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A novel hybrid deep belief Google network framework for brain tumor classification

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Abstract

A brain tumor can lead to headaches, seizures, numbness or weakness in the arms or legs, changes in personality or behavior, nausea, vomiting, visual or hearing disturbances, or dizziness. Brain tumors are lumps or atypical expansions of cells that develop in the brain or central spinal canal. The current study used neural networks to identify with categorize brain tumors, although it has the drawbacks of longer delays in processing, overfitting, and exploding gradient. This study proposed a unique Hybrid Deep Belief Google Network (DBGN) system for brain tumor identification and categorization in order to get over the constraints. Pre-processing and feature extraction with categorization are the components of this method. Utilizing the proposed Modified Global Contrast Stretching (MGCS), Hybrid Median and Wiener Filter (HMWF), and Modified Scharr operator to first pre-process the obtained pictures. Next, a fresh, efficient neural network was proposed by this study to gather and classify the brain tumor. As a result, the method we propose outperforms the existing approaches in relation to accuracy, precision, recall, and specificity.

Keywords: Brain tumor, Medical imaging, Magnetic Resonance Imaging (MRI), tumor classification, deep learning, neural network.

1. Introduction

An arrangement of uncommon or unusual cells that have developed inside the brain is referred to as a brain tumor (Gore et al 2020). The brain's hard outer shell, the skull, serves as a protective barrier in case of injury. A major issue will arise if there is any erratic cell proliferation within it (Fernandes et al 2020 & Khan et al. 2019). Brain tumors come in two different varieties: benign, which may be cured if discovered in advance, & malignant, which can be more serious and challenging to cure Razzaq et al. 2020 & Sharif et al. 2020). Additionally, around 70% of individuals suffer from primary or metastatic brain tumors, often known as gliomas, which are the supreme prevalent kinds of brain tumors that rise from glial cells. The classifications of low-grade (oligodendroglia) with high-grade (glioblastoma) tumor cells both exhibit proliferative behavior (Amin et al. 2020). When a tumor is diagnosed early in the course of the illness, it becomes less dangerous than when it is found later on, when the patient's life expectancy is reduced to a minimum of two years. Chemotherapy, ionizing radiation surgery, or a combination of these is the finest and greatest efficient treatment for cancer patients. Over a million people are diagnosed with a brain tumor every year, also the mortality rate associated with these malignancies is growing quickly, according to Global Cancer Research. In young people and kids below the age of 34, it ranks as the second-highest rate of mortality (Majib et al. 2021 & Sravan et al.2020).

A unique meta-heuristic and ML-based technique is offered in the current study, which is mentioned below, for an early identification of brain cancer to overcome this objection: A Support Vector Machine (SVM)-based tumor identification technique has been suggested (Kabir 2020). When the data set has additional noise, SVM fails to operate as well. The researchers (Chen et al. 2021) created an Extended Kalman Filter with

Support Vector Machine (EKF-SVM), an image processing framework reliant on an SVM, for automated brain tumor identification. The Kalman Filter, is not the best estimator. Additionally, a powerful system for classifying MRI brain images is offered by Mishra et al.2021). For feature extraction and coefficient selection, it uses a variety of wavelet transformations, such as the Discrete Wavelet Transform, Stationary Wavelet Transform, and Dual-tree M-band Wavelet Transform. Although shift sensitivity, weak directionality, with an absence of phase knowledge are drawbacks of the wavelet transform.

In order to categorize the tumor grades, the researchers (Sharif et al. 2020) used an Artificial Neural Network (ANN), where these skulls were extracted utilizing the Brain Surface Extraction (BSE) procedure. To improve segmentation, a picture with the skull eliminated is subsequently sent into PSO. The best choice of characteristics with classification phases is then made using a revised version of the Whale Optimization Algorithm (WOA) that utilizes chaos concept with the logistic mapping approach (Yin et al. 2020). The WOA's shortcoming is that it converges slowly, and accurately, and is prone to a local optimum. Hence, ML-based approaches are time-consuming, and more resources are required and inaccuracy of the interpretation of data, to overcome that, DL-based techniques are proposed to identify & categorize brain tumors:

By using a DNN framework, the researchers (Acharya et al. 2020) aimed to enhance the present best practice model. To improve the precision of segmentation and feature-extraction stages with the subsequent segmentation, this necessitated altering those stages. Additionally, by utilizing swarm intelligence-based techniques like GA, PSO, GWO, and WOA, researchers (Mishra et al.2021 & Irmak 2021) provided a structure for optimizing network settings including the weight and bias vector of DCNN networks. The location and orientation of objects were not properly encoded by the DCNN. Additionally, the researchers (Kujur et al.2022 & Togacar et al. 2021) compare the classification performance of significant research on four CNN forms including CNN trained from scratch, ResNet50, InceptionV3, and Xception, over two brain MRI datasets of pictures analyzed with and without the use of Principal Component Analysis.

A brand-new residual network framework that utilizes multi-scale feature fusion with global average pooling (GPA) has been suggested by researchers (Li et al. 2022 & Jun et al.2022). Still, average pooling entails figuring out the average for every feature map patch. In order to address this, the researchers (Masood et al. 2021) proposed a custom Mask Region-based Convolution Neural Network with a dense net-41 backbone structure that is trained using transfer learning for precise segmentation as well as classification of brain tumors. It works on still images, so cannot explore temporal information of the object of interest. Moreover, the authors (Kumar et al. 2023) made a systematic review of recent deep learning, machine learning, and hybrid models for detecting brain cancers. Thus, this study presented a hybrid deep neural network for brain tumor identification and categorization to get beyond the aforementioned constraints. This study's primary contribution is as listed below:

- The study addresses the common symptoms associated with brain tumors, such as headaches, seizures, numbness, changes in personality, and visual disturbances. It emphasizes the importance of accurately identifying and categorizing these tumors for effective treatment.
- The study utilizes neural networks for brain tumor identification, acknowledging existing drawbacks such as longer processing delays, overfitting, and issues with exploding gradients. This highlights the relevance of advancing neural network techniques to overcome these limitations.
- The proposal of a Hybrid DBGN system, which integrates various pre-processing techniques like MGCS, HMWF, and Modified Scharr operator. These techniques aim to enhance image quality and facilitate more accurate tumor classificaton.
- The study incorporates feature extraction and categorization components within the Hybrid DBGN system to efficiently gather and classify brain tumors. This comprehensive approach ensures robust performance in tumor identification.

As a result, our proposed approach efficiently detects and classifies the brain tumor. The following is how this research study is organized: The overview of brain tumor identification and categorization employing neural networks in Section 2 is followed by a discussion of a novel network that was developed in this study to get beyond the current study's constraints in Section 3. Additionally, Section 4 deliberates the outcomes of this proposed strategy, and Section 5 closes this study article.

2. Literature survey

For the purpose of detecting brain tumors employing MR images, (Rammurthy et al. 2022) offered the Whale Harris Hawks optimization (WHHO) optimization-driven approach. The segments' characteristics, including the variance, the local optical orientation pattern, mean, tumor's size, and kurtosis, are also obtained. For the diagnosis of brain tumors, a deep convolutional neural network (DCNN) is also used, and its training is carried out using a recommended hybrid WHHO algorithm. Although owing to procedures like max-pooling, the deep CNN frequently runs slower. In addition, the hybrid WHHO is susceptible to local optimums and therefore has a poor convergence pace.

Utilizing a dataset from Kaggle and BRaTS MICCAI that included a broad variety of cancers, every having its dimension, position, and appearance together with varying degrees of image intensity, (Solanki et al. 2023). When performing the traditional step of categorization, an overall of six different classification algorithms, including Naive Bayes, KNN, SVM, Logistic Regression, and Multi-layer Perceptron, were applied. After that, a CNN is deployed, showing a considerable improvement in efficiency as a whole when compared to the conventional classifiers.

With a T1C modality MRI image, (Patil et al. 2023) developed a shallow CNN (SCNN) and VGG16 network, and then its precision and loss were assessed. The collected features from the two DL models were combined to increase the classification accuracy of three different tumor kinds, which improved the model's performance with regard to accuracy and information loss. The ensemble DCNN model's (EDCNN) results demonstrated that the combination of DL models increases the accuracy of the challenge of classifying multiple classes as well as tries to solve the issue of overfitting the model for unbalanced datasets.

A transfer learning-based DCNN approach was presented by (Malla et al. 2023) to categorize brain malignancies. The authors employed a pre-trained DCNN framework called VGGNetwork that was validated on a large amount of data before being applied to the target dataset. Additionally, we use transfer learning techniques like optimizing the convolutional network and freezing its parts to improve performance. Additionally, to prevent overfitting concerns and vanishing gradient challenges, for that, GAP is utilized in the output layer.

A unique Hybrid-Brain-Tumor-categorization (HBTC) construction was established by (Nawaz et al. 2022). It was introduced to the test for classifying brain tumors. Hence, the technique's effectiveness is increased while its inherent complexity is decreased. The feature vector was then subjected to a hybrid multi-features optimizing process that resulted in a completely optimized feature dataset.

(Archana et al. 2023) suggested a different process for finding brain malignancies consuming the Bagging Ensemble with KNN (BKNN) with the goal to increase the precision and quality rate of KNN. A U-Net framework is utilized originally for picture segmentation, then a Bagging-based KNN prediction method is utilized for classification. U-Net is used to increase the regularity and precision of parameter distribution in levels. Big data sets make it extremely costly to determine the distance between every new point with every old point, which lowers the technique's efficiency even while accuracy has increased. In the years to come, the accuracy of classification can be improved by employing supervised techniques like CNNs.

To identify brain cancers, (Asad et al. 2023) suggested a deep CNN using a stochastic gradient descent (SGD) optimization technique. Utilizing ResNet-50 model, the public Kaggle brain-tumor dataset is consumed to test the multi-classification of brain tumors.

A Harris Hawks Optimized Convolution Network (HHOCNN) strategy was suggested by (Kurdi et al. 2023). The MRI data gathered from Kaggle dataset, that includes both normal and pathological brain scans, is used to assess the suggested technique. The output is recognized by the totally convolute layers by adjusting the parameter in accordance with HHO algorithm. The Harris Hawks optimizing approach, which draws inspiration from nature, reduces the misclassification error rate and increases total tumor detection precision.

(Kumar et al.), suggested a conditional integration and supplementary classification of brain tumors by pretraining a Style-based Generative Adversarial Network (GAN). In order to enhance classification accuracy when the training data is limited, the discriminator of the pre-trained GAN is tweaked utilizing advanced data augmentation techniques. The scheme works properly even when there are few data points available.

(Saeedi et al, 2023)., a convolutional auto-encoder network, a unique 2D CNN structure, with six widely used ML methods created for brain tumor identification. A $T1$-weighted, contrast-improved MRI dataset consisting of three different kinds of cancers with a healthy brain without tumors was used for this categorization.

(Babu et al 2023)., suggested Artificial Bee Colony (ABC) Optimization to eliminate malignancies from brain MRI data in combination with thresholding. To restore the CNN's learning rate for the last hybrid classification, an additional optimization strategy is utilized. The learning rate of CNN is expanded by utilizing the butterfly optimization procedure for superior categorization. This work might be expanded in subsequent years to segment and pinpoint the location of sub-tumoral sections, i.e., for improving non-enhance and entire tumors. With an objective to increase the accuracy and Diagnostic Confidence Index (DCI) of the present study, we also want to examine an extra robust technique for a sizable archive of healthcare images with a selected classifier by combining a number of classifiers.

The following discussion addresses the disadvantages of the current methods for finding and categorizing brain tumors based on the evaluations provided above: CNN with hybrid WHHO has slower performance due to the max-pooling layer and is more prone to falling into the local optimum, which increases execution time. The VGG-16 network requires more time to train its parameters, the MLP has too many parameters because it is fully connected, which negatively affects performance. This study thus suggested a unique hybrid network for brain tumor identification and categorization to get over the aforementioned constraints.

3. The Novel framework for brain tumor classification

To get beyond the aforementioned drawbacks, this study introduced a unique Hybrid Deep Belief Google Network (DBGN) structure for brain cancer recognition and categorization. The three essential processes in this innovative architecture are pre-processing feature extraction, and classification. Image enhancement, denoising, & recognition of edges are first carried out during the pre-processing step. For image enhancement, this research proposed a MGCS, to denoise the images Hybrid Median and Wiener Filters are proposed, and to detect the edges in the images, this research proposed a modified Scharr Operator. The following phase entails the proposal of a fresh, optimal neural network for the extraction and classification of brain tumor feature information. Here, to extract the features HH-BWO-based DBN is proposed, and following that, the brain tumor is classified by using GoogLeNet auxiliary classifier. Figure 1 depicts the proposed method's design.

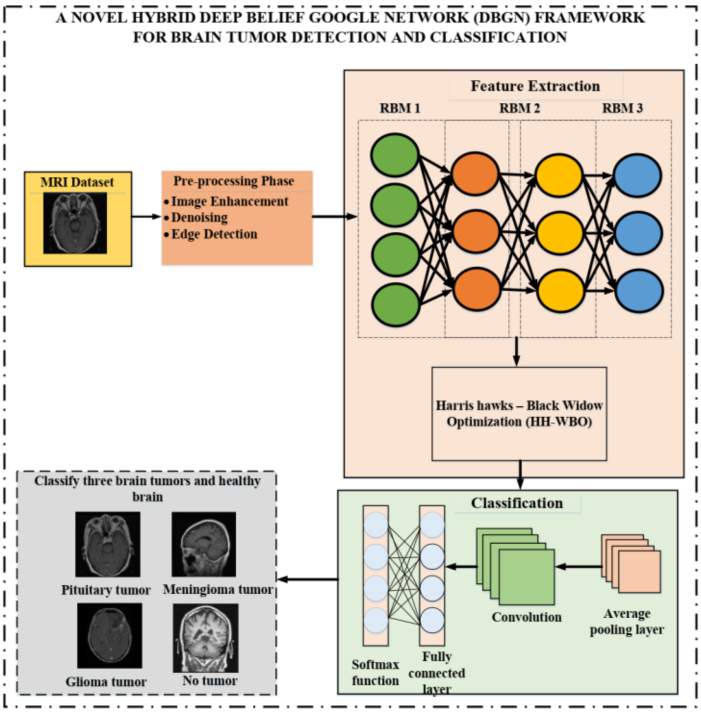

Fig 1. Architecture of the proposed approach

3.1 Dataset description

As demonstrated in **Figure 2**, the model we proposed was analyzed and evaluated using data from an open-source brain tumor dataset (Ozkaraca et al.2023). The data set has an overall four classifications, as illustrated in Figure 2. These are MRI scans of the brain taken from healthy (H), meningioma tumor (MT), pituitary tumor (PT), and glioma tumor (GT). The MRI image dataset includes 7022 files. The collection includes 405 photos of healthy people and 300 photographs each of GT, MT, PT, and H. For this investigation, 800 photos have been taken. We divided this up into 200 photos for glioma, 200 for meningioma, 200 for pituitary, and 200 for healthy people. The Kaggle program offers the dataset as open-source data. This kind of brain tumor is labeled on each 224 224 JPEG file, which is included in the collection. 80% of this dataset is used for training, while 20% is used for testing.

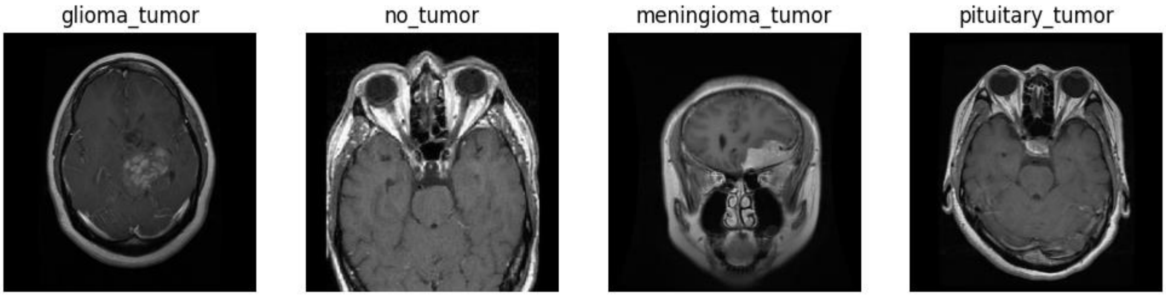

Figure 2. Classes of the dataset

3.2 Pre-processing (P-P) phase

The first phase of the proposed approach is preprocessing, where image enhancement, denoising, and edge detection are carried which is described in the following section.

3.2.1 Image enhancement

The weaknesses of obtained MRI images include blurriness and poor contrast. The contrast enhancement method is essential for enhancing the clarity and contrast of MRI images. Contrast stretching is the technique of widening the color space such that all possible values may be used to enhance a picture. It alters how many digital integers are distributed across every single pixel in a picture along with their range. As a result, the novel MGCS contrast-enhancing approach has been suggested. For every RGB (Red, Green, and Blue) component of the picture, it establishes the most recent lowest & highest values.

In order to calculate the updated lowest and highest possible values for every single of the RGB elements in the image using the MGCS technique, a number of parameters must be acquired. The lowest and highest proportions, the sum of pixels in every pixel point, overall quantity of pixels falling within a specified minimum %, and the total number of pixels falling inside a specified maximum proportion are all included in these figures. Additionally, it enhances contrast by expanding the intensity levels in an image to include a specified range of values. However, the contrast-stretching algorithm is susceptible to noise, so a hybrid median and wiener filter is proposed to effectively reduce the noise, as described below.

3.2.2 Denoising

To eliminate the noise in the enhanced images, this research offered a Hybrid Median and Wiener Filter (HMWF), here, a median filter reduces the noise, in addition, a wiener filter is used to efficiently remove the blurring. Images can be obtained by applying median and Wiener filters. The following is a description of the fundamental steps of the wiener and median filters:

The initial matrix of the spatial noise reduction filter is configured to be of size $m \times n$. For the improved image (section 3.1.1), the matrix is utilized to generate new pixels with sizes according to their values. The median filter then transforms every pixel's value into median pixel value, which is equal to center pixel assessment of the matrix. Additionally, the wiener filter utilizes both variation and average pixel values in m × n-sized matrix, as illustrated in the example below:

$$\mu = \frac{1}{MN} \sum_{m,n\epsilon\eta} a(m,n) \tag{1}$$

$$\sigma^2 = \frac{1}{MN} \sum_{m,n\epsilon\eta} a^2\,(m,n) - \mu^2 \tag{2}$$

Where MN is the image's size, μ is its mean, σ^2 is its variance from noise, m × n is the size of the η neighborhood region, and $a(m,n)$ denotes every pixel in the neighborhood η. Utilizing the estimated values, the Wiener filter is applied to new pixels, that can be expressed as $b_w(m,n)$.

$$b_w(m,n) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}.(a(m,n) - \mu) \tag{3}$$

Where v2 is the matrix's noise variance setting used in the Wiener filter implementation. Regardless of the noise level, the wiener filter reduces the mean square error. To overcome the limitations, this research proposed a hybrid median and wiener filter (HMWF) which is described as follows: Applying the median filter to the backdrop of deteriorated photos, this approach enhances the image quality. Additionally, this HMWF uses the wiener filter to mostly maintain the edge signal. The HMWF approach, which relies on the wiener filter, reduces noise in the deteriorated image by replacing the matrix's pixel values with median values.

The median value ($\tilde{\mu}$) is used in place of the average value (μ) in the wiener filter equation. The following is a representation of the HMWF:

$$b_{HMWF}(\mathrm{m,n}) = \tilde{\mu} + \frac{\sigma^2 - v^2}{\sigma^2}.(a(m,n) - \tilde{\mu}) \tag{4}$$

The proposed HMWF technique removes the background noise signal. Because of this, the HMWF approach can significantly outperform traditional filters in terms of denoising impact. However, the edges of the images are not preserved by the proposed HMWF technique, to overcome the limitations this research proposed a Modified Scharr Operator which is described as follows:

3.2.3 Edge detection

To preserve the edges of MRI images, this research proposed a Modified Scharr Operator, here, we utilize the Laplacian method, and an image's Laplacian indicates areas where the intensity changes quickly. The MRI image's X and Y directions are first evaluated using the Scharr operator, and then the images are sharpened using either a positive or negative Laplacian operator.

Utilizing the Scharr operator, the initial derivative can be utilized to identify and highlight gradient edges or features in a picture. The x and y axes such as (dx = 1, dy = 0; dx = 0, dy = 1) are the two axes that are frequently used to determine gradients. It increases the variance among the pixel values by amplifying the weight coefficient. However, the Scharr derivative cannot be computed for both X and Y directions simultaneously. Therefore, we apply a positive or negative Laplacian operator on the derived results of the Scharr operator. We have a conventional image in Positive Laplacian, where the corner components of the picture must be zero and the center element of the picture must be negatives. We have a typical picture in the negative Laplacian operator, where the center element ought to be positive. The remainder of the components in the mask ought to be -1, while each of the elements in the corner must be set to zero. The sharpened picture is then obtained by subtracting the outcome from the original picture.

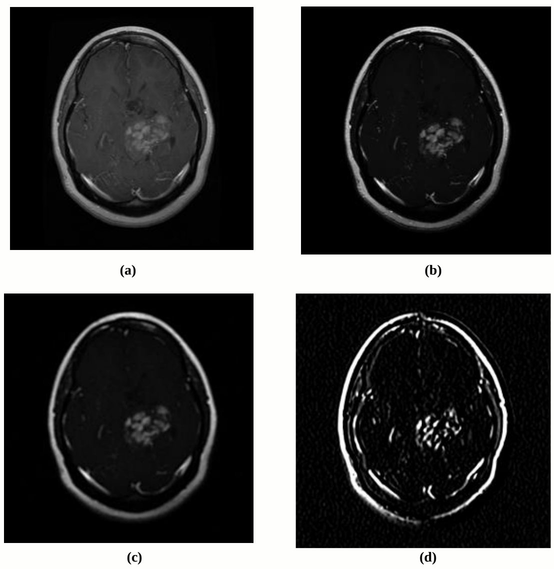

Figure 3. Pre-processed result (a) original image (b) MGCS (c) HMWF (d) Scharr Operator

The pre-processing step of this research improved the MRI images by removing noise and maintaining image edges, which increased the accuracy for identifying and classifying brain tumors.

3.3 The novel optimized neural network proposed

The unique optimal neural network developed for brain cancer feature extraction and categorization is then fed the preprocessed pictures. Here, Deep Belief Network (DBN) is proposed to remove the features in the dataset such as color, and shape features. Moreover, to fine-tune the hyperparameters in the DBN network, this research proposed a Harris hawk – Black Widow Optimization (HH-BWO) that is explained in the part below.

3.3.1 Optimization-based feature extraction

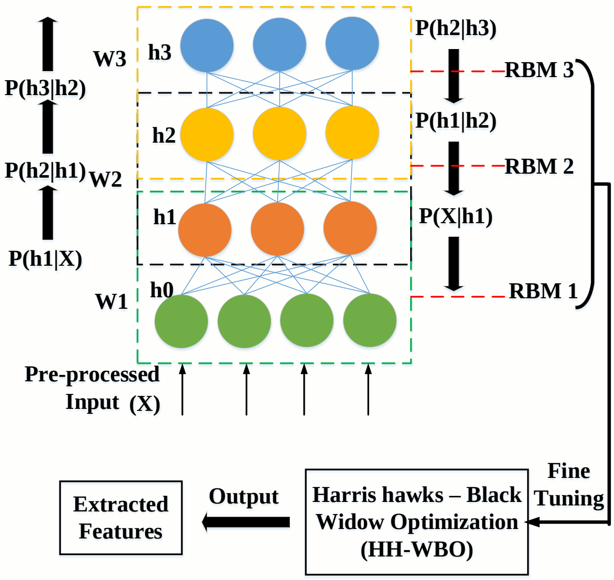

Figure 4. Architecture of Optimized Deep Belief Network.

A stacked Restricted Boltzmann Machine (RBM) and Sigmoid belief network make up the DBN, a generative model of the DNN (see Figure 3). Three stacked RBMs with three hidden layers—$\{hid^1, hid^2, hid^3\}$—can be found in the provided DBN. The procreative stochastic ANN, represented by the RBM1 in Figure 4, is created by connecting the input vector $\{inp\ X = hid^0\}$ and the hidden layer h^1.

The RBM1 was trained using the constructive divergence method because DBN only takes into account one stratum for first- stratum training. To freeze the weight W1 for second-stratum training, the upper stratum of DBN is treated as RBM 2, and lower stratum is treated as a sigmoid belief network. Similar to second- stratum training, 3rd stratum training considers the top stratum to be RBM-3 and the other two to be sigmoid belief networks, freezing weights W1 and W2. Equation (5) presents mathematical representation of the DBN.

$$P(inp\ X, hid^{1}, hid^{2}, \dots hid^{n}) = P(inp\ X|\ hid^{1})\ P(hid^{1}|hid^{2}) \dots P\left(hid^{(n-2)}\middle|\ hid^{(n-1)}\right) P(hid^{(n-1)}|hid^{n}) \quad (5)$$

The probability $P(hid^{(n-1)}, hid^{n})$ of (1) is determined through RBM using (6) and (7).

$$P\left(hid^{i}\middle|\ hid^{(i+1)}\right) = \prod_j P\left(hid_j^{i}\middle|hid^{(i+1)}\right) \quad (6)$$

$$P\left(hid_j^{i}\middle|hid^{(i+1)}\right) = \sigma\left(b_j^{i} + \sum_K^{i+1} W_{kj}^{i}\ hid_k^{i+1}\right) \quad (7)$$

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The RBM has the ability to create characteristics & rebuild inputs. Then, this research presented a Harris Hawks - Black Widow Optimisation (HH-BWO) to precisely adjust the hyperparameters in the DBN network. However, the HHO algorithm can easily fall into a local optimum, this drawback is overcome by HHO-BWO, which provides a fast convergence speed and avoids local optima problems.

A novel meta-heuristic optimizer called HHO and BWO is prompted by the way Harris' hawks and black widow spiders in nature locate food sources. In the initial phase of the Harris Hawks Algorithm, many hawks outbreak a hunt simultaneously to astonish it (exploration stage). Hawks may do a series of quick dives as they approach the target to startle and tire it, which reduces its chances of escaping and fleeing throughout the hunt (exploitation period). The HHO algorithm may change from exploration to exploitation and then between various exploitative phases depends on the target's energy as it is escaping. The energy required for the search can be significantly reduced by jogging. The energy of the target may be described as follows to represent its actions:

$$Energy\ (Egy) = 2E_0\left(1 - \frac{iter}{iter_{max}}\right) \tag{8}$$

Where $iter_{max}$ the greatest amount of iterations, Egy_0 represents the beginning Egy of the target, and Egy symbolizes running and escaping energy of the hunt or target at every iteration of method. The user ought to pick the value for $iter_{max}$. At every stage of this procedure, Egy_0 fluctuates at random within the range (-1, 1). When $Egy_0{}'$s value rises from (0, 1), it implies that target is reinforcing, and once it falls from 0 to -1, it denotes that the hunt is exhausted. After several trials & iterations, the energy of the fleeing target will steadily deplete. As a result, the BWOA starts with a spider search agent (population), where every spider represents a potential applicant. As partners, these early spiders try to produce a new generation. The main components of the proposed BWOA are movement and scent. The following is a description of the BWOA mathematical simulation:

Movement: Formula (9), which describes spider's movements inside the web, shows that they were both linear and spiral.

$$\vec{p_i}(n+1) = \begin{cases} \vec{p}_{best}(n) - q\vec{p}_{r_1}(n) & if\ rand() \leq 0.3 \\ \vec{p}_{best}(n) - \cos(2\pi\delta)\,\vec{p}_i(n) & for\ other\ circumstance \end{cases} \tag{9}$$

Where, $\vec{p_i}(n+1)$ is the newly created location of a pursuit agent, $\vec{p}_{best}(n)$ is preceding iteration's best pursuit agent, q corresponds to a randomly generated float number, r_1 varies from one, and supreme size of pursuit agents produced by a random number, $\vec{p}_{r_1}(n)$ location of r_1 pursuit agent, δ is a randomly created float number in the interim, $\vec{p}_i(n)$ is the location of the current pursuit agent.

Scents: When spiders mate, scents play a vital role. Low scent rates in female spiders are a sign of cannibalistic behavior. Male spiders often do not like scent -poor female spiders. Another female spider might be used in place of it for low scent rates, defined as notches of 0.3 or lower. Formula (10), which monitors the spider's position, tells it to migrate away from female spiders with low scent rates. The scent rate assessment is represented by the equation.

$$\text{Scent}\ (i) = \frac{(fit_{worst} - fit_i)}{(fit_{worst} - fit_{best})} \tag{10}$$

fit_i is the present fitness value of ith pursuit agent, where fit_{worst} is present generation's worst fitness value, fit_{best} is present generation's best fitness value, etc. The proposed strategy improves fitness quality and creates a better balance among the exploration and extraction stages by updating the low scent rate pursuit agent rather than the entire pursuit agent before the following iteration.

As a result, this research extracted the features such as color and shape features by using the proposed Harris hawks – Black Widow Optimization based deep belief network (figure 5). This proposed network provides a fast convergence speed and avoids local optima problem. next that, GooLeNet's suggested Auxiliary classifier, that is covered in the next section, is given the retrieved features.

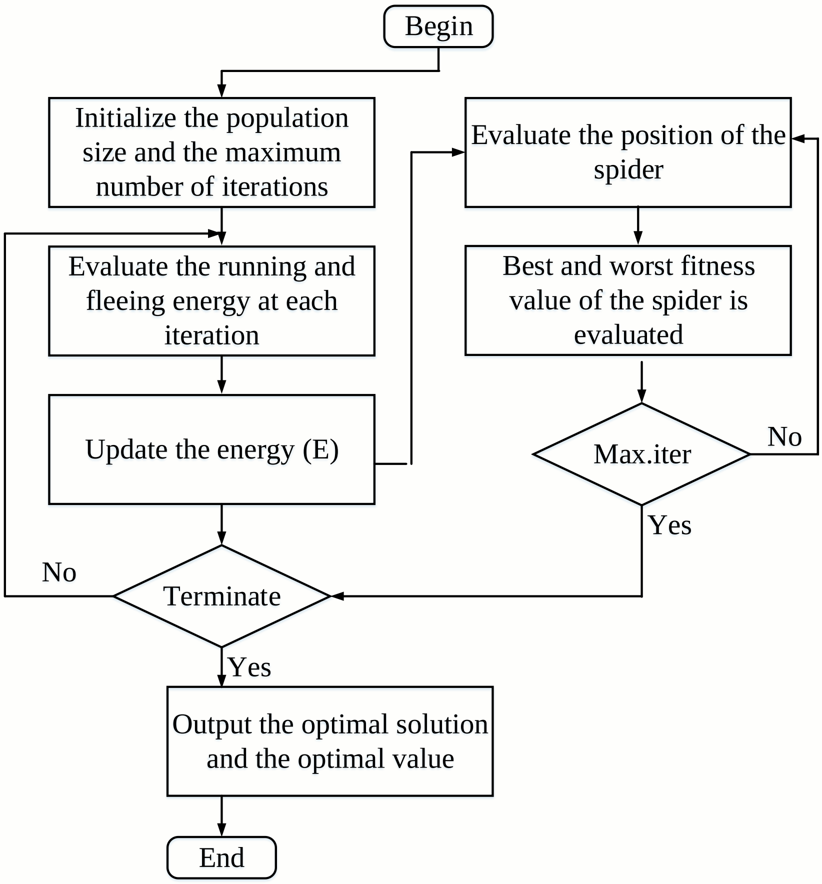


Figure 5. Architecture of the proposed HH-BWO

3.3.2 A novel auxiliary classifier for brain tumor classification

This study used an auxiliary classifier in the Google Neural Network to categorize the brain tumor. After training, a small CNN is used as an auxiliary classifier; any losses it experiences are added to the network's overall losses. GoogLeNet employs auxiliary classifiers for an extra network, in contrast to Inception v3, which utilizes them as a regularizer. In our research, the auxiliary classifier is to perform a classification based on the inputs and adds the loss calculated during the training back to the total loss of the network.

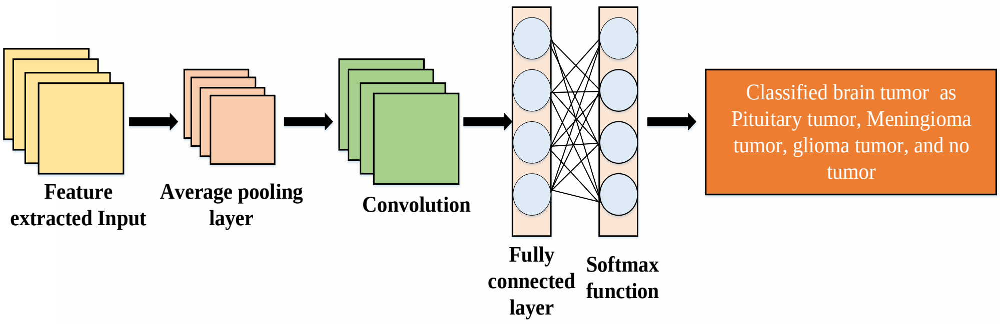


Figure 6. Proposed Auxillary Classifier

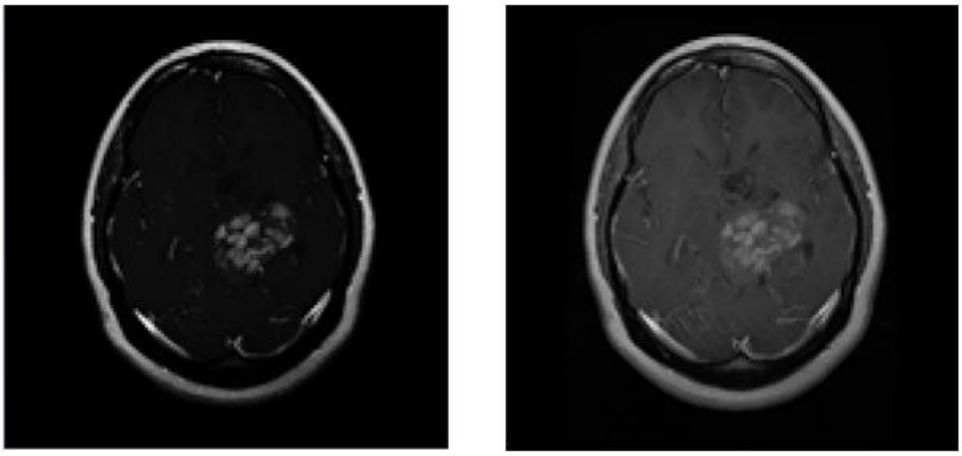
Figure 6 illustrates an auxiliary classifier, that includes layers of average pooling layers fully connected layer, and softmax function. This comprises a softmax categorization level, two fully connected layers with 1024 outputs each and 1000 outputs each, a 3×3 average pooling layer with a stride of 3, 3×3 convolutions, and 128 filters. The loss of the auxiliary classifier units is multiplied by 0.4 and then added to the overall network loss when we train the neural network. These levels offer regularization as well as assistance in overcoming the gradient vanishing issue.

The outlined auxiliary classifier is used to classify the brain tumor as a PT, MT, GT, or H, increasing efficiency and performance parameters (accuracy, precision, recall, and specificity) of brain tumor identification along with categorization. The findings of the unique optimized neural network for feature extraction and classification from brain tumors are then presented in the next section.

4. Results and discussion

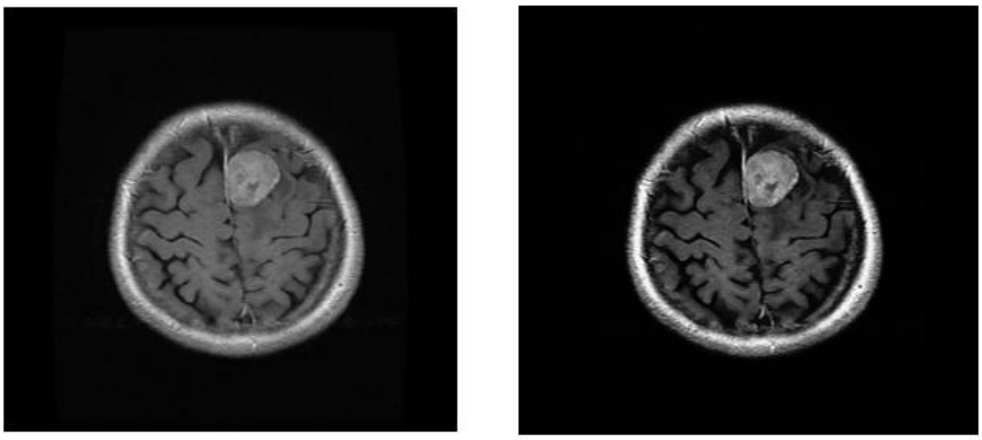
This segment, the proposed approach's performance & comparison findings are discussed in addition to the results of its execution. Python 3 is employed for implementing the results of the proposed neural network for effectively detecting brain tumors and their types.

4.1 Obtained results from the proposed approach



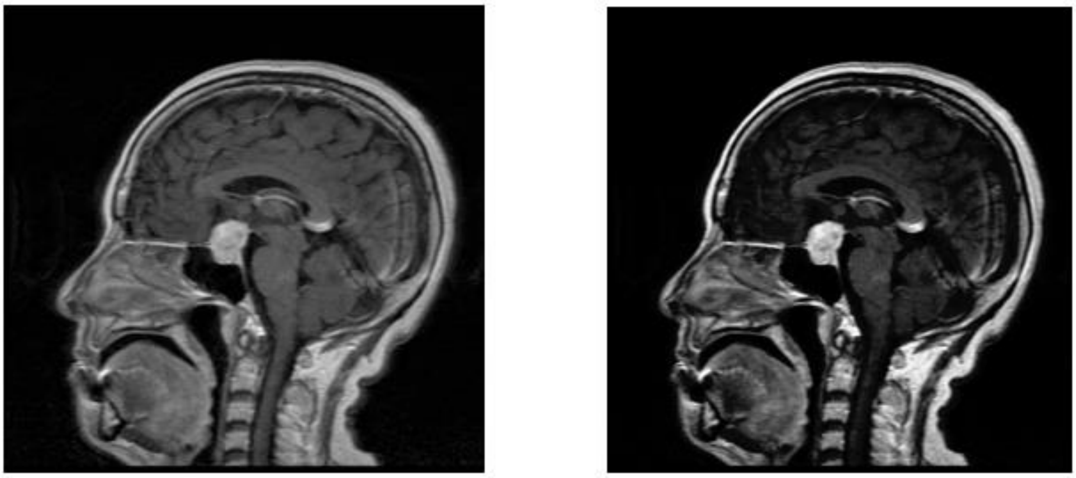
(a) (b)

Figure 7. Results of GT (a) before P-P (b) after P-P



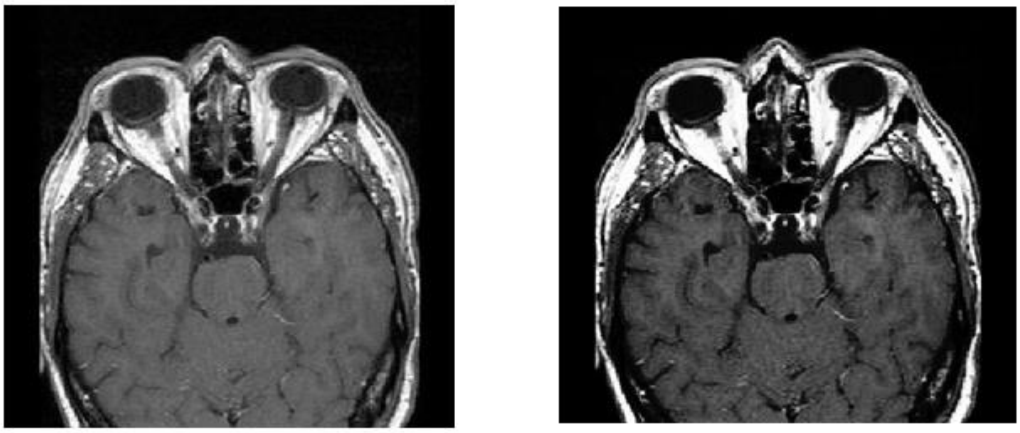
(a) (b)

Figure 8. Results of MT (a) before P-P (b) after P-P



(a) (b)

Figure 9. Results of PT (a) before P-P (b) after P-P



(a) (b)

Figure 10. Results of H (a) before P-P (b) after P-P

Figures 7 to **10** display the pre-processing results for GT, MT, PT, and H. The proposed innovative Hybrid Deep Belief Google Network (DBGN) architecture for brain tumor identification and classification is then fed these pre-processed pictures. The pre-processing procedures increase the brain tumors' accuracy in categorization.

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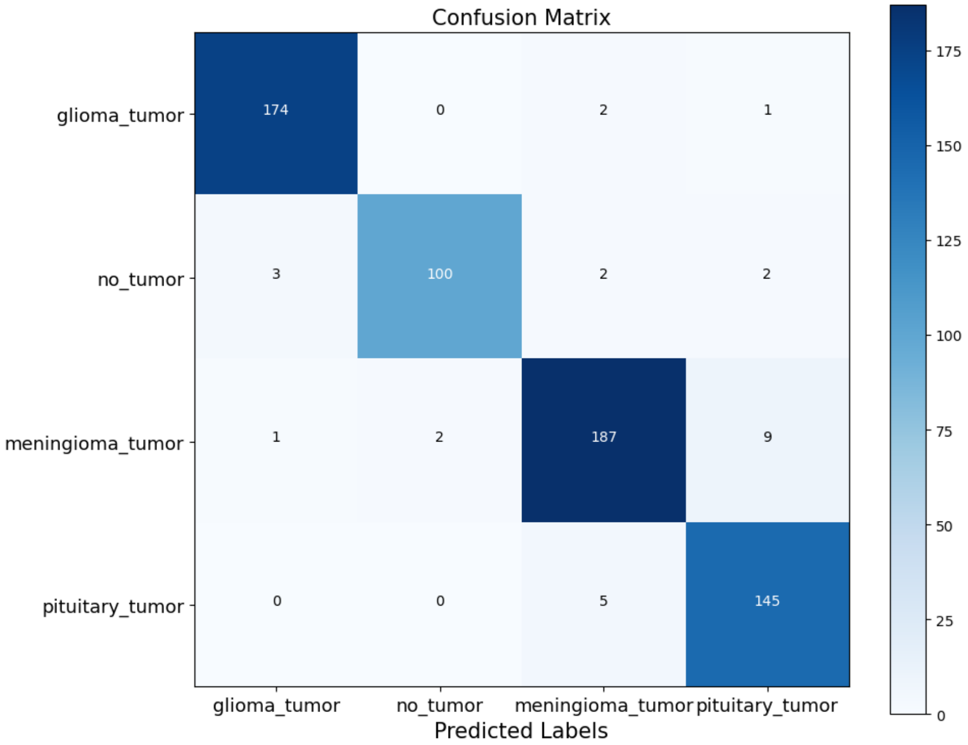

Figure 11. Confusion Matrix

Figure 11 shows the proposed auxiliary classifier's performance for detecting & categorizing brain tumors in Google Net. The brain tumor in the MRI dataset is shown in Figure 11. A confusion matrix on the main diagonal displays the properly detected brain tumor from top left to bottom right. In the other cells, known as genuine negatives or false negatives, the erroneous labels are visible. The proposed hybrid model, therefore, produces superior outcomes.

The performance of the unique strategy for classifying brain tumors is assessed using the performance of the approach we propose and several measures, including accuracy, precision, recall, sensitivity, and specificity. The calculations that follow are used to assess the A_{ccu}, P_{re}, R_{eca} and S_{pec} of various performance characteristics. Here, Tp, Tn, Fp, and Fn stands for True positive, True negative, False positive, and False negative.

$$Accuracy(A_{ccu}) = \frac{\mathrm{Tp+Tn}}{\mathrm{Tp+Tn+Fp+Fn}} \quad (11)$$

$$Precision\ (P_{re}) = \frac{\mathrm{Tp}}{\mathrm{Tp+Fp}} \quad (12)$$

$$Recall\ (R_{eca}) = \frac{\mathrm{Tp}}{\mathrm{Tp+Fn}} \quad (13)$$

$$Specificity\ (S_{pec}) = \frac{\mathrm{Tn}}{\mathrm{Fp+Tn}} \quad (14)$$

4.2 Performance Parameters

The different performance metrics of the presented innovative optimized neural network for the extraction and categorization of brain tumor feature are described in this subsection.

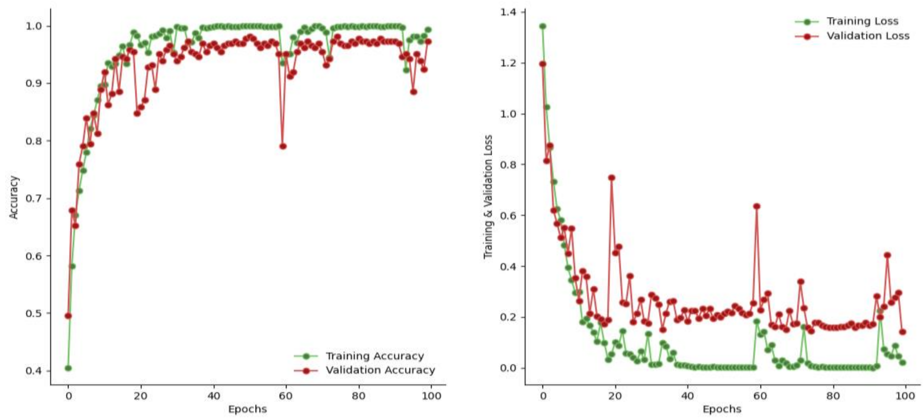

Figure 12. Training and Validation Accuracy, Loss

Figure 12 shows that at epoch 28, the training and validation accuracy scores are 0.83 and 0.9906. The training accuracy is greater than the validation accuracy when using our suggested optimization-based DBN model, proving the effectiveness of the proposed approach. At epoch 27, the loss for training and validation is 0.1747 and 0.0326, correspondingly. According to Figure 12, when employing the optimization-based DBN technique we've proposed, the training loss is lower than the validation loss.

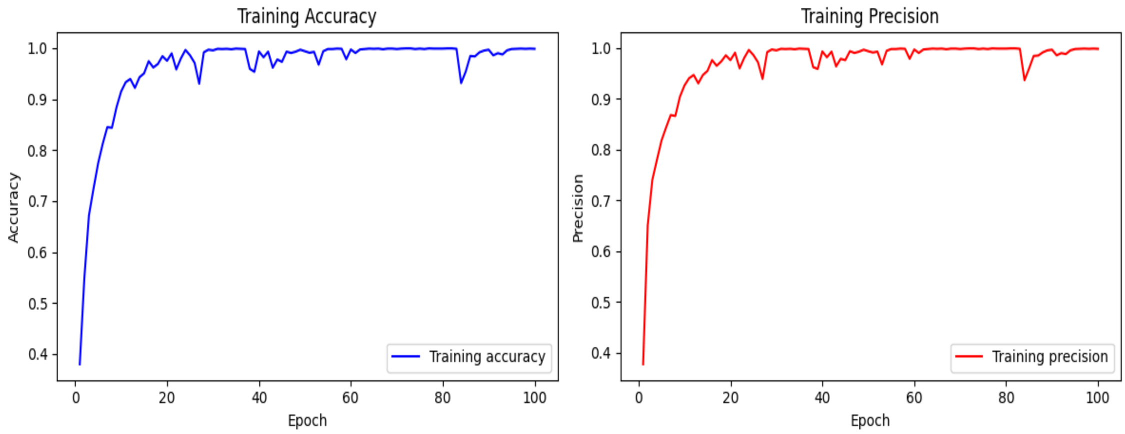

Figure 13. Training Accuracy and Precision

Figure 14. Performance evaluation metrics of the proposed approach

The proposed technique's performance evaluation measures are shown in Figure 14. A_{ccu}, P_{re}, R_{eca} and S_{pec} values were 98.8%, 97.75%, 98.31%, and 99.12% respectively. By adopting a cutting-edge Hybrid Deep Belief Google Network (DBGN) architecture, the performance of our suggested achieves improved accuracy, precision, recall, and specificity.

4.3 Comparison analysis

The proposed technique is compared to existing methods in this section, including, Whale Harris Hawks optimization - Deep Convolutional Neural Network (WHHO - DCNN) (Rammurthy et al. 2022), Basic CNN [34], VGG 16 Net [34], Densenet (Ozkaraca et al. 2023) and Modified CNN (Ozkaraca et al. 2023) .

Table 1. Comparison analysis on existing vs proposed approach

Techniques	Accuracy	Precision	Recall
Whale Harris Hawks optimization - Deep Convolutional Neural Network (WHHO - DCNN) (Rammurthy et al. 2022)	81.1%	-	77.8%
Basic CNN (Ozkaraca et al. 2023)	92.32%	92.25%	90.00%
VGG 16 Net (Ozkaraca et al. 2023)	91.03%	86.25%,	86.25%
Densenet (Ozkaraca et al. 2023)	90.30%	87.75%	87.75%
Modified CNN (Ozkaraca et al. 2023)	98.55%	96.0%	96.0%
Proposed Approach	98.8%	97.75%	98.31%

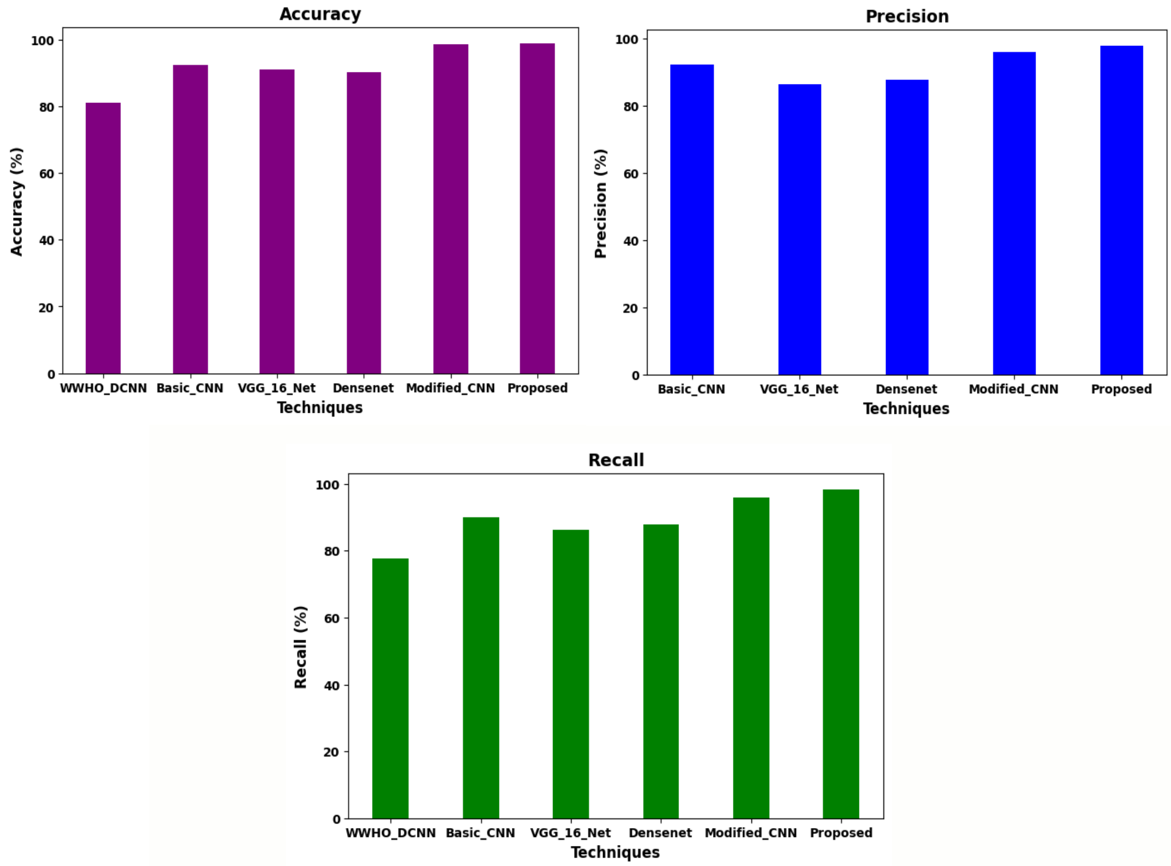

Figure 15. Comparison methods on brain tumor classification of A_{ccu}, P_{re}, and R_{eca}

Figure 15 displays the comparison of total A_{ccu}, P_{re}, and R_{eca}. Utilizing the cutting-edge Hybrid Deep Belief Google Network (DBGN) framework enhances the efficiency of the proposed technique. When compared to the baseline procedures shown in Table 1, our proposed approach achieves improved accuracy, precision, and recall.

5. Conclusion

This study proposes a unique Hybrid Deep Belief Google Network (DBGN) framework for identifying and categorizing brain tumors. The three essential processes in this innovative architecture are pre-processing feature extraction, and classification. Image enhancement, denoising, and recognition of edges have to be carried out during pre-processing step. Then, to remove features of Deep Belief Network (DBN) is proposed, moreover, to fine-tune the hyperparameters in the DBN network, this research proposed a Harris hawk – Black Widow Optimization (HH-BWO). Then, to classify the brain tumor this research utilized an Auxillary classifier in the GoogLeNet. As a result, our proposed approach provides higher performance in terms of accuracy, precision, recall, and specificity of 98.8%, 97.75%, 98.31%, and 99.12% when compared to the existing approaches.

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Conflict of interest

The authors declare that they have no conflict of interest.

Author Contributions

All authors read and approved the final manuscript

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Data sharing not applicable to this article, because it’s confidential.

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