An Efficient Hybrid Clustering and Feature Extraction Techniques for Brain Tumor Classification

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Abstract

Most aggressive and common disease is Brain tumors and it leads to very short life expectancy in its highest grade. For proper treatment, such tumors needs to be identified in early stages and detecting brain tumors, medical imaging is used as an important tool. Although, for diagnosing such tumors, MRI (Magnetic Resonance Imaging) is used very often and it is assumed as a highly suitable technique. From brain magnetic resonance imaging (MRI) data, edema and tumor inference is a challenging task due to brain tumors blurred boundaries, complex structure and external factors like noise. For alleviating noise sensitivity and enhancing segmentation stability, a hybrid clustering algorithm is proposed in this research work. Certain processes like classification, feature extraction, hybrid clustering and pre-processing are included in this proposed model. For segmentation of brain tumors, proposed a morphological operation. Skull stripping and contrast enhancement are two process performed in pre-processing stage. It is possible to detect high contrast regions under contrast enhancement. In second stage, Enhanced K- means algorithm is combined with Fuzzy C- Means Clustering (FCM), where images are segmented as clusters. Algorithm's stability can be enhanced using this clustering techniques while minimizing clustering parameter's sensitivity. Segmented objects are converted into representations using representation and feature extraction techniques. Major attributes and features are described in a better manner using these techniques. The Fast Discrete Curvelet Transform (FDCT) is used for performing feature extraction in this technique for minimizing complexity and enhancing performance. At last, for classification, deep belief network (DBN) is used in this work. And it uses the concept of optimized DBN, for which Improved dragonfly optimisation algorithm (IDOA) is utilized. This proposed model is termed as IDOA-DBN model. When compared with other classification techniques, brain tumors can be detected effectively using proposed model.

Keywords

Improved Dragonfly Optimisation Algorithm (IDOA), Deep Belief Network (DBN), Fast Discrete Curvelet Transform (FDCT), Improved K-means Clustering (IKMC), Fuzzy C- Means Clustering (FCM), Hybrid Clustering, Brain Tumours.

Introduction

In this world, most amazing and complex thing is human brain. Brain is like any other body organ which is exposed to various diseases including tumors (Roy S, 2013) (Gondal, A.H, 2013). In this world, a deadly disease is brain tumor. To cure patient, at early stages, detection and determination of tumor is very important. It is also termed as intracranial neoplasm. In brain, formation of abnormal cells causes this brain tumor and are classified into two classes namely, benign and malignant tumors.

Malignant tumors is also termed as cancerous tumors, whereas, benign tumors are termed as non-cancerous tumors (Borole, 2015). Cancerous or malignant tumors are again classified into primary and secondary tumors. Primary tumors are starts from brain and secondary tumors originates from other parts of body other than brain. This kind of secondary tumors are termed as metastatic tumors.

Various symptoms are exhibited by various brain tumor types according to involved brain's part and it ranges from simple headache to stroke. Type of tumor and stage of it can be identified by diagnosing it (Laddha, 2014) (Dahab, 2012). Observation of human is needed in traditional monitoring and diagnosing techniques of this disease for identifying specific features. Increase in MRI image observation increases number of patients suffering from brain tumor disease.

Within the medical field, medical imaging is a technique used for visualizing organs and composition inside human body. Information about human body's inner system can be provided using medical imaging, which can assist the doctors for diagnosing diseases and for exploring such methods which non-invasive (Natarajan, 2012). For researchers and doctors, tumor diagnosis and detection are crucially investigated. Manual techniques are developed initially.

However, in MRI, certain limitations are shown by these techniques. Tumor portions are neglected by intensity values manual and scattered selection and at central point, tumor detection may get failed (Murugavalli, 2007). In pathological condition assessment, an important role is played by MRI. In musculoskeletal system, for disease analysis medical imaging, MRI is evolved as an accepted modality. In specific, brain and foot MRI due to non-ionizing radiation.

Tissue characteristic's digital representation is provided by MRI, which can be derived from any tissue plane (Vijay, 2013). Images which can be best described as slices in vertical as well as in horizontal planes are produced by MRI scanner.

From complex medical images, information are extracted using an important process called segmentation. In medical field, segmentation has wide applications. For computer-aided diagnosis or radiological evaluation, in most medical image analysis classification, an important process is segmentation (Sharma, 2012). In general, there are three classes of image segmentation techniques, namely pixel based techniques, region-based techniques and edge based techniques.

An image can be partitioned into mutually exclusive as well exhausted regions using image segmentation. So, every region is made spatially contiguous and based on predefined criterion, pixels within the region are homogenous (Patil, 2012). There are two types of image segmentation techniques are used, namely, nonconventional or intelligent and conventional techniques.

In medical image segmentation, feature extraction is an important part. Extra care needs to be taken in this step, for extracting relevant information from input data, which can be used in desired task (Stosic, 2018). For enhancing clustering instability and for alleviating noise sensitivity, proposed a hybrid segmentation algorithm based on clustering. At different scales, from MR images, for extracting features, Discrete wavelet transform (DWT) is used as an effective tool.

In linear edges identification, limitations are shown by wavelets and it fails to identify curved edges, which leads to classifier's malfunctioning and produces false alarms. So, due to the abilities in extracting curved and linear edges, Fast Discrete curvelets transform is used for extracting features. So, segmentation stability enhancement is focused in this work and for brain tumors segmentation, proposed a hybrid clustering algorithm combined with morphological operation is proposed. For enhancing accuracy of classification, feature extraction is done using fast discrete curvelet transform (FDCT).

The rest of the research work is organized as follows, section 2 review the methods for brain tumor detection and its performance results. Section 3 explains the proposed methodology in detail. Section 4 describes the results and discussion. Section 5 deals with the conclusion and future work.

Literature Review

Recent techniques related to brain tumor classification are reviewed in this section. In brain tumor detection, some improvements can be described using each and every techniques using image processing methods.

A segmentation technique based on colour is proposed by Wu et al. In magnetic resonance (MR) brain images, for tracking tumor objects, K-means clustering technique is used in this. Specified gray-level MR image is converted into a color space image in this segmentation technique based on colour. From MR image's other items, tumor positions are separted using histogram clustering and K means clustering. For MR brain images, successful achievement of segmentation can be done using this method as demonstrated in experimentation. It assists pathologists in distinguishing region and lesion size exactly.

For pediatric brain tumor segmentation and classification, in multimodal magnetic resonance (MR) images, a fusing two novel texture features along with intensity are introduced by Iftekharuddin et al. For fractal feature extraction, our Piecewise-Triangular-Prism-Surface-Area (PTPSA) involved in one of two texture features.

This novel fractional Brownian motion (fBm) framework is exploited in other texture feature. For fractalwavelet feature extraction, both wavelet and fractal analyses are combined. Three MR image modalities like FLuid-Attenuated Inversion-Recovery (FLAIR), T2 and T1 (gadolinium-enhanced) are exploited.

Using Self-Organizing Map (SOM), fused the features extracted from these multimodality MR images. Around 100% segmentation accuracy is achieved with 204 T1 contrast-enhanced, T2 and FLAIR MR images which are derived from 9 various pediatric patients.

Better tumor segmentation results can be produced in multimodality MR images using intensity, fractal wavelet and fusion of fractal features are suggested in experimental results when compared with other intensity and fractal features in single modality MR images.

For morphological operators and segmentation based tumor detection an effective algorithm is presented by Mustaqeem et al. At first, enhanced the scanned image's quality and then in this scanned image, tumors are detected by applying morphological operators. Segmentation is used as an major techniques. A threshold based segmentation, morphological operators and watershed segmentation is used in this.

With human brains MRI scanned images, experimentation is conducted using proposed segmentation technique. In images, tumors are located using this technique. Using MRI process, human brain samples are selected and using segmentation techniques, they are processed and produces better results.

From MR images, for diagnosing brain tumor, a automatic system is proposed by Akram et al. There are three stages in this proposed brain tumor detection system. Acquired the MR brain image in first stage and noise is removed by performing pre-processing and image is sharpened. For segmenting brain tumor, on this sharpened image, global threshold segmentation is used in the next stage.

Using tumor masking and morphological operations, post processed the segmented image in third stage for removing false segmented pixels. In MR images, brain tumor can be accurately identified and segmented using our proposed technique as shown experimental results.

Non-cancerous an cancerous Magnetic Resonance Imaging (MRI) of the brain can be easily differentiated using an automated technique proposed by Amin et al. For candidate lesion segmentation, various methods are applied. Using intensity, texture, shape, for every applicant, feature set is selected next. On these features, with various cross validations, applied Support Vector Machine (SVM) classifier for comparing proposed framework's precision.

The proposed technique is approved on three benchmark datasets, for example, Harvard, RIDER and Local. The technique accomplished normal 97.1% exactness, 0.98 territory under bend, 91.9% affectability and 98.0% explicitness. It tends to be utilized to recognize the tumor all the more precisely in less handling time when contrasted with existing strategies.

Murugavalli et al introduced a neuro-fluffy division cycle of the MRI information to identify different tissues like white issue, dark issue, csf and tumor. The benefit of progressive self sorting out guide and fluffy c implies calculations are utilized to order the picture layer by layer. The least level weight vector is accomplished by the reflection level. And furthermore accomplished a higher estimation of tumor pixels by this neuro-fluffy methodology.

The calculation speed of the proposed strategy is additionally considered. The multilayer division aftereffects of the neuro fluffy are appeared to have fascinating results from the perspective of clinical analysis. Neuro fluffy method shows that MRI mind tumor division utilizing HSOM-FCM additionally perform more exact one.

Bahadure et al proposed a Berkeley wavelet transformation (BWT) based mind tumor division. Moreover, to improve the exactness and quality pace of the support vector machine (SVM) based classifier, applicable highlights are extricated from each portioned tissue. The trial aftereffects of proposed method have been assessed and approved for execution and quality investigation on attractive reverberation mind pictures, in view of precision, affectability, particularity, and dice similitude list coefficient.

The test results accomplished 96.51% precision, 94.2% explicitness, and 97.72% affectability, exhibiting the adequacy of the proposed procedure for recognizing ordinary and irregular tissues from cerebrum MR pictures. The trial results additionally acquired a normal of 0.82 dice closeness record coefficient, which shows better cover between the mechanized (machines) extricated tumor district with physically removed tumor area by radiologists.

Ratan et al built up a division technique on 2D and 3D MRI Data. This technique can section a tumor given that the ideal boundaries are set appropriately. This technique doesn't need any introduction while the others require an instatement inside the tumor. The perception and quantitative assessments of the division results exhibit the viability of this methodology.

In this, after a manual division methodology the tumor recognizable proof, the examinations has been made for the possible utilization of MRI information for improving cerebrum tumor shape guess and 2D and 3D representation for careful arranging and surveying tumor. Careful arranging currently utilizes both 2D and 3D models that coordinate information from numerous imaging modalities, each featuring at least one parts of morphology or capacities.

Right off the bat, the work was continued to figure the territory of the tumor of single cut of MRI informational index and afterward it was reached out to compute the volume of the tumor from numerous picture MRI informational index.

Tiwari et al introduced a changed technique for tumor line recognition and division is utilized to isolate the sporadic from the normal encompassing tissue to get a genuine recognizable proof of included and non included zone that help the specialist to separate the included zone correctly. The technique proposed here is cultivated district developing strategy to distinguish the tumor limits in 2D MRI for various cases.

This strategy that can be approved division on 2D MRI Data. In this, after a manual division system, this methodology can be changed over into completely robotized approach.

For brain tumor segmentation, from MR images, a semi-automatic technique is proposed by Dubey et al. Over conventional statistical classification, significant advantages are shown by level set evolutions combining global smoothness with topology changes flexibility followed by mathematical morphology. Either completely outside or inside tumor, there is a need to initialize level set evolution with constant propagation and may leak through boundary or missing parts.

These limitations are replaced by using statistical force instead of constant propagation. In a convergence, it results in a stable solution. Background probabilities and tumors are presented using MR images and from a pre- and post-contrast, tumor regions are computed using difference image and histogram’s mixture modelling fit.

For segmenting tumor boundaries, entire image is used to initialize level set evolution. Various tumors with significant intensity and shape variability are presented by results on two cases. For clinic, above mentioned techniques shows its effectiveness and powerfulness. Comparison with manual expert radiologist demonstrates the validity.

Clustering techniques like fuzzy clustering or soft clustering and hard clustering are used as observed from above review. In hard clustering technique, every object in dataset is restricted to only one cluster, but in fuzzy or soft clustering, every object may belongs to more than one clusters based on membership degree associated with it.

In majority of real situations, objects will be restricted to only one cluster and makes this process as a highly difficult one. So, for hard clustering, hybrid clustering is naturally preferred in practical cases.

Proposed Methodology

Certain processes like classification, feature extraction, hybrid clustering and pre-processing are included in this proposed model. A hybrid clustering algorithm is proposed in this research work. For segmentation of brain tumors, proposed a morphological operation. In specific, in initial phase, two extreme processes called skull stripping and contrast enhancement are used. Figure 1 shows the proposed model's architecture.

- Skull stripping and contrast enhancement are two process performed in pre-processing stage. It is possible to detect high contrast regions under contrast enhancement. From images, non-brain tissues like eyes, dura, scalp, skull are removed during skull stripping.
- For segmentation process, given this resultant pre-processed image *Ip*. The Enhanced K- means algorithm is combined with Fuzzy C- Means Clustering (FCM), where images are segmented as clusters. In specific, they are clustered as abnormal tumour, cerebrospinal fluid (CSF), grey matter and white matter regions. Stability of algorithm can be enhanced using this algorithm, but clustering parameter's sensitivity is minimized.
- Segmented objects are converted into representations using representation and feature extraction techniques. Major attributes and features are described in a better manner using these techniques. The Discrete Curvelet Transform (DCT) is used for performing feature extraction in this technique for minimizing complexity and enhancing performance.
- At last, for classification, deep belief network (DBN) is used in this work. And it uses the concept of optimized DBN, for which Improved dragonfly optimisation algorithm (IDOA) is utilized.

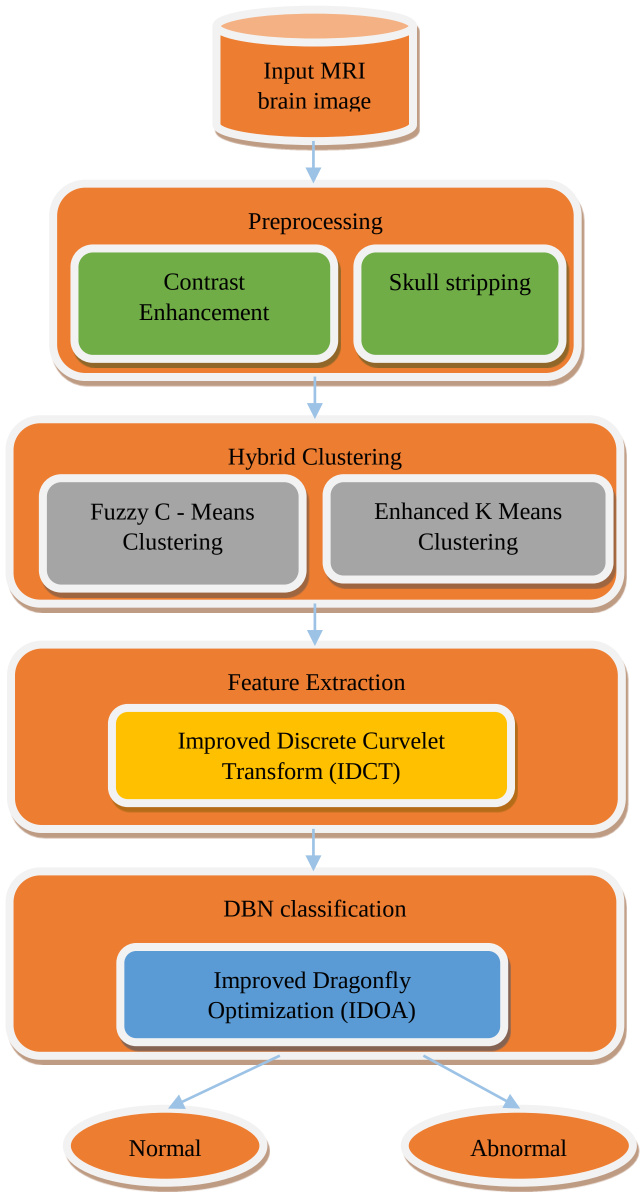

Figure 1 The architecture of the proposed model

Pre-processing

This is an initial process. Skull stripping and contrast enhancement process are performed in this stage.

Contrast enhancement: In this step, enhanced the resized input image *I*'s contrast (Geetha, 2020). Image's intensity is adjusted using this specific process and there will be better enhancement in image's visibility, where, I's relative brightness and darkness are adopted as per expression (1). Image's contrast enhancement is represented as CO. So, a new grey level image is formed by converting the image I. The I^C represents contrast-enhanced image.

$$I^c \to CO = [((\frac{I - low_{in}}{high_{in} - low_{in}})^\wedge gamma) * (high\_out - low\_out) + low\_out](1)$$

Skull stripping: It is an important pre-processing technique, where from brain images, skull part is eradicated. Following specifies the skull-stripping's working principle.

1. Contrast-enhanced image, I^c is given as input.
2. Image is binarized and binarised image is computed as bin I^c_{bin},I^c_{bin} = binarization (I^c).
3. From I^c_{bin}, highly related component $\bar{c}_1$ are identified.
4. With 3 × 3 square structuring element SE_2,$\bar{c}_1$ is dilated.

$$\hat{c}_1 = \bar{c}_1 \oplus SE_2$$

5. Using expression (2), in resultant image or in final image, holes are filled. Until $\hat{c}_{1\hat{k}} = \hat{c}_{1\hat{k}-1}$, same procedure is continued.

$$\hat{c}_{1\hat{k}} = (\hat{c}_{1\hat{k}-1} \oplus SE_2) \cap I^C_c \qquad (2)$$

6. Based on $\hat{c}_{1\hat{k}}$, from original image I^c, segmented the image regions and skull stripped image is obtained as pre-processed imageI_p.

Segmentation

Noise sensitivity can be minimized to some extent using current medical image segmentation algorithm. Segmentation stability is still a huge challenge. The hybrid clustering algorithm called Fuzzy C-means clustering (FCM) and Improved K-means Clustering (IKMC) to enhance clustering algorithm's stability and to alleviate the clustering algorithm's sensitivity to noise. Benefits of two clustering algorithms are included in this hybrid algorithm.

In this work, for cluster centroids deterministic initialization, Improved K-means Clustering (IKMC) is used first and it avoids overfitting. Then, clustering is performed using fuzzy C-means algorithm, which further enhances classification ability.

The non-brain tissue is removed using morphological operations, which enhances segmentation and minimizes computational complexity. In an image, objects skeletons and boundaries are identified using morphological operations. Corrosion and expansion are the most commonly used morphological operations. Image edges are enlarged using expansion, target edges or its internal depression are filled.

Image boundaries are eroded by corrosion. Target edges sawtooth are eroded in this. Corrosion and expansion operations extension is done as an opening operation, where, performed the etching operation at first and for expansion, utilized the same structural elements. This operation is represented as $X \circ Y$and is given by,

$$X \circ Y = (X \ominus Y) \oplus Y \quad (3)$$

Where, brain image is represented as X, structural element is represented as Y, corrosion operation is represented as “∘” and expansion operation is represented as “⊕”. From MR brain image, non-brain tissue images are removed by applying morphological opening operation. Algorithm complexity minimization is mainly focused in this step and to some extent, there will be an enhancement proposed clustering algorithm’s accuracy.

a) Improved K-means Clustering (IKMC)

Maximal number of iterations *N*, number of clusters *k* into which the data is partitioned, set of samples (data) are accepted by classical K-means algorithm (Khan, 2004). Clusters are produced as an output of algorithm and it classifies the data. Simple as well as easy operation is shown by K-means algorithm. But there exist a some drawbacks. First, in K-means algorithm, there is a need to specify number of cluster centroids *k* in advance, where there will be a significant limitation in treating unknown data with unknown clusters count.

Then, there is a need to initialize *k* cluster centroids before clustering using K-means algorithm. Data centroids are randomly selected from data value’s maximum and minimum range. However, K-means algorithm’s clustering classification may get affected significantly due to the selection of cluster centroids.

Uncertainty is shown by cluster centroids in classical clustering algorithms like FCM or K-means. Cluster centroids can be initialized using three techniques namely, hierarchical clustering, Improved K-means and K-means. From every cluster, a point is selected, which may be close to cluster centroid or it may be a cluster centroid. The *k* clustering centres are selected randomly using traditional K-mean algorithm. Poor clustering effect is exhibited by this.

Similar effects are shown by latter two techniques, but K-means has less complexity and it can be implemented easily. So, this work adopts K-means for initializing cluster centroids.

A K-means based clustering technique is Improved K-means Clustering (IKMC), where centroids are initialized deterministically. The IKMC algorithm's basic principle in cluster centroid initialization is for maximization of distance between initial cluster centroids. Cluster centroids are initialized deterministically in this technique, which rectifies the instability initialization drawbacks of Kmeans algorithm. Following shows the IKMC algorithm's initialization process.

1. From dataset, sample point is selected randomly as a first initialized cluster centroid.
2. Remaining cluster centroids are selected as:
   a) In sample space, between every sample, distance is computed and initialized the cluster centroids and shortest distance among them is selected and is represented as di.
   b) Using probability, samples having largest distance is selected as new cluster centroid.
   c) Until computing k cluster centroids, above process is repeated.
3. Using K-means algorithm, final cluster centroids for k initial cluster centroids are computed.

b) Fuzzy C-means Clustering (FCM)

For segmenting images, FCM algorithm is used in specific. In this work, FCM is given with resultant *Ip*as input. Image spaces are separated as various cluster regions using image pixels having same value for achieving segmentation. Following describes the traditional FCM.

Step (1) At least 2 arbitrary centroids are selected and are given with random values.
Step (2) Using expression (4), membership function is evaluated, where $\overline{m}$> 1 and cluster number is given by *cl*.

$$ME_{ij} = \frac{1}{\sum_{\hat{k}=1}^{cl}\left[\frac{|x_i - cl_j|}{x_i - cl_j}\right]^{\frac{2}{\overline{m}-1}}} \quad (4)$$

Step (3) Using expression (5), cluster centre is evaluated.

$$CC = \frac{\sum_{i=1}^{\overline{m}} ME_{ij}^{\overline{m}} * x_i}{\sum_{i=1}^{\overline{m}} ME_{ij}^{\overline{m}}} \quad (5)$$

Features are extracted from segmented image I^S.

Feature Extraction

In any image processing methods, major role is played by extraction of features. In this work, to extract features from image *IS*, proposed a technique based on Fast Discrete Curvelet Transform (FDCT).

Fast Discrete Curvelet Transform (FDCT)

A type of multiscale pyramid is a curvelet transform and it has various positions and directions at every length scale and at fine scales, it has needle-shaped elements (Krishnammal, 2015). This is non-standard pyramid but there are useful geometric features in curvelets and a parabolic scaling relation is obeyed by this curvelets. This states that, every element has an envelop at scale 2-j, which is aligned a "ridge" having 2−j/2 length and 2-j width.

Curvelets are quite interesting one. Objects with edges can be represented optimal in sparse using this. Wave propagators are also represented optimal in sparse and in severe ill-posed problems, optimal image reconstruction can be done using this.

The Curvelets via Wrapping and Curvelets via USFFT are the two less redundant, faster and simpler fast discrete curvelet transforms (FDCTs). For n by n Cartesian arrays, in O (n2 log n) flops, both FDCTs runs. These transforms are invertible with rapid inversion algorithms having same complexity. Curvelet transform shows more faith to mathematical transformation.

Linear nature is shown by these digital transformations and assumes input Cartesian arrays in f[t1, t2], 0 ≤ t1, t2 < n form. Coefficients collection produces the output and it is expressed as,

$$cD(j,l,k) \coloneqq \sum_{0 \le t1, t2 < n} f[t1,t2]\,\overline{\varphi^{D}_{j,l,k}}\,\overline{[t1,t2]} \qquad (6)$$

Where, digital curvelet waveform is represented using every $\varphi^{D}_{j,l,k}[t1,t2]$. This work uses a FDCT based on wrapping and following shows its algorithm.

Fast Discrete Curvelet Transform via Wrapping

The same digital coronization is assumed in "wrapping" technique but for translating curvelets in every angle and scale, it selects some simple choice of spatial grid. A regular rectangular grid is assumed instead of tilted grid and in same manner, “Cartesian” curvelets are defined as,

$$c(j,k,l) = \int \hat{f}(\omega)\, \widehat{U}_j S_{\theta l}^{-1} e^{i(b.\omega)} d\omega \qquad (7)$$

It takes values on a rectangular grid. For FDCT, algorithm is shown in following steps via wrapping.

1. The 2D FFT is applied and Fourier samples $\hat{f}[n1,n2], -n/2 \leq n1, n2 < n/2$ are computed.
2. For every angle l and scale j, product $\widetilde{U}_J l[n1,n2]\hat{f}[n1,n2]$ is formed.
3. Around origin, this product is wrapped and $\tilde{f}_j, l[n1,n2] = W\left(\widetilde{U}_J, l, \hat{f}\right)[n1,n2]$ is obtained, where, n1 and n2 is lies between $0 \leq n1 < L1, j$ and $0 \leq n2 < L2, j$ (for θ in range $(-\frac{\pi}{4}, \frac{\pi}{4})$).
4. Every$\tilde{f}_j, l$ is applied with inverse 2D FFT and discrete coefficients $c_D(j,l,k)$ are collected.

Brain Tumor detection by Deep Belief Network (DBN)

The DBN classifier is given with features *F* as input (Geetha, 2020). In general, there are multiple layers and there are visible neurons in every layer, which establishes input layer and output layer is formed by hidden neurons. In addition, there exist a deep connection with input and hidden neurons. However, in visible neurons, there wont be any connections and between hidden neurons also, there wont be any connections.

Between hidden and visible neurons, there will be an exclusive as well as symmetric connection. For input, an accurate output is determined using corresponding neuron model. Output is specified using expression (8) due to probabilistic nature of stochastic neurons' output in Boltzmann network and in a sigmoid shaped function, possibility is provided by expression (9), where, pseudo-temperature is represented as *tP*. Expression (10) specified stochastic model's deterministic approach.

$$O_q(\zeta) = \frac{1}{1+e^{\frac{-\zeta}{tP}}} \qquad (8)$$

$$\overline{PR} = \begin{cases} 1 & with \quad 1 - \bar{O}_q(\zeta) \\ 0 & with \quad \bar{O}_q(\zeta) \end{cases} \qquad (9)$$

$$\lim_{t^p \to 0^+} \bar{O}_q(\zeta) = \lim_{t^p \to 0^+} \frac{1}{1+e^{\frac{-\zeta}{t^p}}} = \begin{cases} 0 & for & \zeta < 0 \\ \frac{1}{2} & for & \zeta = 0 \\ 1 & for & \zeta > 0 \end{cases} \quad (10)$$

The restricted Boltzmann machine (RBM) layer's set is used for processing feature extraction and multilayer perceptron (MLP) is used for processing classification. For binary or neuron state *bi* is formed by exposing Boltzmann machine's energy in mathematical approach and is expressed in expression (11), where, between neurons weights are represented as $w_{a,l}$ and biases are represented as θ_a.

$$\Delta E(bi_a) = \sum_l bi_a w_{a,l} + \theta_a \quad (11)$$

Expression (12) to (14) specifies energy descriptions based on hidden and visible neurons (*x*,*y*), joint composition. In that stated descriptions, *a* visible unit's neuron or binary state is denoted as *xa*, *l* hidden unit's binary state is referred as *Wl*, biases are denoted as *ka* and *Wa*, which are applied to network.

$$E(x,y) = \sum_{(a,l)} w_{a,l} X_a Y_l - \sum_a K_a X_a - \sum_l W_l Y_a \quad (12)$$
$$\Delta E(x_a, \bar{y}) = \sum_l w_{al} Y_l + K_a \quad (13)$$
$$\Delta E(\bar{x}, y_a) = \sum_l w_{al} x_a + W_l \quad (14)$$

Weights co called parameters are formed by encoding input data's possibility dissemination and it is spread as RBM's learning pattern. Dispersed possibilities can be achieved using RBM training and using expression (15), computed the subsequent assignments of weights.

$$\widehat{W}_{(\widehat{M})} = \max_{\widehat{W}} \prod_{\vec{x} \epsilon N} c(\vec{x}) \quad (15)$$

Expression (16) defines RBM model based on assigned possibility for all hidden and visible vectors pairs $c(\vec{x}, \overrightarrow{hi})$. Where, partition function is specified as PA^F and is given in expression (17).

$$c(\vec{x}, \overrightarrow{hi}) = \frac{1}{PA^F} e^{-E(\vec{x},\vec{y})} \quad (16)$$
$$PA^F = \sum_{\vec{x},\vec{y}} e^{-E(\vec{x},\vec{y})} \quad (17)$$

Under distribution, sampling expectations gaining is a complex process. So contrastive divergence (CD) learning is used in this model. Following are the steps of CD algorithm.

Step 1: The*x* training samples are selected and braced into visible neurons.

Step 2: Using expression (18), visible vector x and weight matrix wˆ’s product $c_y = \sigma(x.\widehat{w})$ is computed for assessing hidden neurons c_y's probabilities.

$$c(\vec{y} \rightarrow |\bar{x}) = \sigma(W_l + \sum_a x_a w_{a,l}) \qquad (18)$$

Step 3: From c_y probabilities, y hidden states are observed.
Step 4: The c_y and vector's x exterior product are assessed and are assumed as positive gradient $\varphi^+ = X.C_y^{tp}$.
Step 5: From y hidden states, x' visible states reconstruction is inspected as per expression (19). Further, from x's reconstruction, it is needed for examining y' hidden states.

$$c(\overrightarrow{x_l} \rightarrow 1|\vec{y}) = \sigma(k_a + \sum_a x_l w_{a,l}) \qquad (19)$$

Step 6: Using negative gradient$\varphi^- = X'.y'^{tp}$, x' and y's exterior product is assessed.
Step 7: Using expression (20), updated weight is computed, where, learning rate is represented as η.

$$\Delta\widehat{W} = \eta(\varphi^+ - \varphi^-) \qquad (20)$$

Step 8: With new values, weight updated is expressed in (21).

$$W'_{a,l} = \Delta W_{a,l} + W_{a,l} \qquad (21)$$

The $(N^{\widehat{M}}, R^{\widehat{M}})$ training patterns needs tobe considered before initializing MLP algorithm based learning process, where training patterns count is specified using $\widehat{M}$, $1 \leq \widehat{M} \leq \bar{0}$, input vector is represented as $N^{\widehat{M}}$, required output vector is represented as $R^{\widehat{M}}$. Expression (22) represents the every neuron error in output layer l.

$$e_l^{\widehat{M}} = N^{\widehat{M}} - R^{\widehat{M}} \qquad (22)$$

The $\widehat{M}$pattern's squared error is represented in expression (22) and mean squared error (MSE) is represented in expression (23).

$$SE_{\widehat{M}}^{mean} = \frac{1}{\bar{o}_y} \sum_{l=1}^{o_y} (N^{\widehat{M}} - R^{\widehat{M}})^2 \qquad (23)$$

$$SE_{avg} = \frac{1}{\bar{o}_y} SE_{\widehat{M}}^{mean} \qquad (24)$$

However, it is difficult to find DBN's optimum parameters. This is due to trapping of search process in local minima. Algorithms like Grey Wolf optimization (GWO) and genetic algorithm (GA) are used for training the network. However, large computational cost is required by these algorithms and they can be easily trapped with local minima and it would not produce network's optimum weights.

So, neural network's inaccurate parameters degrades the DBN classification accuracy. For solving this problem, an improved dragonfly optimization algorithm is proposed in this work.

Dragonfly Optimization Algorithm

Recently proposed meta-heuristic algorithm based on population is Dragonfly Algorithm (DA) (Mirjalili, 2016). Idealized dragonfly's migration mechanism and hunting behaviour called static swarm or feeding are inspired in DA. In nature, food sources are searched by dragonflies by flying as a small group. This process is termed as hunting mechanism. In one direction, dragonflies large group will fly with each other. So, in a process called migration mechanism, swarm migrates. Figure 2 illustrates the feeding as well as hunting mechanism.

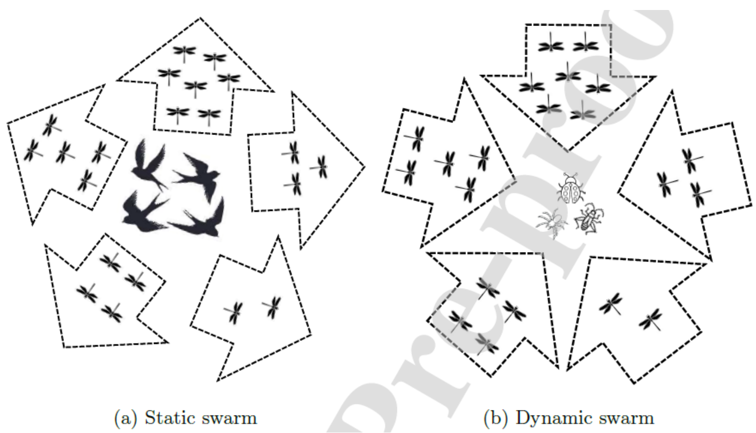

Figure 2 Hunting and feeding swarming behavior of dragonflies when foraging.

Five operators are used for characterizing dragonflies swarming behaviour.

1) In neighbourhood, proper distance between search agents are ensured using a mechanism called **Separation.** Expression (25) shows the separation behaviour's mathematical modelling.

$$S_i = -\sum_{j=1}^{N} X - X_i \quad (25)$$

2) In neighbourhood, matching between specific search agents velocity and other search agents velocity is indicated using **Alignment.** Expression (26) indicates alignment behaviour's mathematical modelling.

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{26}$$

Where, j-th neighbor's speed is represented as Vj.

3) Flying of individuals from neighbourhood area to mass centre is indicated using **Cohesion.** Individual's tendency to fly towards mass's neighbouring centre is referred by this. Expression (27) indicates the cohesion behaviour's mathematical modelling.

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{27}$$

4) Attraction of individuals by food source which fly towards it is represented using **attraction.** Expression (28) indicates the attraction behaviour's mathematical modelling.

$$F_i = F_{loc} - X \tag{28}$$

Where, food source's position is represented as F_{loc}.

5) Individual's tendency to fly away from an enemy is referred using **distraction.** Expression (29) indicates the distraction between ith solution and enemy.

$$E_i = E_{loc} + X \tag{29}$$

Where, enemy's position is symbolised using E_{loc}.

Candidate with best fitness value is used for updating food source's location and fitness during search process in DA. Further, enemy's location and fitness are updated using worst candidate. This moves the divergence away from un-favourable search areas into favourable search areas.

Dragonfly's position are updated using two vectors as in DA. They are, position vector and step vector (ΔX) which is similar to PSO velocity vector. Movement of dragonflies are altered using step vector, which is modelled in expression (30).

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta + \Delta X_t \tag{30}$$

Where, coefficient s represents separation weight Si, a represents alignment Ai, c represents cohesion Ci, f represents movement speed into food source Fi and e represents i-th individual's enemy disturbance level Ei. For maintaining better balance between exploitation and exploration, during optimization process, these parameters are tuned adaptively as shown in expression (31). Inertia weight is represented as w and it is computed according to expression (32). Elaborated details of these coefficients and its effect on DA behaviour are studied from literature.

$$\begin{aligned} s&=2\times r\times pct \\ a&=2\times r\times pct \\ c&=2\times r\times pct \\ f&=2\times r \\ e&=pct; \end{aligned} \tag{31}$$

$$\omega = 0.9 - Iter * \frac{(0.9-0.4)}{Max\_iter} \tag{32}$$

Where, using expression (33), computed the pct.

$$pct = \begin{cases} 0.1 - \frac{0.2\times iter}{\max\_iter}, & if\ (2\times Iter) \leq Max\_Iter \\ 0, & otherwise \end{cases} \tag{33}$$

Where, a random number is represented as r and its value lies between 0 to 1.

Using expression (34), updated the individual's position.

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{34}$$

Where, present step represented as t.

A population is generated randomly by this algorithm initially and using random step vectors, it is initialized. Until satisfying termination criterion, following steps are executed by this algorithm. At first, in population, every individual is evaluated using fitness function. Then, major coefficients i.e., s, w, a, c, f, and e are updated using this algorithm.

In third stage, using expressions (25) to (29), altered the operations enemy (E), food source (F), cohesion (C), alignment (A) and separation (S). At last, dragonfly position and step vectors are updated using expression (30) and (34). Consequently, returned the best solution obtained so far.

Improved Dragonfly Optimization Algorithm (IDOA)

Exploitation-intensification and exploration-diversification are the two major factors having high influence on any metaheuristic algorithm based on population's performance. In population, diversity of solution is indicated by exploration, where global exploration of search space is done. Current good solution's neighbouring area is focused by exploitation. Trapping of solutions in local optima is avoided using randomization based exploration and population diversity can be increased using this.

Converging of searching process with optimum solution is assisted by exploitation on the other side. Global optimality can be achieved by having better balance between these components.

In search space, various regions needs to explored in optimization process's early stages. It is plays an important role. Thus, this stage requires an exploration. However, in explored regions, it is mandatory to discover best solutions in search process's last stages. So, in these stages, exploitation plays a key role.

As indicated in original DF algorithm, coefficient s represents separation weight Si, a represents alignment Ai, c represents cohesion Ci, f represents movement speed into food source Fi and e represents i-th individual's enemy disturbance level Ei.

For generating new agents, portion size that should be derived from current agents are determined using an operator a. According to alignment operation expression (31), portion size is computed by value of 'a'. During search initialization, value of 'a' is updated randomly from 2 and degraded to 0 in original DF.

Adaptive Function based Dragonfly Algorithm (AF-DA)

Expression (35) shows the adaptive function (AF) utilized in DA. In a non-linear structure, updated the coefficient values. Range of coefficients used are similar to DA. Non-linear decrease or increase in coefficient is shown by DA curves in figure 3. The DA's search behaviour is affected by this, which leads to fast exploitation or exploration of base when compared with linear structure.

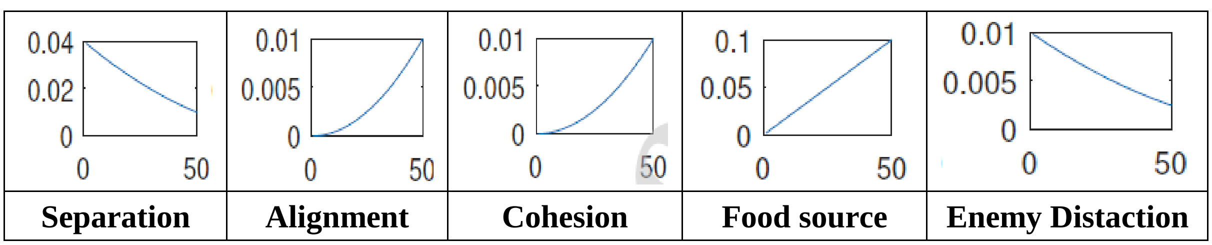

Figure 3 Co-efficient ranges

$$s=0.2-(0.2*\frac{iter}{max_{iter}})^2$$
$$e=0.1-(0.1*\frac{iter}{max_{iter}})^2 \qquad (35)$$
$$a=0.0-(0.2*\frac{iter}{max_{iter}})^2$$
$$c=0.0-(0.2*\frac{iter}{max_{iter}})^2$$
$$f=0.0-(2.0*\frac{iter}{max_{iter}})^2$$

With small value of iter, there will be a rapid increase or decrease of such coefficients from maximum. Value of such coefficients will increase slowly from zero. With large value of iter, there will be a gradual increase or decrease of such coefficients to zero. Value of such coefficients will increase rapdily to maximum.

Results and Discussion

In MATLAB 2014a, implemented the proposed MRI based brain tumor detection technique. Dataset is derived from URL-https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4833122/ and it includes abnormal as well as normal images. In specific, there are 29 normal and 29 abnormal images. Proposed technique's performance is proven in this section and comparison is made with available techniques. For evaluating proposed brain tumor detection techniques performance, below mentioned metrics are used.

Ratio between correctly found positive observations to all the expected positive observations defines precision.

$$\text{Precision} = TP/TP+FP \qquad (36)$$

Ratio between correctly identified positive observations to over-all observations defines sensitivity.

$$\text{Recall} = TP/TP+FN \qquad (37)$$

Recall and Precision's weighted average will produce F1 score. False negatives and false positives are included in this.

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \qquad (38)$$

With respect to negatives and positives, accuracy is computed as,

$$\text{Accuracy} = (TP+FP)/(TP+TN+FP+FN) \qquad (39)$$

Table 1 illustrate the overall comparions of the proposed and existing methods.

Metrics	SVM	DBN	GW-DBN	IDOA-DBN
Precision	86.24	88.45	90.47	92.99
Recall	85.21	87.68	89.54	91.98
F-measure	85.72	88.12	90	92.49
Accuracy	87.24	89.15	91.24	93.99

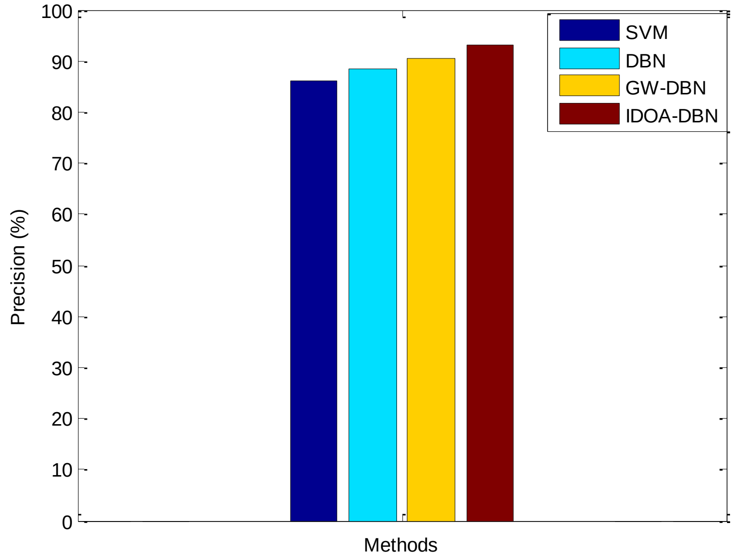

Fig. 3 Precision comparison of proposed IDOA-DBN

Precision metric comparison between proposed IDOA-DBN and available techniques are shown in figure 3. Around 92.99% precision results are produced by proposed IDOA-DBN technique, where only 86.24% is produced by SVM and 88.45% is produced by DBN, 90.47% is produced by GW-DBN techniques. When compared other available techniques, brain tumor detection based on deep belief network has high precision value as indicated in results.

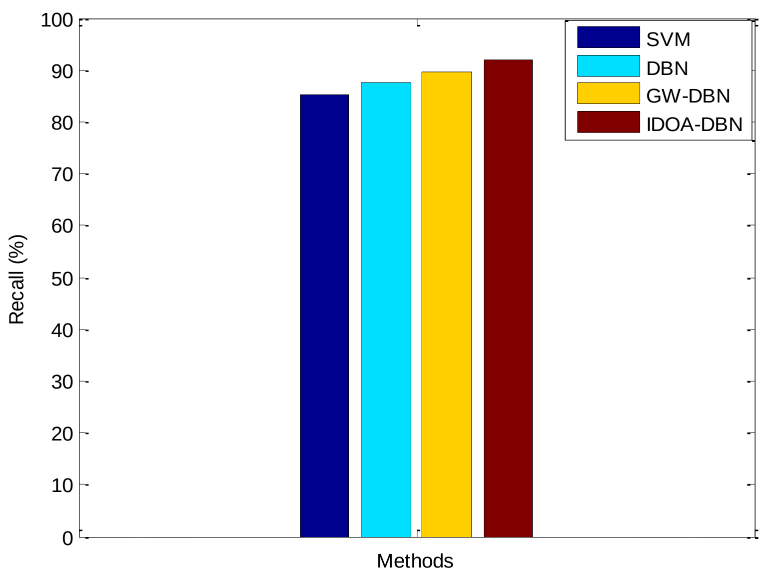

Fig. 4 Recall comparison of the proposed IDOA-DBN

Recall metric comparison between proposed IDOA-DBN and available techniques are shown in figure 4. Around 91.98% recall results are produced by proposed IDOA-DBN technique, where only 85.21% is produced by SVM and 87.68% is produced by DBN, 89.54% is produced by GW-DBN techniques. When compared other available techniques, brain tumor detection based on deep belief network has high recall value as indicated in results.

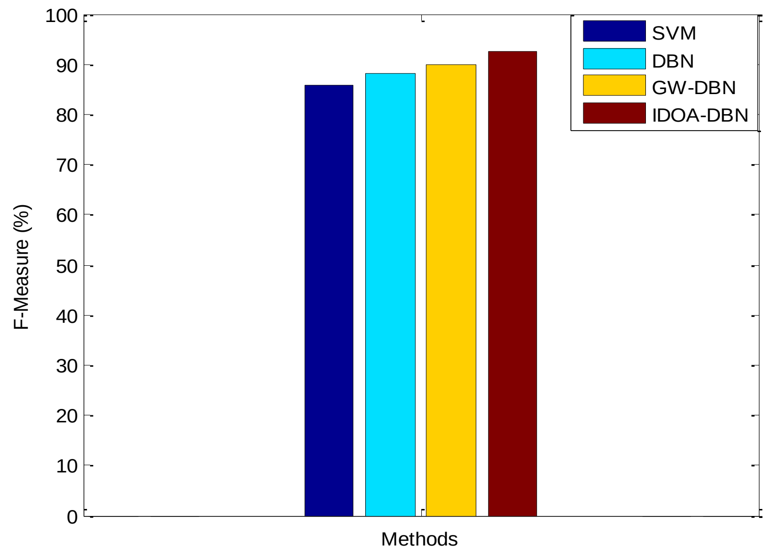

Fig. 5 F-measure comparison of proposed IDOA-DBN

F-measure metric comparison between proposed IDOA-DBN and available techniques are shown in figure 5. Around 92.49% F-measure results are produced by proposed IDOA-DBN technique, where only 85.72% is produced by SVM and 88.12% is produced by DBN, 90% is produced by GW-DBN techniques. When compared other available techniques, brain tumor detection based on deep belief network has high F-measure value as indicated in results.

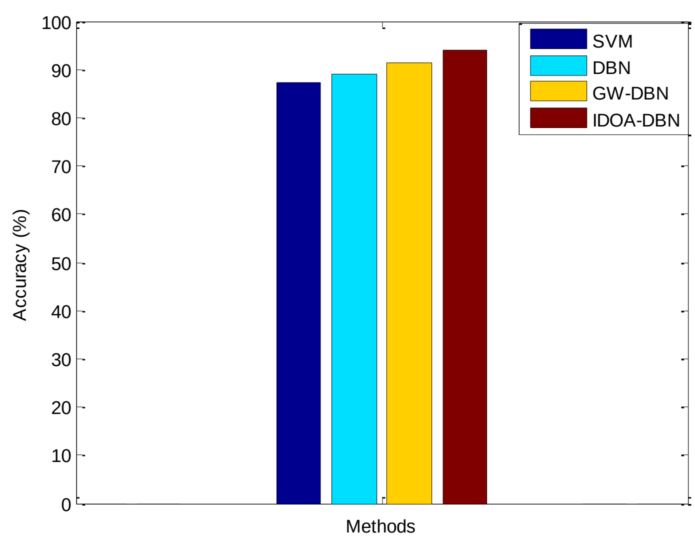

Fig. 6 Accuracy comparison of proposed IDOA-DBN

Accuracy metric comparison between proposed IDOA-DBN and available techniques are shown in figure 6. Around 93.99% accuracy results are produced by proposed IDOA-DBN technique, where only 87.24% is produced by SVM and 89.15% is produced by DBN, 91.24% is produced by GW-DBN techniques. When compared other available techniques, brain tumor detection based on deep belief network has high detection accuracy as indicated in results.

Conclusion

For brain tumor automatic detection, an effective feature extraction technique and hybrid clustering algorithms are proposed in this research work. In pre-processing stage, for brain tumor image segmentation, proposed a morphological operations based filtering technique. The outer membrane is removed initially using morphological operations in this algorithm. Clustering iterations count and computational complexity are minimized using this algorithm. For initializing clusters' centroids in clustering stage, it exploits Improved K-means clustering (IKMC) algorithm. Uncertainty having association with cluster centroids initialization will leads to unstable clustering and these problems are solved using this technique. A stable clustering result is produced by every cluster. Further, overfitting is also prevented using this proposed technique. Then, Fast Discrete Curvelet Transform (FDCT) is used for performing feature extraction. This minimizes complexity and enhances performance. At last, for classification, deep belief network (DBN) is used in this work. The concept of optimized DBN is used here and it uses Improved dragonfly optimisation algorithm (IDOA). With respect to F-measure, precision, recall, accuracy, comparison is made between proposed IDOA-DBN model and other technique. Around 92.85% accuracy rate is produced by this detection model and is a higher value. In future, for 3D image's color based segmentation, this proposed model can be extended. For this purpose, a classification technique is required for organizing three dimensional objects into separate feature classes, where brain diseases diagnosing can be done using its characteristics.

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