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RESEARCH ARTICLE

Cancer Detection Framework using Cellular Automata based Segmentation and Deep Learning

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ABSTRACT

Image processing plays vital role in medical sciences. Medical image processing reduces diagnosis time and cost. Early detection of cancer may reduce life risk. Earlier works on cancer detection mostly focused on specific organs and imaging modalities. This work aims a generalized framework for detecting tumors in various organs by analyzing different imaging modalities. Here, Cellular Automata helps in image segmentation through region growing, and deep learning algorithms made performance analysis in terms of accuracy and loss. Analyzing CT-Scan, MRI images of brain, breast, lungs, the proposed framework may assist to detect the region of mass being developed. Proposed CA-based segmentation technique segregates the region of interest or tumor area from its background. Segmentation through region growing is performed using Moore neighborhood concept. First, noise has been reduced using filters. Then enhanced image is converted into image matrix, and CA rule is applied to it for segmentation. Generally, area of the tumor appears with high-intensity values. Here, segmentation is done by identifying the high-intensity pixel values of the image and then gradually performing region growth to include entire tumor area. Deep learning algorithms are applied to transformed image set of cancer. Finally, performance analysis is made. The parameters of performance analysis are compared between transformed and original image sets, and the results obtained with the transformed image set produced higher accuracy than the results produced from original image set of tumors. The proposed framework may help medical practitioners in detecting tumors in different organs efficiently.

Keywords: Cellular automata, CNN, Imaging modality, Image segmentation, Region growing, ResNet, VGG

Introduction

Cancer is a challenging disease and it may cause death if it is not being diagnosed properly at an earlier stage. It is necessary to detect it in proper time. Diagnosing cancer using different imaging modalities is time consuming and need expertise from radiologists to diagnose it properly. Digital image processing[1] plays an important role here. Digitizing the different imaging modalities and analyzing them, can make the task easy and less time consuming. Moreover, the existing methods of cancer detection, aim to detect cancer in a particular organ by analyzing a specific imaging modality. Hence, a generalized framework is preferable that can efficiently detect cancer. Cancer can be initiated as a form of tumor in various organs like brain, breast, lung, etc. and if it can't be detected in primary stage then the tumor may become cancerous. It can be said that by detecting tumor in the organ the chances of developing cancer may be reduced. So, tumor detection can be considered as a primary step in cancer detection. A solid mass of tissue forms a tumor by grouping the abnormal cells. Various organs, glands, skins, tissues, etc. can be affected by tumors. Some of the tumors are benign and they are not cancerous, but treatment is still needed with proper diagnosis. Malignant tumors are cancerous and can be life-threatening hence proper

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treatment in proper time is highly required. Analysis of different imaging modalities like CT-scan, X-ray or MRI images may help to identify the abnormal cell growth in different organs.

In human beings, the impact of different cancers varies depending on the severity of the cancer. Various cancers[2] in different organs may pose a life risk. Brain tumor[3] is one of the critical cancers which may lead to death. Brain tumor is identified as the growth of abnormal cells in the brain tissues. It can be benign or malignant. If the abnormal growths of the cells are massive in brain, then it may lead to cancer; hence it is required to be detected at an earlier stage to avoid the severity. A brain tumor can be detected by identifying the area of development of the abnormal growth of mass in brain. Analyzing the CT image of brain, the affected area can be easily marked. Like brain tumor, breast tumor[4] is also a serious disease mostly found in women and rarely in men. Due to abnormal growth of some breast tissues or cells, breast cancer occurs. Most observable symptom in breast cancer is usually a lump, in other words area of viscous breast tissue. Malignant tumors may become cancerous. Analyzing the mammography images of breast, breast cancer can also be detected as well by identifying the lump present in the breast. Lung cancer is one of the most common and second most diagnosed cancer which causes life risk. Lung cancer[5] occurs due to uncontrollable cell division in the lungs causing tumors to grow. In some cases, lung cancer does not show any indication until it reaches to the advanced stage; hence it is necessary to diagnose lung cancer in early stages. To reduce the life risk caused by any kind of cancer, it is highly required to correctly diagnose the cancer at the proper time. Medical image processing can help to diagnose cancer in different organs. Inspecting different imaging modalities like CT-Scan, MRI, mammography, X-ray, etc. the diagnosis of tumor or cancer in different organs can be easy and almost accurate.

In various medical imaging applications, image segmentation[6] plays a major role. Using different image segmentation techniques tumor detection in any organ can get easy. Image segmentation divides a digital image into subgroups known as image segments. A digital image can be divided into segments and further processes can be performed only on the required segments of the image instead of processing the entire image. Image segmentation can be performed using several approaches like edge detection, region growing, region splitting, etc. The application of image segmentation is hugely found in medical image processing. Different cancers can be recognized by detecting the tumors in different organs. Image segmentation helps to distinguish the area of abnormal growth of cells from its background. When segmenting an image, region growing[7] techniques extract groups of pixels and include them in a growing region if a homogeneity criterion on pixel intensity is met. Digital mammography, CT- scan images, MRI images and other imaging modalities provide non-invasive mapping the anatomy of a subject very efficiently. Performing a suitable transformation operation in different imaging modalities tumor can be detected as well. Sometimes the conventional image segmentation techniques produce over segmentation as well noises are also there. Moreover, some of the unwanted parts or features appear in the transformed image which is not desired at all. Still image segmentation can be done for obtaining a better understanding of the area of interest of any kind of image object.

Cellular Automata (CA)[8] is an efficient mathematical tool considering its clarity and computation time. CA can be applied for effective image segmentation for medical imaging. CA comprises of grid of cells. Every cell contains a finite number of states. The state of the cell gets updated with a regular interval of time and the value of the state is decided by depending on the previous states of the adjacent neighborhood cells. A specific transition rule is to be applied to perform this. Digital image is being expressed by two-dimensional arrays of pixels; hence for processing an image two- dimensional CA model is used. The adjacent cells to the central cell or the core cell are considered as neighborhoods of a cell. In CA, various concepts of neighborhood structures are used. Neighborhood concept of CA can make the image segmentation more effective as it operates on individual pixels. The 9-neighborhood concept has been used here to isolate the area of growth of abnormal cells from its background image or the surrounded normal cells.

In this proposed work, cancer detection in various organs like brain, breast, and lungs have been done using cellular automata based segmentation techniques. Here, Different imaging modalities of the mentioned organs have been analyzed. Using CA based image segmentation technique, the presence of tumor in organs have been identified as a part of cancer detection. By analyzing the imaging modalities, the proposed system will produce the transformed images. Here, the image segmentation has been planned focusing on the area of high intensity pixel value of an image as most commonly it has been observed that the tumor area of any organs appeared with high intensity pixel values for any imaging modalities. The transformed images indicate the segmented area of abnormal growth of cells in different organs. Then the new image set will be created with these transformed images. Finally, using image classification methods it'll detect tumor in different organs automatically with good accuracy.

Though biopsy is required for determining malignancy still tumor detection may be helpful as primary and fast diagnosis of cancer. Here, this entire process to be enforced on existing image set of breast tumors, brain tumors and lung cancer and the image classifications to be performed on the obtained transformed image set for getting better accuracy in results. For image classifications CNN, ResNet, VGG have been considered here to make the system intelligent.

The cancer detection mechanisms proposed earlier are mostly developed for a particular type of cancer detection. The earlier works are either based on only image segmentation methods or purely on basis of image classification or following cellular automata based image segmentation. The same method has not been applied for detecting cancer in different organs considering different imaging modality.

The proposed work contributes the following:

- This work aims to detect cancer in various organs by identifying the region of tumor in various organs with the help of image segmentation through neighborhood concept of cellular automata. Region growth helps to cover the entire tumor area and deep learning algorithms support the detection effectively.
- Generally, tumor areas found in any imaging modalities appear with high intensity gray values. The work is initiated with tumor area segmentation using region growth followed by automatic detection of cancer in various organs. For advancement, training a large image set of different cancers, it is possible to detect the disease with effective accuracy.
- The proposed work finally produces a result with high accuracy for brain tumor and breast cancer detection for the obtained transformed image set whereas for lung cancer detection it produces comparatively less accuracy. The accuracy of the cancer detection has been compared with the transformed image set obtained by applying the proposed segmentation technique and without applying the proposed segmentation technique.
- Detection of cancer in an early stage is much needed to save a life. The proposed work may help medical practitioners to detect cancer in various organs. By analyzing the different imaging modalities, the proposed system may detect cancer in different organs with fruitful accuracy.

In Section 1, the establishment and the purpose of cancer detections in various organs using medical image processing have been mentioned. In Section 2, the required background study for the proposed methodology has been discussed. For this work, the knowledge of cellular automata, image segmentation and the concept of image classification have been illustrated. These two sections serve as the first contributions. In Section 3 mapped with the second contribution, illustrated as it has two stages; image segmentation followed by image classification. Results and discussion have been discussed in Section 4 along with a comparative study as is discussed in the third contribution. At last, the conclusion has been mentioning the future scope of the work. The last contribution shows the applications of the proposed cancer detection system.

Literature review

In this section 2, the basic concept of cellular automata, cellular automata-based image segmentation with different deep learning mechanisms has been illustrated. Here, in the proposed work, for segmenting the abnormal mass growth area in different organs cellular automata have been used and with the working principle of CNN, ResNet, VGG the automated detection of tumor in various organs has been implemented.

A. Cellular automata

Cellular Automata [9] was introduced by S. Ulam and J. von Neumann in 1950. A cellular automaton is a collection of grids of cells which has some finite states. It is dynamic as it depends on value of states of neighboring cells to change its further state value. CA consists of a set of finite states where an individual state is being held by each cell. The cells modify their states on basis of a local rule that produces an updated state value depending on the previous state values of the cell and its neighbors. Every cell is known as grid. The local update rules are to be enforced in the entire immediate neighboring cell. A CA can be represented with four-tuples: $A = \{L, M, Q, \delta, q_0\}$. where the regular lattice of cells is represented by L, Q is the finite set of states, the initial state is q_0 and $q_0 \in Q$, M is a finite set (of size m = |M|) of neighborhood indices such that for all $r \in L$, for all a ∈ M: r + a $\in L$ and the transition function is δ: Qm $\rightarrow Q$.

CA with different dimensions like one, two or three can be applied to get solutions to various problems. 1D CA are denoted by a horizontal array of infinite cells. The possible states of a 1-D CA are 0 or 1. 2-D CA consists of hexagonal or rectangular grid of cells. 2D CA is good fitting to illustrate a digital image. An image pixel can be denoted by an individual cell of a 2D CA and the pixel intensity can be expressed

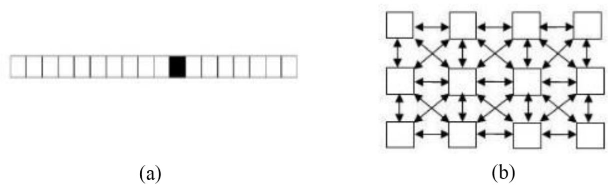

Fig. 1. (a) Structure of 1D CA (b) Structure of 2D CA.

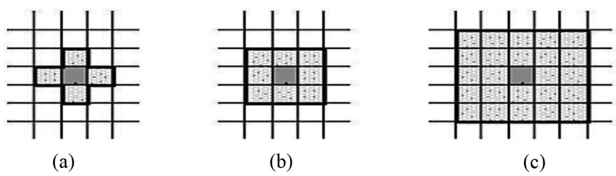

Fig. 2. (a) Von Neumann (b) Moore neighbor (c) Extended Moore neighbor.

as the state of that cell. An image can be converted to the output image as per requirement by applying suitable neighborhood operations[10] of CA. Von Neumann neighborhood or 5-neighborhood CA comprises a core cell and two vertically adjacent and two horizontally adjacent neighbor cells. Moore neighborhood CA consists of core cell and adjacent eight neighbors and is called as 9-neighborhood CA. In image processing, CA has a major application because of its 2D matrix form and flexible transition rules. For processing an image, the required transformation function is the interpretation of the transition rules.

The structure of a linear 1D CA and 2D CA has been shown in Fig. 1. It also expresses the 2D CA neighborhood concept. Fig. 2 illustrates different neighborhood models which are Von Neumann, Moore neighborhood models and extended Moore neighborhood models.

The digital image is represented as two-dimensional matrix and 2D CA can be used to operate with an image where the pixel values are considered as the state of the CA.

Wongthanavasu S, Tangvoraphonkchai V.[11] described applications of CA based algorithms in the field of medical image processing. CA algorithm and variation of it have been applied to the binary and gray scale image of mammograms. Gray level edge detection, binary edge detection, noise filtering and spot detection have been performed here using the CA algorithm.

Rosin PL, Sun X[12] illustrated that CA can be used as an efficient tool for image processing. Here several no. of existing neighborhood patterns has been considered and they have been used for specific transformation. For the patterns, several schemes and possible rules have been described for automatic learning purposes.

B. Image segmentation

Nowadays, in different medical application domains different image processing approaches are popular for detecting various diseases by analyzing different imaging modalities. For easy detection of cancer in various organs medical image processing supports a lot. Sometimes it is very much needed to diagnose the disease earliest. Image segmentation[13] is much useful technique for identifying various tumors in various organs. Image segmentation is a necessary operation for the imaging analysis of subsequent jobs. Segmentation techniques usually split the entire image into different segments on the basis of different regions of the objects. The purpose of performing image segmentation is the simplified presentation of different imaging modalities into more relevant output images which can be easily analyzed. Through image segmentation, objects can be detected and also the edges or boundaries of images can be segregated. Determination of the threshold value is crucial in image segmentation. On the basis of this threshold value image segmentation can be done more accurately depending on the quality of the input images. A basic technique for segmenting images based on regions is known as region growing.[14] The method is categorized as pixel-based picture segmentation as well since initial seed points must be chosen. By using predetermined criteria, region growing is a complex computational process that groups pixels or subregions into bigger, coherent regions. The iterative procedure begins with carefully placed seed points throughout the image. These seeds are the origin of region expansion, wherein nearby pixels meeting certain similarity criteria such as color ranges or intensity, gradually become integrated into the expanding region, drawing cogent borders. CA rules produce better results in terms of clarity, continuity and computation time. CA rules help to figure out the edges of the object of interest that is present in the medical images. The region of interest of an imaging modality can be segmented more accurately by applying CA based segmentation techniques. Applying different transition rules of CA, salient features can be segmented by analyzing various imaging modalities that can help to detect the development of abnormal cells in different organs.

Sarma R, Gupta YK.[15] made a comparative analysis among several existing techniques of image segmentation and its modification for approaching new improved segmentation techniques which may overcome the demerits of existing techniques. Pham et al.[16] illustrated the role of image segmentation in medical image processing and its applications. Here the present status of automated and semi-automated mechanisms for image segmentation has been used and reviewed for further improvement.

A cellular automaton is a popular mathematical tool which can be used for image segmentation. Image segmentation [17] is very helpful for analyzing medical images to diagnose disease; hence it is required to make the segmentation appropriate and cellular automata are very useful for this purpose. The results produced by CA based image segmentation are clear and continuous. Different approaches of CA transition rules can be applied for differentiating the area of interest from its background image. The neighborhood concept of CA can be used for image segmentation purposes. Depending on the requirement Von Neuman neighborhood concept or Moore neighborhood concept as well as different CA transition rules can be used to perform the image segmentation.

Qadir and Khan [18] approached one segmentation technique based on CA. In the proposed methodology, for enhancing the quality of the input image a filter has been applied and it was smoothened. For better visibility the thick bands had been converted to less thickness by applying the sweeping operation to the filtered image. Hence on the basis of a suitable threshold value the ROI has been differentiated from its background.

Hamamci et al. [19] proposed a methodology of tumor segmentation by examining the cellular automata (CA) algorithm which shows the result of the state evolutes to converge to that of the shortest path algorithm. Here using CA, the seed selection has been done and spatial smoothness has been imposed. Here the challenge is proper seed selection though it performs with a better overlap ratio with fixed heuristic values.

Ascencio-Pina et al. [20] proposed a method of image segmentation following the concept of CA based image segmentation. The proposed method consists of three phases. During the first two stages of the procedure, the main goal was to remove noise. To accomplish this, a set of rules is created that alter each cell's or pixel's state value by the states of the elements that surround it. Every element is given a state in the third step, which is selected from a list of predetermined states. The final segmentation values for the respective elements are directly represented by these states. A variety of photos were used to assess the suggested strategy while taking significant quality indicators into account.

C. Image classification

Image classification [21] is the approach of segmenting images into different groups on the basis of some features. A feature may be defined here as the edges of an image or the intensity of the pixel as well as the change in the pixel values, and many more. It helps to extract the desired features from the input images. The purpose of the image classification mechanism is for categorizing every pixel of one image into equivalent classes of the same pixel values. Image classification [22] is performed via certain steps like image pre-processing, detection of objects followed by image segmentation and training and finally the classification of desired objects is being made. A Convolutional Neural Network (CNN) [23] is a set of deep neural networks. It is mostly applicable for analyzing visual imagery features. A CNN [24] may take images as input. During the process, biases are assigned and the learnable weights are used with various aspects which exist in the input images to get segregated from each other. It is also expressed as an artificial neural network which is mostly used for analyzing different images. Performing image classification and recognition using CNN, a good accuracy can be obtained. VGGNet, ResNet are the most commonly used architectures of convolutional neural networks. Visual Geometry Group (VGG) [22] follows deep Convolutional Neural Network architecture consisting of collective layers. It includes multiple blocks and every block consists of 2D convolution and max pooling layers. VGG has the most important features of CNN. Residual Networks abbreviated as ResNet, [25] is a component of neural networks that is used as the pillar for several computer vision related processes. The concept of skip connection was first introduced in ResNet. For adding the output from an earlier layer to a later layer, the concept of skip connection is used. As ResNet goes deeper, every layer of a ResNet is divided into several blocks, generally within a block the number of operations is increased, but the total number of layers doesn't change, it remains the same.

Yurttakal et al. [26] proposed one CNN architecture that consists of six groups of convolutions, five max-pooling layers and ReLU, batch normalization, one dropout and one fully connected layer with a softmax layer. Adaptive Moment Estimation optimizer is used in the network during the training process. Three convolutional layer filters with various kernels of various sizes have been applied to the model input image. In the proposed model all convolutional layers are interconnected with batch normalization layers and intervening max-pooling layers.

Hussain et al. [27] used various segmentation techniques for segmenting brain tumors by analyzing MRI images. Edge detection methods have been applied here followed by K-Means clustering methods with different numbers of clusters.

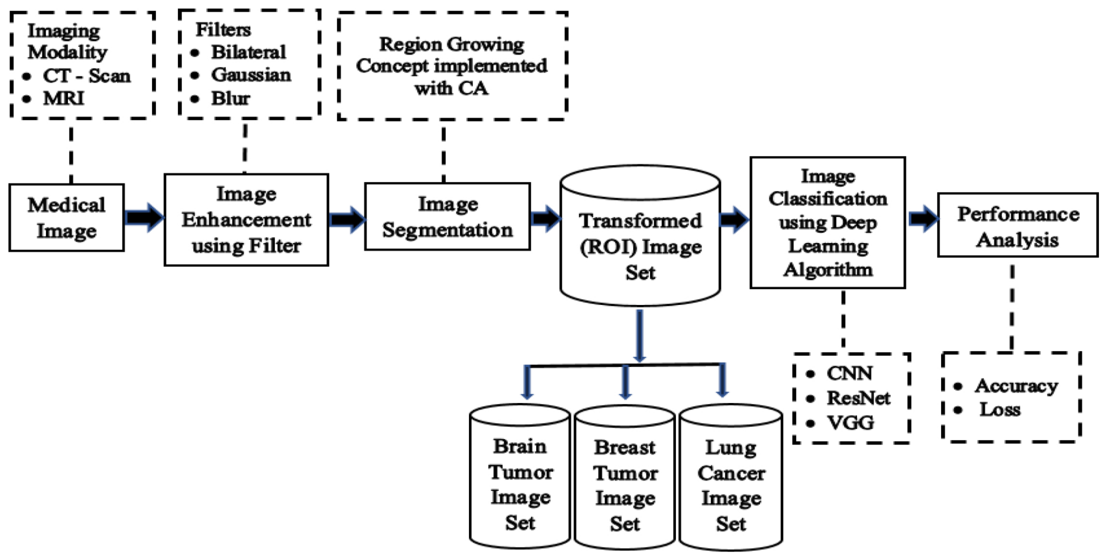

Fig. 3. Work flow of the proposed framework.

Huang et al.[28] considered mammography images of breasts with masses. In this method, the number of breast mammography images was increased to a higher number using data augmentation. On breast mammography images, data augmentation has been applied, and here the CNN models have been used including DenseNet, AlexNet and ShuffleNet for classifying the considered breast mammography images.

Present days, different tumors are very common and widespread among human beings. Some of the tumors become malignant which leads to cancer. Cancer is one of the major diseases among human beings. To avoid severity, it is required to detect tumor in the early stages. MRI and CT-Scan can help to diagnose tumor in different organs. Detection of tumor or cancer in different organs from different imaging modalities through human interception may get delayed. It is required to implement a generalized framework to detect tumor in different organs. It may help to produce results with fast and accurate diagnoses that will help people with treatment and recover from these life-threatening diseases.

Proposed methodology

In this section, the proposed approach for detecting various tumor in various organs has been discussed in details. Analyzing different imaging modalities, the proposed methodology is capable enough to detect tumors in various organs with a higher accuracy and less error compared to the well-known conventional image classification algorithms. Here, with the help of different image classifiers a performance comparison also has been made considering the original images and the output images obtained after transforming the input images applying this proposed methodology. This proposed methodology has two stages, the first is to locate the area of interest from the input images using cellular automata-based segmentation. Next, the image set has been prepared with the obtained transformed or output images after applying the proposed CA based image segmentation technique. Different image classification algorithms have also been applied to detect cancer in different organs with high accuracy. As input CT - Scan, MRI images of brain tumor, lung cancer, breast tumor, etc. have been taken here for analyzing and hence tumors in the mentioned organs have been detected automatically.

Fig. 3 represents the flow of works for the proposed framework. Here the different imaging modalities of brain, breast and lungs, have been considered as input medical images. To remove the noise from the input, image enhancement has been performed by applying suitable filter to the original image. After enhancing the quality of the input image, image segmentation has been performed with the proposed cellular automata based image segmentation technique which is based on the concept of region growing. As result, the tumor area of different organs has been segmented from its background. Image set has been prepared with these transformed images. Different image classification algorithms like CNN, ResNet, VGG have been applied to detect and determine the presence of tumor or cancer in different organs.

A. Image segmentation mechanism

In this section, the region of interest (ROI) has been obtained using proposed cellular automata-based

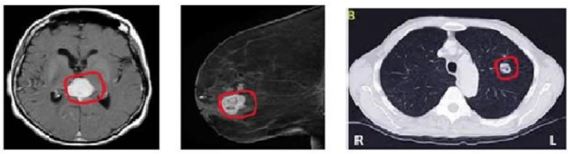

Fig. 4. Brain tumor Breast tumor Lung cancer.

image segmentation technique. The main idea behind the CA based segmentation technique is to group the neighborhood pixels with nearby values and replace the similar kinds of pixels with a certain value. In different imaging modalities, it has been observed that the growth of the abnormal cells has higher grey values than its background pixels and the surrounding pixel value of the affected area (cancerous cell) slightly varies with the cancerous cell pixel values. Here, on basis of this understanding one CA based segmentation technique has been implemented and in this proposed methodology one marginal value has been taken respective to the affected cells and it is helpful to discriminate the region of interest from its background. Here in Fig. 4, the encircled portion refers the tumor area in brain, breast and lung respectively.

Here the image segmentation has been done by grouping similar kinds of pixels. For identifying the abnormal cell growth or the developed mass in different organs like lungs, breast and brain, this proposed method has been enforced to the various imaging modalities. In the proposed methodology, other imaging modalities of different organs have been considered as input images. Analyzing X-ray, CT Scan images of different organs it can detect the abnormal growth of mass. Here, the discrimination between the region of interest and its background has been done using neighborhood concept of Cellular Automata.

First, the noise from different input images has been removed. Noise removal is done for decreasing the noises present in an image. Input image quality can be enhanced by removing noise from the images. Depending on the imaging modality, the noise removal filter to be chosen such as Gaussian filter, blur filter, bilateral filter, etc. Here, all these filters have been used to check the enhanced images and it has been observed that the bilateral filter produces better results for most of the input images and for a few cases Gaussian filter helps to reduce the noise more effectively. Hence, the bilateral filter has been used here for all of the images for image enhancement.

Then the enhanced image has been converted to an image array for performing further operations. The maximum pixel values of each row of the image matrix have been identified and have been stored in ‘max’. As the basic concept is here to make the cluster of nearby pixel values of the cancerous cell i.e., the pixels with higher grey values; hence to make the cluster, the maximum pixel value of each row or the seed point has been noted and by applying the region growing method the nearby values of ‘max’ have been considered for the cluster. For considering the margin of nearby values of ‘max’, the average value of the Extended Moore neighborhood pixels has been considered and kept in ‘avg’. The value of this ‘avg’ can be considered to get the nearby pixel values to the ‘max’. This way the group of the similar kind of pixels to the ‘max’ value can be formed. Basically, it’ll make the cluster of higher pixel values. Depending upon the images the higher pixel values of each row will be found out.

Next, each pixel of the image will be taken as a core cell or reference cell. One threshold value has been added to the core cell or reference cell and has been compared with the affected pixel values within a range to group the similar kinds of pixels. With different threshold values like 10, 15, 20, 25 it has been checked and it has been observed that depending on variety of medical images clarity of the transformed images varies. If the core cell value added to the threshold value is within the range of ‘max’ value, it’ll replace the value of reference cell with 255 and if returns false then 0 will replace the value of the reference cell. By this neighborhood operation the considerable pixels will turn black and rest as white. Region growing has been performed in this way and the segmentation is done and the output image or the transformed image is obtained which behaves like a binary image in which the tumor area is segmented. In the proposed approach, various image sets have been considered as input images and using this illustrated CA based segmentation technique a new image set has been prepared with the transformed images. For the transformed image set it has been observed that the region of interest of all images is easily understandable. Fig. 5 describes the steps followed in this proposed approach for recognizing the area of cells growth abnormally in various organs.

Cellular Automata can also be represented by the quadruple: d, q, N, F. Here d represents the dimensions of CA, q is the number of cell states which are being used, N denotes the neighborhood that has been applied and F defines the used transition rules. For this work d represents 2-dimensional CA and ‘q’ represents 2 no. of state values as state value either can be 0 and 255. In this work, the working principle of Moore neighborhood concept has been applied so the variable ‘N’ represents here 9-neighborhood model. Here, the transition rule ‘F’ can be defined as the state value of the core cell or central cell will be replaced by 255 if the value of the central cell along with a threshold value is within the range of the maximum value of each row adjusted with an allowable value 50, otherwise the value of the reference cell will be 0.

Fig. 5 shows the flowchart of the proposed image segmentation mechanism. The above system flow diagram has been described below with more formal approach. Here the different imaging modalities have been considered as input images. The input images are grey images. The maximum pixel value of each row has been represented as 'max'. Reference cell is the core cell or the cell which is under operation and all the pixels will be considered as the reference cell one-by-one for the m × n pixels of the entire image matrix. Threshold is the threshold value given by the user and transformed image is the output image obtained after applying the neighborhood operation.

Proposed algorithm for image segmentation:

Input: images (different imaging modalities of various organs) and Threshold
Output: Transformed images

Begin:

Step 1: Reduce noise using suitable filter
Step 2: Convert the input image in image matrix with gray value (0 to 255)
Step 3: Find the maximum pixel value of each row of image matrix and set it as 'max'
Step 4: Find the average of Extended Moore Neighborhood pixels for all pixels and set it as 'avg'
Step 5: Apply neighborhood operation of Cellular Automata for extracting features:
if (max – avg $\geq$ reference cell + Threshold $\geq$ max + avg)
then, reference cell = 255
otherwise, reference cell = 0
Step 6: Repeat steps 4 and 5 for processing m x n no. of pixels present in image matrix

End

The above mentioned algorithm describes the first part of the proposed mechanism that emphasize the process of image segmentation by means of region growth using the CA neighborhood concept. Here, for every step, on basis of its current state and the state of its immediate neighborhood cells, every cell updates its state as per specific transition set rule F. Here simultaneously, all the cells of the CA grid change their state values which leads to a total parallel system. The variable N defines the neighborhood of each cell.

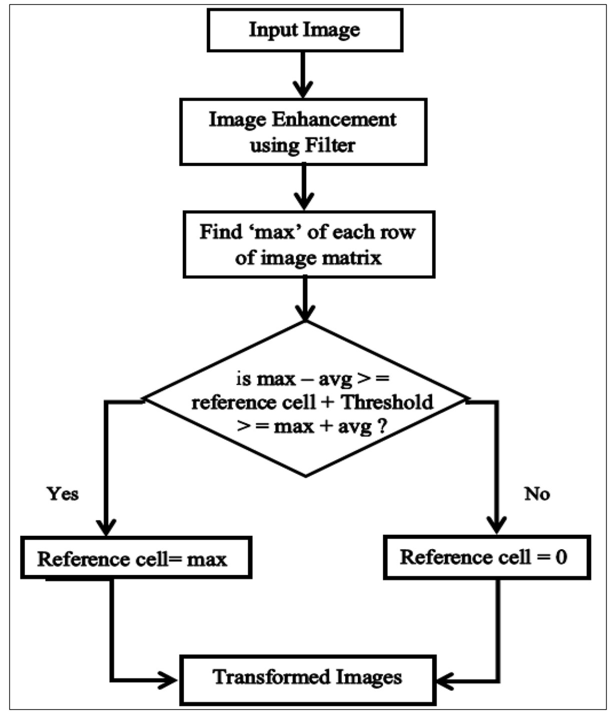

Fig. 5. Flowchart for image segmentation.

B. Image classification techniques

In the later part different classification algorithms have been applied to the image set prepared with transformed images to make the system automated that can detect tumors in different organs with a good accuracy and less loss. For this purpose, different image classifiers like CNN, ResNet, VGG have been used here. Image classifiers help to get information from the image. In this work, different classification algorithms have been applied to the image set of cancer in various organs and the performance has been recorded and it has been compared with the performance recorded after applying the same classification algorithms to the transformed image set obtained after applying the proposed cellular automata-based segmentation technique. Individual image sets of breast cancer, brain cancer and lung cancer have been considered and this proposed segmentation algorithm has been applied to each image and a new image set of the mentioned cancer has been prepared and CNN, ResNet, VGG classification algorithms have been applied to this new image set and the accuracy and training loss has been measured.

Here, the transformed images of all image sets have been scaled to a size of 256 × 256. Next all rescaled images are multiplied with several feature detectors that have a stride of 1. To get the best feature from the transformed image set rectilinear activation function (ReLU) has been used also; hence, two different

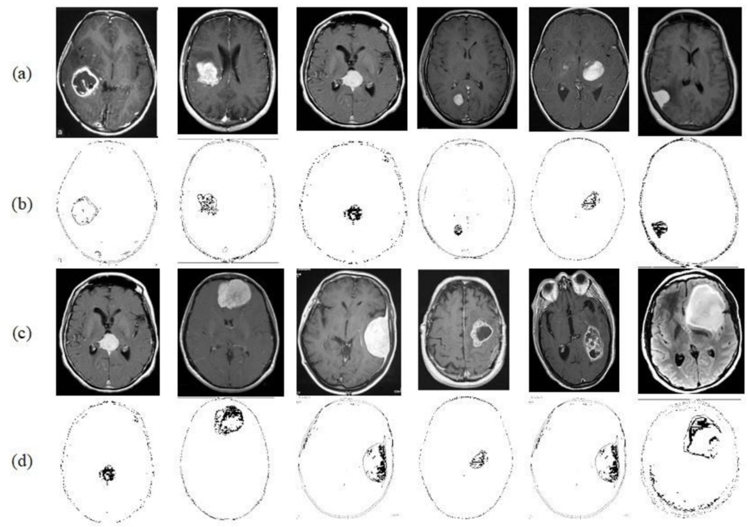

Fig. 6. Sample original image and transformed image of brain tumor.

feature maps have been obtained. Then 3 × 3 feature detector was taken and multiplied with the considered input image matrix for reducing the size of the image matrix. Next maxpooling is done, and a box of two-by-two pixels has been considered and it is placed in the top left corner. After that the maximum value is to be found in that box and then the obtained value is to be reduced. Next it has been moved to the next box to the right with a stride of 2. Again, Max pooling is done for reducing the size of the 32 different feature maps and 32 pooled feature maps have been obtained as a result. After that the dataset of brain cancer, breast cancer, lung cancer with the transformed images and the original images of tumor has been considered for classification with a target size of 300 × 300, batch size of 2 and 30 epochs and the steps per epoch is 5.

Results and discussion

In section 4, the experimental setup required for implementing the proposed methodology has been discussed as well as the results obtained using this methodology have been illustrated along with the accuracy and loss for detecting the tumor automatically.

A. Experimental setup

Here to implement the entire proposed functionalities, Python has been used. To get support for different imaging functions NumPy and OpenCV have been imported. With the help of these modules, different kinds of image operations like image enhancement, neighborhood operations have been performed. The implemented method has been applied to the available different image sets of brain CT images, breast mammography images and also to the CT images of lungs. Thereafter, the areas of abnormal growth of cells or the area of interest have been differentiated from the various imaging modalities.

Here different threshold values 10, 15, 20, 25 have been taken for making a comparison with the core pixel. After performing segmentation using the proposed CA based approach, all the transformed image sets that have been obtained will be trained with different image classification algorithms. In this approach around 500 number of said individual image sets have been considered for preparing the image dataset of brain, breast and lung cancer. The required segmentation has been performed from all of the image sets using this proposed methodology and finally the working image set for each of the mentioned cancers have been prepared. Among these images dataset 30% images of each set have been considered as a test set and 70% images have been used as training sets. Different image classification techniques like CNN, ResNet, VGG have been applied with different epochs to make the detection system automated with good accuracy.

B. Experimental results

In this work, image sets of breast tumor, brain tumor, and lung cancer have been considered as input image sets. The proposed methodology has been applied to this image set and the following are some output images obtained after transforming. From Kaggle the different images set have been taken for processing.

In Fig. 6, (a) and (c) represent the original images of brain tumor and (b) and (d) are the corresponding

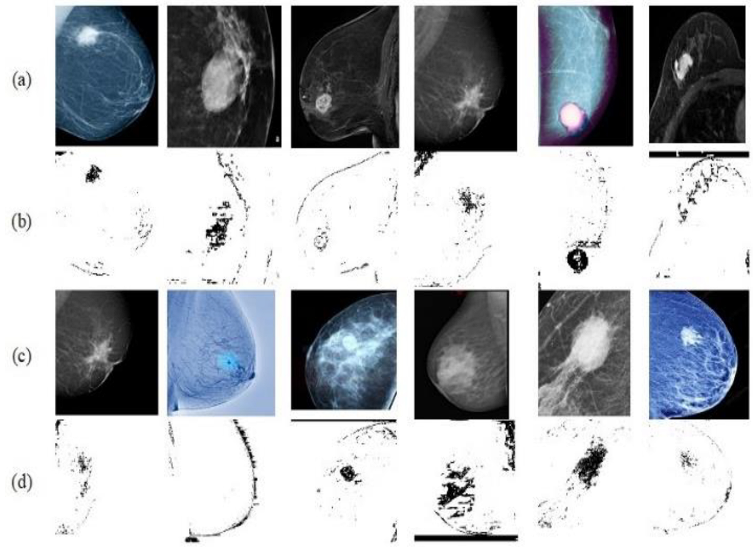

Fig. 7. Sample original image and transformed image of breast tumor.

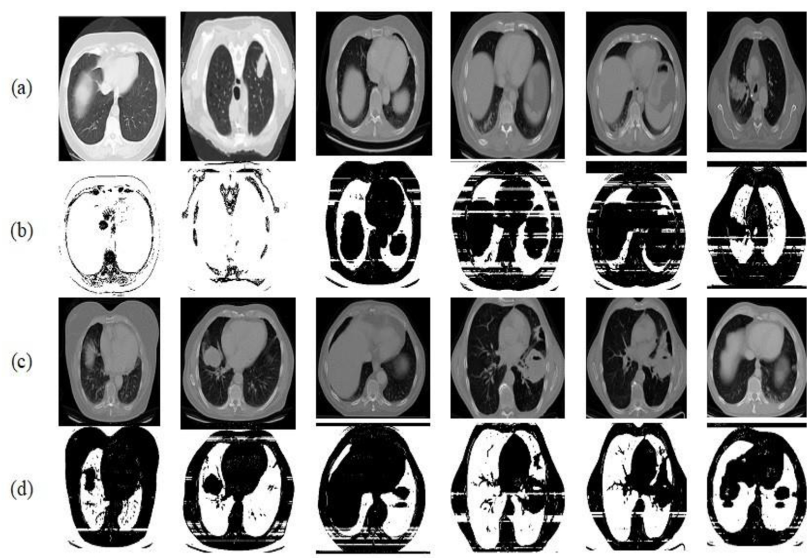

Fig. 8. Sample original image and transformed image of lung cancer.

transformed images obtained after applying the proposed segmentation algorithm. Here, the tumor has been segmented from its background image very clearly.

In Fig. 7, (a) and (c) are the original images of breast tumor and (b) and (d) are the corresponding images obtained after applying the proposed segmentation technique. Due to presence of dense tissues in breast here the obtained regions of interest are not so much clear like the brain tumor.

Original images of lung cancer have been shown in Fig. 8(a) and (c) and the respective transformed images are represented in Fig. 8 (b) and (d). Through these images the area of tumor has been highlighted as well.

The above images are the transformed images using proposed methodology. The proposed approach has been applied to the entire image set and the new image set with these transformed images has been obtained for cancer in various organs. Different image classification algorithms have been applied to this image set with the above-mentioned ratio of training and test datasets.

CNN, ResNet, VGG models have been applied to the new image set which has been obtained using the proposed feature extraction algorithm. One comparison also has been made regarding the accuracy and the data loss for the said algorithm with an obtained image set. Another comparison has also been made here applying the proposed segmentation

Table 1. Results obtained with and without segmentation algorithm.

Image Set Name	Performance Measure	CNN with segmentation algorithm	CNN without segmentation algorithm	VGG with segmentation algorithm	VGG without segmentation algorithm	ResNet with segmentation algorithm	ResNet without segmentation algorithm
Brain Tumor	Accuracy	0.9844	0.6719	0.9997	0.9902	0.9062	0.7028
	Loss	0.0237	0.6580	7.06e-3.1	0.0518	0.3652	0.6254
Breast Tumor	Accuracy	0.8925	0.6224	0.9257	0.9226	0.8568	0.5209
	Loss	0.0378	0.4502	1.0685	0.12.3	0.0869	0.4205
Lung Cancer	Accuracy	0.7268	0.5971	0.8546	0.8002	0.8254	0.6023
	Loss	0.0315	0.6608	0.5684	0.0621	0.4528	0.5525

algorithm and without applying the proposed methodology.

Table 1 describes the accuracy and training loss obtained for two cases i.e. one set of results with segmentation technique applied to the original image set and another set of results for without applying the segmentation technique. The accuracy and loss obtained for the image set prepared with transformed images and the performance has been measured by applying different classification algorithms. All the above mentioned classification algorithms have been applied to the new image set prepared with the transformed images after applying the proposed CA based segmentation technique. Here the obtained accuracy has been measured considering 30 epochs. Performances for different epoch sizes like 15, 20, 25, 35 also have been observed. As per the obtained values, VGG results from better accuracy and less error. CNN with three layers produces better accuracy than ResNet in case of brain tumor images but in case of breast cancer image it gives better accuracy than ResNet. Looking at Table 1, it can be said that the proposed algorithm for feature extraction can detect growth of abnormal mass in different organs with a good accuracy. As a result, for brain tumor image set average of 96% accuracy has been obtained, and for breast tumor it is detected with average of 89% accuracy and for lung cancer it produces 80% accuracy on average. For the original images, the proposed CA based segmentation algorithm has not been applied to obtain the transformed images. All the mentioned classification methods have been applied directly. It has been observed that for the same image set, applying different image classification algorithms to the original image set produces less accuracy than the accuracy obtained using the proposed transformation function to the original image set. For brain tumor image set average 79% accuracy has been obtained, and for breast tumor it is detected with average 69% accuracy and for lung cancer it produces 67% accuracy on average. Hence, it can be said that the classification algorithms are performing better on image set prepared with proposed segmentation algorithm than the original image set for detecting tumor in various organs.

Comparative analysis

In this section, a performance comparison has been made with some existing work. The various image set of different organs like brain tumor, breast tumor and lung cancers have been analyzed and the performances have been measured using some existing techniques. In these mentioned methods only, the accuracy has been measured but other parameters like training loss have not been measured whereas in the proposed methodology, loss also has been considered as a performance parameter along with the obtained accuracy.

Table 2 shows a comparative analysis of the performance among the existing segmentation

Table 2. Comparison among various cancer detection algorithm.

Image Set Name	Authors & Year	Used Methods	Accuracy
Brain Tumor	Goyal et al.[29] / 2021	Watershed Segmentation	88.5%
	Vani et al.[30] / 2017	SVM	82%
	Ullah et al.[31] / 2022	Inception	94.48%
		Resnet	63.34%
Breast Tumor	Mohapatra et al.[32] / 2019	CNN	81%
	Gaikwad et al.[33] / 2015	SVM	83%
	Ansar et al.[34] / 2021	VGG	70.7%
Lung Cancer	Saric et al.[5] / 2018	VGG	97.3%
		ResNet	72%
	Ismail et al.[2] / 2021	CNN	65%

methodologies. Accuracy is considered as the performance measurement parameter for the same image set.

It has been observed that in general case the accuracy obtained for the segmentation with the proposed method here is higher than these mentioned existing methodologies in case of detecting brain tumor and breast tumor. But in case of lung cancer detection, the accuracy obtained with the existing methods is slightly higher than the accuracy obtained by performing segmentation with the proposed methodology.

Conclusion

The proposed framework can be used to detect cancer in different organs by analyzing different imaging modalities in less time. This work has two phases; image segmentation and image classification. In the first phase, it segments the region of interest from the background of the input images and detects the abnormal growth of cells in different organs. In the next, the classification algorithms are applied to the transformed images, accuracy and loss have been recorded. In this work, cellular automaton based image segmentation mechanism has been proposed and implemented along with a module of deep learning for performance analysis. The performance measurement has been done for the image set obtained after applying the proposed CA based segmentation mechanism and without applying the proposed methodology. It has been observed that better accuracy is obtained for the first case. A comparison also has been shown with some of the existing methods.

This work is advantageous in terms of clarity and computation time. In this work, at the intermediate level a transformed image set for the segmented image has been obtained and it can be used further for checking the tumor area in the imaging modalities. Different classification algorithms help to produce results with high accuracy and less error.

The proposed CA based segmentation approach has identified the area of abnormal growth of cells in the brain and breast clearly whereas the same for the lung is not so clear. It may be due to the dense tissue in the breast and the presence of ribs in the lungs.

In future scope, the proposed framework can be modified so that it can produce better results for lung cancer. Furthermore, a generalized framework is to be developed by modifying the proposed methodology so that it can be applied to detect tumors in other organs. It may help in the area of medical sciences.

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Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at JIS College of Engineering, West Bengal, India.

Authors' contribution statement

Author R. B. performed the entire work under guidance of Dr. N. B. J. N. and Dr. A. S.

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إطار عمل الكشف عن السرطان باستخدام التجزئة القائمة على الأتمتة الخلوية والتعلم العميق

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الخلاصة

تلعب معالجة الصور دورًا حيويًا في مجال العلوم الطبية. تقلل معالجة الصور الطبية من وقت التشخيص والتكلفة. يساعد الاكتشاف المبكر للسرطان في تقليل مخاطر الحياة. ركزت معظم الأعمال السابقة في مجال اكتشاف السرطان على أعضاء معينة ووسائل التصوير. الهدف: يقترح هذا العمل إطارًا عامًا للكشف عن الأورام في أعضاء مختلفة من خلال تحليل وسائل التصوير المختلفة. في هذا العمل، تساعد Cellular Automata في تقسيم الصورة من خلال نمو المنطقة، وتقوم خوارزميات التعلم العميق بإجراء تحليل الأداء. هنا، يتم النظر في الدقة وفقدان البيانات لتحليل الأداء. من خلال تحليل صور الأشعة المقطعية، وصور الرنين المغناطيسي للدماغ والثدي والرئتين، قد يساعد الإطار المقترح في التعرف على منطقة الكتلة التي تتطور. تفصل تقنية التجزئة المقترحة القائمة على CA منطقة الاهتمام أو منطقة الورم عن خلفيتها. يتم إجراء التجزئة من خلال النمو الإقليمي باستخدام مفهوم جوار مور. لتحسين الصورة، تم تقليل الضوضاء باستخدام المرشحات. يتم تحويل الصور المحسنة إلى مصفوفة صورة، ويتم تطبيق قاعدة CA على مصفوفة الصورة للتجزئة. بشكل عام، يبدو أن منطقة الورم لها قيم عالية الكثافة. هنا، يتم التجزئة من خلال تحديد قيم البكسل عالية الكثافة للصورة ثم إجراء نمو المنطقة تدريجيًا لتشمل منطقة الورم بأكملها. يتم تطبيق خوارزميات التعلم العميق على مجموعة الصور المحولة للسرطان في أعضاء مختلفة. أخيرًا، يتم إجراء تحليل الأداء. النتائج: تمت مقارنة معلمات تحليل الأداء مع مجموعات الصور المحولة والأصلية، وقد لوحظ أن النتائج التي تم الحصول عليها باستخدام مجموعة الصور المحولة تنتج دقة أعلى وفقدان معلومات أقل من النتائج الناتجة عن مجموعة الصور الأصلية للأورام. الاستنتاج: قد يساعد الإطار المقترح الممارسين الطبيين في اكتشاف الأورام في الأعضاء المختلفة في وقت مبكر وبكفاءة.

الكلمات المفتاحية: تقسيم الصورة، الأتمتة الخلوية (CA)، النمو الإقليمي، نمط التصوير، CNN، ResNet، VGG