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Detection of Brain Tumour in MRI Images using Deep Belief Network (DBN)

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ABSTRACT

One of the world's deadliest illnesses is brain cancer. It is a cancer that often affects adults as much as children. It is the least likely species to survive, and its diversity is determined by its location, sweetness and structure. The negative effects will stem from the incorrect classification of the tumour brain. Therefore, determining the specific type and rank of the tumour in its early stages is required to select a specific treatment plan. A major concern is the elimination, segmentation and detection of tumour areas infected by magnetic resonance imaging (MRI). Despite the fact that it is a laborious and tedious task done by clinical experts or radiologists whose precision depends entirely on their experience. Computer-aided technology is becoming more and more important for circumventing these limitations. This study investigates a multi-layer Deep Belief Network (DBN) technique for MRI tumour detection. The proposed model is named as Brain Tumour Deep Belief Network (BT-DBN). The BT-DBN was tested with two datasets. The results demonstrate the importance of accuracy parameters relative to the most recent approaches. The results exhibit that the BT-DBN was effective in identifying different types of tumour tissue in MR images of the brain. The precision is 99.51%, the specificity is 94.28%, and the sensitivity is 98.72%.

1. Introduction

The integral part of the body is brain which controls all the activities of body and takes decision for action of human. The brain does not work properly if any infection of disease occurs in brain. In view of this brain tumour is one of it. Brain tumours are defined as the proliferation of tumour cells in the brain. Brain tumours are the most commonly occurring type of brain disease [1,2]. This is one of several cancers which can cause death. Brain tumours can be harmless or malignant.

As reported by the WHO and the ABTA [3], the most used classification system which scale from Class I to II as light and Class III to IV as malignant. The development of abnormal cells within the brain is known as brain tumour [4]. The status of brain tumours is being monitored and analysed by the National Brain Tumour Society. In the USA, approximate more than 29000 humans were suffering from brain tumour (primary) in 2015 [5]. In 2019, approximate more than 23,820 new cases of brain

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tumour cases were reported and approximate more than 1760 death cases were observed in US [6]. In US, approximately 24,530 incidences of brain tumour were predicted in 2021 [7]. Brain tumours can occur in primary as well as secondary [8]. The first category (primary) brain tumour is limited to the area in which it is occurred and grows slowly [9]. As per the statistics of Asia in 2020 of global cancer report, approximate 308,102 patients of brain cancer were observed and approximate death 251,329 patients observed [10]. Among various medical techniques, MRI is the best one [11].

Medical imaging technologies use segmentation to locate contaminated tumour tissue. Segmentation is the process of splitting an image into more than one section or block. It's possible that it has the same colour, roughness, contrast, intensity, borders, and grey level. Utilizing MRI imaging or other imaging modalities, brain tumour segmentation is the process by which cancer cells are separated from normal cells, like edema and dead cells, cancer cells like WM, GM and CSF [12-15].

An effective CAD system requires a method for extracting functions [16]. Since the accuracy of the classification depends on the important duties acquired, the difficulty of the task requires prior knowledge of the subject matter

wavelets and frequency characteristics, contextual and hybrid characteristics, etc. Where deep learning is used, CAD modelling methods give better results. A computer vision subset called Deep Learning (DL) does not need to manually create functionality [17,18].

It has been shown to work better than previous methods and to close the gap between computer vision and optical acuity in categorizing models [19]. In a number of areas, including text creation [20], facial identification [21], image characterization [22], Go [23] and great difficulties [24], it worked better than other methods. The use of DL in image classification and segmentation has been motivated by performance improvements in many areas [25-31]. It is expected that the number of studies using deep learning for diagnostic imaging will continue to increase in future years, as indicated in [32]. About 220 studies were published during 2016. Approximately 190 of the respondents used CNN.

DL, particularly AlexNet [33], GoogLeNet [12] and ResNet-34 [13], can be used to categorize brain tumours in medical images using a pre-formed CNN model. Over the large datasets (millions of images) of ImageNet [24], CNNs have significantly improved their performance. However, it is difficult to use CNs of the same high standard in the medical field. Because it takes time, effort and money to physically assess and classify images, health datasets are often small, requiring first access to experienced radiologists. Secondly, it is difficult to train CNN on a limited data set due to differences and adjustment issues. Third, rewriting the model and changing its parameters to enhance performance requires expertise in this area. Therefore, acquiring CNN training early on is a difficult and time-consuming process that requires considerable diligence and perseverance.

The contributions are:

i. A single, robust model to detect automated brain tumour is presented to identify key features from the MRI dataset.
ii. The BT-DBN model suggested to use 3 x 3 nuclei for all completely connected. It contrasts with earlier models that use 11 x 11 or 9 x 9 cores with longer strides.
iii. Compared to other strategies that require tumour segmentation prior to classification, the innovative model surpasses the high precision of brain tumour classification with little pre-treatment.
iv. In comparison to new baseline dataset techniques, our model provides adequate classification accuracy.

The following is how the paper is organised: The sections below provide information on related works: Section 2, materials and methods showing the stages of the suggested method, Section 3, experimental findings and discussions, Section 5's comparison of the various models, and Section 6's conclusion and recommendations for further research.

2. Existing Research

To detect brain tumours, it is crucial to segment medical images. Many approaches developed using MR images for brain tumours classification. The various literatures are summarized in this section.

The study [34] of Thaha *et al.,* Designed an algorithm named as Bat using CNN model. To enhance image quality and eliminate image noise, the dataset was pre-processed. The proposed algorithm showed the performance about 92% accuracy and quoted good as compared to the existing model.

The study [35] of Talo *et al.,* designed a procedure for classification brain tumour using MRI images and models for various model such as VGG-16, ResNet-34 and ResNet-50. The proposed procedure automatically detected the various features of the brain tumour. Using the ResNet-50 model, the proposed method achieved 95% accuracy.

The study [36] of Sharif *et al.*, developed a procedure that utilizes CNN architecture to detect brain tumours. Segmentation and particle swarm optimization algorithms were used in the proposed procedure. Two different datasets (BRATS2013 and BRATS2018) were used to train and test the procedure. Authors quoted about 92% accuracy for brain tumour detection of proposed approach.

The study [37] of Naser and Jamal designed a CNN model using DL based strategy to classify brain tumour. Authors used dataset of cancer imaging of MRI. Authors quoted about the result of proposed model that was 92% accuracy for classification of brain tumour. The authors stated that the proposed model had a validity of 89%.

The study of [38] Huang *et al.,* proposed an approach named as differential feature neural network for classification of brain tumour. Author involved two different dataset of MRI images. Authors quoted the result of proposed framework that was 99.2 % accuracy using Dataset-I and accuracy 98% using dataset-II.

The study [39] of Khalil *et al.,* designed an algorithm to handle the issue of varying size and structure of tumour. Three steps were involved in the proposed algorithm. The first step handled pre-processing of MRI images and found the boundary of tumour. The next two levels found the tumour of varying size using approach of clustering. This study involved dataset (BRATS017) for training and testing the suggested algorithm. This study quoted that proposed algorithm achieved accuracy with approximate 98%.

The study [40] of Khairandish *et al.,* designed a model by integrating support vector machine and CNN for detection brain tumour for MRI images. In this model, three stages of pre-processing method were applied to increase the quality for detecting the brain tumour.

The study of [41] of Azhari *et al.,* designed a technique for identification of malignant cell. The proposed technique used five levels of operations. These levels included various operation such capturing of image, detection of edges, clustering and pre-processing. Author used public dataset of MRI.

A modified neural network was utilized by Hemanth and colleagues [42]. The proposed method was tested with 540 MR brain images. Four types of tumours are present in the 256 by 256 pixels sample: meningioma, glioma, astrocytoma, and metastases. A component of the preprocessing procedure is normalization. On the basis of the first-order histogram and GLCM, eight features are derived. The proposed method yields promising results with 95% sensitivity, 98% specificity, and 98% accuracy.

A neural network-based method presented by Damodharan and Raghavan [43] for identifying and classifying brain tumours. This method asserts a precision rate of 83% to segment the tumour region with a neuronal network classifier. Each segment's quality rate is provided separately.

The MR images of the brain must be divided into two distinct areas in order to remove the brain tumour [44]. One section contains cells from brain tumours, while the other section contains normal brain cells [45]. Zanaty [46] suggested a hybrid strategy for brain tumour segmentation that combines growth of seed regions, FCM and Jaccard's coefficient of similarity algorithm. It assesses segmented white matter and grey matter tissue based on MRI images. With noise levels of 3% and 9%, this approach led to an average S segmentation score of 90%.

Yao *et al.,* Torheim and others [47], Guo and others [48], By combining texture characteristics, the wavelet transform, and the SVM algorithm, developed a method that effectively categorized textural features, controlled nonlinearity in actual data, and addressed various image protocols.

Kumar and Vijayakumar [49] describe the classification and segmentation of brain tumours using PCA and SVM. They claim a 96.20 per cent likeness index, a 95 per cent overlap fraction, and an additional 0.025 per cent. This method for identifying the kind of tumour has a classification accuracy of 94%, and 7.5 percent of all errors are found.

To extract statistical characteristics for classification, Ismael *et al*., [50] used the discrete wavelet transform (DWT) and the Gabor filter. In this strategy, the input and classifier are a segmented tumour as well as a multi- layer perceptron (MLP). About 91.9 percent accuracy was achieved.

A method for diagnosing brain tumours was proposed by Chaddad [51] that utilizes the Gaussian mixture model (GMM) to automatically extract features from MR images. This strategy, which utilizes principal component analysis (PCA) and wavelet-based features, enhances the performance of GMM feature extraction. The accuracy of T1-weighted and T2-weighted MR images is 97.05%, while FLAIR-weighted MR images have an accuracy of 94.11%. Demonstrate the detection, segmentation and extraction of multi-class brain tumour features, Sachdeva and others, [52] used 428 MR images. When the authors employed ANN followed by PCA-ANN in this strategy, the accuracy rate increased from 77 percent to 91 percent.

Another piece of work for the classification of AD is provided by Guo and others [53]. Using GCNN, the author divides AD into two and three categories. The proposed GCNN scores 93 percent for two-class classification, while the established ResNet architecture scores 95 percent and the SVM classifier scores 69 percent, respectively. In the three-class detection scenario, the suggested GCNN achieves 77%, while ResNet and SVM achieve 65% and 57%, respectively.

Ghassemi and others [54] also proposed a new CNN model for the classification of multiple categories of brain tumours. Three cancers were then distinguished using a SoftMax classifier in place of the final fully linked layer. There are six levels in the proposed model. It was used in conjunction with other means of improving the data. It was accurate for introduced splits at 93.11 percent and random splits at 95.6%, respectively.

Similar to that, Pashaei *et al.,* [55,58] created a novel architecture for classifying brain cancers. There are five layers for feature extraction in the proposed model. The collection of features is used to identify images using a kernel of Extreme Learning Machines (KELM). It achieved accuracy around 93.68 percent.

Padole *et al.,* uses a GCNN architecture that has been modified [56,59] to detect Alzheimer's disease early. 160 patient images from the ADNI dataset were tested using the proposed method. The five-fold CV is used for performance calculation of the model. The accuracy rate is greater than 90%

3. Materials and Methods

Recently, deep learning has been widely used in a variety of medical imaging applications. Particularly when it comes to classifying and segmenting MR brain tumours. This article proposes a novel Deep Belief Network (DBN) model to detect multi-class brain tumour.

3.1 Datasets

Figshare [57,60] is publicly accessible dataset. Between 2005 and 2010, it was gathered at Tianjin Medical University's General Hospital and Nanfang Hospital in Guangzhou, China.

Table 1
Figshare image dataset

Types of Tumours	No. of Samples	No. of slices
Meningioma	85	758
Pituitary	64	937
Glioma	93	1429

3.2 Radiopaedia Dataset

The second sample used in this article is Radiopaedia [61]. According to Table 2, it has 148 MR images that correspond to four distinct grades. This dataset only contains a few photos for each grade. On the other hand, having a lot of data and a variety of examples is necessary for the successful implementation of multiple deep learning models [62].

Table 2
Radiopaedia dataset

Grades of Tumour	Tumour type	No. of images	
		Without Alteration	Alteration
I	Menigiomas	39	647
II	Glioblastmoas	42	579
III	Gliomas	29	454
IV	Gliomas	38	524

3.3 Proposed Model (BT-DBN)

Two MR brain images with 512 by 512-pixel resolution were used by the BT-DBN (Figure 1) with two readily available data sets. These images where grayscale before any further processing could take place. The implementation of the algorithm is the subject of the following sections.

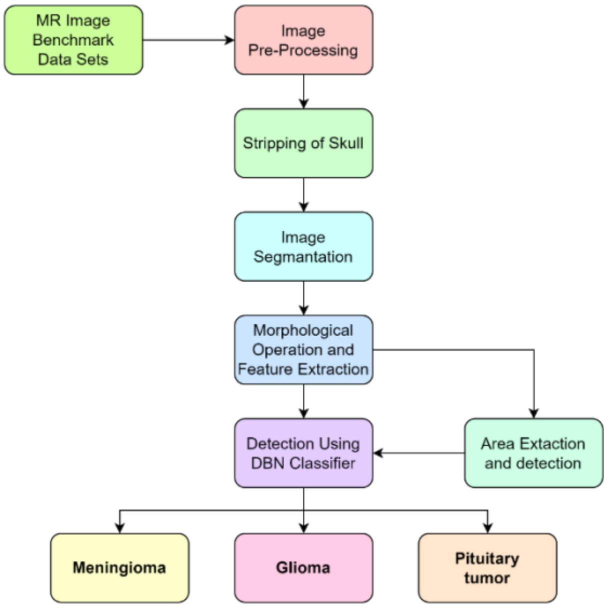

Fig. 1. BT-DBN Model

i. Preparation: Pre-processing enhances the MR image's visual appearance, eliminating irrelevant noise and undesirable origin parts, smoothing the internal portion of the region, and maintaining its edges. The signal-to-noise ratio was improved by using a modified sigmoid function for progressive image enhancement. This resulted in a better resolution for the raw MR images.

ii. Decapitating the head: Cranial stripping is the process of removing all brain tissue in imaging. Using skull stripping, fats, skin, and other brain tissues can be removed from brain imaging. Using image contour, segmentation, and features extraction, skull stripping can be automated in a number of ways.

iii. To segment the contaminated brain MR regions, the following procedures are utilized:
   - Converting the brain MR image that has been pre-processed into a binary image
   - Selecting a cut-off threshold of 128.
   - Map the pixel values to white for value greater than the threshold
   - Map the pixel values to black for value less than the threshold
   - As a result, distinct zones develop around the infected tumour tissues that have been clipped off.

iv. The process of extracting more specific information about a picture, such as its shape, texture, colour, and contrast, is known as feature extraction [63,64, 65].

The Deep Belief Network (Figure 2), or DBN: Deep belief networks (DBNs) are generative auto-encoder neural networks that use layered Recurrent Boltzmann Machines (RBMs). DBN might have several layers that are trained layer-by-layer to deal with picture classification issues. DBN is made up of two kinds of neural networks: belief networks and RBMs in a recurrent neural network known as RBM, undirected edges connect binary units. Learning is also more efficient thanks to RBM's single layer of hidden units with few connections between them.

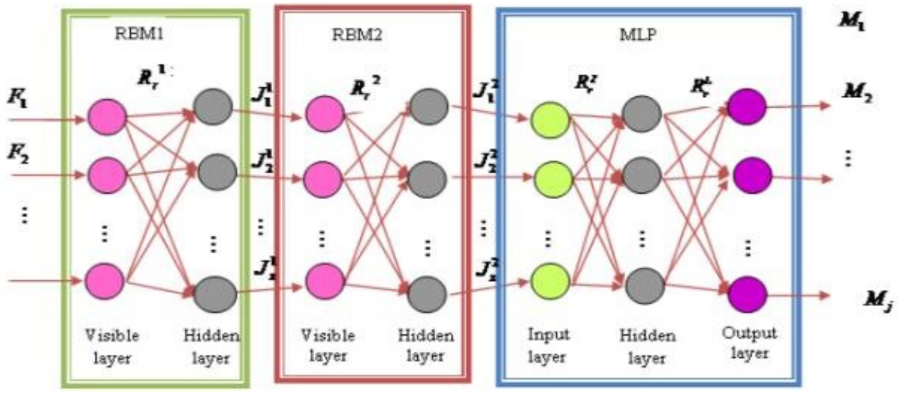

Fig. 2. Working Architecture of DBN

$$A(n, p) = 1 \exp(-E(n, p)) \quad (1)$$

Where

$$z = \sum_{n,p} \exp(-E(n, p)) \quad (2)$$

The function is an energy-based paradigm this can be learned through practice, and the partition function is represented by z. v and h represent the both open and closed units, respectively. If there are unidentified pictures set in the training set, DBN undertakes unsupervised training to identify the unlabelled images for model training. The approach could also be applied to a set of image data using deep neural networks.

3.4 Performance Indicators

The effectiveness of image classification into three classes is evaluated using Accuracy, Specificity, Sensitivity, Precision, and F1 Score. In Eq. (3) to Eq. (7), the formula for computing these performance measures is as follows:

$$Accuracy = \frac{\mathrm{T}(+) + \mathrm{T}(-)}{\mathrm{T}(+) + \mathrm{T}(-) + \mathrm{F}(+) + \mathrm{F}(-)} \quad (3)$$

$$Specificity = \frac{\mathrm{T}(-)}{\mathrm{T}(-) + \mathrm{F}(+)} \quad (4)$$

$$Sensitivity\ (Recall) = \frac{\mathrm{T}(+)}{\mathrm{T}(-) + \mathrm{F}(+)} \quad (5)$$

$$Precision = \frac{\mathrm{T}(+)}{\mathrm{T}(+) + \mathrm{F}(+)} \quad (6)$$

$$F1\ Score = \frac{Precision * Recall}{Precision + Recall} * 2 \quad (7)$$

T(+) signifies True Positive, T(-) signifies True Negative, F(+) signifies False Positive, and F(-) signifies False Negative. These characteristics are computed using the confusion matrix, which contains information on the incorrect and correct detection of images from all classes.

4. Result and Discussion

The BT-DBN is run on the RAM-64GB system configuration and an Intel Xeon E5-2620 v4 processor. Python 2.7 was used to write it, along with the Keras framework and Tensor Flow. A novel DBN model to classify brain tumours is presented in this paper. It is tested on two typical datasets. Figure 3 shows brain tumours in three instances.

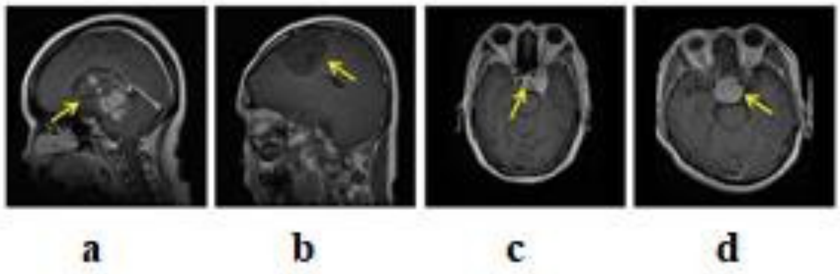

Fig. 3. Brain tumours: Gliomas (a, b), meningioma (c) and pituitary (d)

Figure 4 depicts the tumour position with area mark, the improved image.

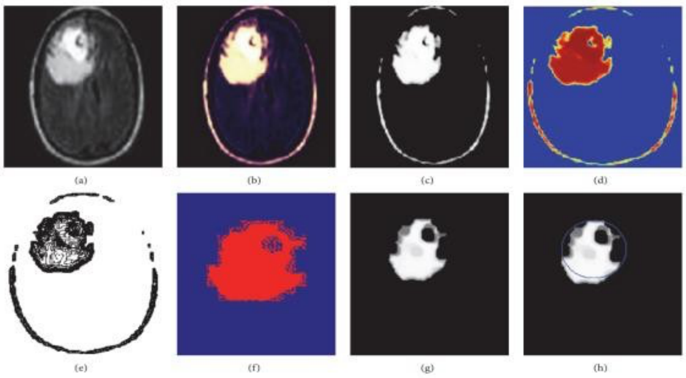

Fig. 4. Results of a sample image

4.1 Figshare Dataset Experimental Result

As presented in Table 3 and Figure 5, the suggested technique has accuracy for glioma, pituitary tumour and meningioma. Ratings of 90.68 per cent, 95.46 per cent, and 98.53 per cent were given for sensitivity, which is another aspect of classification performance. The model properly identifies samples without specific disease because all classes are highly specific.

Table 3
Results of Experiment

Class	Precision	Specificity	Sensitivity	Accuracy	F1-score
Glioma	97.43	98.67	95.56	97.58	96.45
Meningioma	96.23	97.9	90.78	90.88	90.78
Pituitary tumour	99.43	98.17	98.53	96.99	98.45

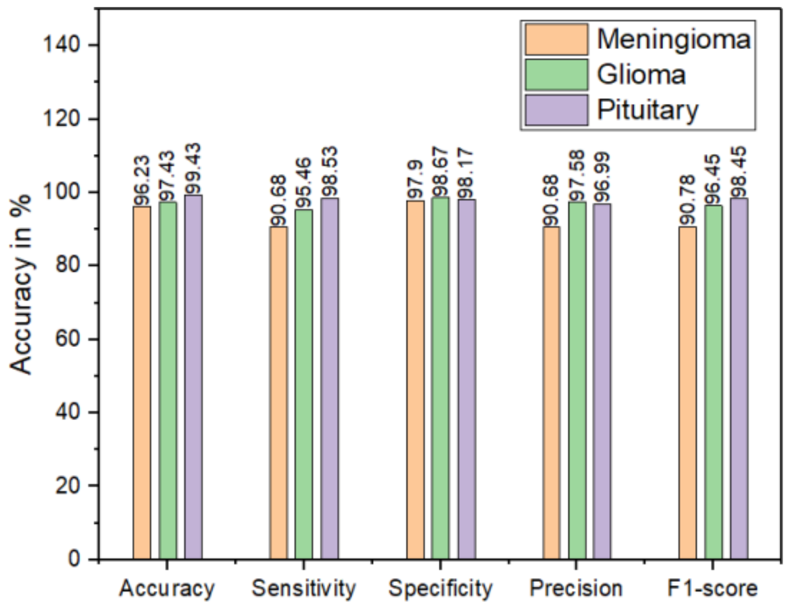

Fig. 5. Experimental results of BT-DBN model on Figshare Dataset

4.1.1 Radiopaedia dataset experimental result

Table 4 and Figure 6 presents the results on Radiopedia dataset.

Table 4
Experimental results on Radiopaedia Dataset

Grades	Accuracy	Specificity	Sensitivity	Precision	F1-score
I	97.52	97.74	91.76	97.95	96.66
II	96.51	96.58	94.69	88.88	92.69
III	94.48	98.67	91.88	92.45	92.15
IV	98.91	98.85	99.27	98.68	99.18

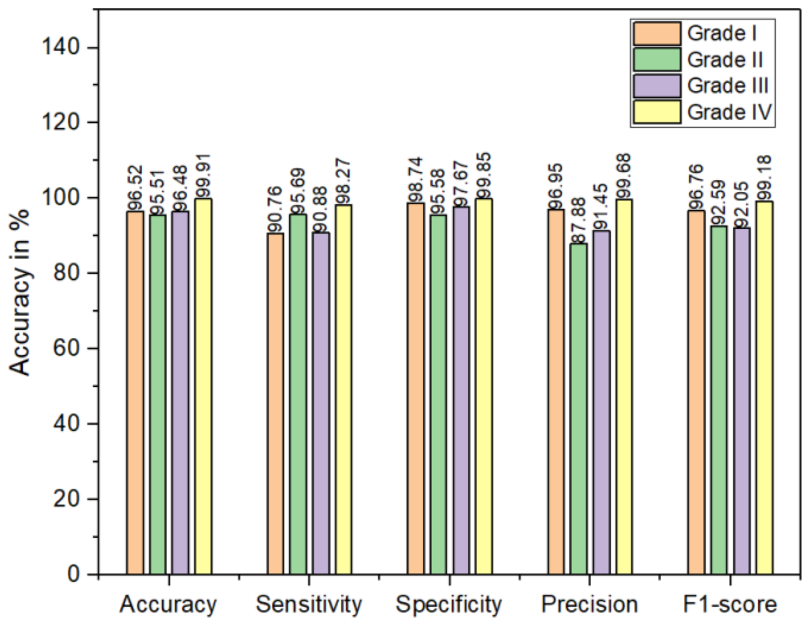

Fig. 6. Experimental results of BT-DBN model on Radiopedia Dataset

4.2 Comparison

Table 5 compares the accuracy of results without and with extracting features and demonstrates that feature extraction improves classifier performance on tumour diagnosis from brain MR images.

Table 5
Comparison of the accuracy with and without extracting features

Models	Accuracy (%) Without extracting features	Accuracy (%) after extracting features
KNN	84.29	87.57
MLR	86.55	86.06
SVM	88.14	93.04
BT-DBN	92.54	98.51

The calculation of statistical properties like sensitivity, specificity, and accuracy is used to compare the DBN classifier's test performance to that of other classifier algorithms in Table 6 and Figure 7. Better performance is also suggested by higher accuracy and sensitivity scores in conjunction with lower specificity values.

Table 6
Result Comparison

Parameter	KNN	MLR	SVM	BT-DBN
Specificity(%)	86.54	87.77	89.74	94.28
Sensitivity(%)	98.53	95.33	96.63	98.72
Accuracy(%)	95.57	92.06	98.53	99.51

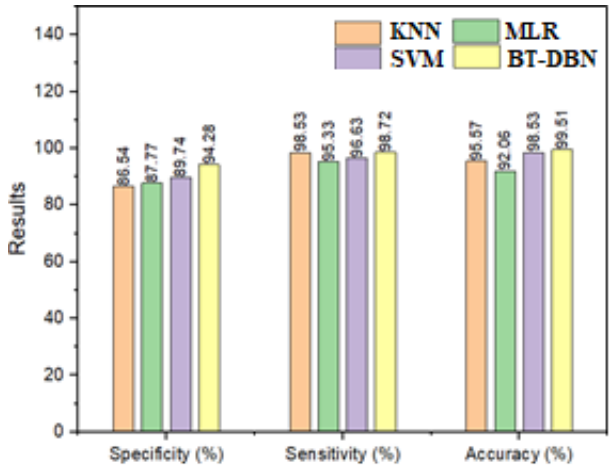

Fig. 7. Accuracy Comparison

As shown in Table 6, our segmentation method performs better than existing methods. For a radiologist or clinical doctor, even a small increase in the sensitivity parameter is very important when planning surgery.

5. Limitation

i. The dataset and models used for classifying brain tumours may affect the experimental findings.
ii. The classifiers used default values. The tuning parameters can be changed to increase

efficacy.

6. Conclusion and Future Work

The brain was divided into normal grey matter, cerebrospinal fluid (the background) and tumour-infected tissue using MRI images in this paper. Two datasets with brain tumours served as the basis for testing the model. A number of performance indicators were examined to ascertain the system's robustness and the model's accuracy. In terms of classification accuracy, the proposed DBN model outperformed previous comparable efforts on the same dataset. In the future, we intend to use images from T1, T2, and Flair, among other modalities, to strengthen our scheme and expand the dataset.

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