality in which training was done using WHHO technique. In the intended technique, Whale Optimization Algorithm (WOA) was put together with Harris Hawks optimization (HHO). The intended method WHHO had provided the accuracy around 0.816 and sensitivity around 0.974. However, the efficiency provided through this method was computed poor.

Aly et al. (2019) presented an approach in which 3 meta-heuristic optimization techniques were utilized namely BPSO (Binary Particle Swarm Optimization), ACO-TSP (Ant colony Travel salesman problem) and ABCO (Artificial Bee colony optimization) to detect the brain tumour [49]. Initially, the K-means cluster was deployed for segmenting the MRI (Magnetic Resonance Imaging) images. Subsequently, the attributes were extracted from the segmented images. A comparison of the performance was conducted on the presented techniques to select the efficient solution to extract the attributes. The results depicted that the presented approach obtained an accuracy of 88.9% while detecting the brain tumour.

Yin et al. (2019) recommended a novel meta-heuristic technique for detecting the brain tumour at premature phase [50]. There were three stages of this technique in which background was eliminated, attributes were extracted and classification was performed using MLP (multilayer perceptron) neural network. An enhanced model of the WOA (whale optimization algorithm) was introduced based on the chaos theory and logistic mapping method for selecting the attributes and carrying out the classification. The comparison of recommended technique was done with traditional algorithms. The outcomes revealed that the recommended technique generated superior results in contrast to others concerning CDR (correct detection rate), FAR (false acceptance rate), and FRR (false rejection rate).

III. Conclusion

Brain tumour detection has various phases which include taking the MRI image as the input, pre-processing of the given input image, Segmentation of the pre-processed image, Extraction of the relevant features from the segmented region and classification. Pre-processing is the phase that removes noise from the image. Segmentation is done in the second phase. In the third phase, textural features of the image are extracted and in the last classification technique will be applied which can classify the image as the one with tumour or non-tumour. To improve accuracy for brain tumour detection hybrid classification method should be implemented.

TABLE 3: OPTIMIZATION TECHNIQUES

Author	Year	Advantages	Disadvantages
Muhammad Sharif, Javaria Amin, Mudassar Raza, Mussarat Yasmin Suresh Chandra Satapathy	2019	This technique provided an accuracy of up to 99% and it was proved efficient and unique as compared to state-of-art schemes.	The presented technique was unable to detect the substructures of tumour.
Vasupradha Vijay, A. R. Kavitha, S. Roselene Rebecca	2016	The designed algorithm provided superior quality rate for the given images.	The performance of algorithm was not efficient in terms of robustness.
D. Rammurthy, P. K. Mahesh	2020	The intended method provided an accuracy around 0.816 and sensitivity around 0.974.	The efficiency provided through this method was computed poor.
Rabab Hamed M. Aly, Kamel H. Rahouma, Hesham F. A. Hamed	2019	The results depicted that the presented approach obtained an accuracy of 88.9% while detecting the brain tumour.	A lot of complexity was involved in the devised algorithm.
Bo Yin, Chao Wang, Francis Abza	2019	The outcomes revealed that the recommended technique generated superior results in contrast to others concerning the parameters like CDR, FAR, and FRR.	The network architecture used in this work was very complex in nature.

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