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Brain tumour segmentation in MRI using fuzzy deformable fusion model with Dolphin-SCA

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Abstract
It is evident that when the human brain stops functioning for a small period of time, it will lead to death. As a result, dealing with brain disorders should be done early and properly. A brain tumour is one of the most serious brain illnesses. The development of tumours can be detected using Magnetic Resonance Imaging (MRI). However, because an MRI image has loud noise, it can be hard to diagnose a tumour. The diagnosis process is slow, yet illness necessitates prompt and accurate medical attention in order for patients to survive. One of the solutions for tumour diagnosis is to employ MRI brain picture segmentation. In this designed model, MRI of the brain is collected and pre-processed with Non-Local Means (NLM) to reduce noise from captured raw data. This pre-processed image is first segmented with Region of Interest (ROI) for identifying regions of interest and then with a fusion deformable fuzzy system, which combines fuzzy C-means (FCM) and deformable systems. By analyzing the fitness value of α and β constants, segmented pictures from models are fused using the Dolphin Sine Cosine Algorithm (SCA) method to combine the model results. The integrated output from the algorithm is classified with the deep Convolutional Neural Network (CNN) classifier. The created model experimental findings are analyzed and compared to current methodologies. The proposed model performance measures are 0.90, 0.89, 0.88, and 0.10 in terms of selectivity, precision, accuracy and errors. As a result, when compared to previous strategies, the proposed approach outperforms them.

Keywords
Dolphin-SCA, FCM, deformable model, ROI, NLM, tumour segmentation

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УДК 004.89

Сегментация опухоли головного мозга на магнитно-резонансной томографии с использованием нечеткого деформируемого слияния и алгоритма Dolphin-SCA

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Аннотация
Прекращение функционирования мозга человека на небольшой промежуток времени приводит к смерти. Лечение нарушений головного мозга должно проводиться на ранней стадии и до появления клинических симптомов. Опухоль головного мозга является одним из самых серьезных заболеваний. Развитие опухоли можно обнаружить с помощью магнитно-резонансной томографии (МРТ). В связи с наличием шумов на изображении МРТ опухоль сложно точно и быстро диагностировать. Одно из решений в диагностике опухолей — использование

сегментации изображений головного мозга на МРТ. В работе представлена модель томограммы головного мозга обработанная с помощью нелокальных средств (Non-Local Means, NLM) для уменьшения шума от захваченных необработанных данных. Полученное изображение сегментировано с помощью определения областей интереса (ROI) и деформируемой нечеткой системы слияния. Система слияния сочетала в себе метод нечеткой кластеризации C-средних (Fuzzy C-Means, FCM) и деформируемых систем. Выполнен анализ значений пригодности констант α и β сегментированных изображений моделей, объединенных с использованием алгоритма синус-косинуса на основе эхолокации Dolphin-SCA. Интегрированный вывод алгоритма классифицирован с помощью глубокого классификатора (Convolutional Neural Network, CNN). Проведен анализ и сравнение экспериментальных данных созданной модели с текущими методологиями. Значения показателей эффективности предлагаемой модели для селективности, прецизионности, правильности и ошибок составили 0,90, 0,89, 0,88 и 0,10 соответственно. Таким образом, по сравнению с предыдущими стратегиями, предлагаемый подход превосходит ранее применяемые методы.

Ключевые слова

Dolphin-SCA, метод нечеткой кластеризации C-средних, FCM, деформируемая модель, определение областей интереса, ROI, нелокальные средства, NLM, сегментация опухоли

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Introduction

Brain tumours develop as a result of aberrant cell division and uncontrolled growth in the brain. The formation of tissues is classified as benign or malicious, and it takes into various parts of the brain that aren't affected by tumours [1]. As a consequence, tumours must be detected as soon as possible to avoid their development into an uncontrollable state. The ability to accurately segment tumours using medical pictures is critical because it gives information that is needed for cancer assessment and diagnosis, and also planning out therapy choices and tracking disease progression [2]. Brain tumours are among the most lethal malignancies in the world, and they are divided into primary and secondary tumour types based on their origin [3]. Glioma, which arises from brain glial cells and accounts for 80 % of all malignant brain tumours, is the most frequent histological form of primary brain cancer [4]. Gliomas could be of two types: slow-progressing low-grade which has a good prognosis, or aggressive and infiltrative high-grade glioma or glioblastoma which requires prompt treatment.

The approach used to detect brain tumours is Magnetic Resonance Imaging (MRI). It is a complicated technique that provides information on the human soft tissue structure which is then expanded to examine the anatomy of the region and aids in the creation of elaborate representations in each direction [5]. MRI is a sort of medical imaging that may identify a variety of changes in soft tissues all over the body. Fluid Attenuated Inversion Recovery (FLAIR), T2-weighted, T1-weighted, and post-contrast T1-weighted (T1ce) are examples of complementing 3D MRI techniques [6]. The tumours highlighted sub-regions throughout the varying intensity of these patterns, like the entire tumour, are far more evident in T2 modalities and FLAIR [7]. T1 and T1ce scans, on either hand, reveal the tumour centre without any peritumoral oedema. It allows for the detection of various tumour sub-regions using such scans in conjunction with extra information they supply.

Nowadays, the clinical procedures used in the medical profession for detecting tumours utilizing MRI images of the brain are not very effective or stable [8]. Various techniques for image segmentation have been developed, and some of the most commonly used methods include clustering-based methods, histogram-based methods, thresholding, region-growing methods, edge detection, and so on [9]. Clustering algorithms attempt to find patterns in a dataset in order to extract additional information. There are several clustering methods available today, including clustering based on the distribution, hierarchical clustering, k-median, k-means and many others [10]. The MRI is segmented across this proposed approach utilizing a deformable model and the Fuzzy C-Means (FCM) system. For properly segmenting brain tumours from MRI, the segmented image of two models is fused with the fusion rule on the basis of weighted variables represented as α and β. The proposed model primary contributions are as follows:

- Development of a fusion-based image segmentation technique for brain tumour cells using MRI.
- To filter the noise from the raw data, the Non-Local Means (NLM) filter is used as a pre-processing technique.
- The Region of Interest (ROI) and Fuzzy deformable fusion models based on fitness evaluation of and with Dolphin — Sine Cosine Algorithm (SCA) are employed to segment pre-processed picture.
- Deep Convolutional Neural Network (CNN) was employed to forecast the performance of the proposed segmentation technique.

Literature survey

Many studies used a variety of ways to segment a brain tumour using MRI images. Most of the existing techniques are studied, and among those techniques a few of them are reviewed below.

Sheela C.J.J. & Suganthi G. [11] had performed MRI-based segmentation of brain tumours automatically. The approximated ROI is established first in every developed model by removing the non-tumour portion of the picture by utilizing two-level morphological reconstruction methods like dilation and erosion. A mask is constructed by thresholding the reconstructed image but then degraded to improve segmentation accuracy in the Greedy Snake technique. By employing mask boundary as the snake initial contour, the greedy snake method computes new tumour borders. These limits are more accurate in areas with sharp edges and less accurate in areas with ramp edges. Lastly, a region with the biggest circumference is picked to eliminate areas that were incorrectly divided.

Hrosik R.C. et al. [12] had developed k-means clustering, and the firefly method was used to segment brain images. Metastatic adenocarcinoma, sarcoma, glioma, and metastatic bronchogenic carcinoma are four distinct primary brain tumours that can be detected using MRI, Single-Photon Emission Computed Tomography, Positron Emission Tomography pictures, and methods for brain image segmentation have been formed with the aim of showcasing them. The created picture segmentation technique depends on the firefly algorithm which results in enhanced by the k-means clustering method, and the fitness function is Otsu's criterion. This method enhances segmentation when traditional segmentation quality measurements like normalized root square mean error, peak signal to noise, and structural similarity index is utilized.

Huang H. et al. [13] had performed segmentation of brain images using the FCM clustering algorithm. The image is first segmented into several tiny portions depending on discernible attribute relationships, and then an attribute value table is built based on FCM segmentation findings for various clustering numbers. The weights of every characteristic are obtained by the decreased amount and user base for calculating difference across regions, following which similarity of every region is determined utilizing equivalence link supplied by difference degree. Finally, regions are merged, and picture segmentation is completed using the final equivalence relation provided by similarity. This technique is used to confirm the segmentation of artificially induced images, MRI images and brain Computerised Tomography scans.

Srinivas K. & Kantapalli B. [14] had designed segmentation of MRI using Unified Iterative Partitioned Fuzzy Clustering (U-IPFC). In medical sector applications, detecting tissues from the MRI brain is a difficult problem. To effectively identify the tissues from the MRI, the segmentation technique is used. This model is comprised of a pre-processing method for detecting several tissues in MR brain images and calculating tissue area. The efficiency of the designed U-IPFC technique has been demonstrated by the extensive simulated study. The major objective is to enhance the accuracy of existing FCM and k-means clustering methods for the identification of multi-tissues.

Ali M. et al. [15] had performed Deep Neural Networks for brain tumour picture segmentation. In this paper, 3D CNN and U-Net are used to create an aggregation of two segmentation networks, which results in more accurate and effective forecasts. These two classifiers are developed separately on BraTS-19 benchmark datasets and examined to produce segmentation maps which were considerably diverse in terms of segmented tumour sub-regions and overall variance in order to get the final forecast. For augmenting tumour, total tumour, and tumour core, the developed ensemble got maximum dice values.

Proposed methodology

Brain tumours can affect in a variety of sizes and forms as well as varied picture intensity. Currently, clinical approaches utilized in the medical field are not very accurate or robust in identifying tumours using MRI scans of the brain. As a result, the proposed method is meant for precise brain tumour segmentation and identification.

The proposed model process flow is depicted in Fig. 1. In this designed model, an MRI of the brain is collected and pre-processed with NLM reduce noise from captured raw data. This pre-processed image is first segmented with ROI for segmenting interested regions and then again segmented with a fusion deformable fuzzy model that consists of an FCM system and deformable system. Through measuring the fitness value of α and β constants, segmented images from classifiers are merged using the Dolphin-SCA method to combine the model results. The integrated output from the algorithm is classified with a deep CNN classifier.

Pre-processing. Collection of data is the process of gathering the necessary data, such as text or images, to be predicted. These collected data consist of raw data that cannot be segmented or classified with high accuracy. Hence, specific pre-processing procedures are employed to achieve high accuracy.

NLM. A weighted filter is a linear coefficient of the resemblance image patches in an image [16] and it is the foundation of NLM denoising method. The pixel indexes are i and j, and the following equation describes NLM:

$$y(i) = \sum w(i, j)v(j), j \in s_i, \tag{1}$$

where $v(j)$ represents the centered position at j; $w(i, j)$ is weight function among image patches around i and j

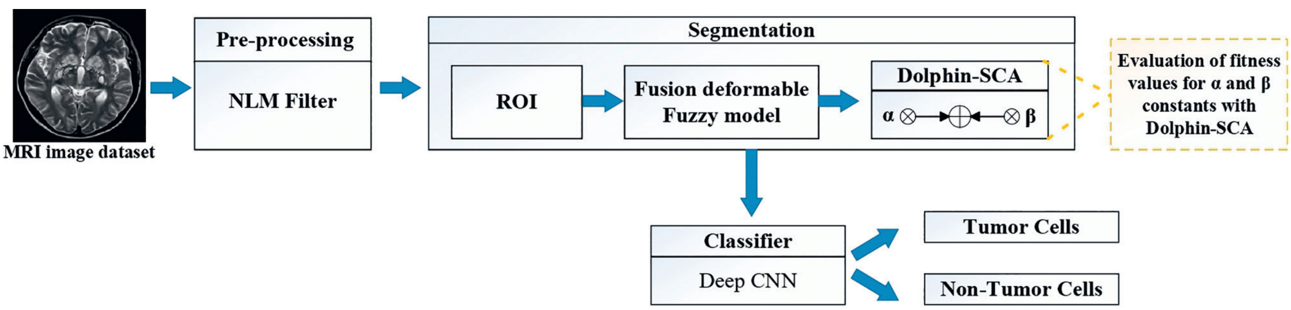

Fig. 1. The proposed model process flow

described by $y(i)$; and j is indeed searching window $s \times s$ of about i. NLM denoising is an excellent image denoising technique that reduces the computational complexity by using the accelerating mechanisms. The majority of representational approaches have implemented dimensionality reduction, although this procedure comes at a high expense of output operations.

Segmentation. Segmentation is mainly useful for eliminating the unwanted portions of the image to reduce the computational time and wrong predictions. In this designed model, the Grab cut algorithm is used for segmentation.

ROI align. ROI is used to identify the particular portion of a 2D/3D/4D image. The pixels are classified under two categories, X and Y (objects and backgrounds, or conversely) when the region is identified [17]. Pixels at levels $[1, \ldots, K]$ make up X, while pixels at levels $[K + 1, \ldots, L]$ make up Y. The variance between the two classes is expressed in equation

$$\sigma^2(k) = \frac{[\lambda_T w(k) - \lambda(k)]^2}{w(k)[1 - w(k)]}, \tag{2}$$

where $\sigma(k)$ is the variance of threshold level, $w(k)$ is the weight of the threshold level, $\lambda(k) = \sum_{i=1}^{k} ip_i$, and $\lambda_T(k) = \sum_{i=1}^{k} ip_I$. λ_T is the arithmetic mean for the entire image and $\lambda_T = w_X\lambda_X + w_Y \lambda_Y$. The maximum variance value will be considered as the ROI value. The feature aligned from the ROI is given to the fully connected layer and convolution layer.

Fusion deformable Fuzzy model. In this model, the segmentation of the MRI is done using the deformable and FCM model. The models result is combined with Dolphin-SCA algorithm-generated optimal constants. Give FCM and deformable method ROI-segmented images. The deformable model outputs and the FCM resulting images are merged with constants acquired from the Dolphin-SCA method leading to changes in the outputs of both pictures. The output of fuzzy deformable fusion technique for brain image O following segmentation is denoted by

$$O = \alpha D_m + \beta F_m,$$

where D_m is deformable model outputs after segmentation and F_m is the FCM model segmented outputs. Furthermore, their constants α and β indicate the Dolphin-SCA method optimal constants.

Deformable model. In image segmentation, active contours are the most extensively employed deformable model [18]. The snake is an active contour method which is constrained by extraneous factors and guided by image pressures that tug it toward specific characteristics like edges and lines. A snake system is described as a direct parametric curve with the following formula:

$$n(s) = [a(s), b(s)],\ s \in [0, 1], \tag{3}$$

where s is normalized arc lengths within range of $0 < s < 1$ and $n(s)$ is a set of nodes like a snake.

FCM model. For such a clustering procedure, FCM creates fuzzy matrices by calculating Euclidean distance [19]. Clustering yields a matrix depending on FCM which is expressed as

$$M = \sum_{c=1}^{i} \sum_{d=1}^{j} i_{cd} r_{cd};\ 1 \leq \infty, \tag{4}$$

where r_{cd} signifies Euclidean distance, i_{cd} means membership function matrix, c signifies pixel location, and d is the overall number of pixels representing fuzziness parameter.

Determination of segmentation constants using Dolphin-SCA algorithm. The optimal constants are obtained utilizing the output of deformable and FCM methods [20] and the Dolphin-SCA method. The characteristics of the Dolphin Echolocation (DE) method and Sine Cosine Algorithm (SCA) are combined in this algorithm. The SCA technique uses features of sine and cosine functions to discover ideal outputs, whereas the DE method is inspired by Dolphin behaviour.

Initialization. The Dolphin-SCA first sets up solution space in order to get the best values for constants. A response area is provided by Dolphin-SCA which is described as

$$Y = \{Y_1, Y_2, \ldots, Y_a, \ldots, Y_b\},$$

where Y_a denotes a^{th} option of dimensions 1×2, and b denotes overall possibilities.

1) *Evaluation of the fitness*.

To determine the best solution, we calculate the fitness of each unique solution. The fitness is calculated using the segmented image centre and pixel covering the segmented image centre pixel. The ideal option is one that provides the least amount of fitness value. The Dolphin-fitness SCA algorithm for calculating segmentation constants is as follows:

$$fitness = \sum_{L-1}^{j} \sum_{\substack{F=1 \\ F \in k}}^{T} (R^k - M_F).$$

Parameter T denotes the diameter of the brain picture, while R^k specifies the image segment centre. The F^{th} pixel in the k^{th} segment is represented by P^k and M_F. Assume the k^{th} segment of the image that has T pixels and is indicated by M_F for every pixel. The segmented image centre is calculated as

$$R^k = \frac{1}{T} \sum_{F=1}^{T} M_F \in P^k.$$

2) *Update solution using Dolphin-SCA*

SCA provides two services depending on sine and cosine update formulas accordingly. The equations are updated by the Dolphin-SCA algorithm utilizing response updates calculated by the DE algorithm. For sine and cosine functions, the updated answer are:

$$X(y + 1) = \frac{1 - z_1 - z_2}{1 - z_1 - z_2 - 1 + \beta_1 \sin(\beta_2)} \times$$

$$\times \left[\frac{\beta_1 \sin(\beta_2)}{1 - z_1 - z_2} [u(y) + z_1 K + z_2 M] - \frac{z_1 K}{1 - z_1 - z_2} - \right.$$

$$-\frac{z_2M}{1-z_1-z_2}+\beta_1\beta_3\sin(\beta_2)M\Bigg];\ \beta_4\le 0.5.$$

$$X(y+1)=\frac{1-z_1-z_2}{1-z_1-z_2-1+\beta_1\cos(\beta_2)}\times$$
$$\times\Bigg[\frac{\beta_1\cos(\beta_2)}{1-z_1-z_2}[u(y)+z_1K+z_2M]-\frac{z_1K}{1-z_1-z_2}-$$
$$-\frac{z_2M}{1-z_1-z_2}+\beta_1\beta_3\cos(\beta_2)M\Bigg];\ \beta_4>0.5.$$

The update solution for the Dolphin-SCA algorithm is provided by two reactions within the preceding equation.

3) *Finding the best solution using fitness*.

To determine whether a new approach is feasible, the fitness function is applied to update the solution. The best solution for delivering less fitness value is to provide fewer fitness values.

4) *Termination*.

The modified answer is replicated till Y_{max}, the highest number of iterations, is reached. After multiple repetitions, the best segmentation number is discovered.

Classification. Classification is a method for predicting the outcome of supplied data sets. Classes are described using terminology like targets, labels, and categories. To categorize tumour and non-tumour cells, a deep CNN approach is designed.

Deep CNN. Finally, the Deep CNN classifier was used as a training example and the feature vectors are built using obtained characteristics. Deep CNN is utilized to distinguish between tumour and non-tumour regions. It is made up of three layers, such as convolutional layer, pooling layer, and fully connected layer. The greatest significant layer is a convolutional layer which became liable for intensive processing and hoisting control. In addition, this layer is in charge of collecting numerous features from input photos. The pooling layer, which is sandwiched among convolutional layers, is the following layer. The feature maps are subsampled by pooling layers and lower the spatial scale of depiction to decrease variables and network calculation. The fully connected layer manages the established links by previous layers and serves as a classifier for categorizing inputs. Consider the following source to Deep CNN:

$$(B_\delta^l)_{u,y}=(E_\delta^l)_u+\sum_{\beta_1=1}^{v_1^{\beta_1-1}}\sum_{\beta_1=-v_1}^{v_1^l}\sum_{\beta_1=-v_2}^{v_1^l}(K_{\delta,\beta_1}^l)_{\beta_3,\beta_2}*(B_{\beta_1}^{l-1})_{u+\beta_2,y+\beta_3},$$

where $(B_\delta^l)_u$ symbolizes created output from l^{th} conventional layer centred as (u, y), K_{δ,β_1}^l signifies convolutional operators for producing local designs from conventional layers, symbol * indicates convolutional operators for producing local features from conventional layers, β_1, β_2 and β_3 describe feature maps produced from every conventional filter via reading its input image, and E_δ^l represents a bias of l^{th} conventional layer. An activation function is employed to streamline calculations or to eliminate undesirable results. The activation function of $(l-1)^{th}$ layer generates outputs from ρ^{th} conventional layer which is written as

$$B_\delta^l = AFN(B_\delta^{l-1}).$$

The pool layers were modified to perform a defined function, and their characteristics were passed onto fully linked layers. The image is converted to a vector which is then classified. Fully connected layers yield the following output:

$$G_\delta^l=\eta(B_\delta^l)With(B_\delta^l)=$$
$$=\sum_{\beta_1=1}^{v_1^{\beta_1-1}}\sum_{\beta_1=-v_1}^{v_1^l}\sum_{\beta_1=-v_2}^{v_1^l}(K_{\delta,\beta_1}^l)_{\beta_3,\beta_2}*(B_{\beta_1}^{l-1})_{u+\beta_2,y+\beta_3},\qquad(5)$$

where h denotes the normalization factor.

Thus, the fused images from the fusion fuzzy deformable model are classified using the deep CNN model.

```
Algorithm 1: pseudocode for
classification and segmentation of
brain tumours
Input: Dataset of MRI (D=x1,x2,x3…xn)
#Pre-processing
NLM = Non-linear filter(D) // by using
equation (1)
ROI=Region of interest(NLM) // by
using equation (2)
#Segmentation
DM=Deformable model(ROI) // by using
equation (3)
FM=FCM(ROI) // by using equation (4)
#Fusion with Dolphin-SCA algorithm
If (α+β=1)
O=DM+FM
Else
Search for other optimal values for
fusing
End if
#classification
DCNN=Deep CNN(O) // by using equation
(5)
If (class = 0)
Output=tumour cell
Else
Output=non-tumour cell
End if
Output: classified output of brain
tumour cell
```

Result and discussion

The proposed approach for brain tumour segmentation is implemented using an MRI brain imaging dataset and MATLAB software to test its functionality and performance. The 8.0 GB Memory (RAM), CPU @ 2.80 GHz, Intel(R) Core(TM) i5-3450S processor, and system type of 64-bit operating system are used in testing. The tumour is divided and categorized using MRI brain pictures in this proposed system. To remove noise in collected original data, an MRI of the brain is gathered and pre-processed utilizing NLM. This pre-processed

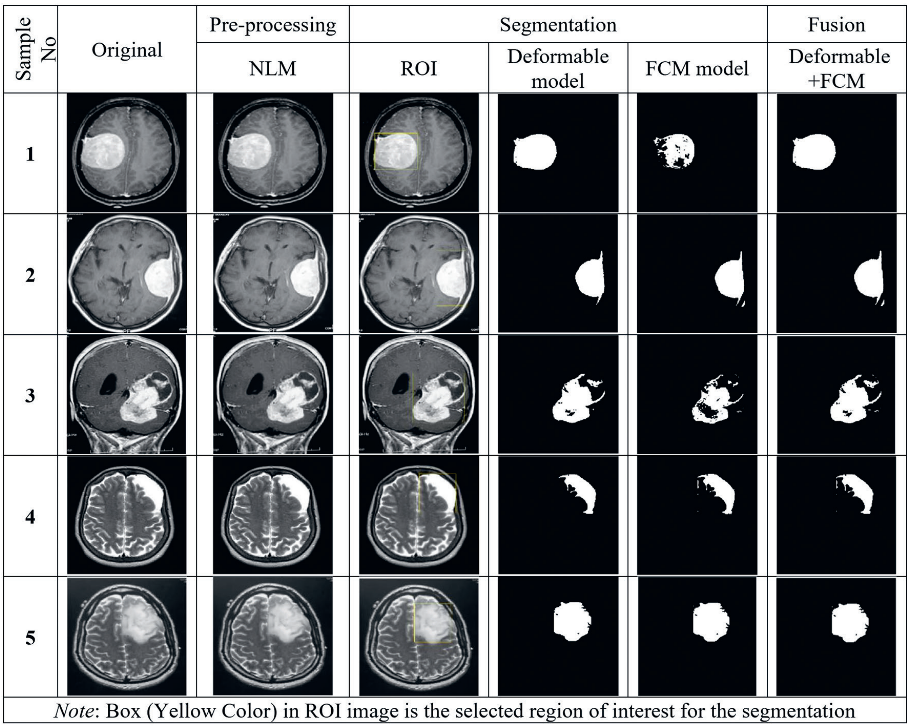

Fig. 2. Conversion of sample images using pre-processing and Segmenting techniques

image is first segmented with ROI to isolate areas of interest and then with a fusion deformable fuzzy system, which combines FCM and deformable methods. Through analyzing the fitness value of α and β constants, segmented images from models are merged using the dolphin SCA method to incorporate the output of the model. The integrated output from the algorithm is classified with a deep CNN classifier.

Dataset. In this dataset [21], the Glioma type of brain tumour is collected, which can affect your brain function and life-threatening depending on its location and rate of growth. Gliomas are one of the most common types of primary brain tumours. In this dataset, 224 pictures are collected for the categorization of tumour and non-tumour cells. In this case, 80 % of the data is utilized for learning, and 20 % is employed for evaluation.

Fig. 2 illustrates the conversion of sample images using pre-processing, segmentation and fusion techniques. Based on this converted images, the DCNN classifier is trained and tested for evaluating the performance of the model. Dolphin-SCA + FNB, PFCM + KNN, Deformable model + FNB, FCM + SVM are previous methodologies that are compared with the proposed technique using performance metrics like F1-score, Specificity, kappa, Sensitivity, Matthews Correlation Coefficient (MCC), Accuracy, False Positive Rate (FPR), False Negative Rate (FNR), Precision and Error.

The proposed method confusion matrix (error matrix) is depicted in Fig. 3. This error matrix is used to evaluate the actual and predicted data from the given dataset. The prediction of data for ‘no’ and ‘yes’ classes are 64 and 93. The total data used for testing is 179. 157 of them are predicted according to the actual class, and the rest of the 22 are predicted wrongly.

Fig. 4 explains the comparison performance metrics for proposed and existing methods. Performance of the proposed model, such as Accuracy, Sensitivity, Specificity, Precision, Error, Kappa, FPR, FNR, F1-score and MCC, are 0.90, 0.89, 0.88, 0.89, 0.10, 0.72, 0.10, 0.12, 0.85 and 0.73. These evaluated proposed model values are greater than the existing techniques. Thus, the designed Dolphin-SCA+DCNN model accurately segments and predicts the brain tumour.

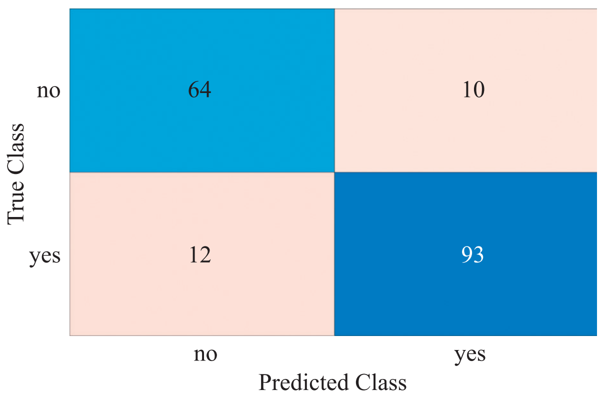

Fig. 3. Error matrix for the proposed model

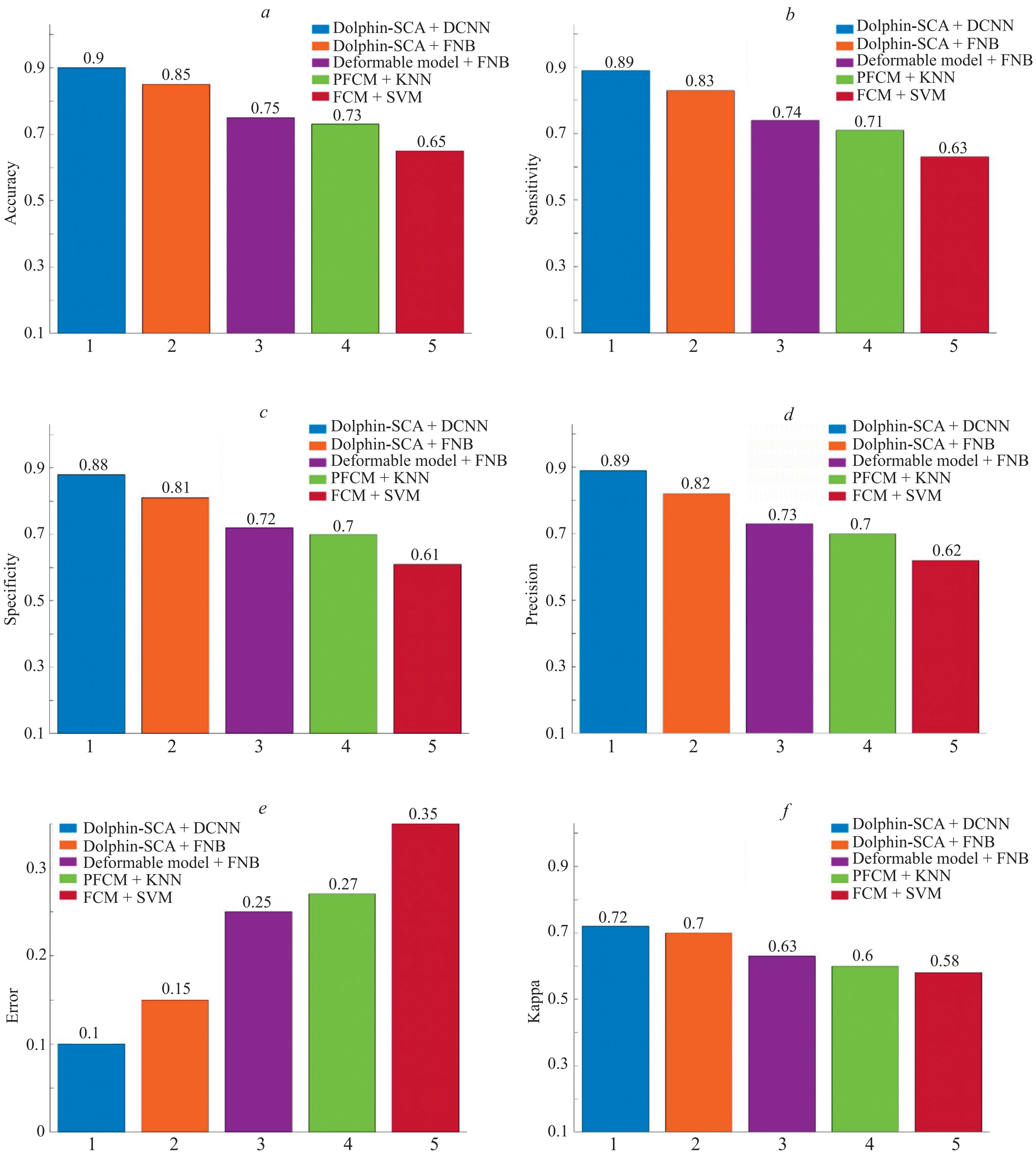

Fig. 4. Performance metrics: Accuracy (*a*); Sensitivity (*b*); Specificity (*c*); Precision (*d*); Error (*e*); Kappa (*f*); FPR (*g*); FNR (*h*); F1-score (*i*); MCC (*j*)

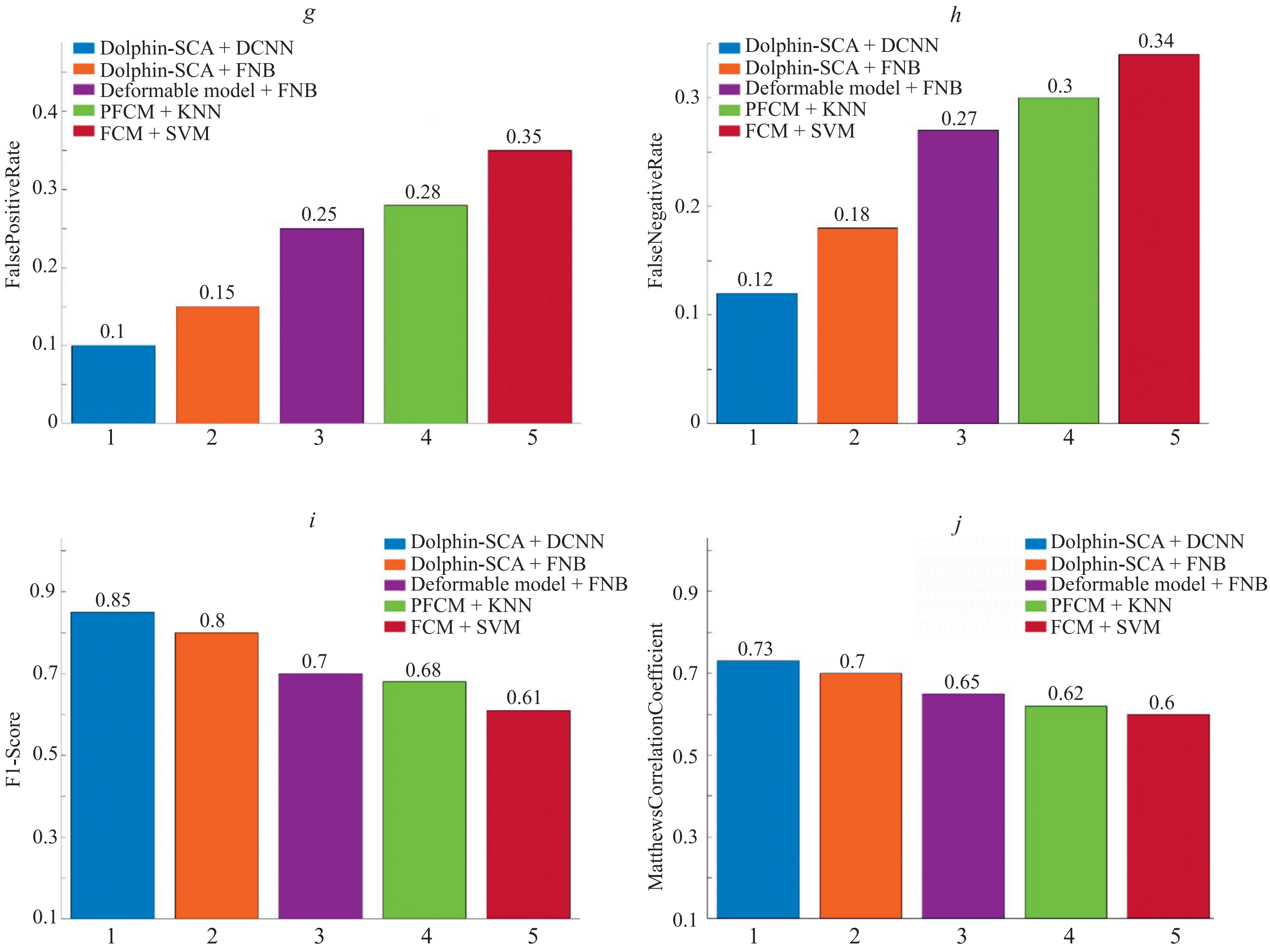

Fig. 4. Continued

Conclusion

In able to locate and predict brain tumours at an early point, segmentation is critical. In clinical practice, segmenting MRI images takes time since it requires physical evaluation. Additionally, boundary inadequacies like missing borders and loss of textural difference among ROI and backdrop make segmentation of regions difficult. As a result, for speedy and reliable diagnosis of cancers, appropriate segmentation approaches are necessary. In this designed model, the fusion deformable fuzzy model is introduced for segmenting tumour cells from the MRI of the brain. The ROI is employed to partition the region of the tumour with the bounding box, and the NLM filter is used to remove noise from brain MRI. Finally, output from the fusion deformable fuzzy model is classified using deep CNN. The experimental results of the proposed model are evaluated and compared with existing techniques. Performance metrics of the proposed model, such as Accuracy, Precision, Specificity, Error, Sensitivity etc., are 0.90, 0.89, 0.88, 0.10 and 0.89. Thus, the performance metrics of the proposed model are better compared to existing techniques. In the coming decade, the proposed algorithm could be used to forecast tumour cells from a big collection of brain MRI images.

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