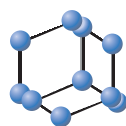
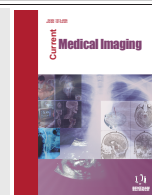


## RESEARCH ARTICLE

BENTHAM  
SCIENCE

## Brain Tumor Detection and Classification by Hybrid CNN-DWA Model Using MR Images

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**Abstract: Objective:** Medical image processing is an exciting research area. In this paper, we proposed new brain tumor detection and classification model using MR brain images to help the doctors in early detection and classification of the brain tumor with high performance and best accuracy.

**Materials:** The model was trained and validated using five databases, including BRATS2012, BRATS2013, BRATS2014, BRATS2015, and ISLES-SISS 2015.

**Methods:** The advantage of the hybrid model proposed is its novelty that is used for the first time; our new method is based on a hybrid deep convolution neural network and deep watershed auto-encoder (CNN-DWA) model. The method consists of six phases, first phase is input MR images, second phase is preprocessing using filter and morphology operation, third phase is matrix that represents MR brain images, fourth is applying the hybrid CNN-DWA, fifth is brain tumor classification, and detection, while sixth phase is the performance of the model using five values.

**Results:** The novelty of our hybrid CNN-DWA model showed the best results and high performance with accuracy around 98% and loss validation 0.1. Hybrid model can classify and detect the tumor clearly using MR images; comparing with other models like CNN, DNN, and DWA, we discover that the proposed model performs better than the above-mentioned models.

**Conclusion:** Depending on the better performance of the proposed hybrid model, this helps in developing computer-aided system for early detection of brain tumors and helps the doctors to diagnose the patients better.

**Keywords:** Brain tumor, MRI, hybrid CNN-DWA, classification, detection, accuracy, and loss validation.

## 1. INTRODUCTION

Usually, initial identification of brain tumor regions helps the medicines in the early detection of an affected patient, and it is considered a factor to reduce the number of deaths. The medical imaging techniques have been known in the past, and in recent years, interest in their applications has increased [1]. Medical images are stored in a digital environment! Understanding the internal background is difficult and time-consuming [2, 3]. MRI is a well-known medical activity used to diagnose and analyze cancerous tumors.

Litjens *et al.* [4] give a complete list of papers and research published in this field, Shen *et al.* [5] and Suzuki [6] provided a general summary on this topic, Greenspan *et al.* [7] conducted a comprehensive review of the essential and recently published papers. This was composed by searching

for books in the Elsevier, IEEE Xplore, and Springer databases. D.Adams *et al.* [8] created a list of the 200 most highly-cited articles from Google Scholar, using the terms 'MRI' 'deep learning' and 'medical image analyses' in October 2017 using citation software.

Shin *et al.* [9] explain the importance of CNN structures and machine learning in detecting inflammation in the glands, echo, abdomen, and brain, as well as in irrigation diseases in computerized tomography. They discovered that machine learning is necessary and essential despite a difference between standard and medical images. S. Zhou *et al.* [10] glimpse the importance of complete automatic localization on ultrasound, depending on the CNN and then training them in advance on ImageNet. It has shown that the higher the learning level, the better the CNN performance.

Uncertainty samples are one of the most common methods [11] for looking at the least clear uncertainty samples (US) classified with different measures of uncertainty used. Gal *et al.* [12] combined recent advances in Bayesian deep learning into the active learning framework in a practical way, and they developed an active learning model for high

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dimensional data. Moreover, recently Sener *et al.* [13] select questions that best wrapped various parts of the feature space taken by the rest of the unlabeled samples. Despite the ability of these algorithms to evolve into models, their disadvantages are that they are too slow for large data sets, as evident in their experiments, and the methods are not different from the uncertainty of complex CNN parameters.

To choose an appropriate segmentation method for brain MRI images for analysis and diagnosis, Hiralal and Menon [14] gave a comprehensive overview of methodologies for the segmentation of brain MRI images. To maintain intensity, heterogeneity, noise, and partial volume, Yazdani *et al.* [15] Give general summaries of methodologies for brain image segmentation based on workflow process and principles of segmentation. To reduce the computational nodule without affecting the accuracy factor, Chenetal *et al.* [16] introduced the WAE symbol short wave using a neural network that analyzes the original images into low-resolution images for classification. These images are also used as an input to the convolutional neural networks (CNN).

Vincent *et al.* [17] created an automatic encoder to reduce noise using a deep learning network. An in-depth neural network approach was considered wherein wave transduction technology was used to extract the acoustic features of a set of musical data. Klec *et al.* [18] proposed an approach of deep neural network (DNN) with new audio features extracted using STW. The implementation of a two-step optimization approach as a stream tensor decomposition approach to enhance the acceleration of the convolutional neural network (CNN) has been proposed by Lebedev *et al.* [19].

Autoencoder [20, 21] is an optimization technique used to extract and automate learning when using and distributing big data and image extraction, compression, and noise removal. It is often considered a deep learning method because it has a deeper network that manages by itself to match the required environment. In this work, an automated encoder has been considered as the preferred preprocessing technique for the classification of images using deep neural networks. Training of standard and original automatic encoders is challenging compared to any other type of extending mechanical encoder. Considering the sparse AR encoder [22], it contains a large number of hidden units compared to the input units, which is a competitor with the standard automatic encoder. With restrictions in place, only a small number of hidden companies can be activated at any time. The learning algorithm learns sparse feature encoding automatically from unlabeled data.

In this paper, we proposed a hybrid CNN-DWA model, the novelty and accuracy of this model tested and compared with other models based on the different values.

## 2. MATERIALS AND METHODS

The dataset contains six databases, which include both MR brain with and without Tumor.

250 MRI brain images from BRATS2012, 300 MRI brain images from the BRATS2013 database, 1000 MRI

brain images from BRATS2014, 1000 MRI brain images from BRATS2015, and 1050 MRI brain images from ISLES-SISS 2015 were used. The database consists of 3650 MRI brain images, 1650 without tumor, and 2000 with a tumor. The samples of databases are shown in Fig. (1).

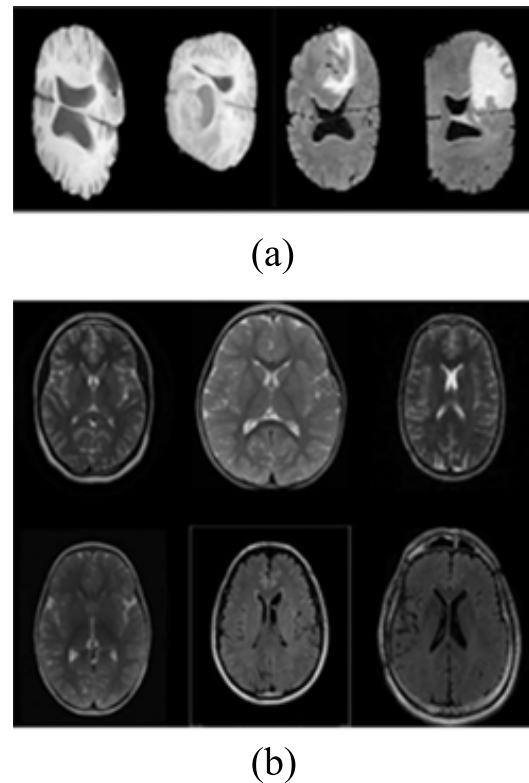


**Fig. (1).** (a) described the FLAIR, T1-T2w eight MRI brain images with Tumor, (b) described The FLAIR, T1-T2-weight MRI brain images without Tumor.

(Fig. 2) shows a proposed model that used a hybrid CNN-DWA model to diagnose brain tumors using brain MRI images. It is saved in JPG format for medical computer memory format. The JPG file is processed, and the images are extracted and processed. All brain MRI images are displayed in a two-dimensional array format after the image preprocessing stage. Then the two-dimensional arrays are spread out, showing all the images in a two-dimensional dataset format. To obtain high resolution and excellent performance, we divided the images into several small sub-arrays. Sub-matrices process the brain MRI images by applying the hybrid CNN-DWA to get the coded images. In the final stage, the proposed model outputs are obtained, including the classification using “no tumor or yes tumor,” tumor region area, and the performance of the proposed model using five values.

### 2.1. Convolution Neural Network (CNN)

To determine what is normal and abnormal, the two-dimensional and three-dimensional structures of the device are significant. CNNs are very suitable for performing image

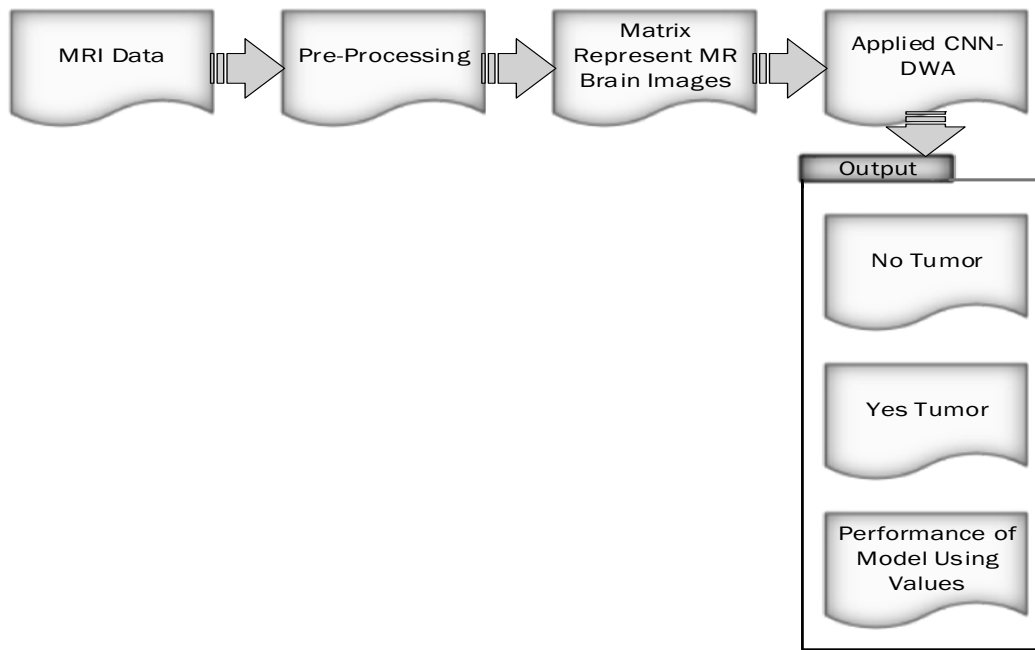


**Fig. (2).** The proposed architecture of MR brain images classifier for brain tumor detection based on the hybrid CNN-WDA model.

recognition tasks while maintaining local spatial relationships. CNNs are operated in several ways such as registration, detection, image segmentation, classification, and localization. Due to its unique characteristics of maintaining local image relationships during dimensional dimensionalization procedure. CNNs are the most common machine-learning algorithm used for image recognition and visual learning parameters. It is reducing the number of parameters. CNN can be used as input and manipulate both 2D and 3D images with slight modifications; this captures important feature relationships. Medical image analysis has been studied and used in Unsupervised learning algorithms. These include Restricted Boltzmann Machines (RBMs), autoencoder Generative Adversarial Networks (GANs) and Deep Belief Networks (DBNs).

In contrast to a fully connected neural network in which the weights between the layers are more numerous and usable one. Equivalent quality is given shown due to parameter sharing; this means that input translations result in a corresponding feature map translation. The convolution operation is realizing by the  $*$  symbol. An output (or feature map)  $s(t)$  is convolved with a filter or kernel  $l(t)$ .

$$s(t) = (1 * K)(t) \quad (1)$$

If  $t$  can only take integer values, the discretized convolution is given by:

$$s(t) = \sum_a I(a) \cdot K(t-a) \quad (2)$$

## 2.2. Deep Watershed Autoencoder

Supervised learning is essential in all branches of artificial intelligence, as it is the most powerful tool available. Re-

gardless of its achievement, it is considered extremely beneficial. Input properties are run manually for readability with many algorithms. Methodology, there are areas in which it does not expand well. To overcome the above problem, we urgently need some supervised learning methods. To discover and interpret the features of sorting, there are many algorithms in Rich learning that use neural network techniques.

## 2.3. Performance Evolution

To verify the tumor area in the brain MRI scans and the hybrid model performance, we used five values such as DSC [23], ACC, SP, SE, and precision as in equation (3) to equation (7), false negative (FN) Expresses the tumor pixels not classified by the hybrid CNN-DWA model. False positive (FP) expresses numeric pixels classified as errorless. True positive (TP) expresses the location of the Tumor comprehensively, True negative (TN) represents non-tumor pixels.

### 2.3.1. Dice Similarity Coefficient (DSC)

Calculates to represents an automatic and manual segmentation account defined in equation (3):

$$DSC = \frac{2TP}{FP+2TP+FN} \quad (3)$$

### 2.3.2. Sensitivity

The sum of positives predictable properly as defined in equation (4):

$$SE = \frac{TN}{TN+FN} \quad (4)$$

### 2.3.3. Specificity

The total of negatives acknowledged suitably as defined in equation (5):

$$SP = \frac{TN}{TN+FP} \quad (5)$$

### 2.3.4. Accuracy

The amount of perfection of the recognition as defined in equation (6):

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

### 2.3.5. Precision

The proportion of predicted positives which are genuine positive as defined in equation (7):

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

## 3. EXPERIMENTS

To obtain a constant size of the hybrid CNN-DWA model, we performed a pre-treatment step that involved converting each of the RGB images to a 1.0 scale and resizing the images to 240×240×3. the brain MRI images were inserted into a machine-learning algorithm. Additionally, in all experiments presented in this paper, we have used magnetic resonance brain images augmentation to improve our results, including rotation, horizontal and vertical shift, shear, and horizontal magnification as operations. We randomly selected a subset of the brain MRI type that did not contain a tumor. A second one contained a tumor, and we trained them using the hybrid CNN-DWA 100 epochs. All these experiments were performed using deep learning framework Tensorflow and Keras using spyder.3.7 [24].

### 3.1. Hybrid CNN-DWA Model Training

The input layer has n units; the hidden layer has q units. Training samples  $y = [y_1, y_2, \dots, y_n]$  the output of hidden unit I can be calculated as in equation (8):

$$gi(out) = \varphi \left( \frac{\sum_{l=1}^n V_{il} y_l - e_i}{b_i} \right) \quad (8)$$

$\varphi(\cdot)$  represent wavelet activation function.

$YI$  ( $r=1, 2, \dots, n$ ) is the  $l$ th dimension input of training sample

$Vil$  ( $I = 1, 2, \dots, q$ ) is connection weight between input unit  $l$  and the hidden unit  $i$ .

$Bi$  and  $e_i$  represent  $t$  sales factor and shift factor of wavelet activation function for hidden unit  $i$ .

$$\varphi(a) = \frac{a}{\sqrt{2\pi}} \exp\left(-\frac{a^2}{2}\right) \quad (9)$$

Based on equations (8) and (9), the output of remote unit I is written as in Equation (10):

$$Gi(out) = \left( \frac{\sum_{l=1}^n V_{il} y_l - e_i}{b_i \sqrt{2\pi}} \right) \times \exp\left(-\frac{1}{2} \left( \frac{\sum_{l=1}^n V_{il} y_l - e_i}{b_i} \right)^2\right) \quad (10)$$

The output vector of WAE  $\hat{y} = [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n]$  can calculated as equation (11):

$$\hat{y} = \text{sigm} \left( \sum_{i=1}^q V_{ri} \left( \frac{\sum_{l=1}^n V_{il} y_l - e_i}{b_i \sqrt{2\pi}} \right) \times \exp\left(-\frac{1}{2} \left( \frac{\sum_{l=1}^n V_{il} y_l - e_i}{b_i} \right)^2\right) \right) \quad (11)$$

The modified reconstruction error function of designed CNN-DWA on  $u$  unlabeled training example set  $\{y_1, y_2, \dots, y_u\}$  a be defined as in equation (12):

$$F = \frac{1}{2u} \sum_{u=1}^u \sum_{r=1}^n (\hat{y}_r^u - y_r^u)^2 + \beta \left( \sum_{i=1}^q \rho \log \frac{\rho}{\hat{\rho}_i} + (1-\rho) \log \frac{1-\rho}{1-\hat{\rho}_i} \right) + \frac{\lambda}{2} \sum_{H=1}^H \frac{1}{2} \sum_{R=1}^R \sum_{I=1}^I (V_{ir}^H)^2 \quad (12)$$

$y_r^u$  and  $\hat{y}_r^u$  represent  $r$ th dimension input and reconstruct output of  $u$ th sample  $y_u$ , respectively.

$\beta$ : Is sparse penalty factor.

$\hat{\rho}_i$ : Average activation value of hidden unit  $i$

$\rho$ : Sparse parameter

$\lambda$ : Weight decay parameter for the adjusts the weight.

UH: no of weight in layer H ( $u_1 = u_3 = n = 1, u_2 = q$ )

$V_{ir}^H$ : Weight in layer H

Here  $V_{ir}^1 = V_{ir}, V_{ir}^2 = V_{ir}$

Generally, the backpropagation learning algorithm is used to update these parameters, which can be expressed by equations (13-16):

$$Vir(a+1) = Vir(a) - \eta \frac{\partial F(a)}{\partial V_{ir}} \quad (13)$$

$$Vil(a+1) = Vir(a) - \eta \frac{\partial F(a)}{\partial V_{il}} \quad (14)$$

$$b_i(a+1) = bi(a) - \eta \frac{\partial F(a)}{\partial b_i} \quad (15)$$

$$Ei(a+1) = ei(a) - \eta \frac{\partial F(a)}{\partial e_i} \quad (16)$$

## 4. RESULTS AND DISCUSSION

To support the magnetic resonance device and improve its performance, the computer-assisted diagnostic tool that does not rely on specialized equipment is the key to solving this problem, given the importance of making early diagnosis techniques more accessible in the world. To reach this solution, we present the results obtained by the hybrid CNN-DWA model as described in this paper. Given the low amount

of images for testing, there may be some slight bias to the CNN-DWA model, so it is important to note that we were forced to reduce the number of images used for viewing the set of images that are not balanced and of usable quality and that the data separation between training, validation, and testing. CNN-WDA model that can classify tumors using yes or No tumor is described in Fig. (3a, b). In addition, it can de-

tect the region of the tumor through segmentation technique way as illustrated in Fig. (4).

The hybrid CNN-DWA model gives the best accuracy validation of 97% as described in Fig. (5a) and produced low loss validation values 0, 1 as described in Fig. (5b) when compared with another model like CNN, DWA.

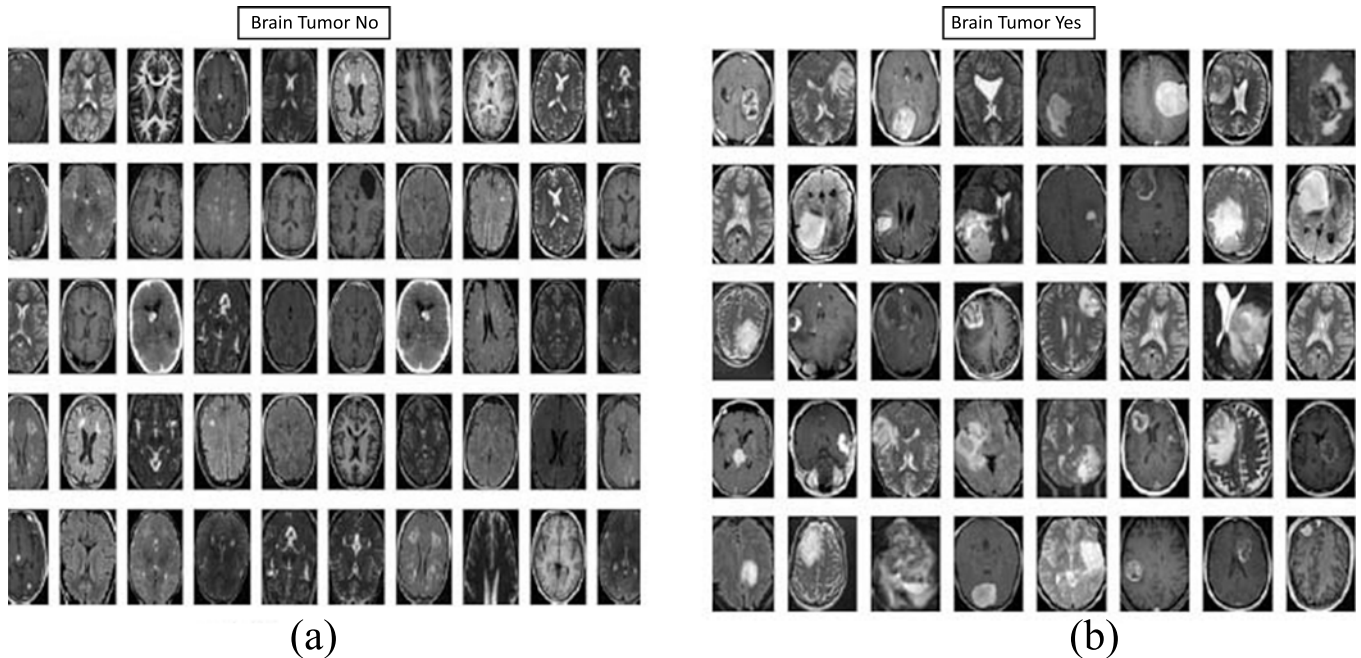


**Fig. (3).** (a) described the Result classification of hybrid CNN-DWA Model Using No Tumor MR Brain Images and (b) described the Result Classification of hybrid CNN-DWA Model using Yes Tumor MR Brain Images.

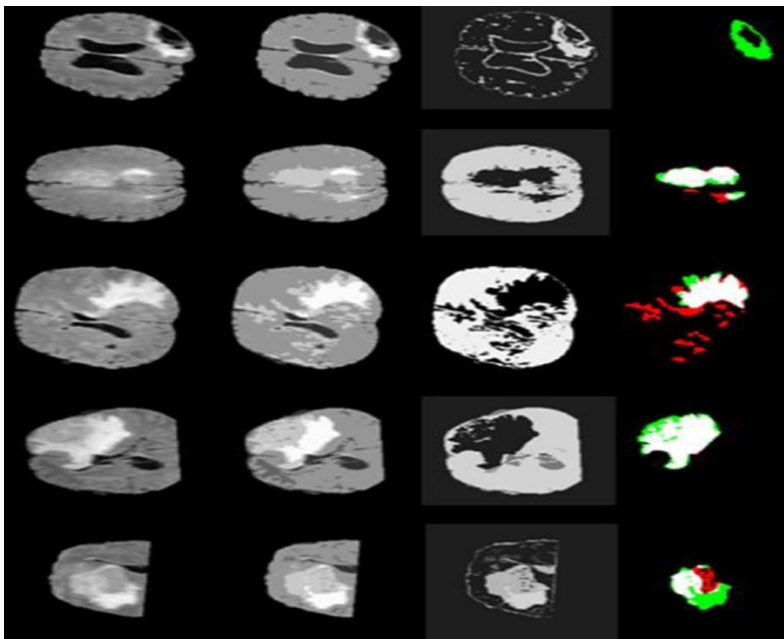


**Fig. (4).** Tumor area detected on MR images using a hybrid CNN-DWA Model. (A higher resolution / colour version of this figure is available in the electronic copy of the article).

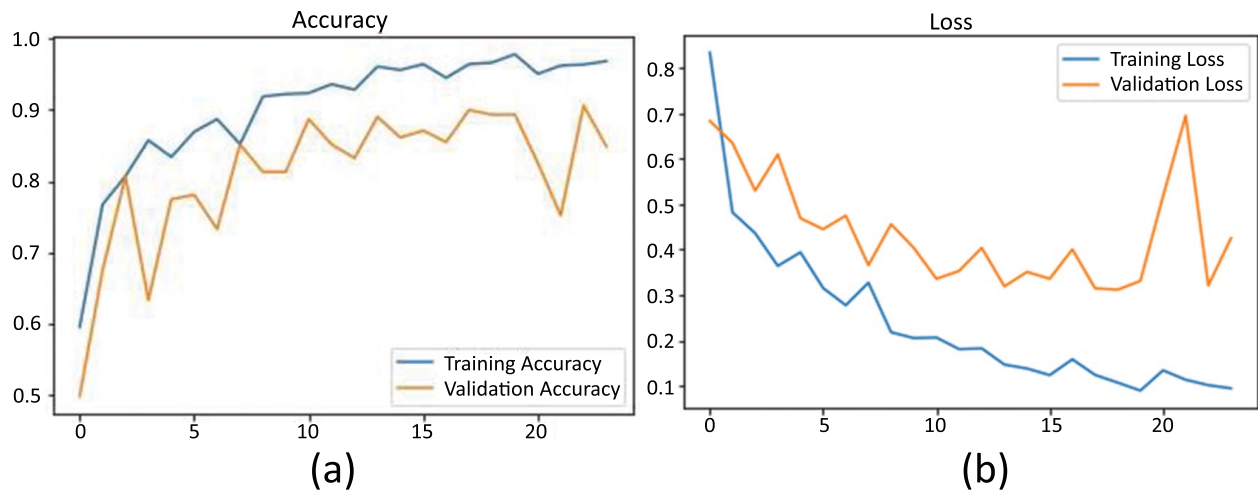


**Fig. (5).** (a) described the Result of the Accuracy values using the Hybrid CNN-DWA Model, (b) Described the Result of Loss value of the Hybrid CNN-DWA Model. (A higher resolution / colour version of this figure is available in the electronic copy of the article).

Depending on the results of the experiments mentioned above, the performance of the hybrid CNN-DWA model is much better than the previous approaches described in Tables 1-6, which indicates the applicability of the proposal.

**Table 1. Hybrid CNN-DWA Model results on ISLES-SISS 2015 dataset.**

| Method                        | DSC              | SE               |
|-------------------------------|------------------|------------------|
| Hybrid CNN-DWA                | <b>0.965517%</b> | <b>0.958904%</b> |
| Chen <i>et al.</i> [25]       | 67.0%            | -                |
| Haeck <i>et al.</i> [26]      | 78%              | 80%              |
| Larochelle <i>et al.</i> [27] | 69%              | 67%              |
| McKinley <i>et al.</i> [28]   | 85%              | -                |
| Mahmood <i>et al.</i> [29]    | -                | 50%              |

**Table 2. Hybrid CNN-DWA Model results on BRATS 2013 (synthetic) data.**

| Method                                  | DSC           |
|-----------------------------------------|---------------|
| Hybrid CNN-DWA                          | <b>96,55%</b> |
| Proposed 100% Abbasi <i>et al.</i> [30] | 93%           |
| Cordier <i>et al.</i> [31]              | 84%           |

**Table 3. Hybrid CNN-DWA Model results on BRATS 2015 dataset.**

| Method                       | DSC           | SE               | SP             | ACC        |
|------------------------------|---------------|------------------|----------------|------------|
| Hybrid CNN-DWA               | <b>96,55%</b> | <b>0.958904%</b> | <b>0.9375%</b> | <b>98%</b> |
| Dong <i>et al.</i> [32]      | 86%           | -                | -              | -          |
| Pereira <i>et al.</i> [33]   | 78%           | -                | -              | -          |
| Havaei <i>et al.</i> [34]    | 79%           | -                | -              | -          |
| Kamnitsas <i>et al.</i> [35] | 90%           | 90,4%            | -              | -          |

**Table 4. Hybrid CNN-DWA Model results on BRATS 2014 dataset.**

| Method                  | DSC           | SE               | SP             | ACC        |
|-------------------------|---------------|------------------|----------------|------------|
| Hybrid CNN-DWA          | <b>96,55%</b> | <b>0.958904%</b> | <b>0.9375%</b> | <b>98%</b> |
| Reza <i>et al.</i> [36] | 89.6%         | 84%              | -              | 82.2%      |

**Table 5. Hybrid CNN-DWA Model results on BRATS 2012 (image) dataset.**

| Method                               | DSC           |
|--------------------------------------|---------------|
| Hybrid CNN-DWA                       | <b>96,55%</b> |
| Proposed 98.4% Wu <i>et al.</i> [37] | 62%           |
| Bauer <i>et al.</i> [38]             | 73%           |
| Huang <i>et al.</i> [39]             | 75%           |

**Table 6. Hybrid CNN-DWA Model results on BRATS 2013 (image) dataset.**

| Method                     | DSC           | SE               | SP             | ACC        |
|----------------------------|---------------|------------------|----------------|------------|
| Hybrid CNN-DWA             | <b>96,55%</b> | <b>0.958904%</b> | <b>0.9375%</b> | <b>98%</b> |
| Zikic <i>et al.</i> [40]   | 83.7%         | -                | -              | -          |
| Reza <i>et al.</i> [36]    | 90.9%         | -                | -              | 86,7%      |
| Havaei <i>et al.</i> [34]  | 88%           | 89%              | 87%            | -          |
| Pereira <i>et al.</i> [33] | 88%           | -                | -              | -          |
| Goetz <i>et al.</i> [41]   | 83%           | -                | -              | -          |
| Huang <i>et al.</i> [40]   | 88%           | -                | -              | -          |

Based on seventeen previous certified references to evaluate the performance of the hybrid CNN-DWA model, such as [25-41]. It is tried on more than 700 strokes of sore MR images. The desire enhancement technique was used to identify stroke ulcers and obtained a DSC 94% [25]. It has 78% DSC and 80% SE [26]. Stroke discovery using the CNN model [27]. Reduction detection methods are combined with

the Forest Decision Strategy and RFC of the Stroke Division [28, 29]. BRATS 2013 engineering data set was tested using the Otsu and Random Forest strategy to identify glioma. It has 93% DSC [30]. To determine mind sore, they used a repair strategy based on segmentation [31].

For the identification of mind sore, they used the U-Net Based Fully CNN model, and it has 86% DSC on BRATS 2015 dataset [32]. To identify the mind tumor, they tried using the CNN model [33]. To recognizing the mind, sores tried on BRATS2013 data collection using the Information Cascade model (CNN) [34]. To detect cerebrum injury are used 3D completely associated contingent arbitrary field. It has 90% DSC and 90.4% SE individually [35]. Texture features are utilized for brain tumor identification. This method obtained 89.6% DSC, 84% SE, and 82.2% ACC on BRATS 2014 dataset [36]. Conditional random fields (CRF) model with the pixel-pairwise affinity and super pixel level features are used for glioma identification [37].

On BRATS 2012 images dataset Progressive regularization and grouping strategy is used and obtained 76% DSC [38] to order the class names, Neighborhood autonomous projection-based characterization (LIPC) strategy is used and acquired 88% DSC [39] after tried on Whelps 2013 images dataset. CNN model [40] and extremely randomized trees [41] are utilized for glioma identification. It obtained 83.7% and 83.0% DSC on the BRATS 2013 images dataset. During observing the aforementioned experimental results, the performance of the hybrid CNN-DWA model proposed is better as compared to previous methods, which demonstrate the applicability of the proposed model.

## CONCLUSION

In this paper, we proposed a hybrid CNN-DWA model for brain tumor detection and analysis. We evaluated the proposed method using different challenges datasets and three MRI modalities such as Flair, T1, and T2. The achieved results are 96, 55 DSC, 0.958904% SE, SP 0.9375%, ACC 98% and loss validation 0, 1. To validate the hybrid CNN-DWA model, we used some database and performance values. Based on this number of data sets and performance measures, this confirms that the proposed model works well on various data sets and has excellent performance. These results were compared with the current approaches, which showed that the proposed approach performs better and gives optimal results in terms of accuracy, loss, DSC, SP, and SE values. These experiment results display that the hybrid CNN-DWA model and new deep learning techniques are already strong enough to assist in computer-aided diagnosis. These techniques provide a good solution to estimate the rate of infection through early diagnosis and thus reduce the number of deaths from brain cancer because the consequences of the undiagnosed tumor quickly and accurately are dangerous and increase the number of deaths.

## LIST OF ABBREVIATIONS

MRI = Magnetic Resonance Imaging  
CNN = Convolution Neural Network

DWA = Deep Watershed Auto-Encoder  
SE = Sensitivity  
SP = Specificity  
DSC = Dice Similarity Coefficient  
ACC = Accuracy Value  
STW = Scattering Wavelet Transform (SWT)

## ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

## HUMAN AND ANIMAL RIGHTS

No animals/humans were used for studies that are the basis of this research.

## CONSENT FOR PUBLICATION

Not applicable.

## AVAILABILITY OF DATA AND MATERIALS

This work is based on open-source datasets.

## FUNDING

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## CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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