Soft Computing
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APPLICATION OF SOFT COMPUTING

Deep convolution neural networks learned image classification for early cancer detection using lightweight

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Abstract

Essentially, cancer refers to the formation of abnormal cells in any section or area of the body. The goal of early cancer detection is to identify patients who are showing signs early on in order to maximise their chances of a successful therapy. Early detection and treatment of cancer reduce the disease mortality. A wide range of image processing and machine learning techniques have been presented for the identification of cancer. There was no improvement in detection accuracy or efficiency with existing systems. To overcome these problems, we present the Least Mean Square Filterative Ricker Wavelet Transform-based Deep Convolutional Neural Learning Classifier Model (L-DCNLC). By using a fully connected max pooling deep convolutional network with higher accuracy and reduced time consumption, the L-DCNLC Model aims to identify cancer early. There are three hidden layers and one output layer in the fully linked max pooling deep convolutional network. The number of patient photographs in the database is used as input in the L-DCNLC Model's input layer. Following that, preprocessing is performed in hidden layer 1 to perform denoising in order to improve image quality. This is accomplished by employing the Least Mean Square Weiner Filtering process, which has a higher peak signal-to-noise ratio. The Continuous Ricker Wavelet Transform is then used to extract the image features from the preprocessed image in hidden layer 2. Finally, the classification process is performed in hidden layer 3 using the Kulczynksi Similarity Coefficient to detect the cancerous image by comparing the testing and extracted features. Thus, the cancerous image is detected and displayed with a low error rate in the output layer. The brain cancer and lung cancer datasets are analysed to determine peak signal to noise ratios (PSNR), cancer detection accuracy, and cancer detection time. The evaluation results indicate that the L-DCNLC Model improves accuracy and PSNR while requiring less computational time than previous works.

Keywords Machine learning · Classification · Image processing · Cancer detection · Continuous ricker wavelet transform

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1 Introduction

In the world, cancer is the most prevalent cause of death, as reported by the World Health Organization (WHO) (WHO). Cancer is a deadly disease that can be prevented if it is detected early enough. Developing computer-aided detection methods is a demanding endeavour that has remained an unresolved problem because of the shape fluctuation and cancer area. A variety of methods for detecting brain cancer using MR and CT images were reviewed, as well as the advantages and disadvantages of detecting brain and lung cancer. Mishra (2019) used a discrete orthonormal S-transform (DOST) and principal component analysis (PCA) to mine texture features, and linear discriminant analysis was used to reduce dimensionality (LDA). Classification was performed using the Adaboost algorithm with random forest (ADBRF) classifier. On the other hand, this did not affect the ability to identify cancer. Prostate cancer detection in CEUS pictures has been established using a deep learning framework. Convolution was used to extract features from temporal dimensions for cancer detection. The deep learning framework, on the other hand, did not result in a reduction in the time required to detect cancer. Mallick et al. (2019) introduced deep wavelet autoencoder (DWA) image compression with image decomposition and feature reduction. Combining the two significantly reduced the sinking feature set size for DNN classification tasks. DWA had no effect on classification accuracy, however, Kong et al. (2019) based on fuzzy theory and a region-growing algorithm, a region-growing algorithm was devised. Images were partitioned and segmented using the technique developed. Cancer detection times were not reduced by using the method for expanding regions. Improved classification accuracy was achieved by the use of Kumar et al. (2020) an optimised deep learning technique termed Dolphin SCA-based Deep CNN. Statistical features were used to guide the feature extraction procedure. In spite of the higher precision, the feature extraction process took a long time to complete. Togacar et al. (2020) established the concept of feature extraction and categorization using convolutional neural networks (CNNs). In order to improve classification accuracy, picture augmentation techniques such as cutting and filling were implemented. The inaccuracy rate did not decrease under CNN's guidance. For the classification of dermal cell pictures and the detection of skin cancer, a deep learning model was developed (Ali and Riyaee 2020). Deep learning techniques were used to construct a model-driven architecture for predicting skin cancer. The deep learning model, on the other hand, did not reduce computational complexity. Gumaei (2019) introduced a hybrid feature extraction method for cancer categorization. Preprocessing was used to enhance the quality of the designed approach. However, the feature extraction technique was not used to perform the image denoising. Karthiga and Rekha (2020) developed the Artificial Bee Colony Algorithm for the selection and classification of cancer features. The classification time, on the other hand, was not shortened. Mohamed Shakeel et al. (2019) introduced a weighted mean histogram equalisation approach for the purpose of removing noise and improving image quality. The affected area was divided up using a clustering approach. Using the weighted mean histogram equalisation method had little influence on the peak SNR, though (Table 1).

A lower peak signal-to-noise ratio, lesser accuracy, longer duration, higher computational cost, and higher computational complexity are some of the drawbacks of current cancer detection systems. The malignant disease was not detected at the onset using an improved detection method. The L-DCNLC Model has been developed to address the aforementioned problems.The paper is divided into five distinct sections. The proposed L-DCNLC Model is briefly described in Sect. 2 with different cancer detection stages. The third section discusses related works in cancer detection techniques. Section 4 presents experimental settings along with a detailed database explanation. Section 5 analyses the results for three different parameters. Section 6 contains the conclusion.

2 Related works

To detect brain tumours in MR images of the brain, an extreme learning machine algorithm was described in Özyurt et al. (2020). On the other hand, the computational cost was not reduced. An effort was made in BhaskarraoBahadure et al. (2017) to make the Berkeley wavelet transformation (BWT) simpler and more accurate. A support vector machine classifier was employed to extract useful characteristics from the segmented area. Despite the improvement in accuracy, there was no reduction in the amount of time required.

The article Soltaninejad et al. (2017) described an automated method for detecting and segmenting abnormal tissue using Magnetic Resonance Imaging. The fully automated method, on the other hand, did not result in a reduction in time consumption (Rajan and Sundar 2019). In Özyurt et al. (2020), an extreme learning machine method was presented as being used to detect brain tu For the identification and segmentation of tumours, a novel hybrid energy-efficient technique has been presented. The tumours were segmented using the Fuzzy C-Means approach. Error rates were not affected by the use of the hybrid energy-efficient approach.

Table 1 Cancer Detection Time for brain cancer dataset

Number of input images	L-DCNL	DOST + PCA + LDA + ADBRF	Deep Learning frame work
25	7.5	11.9	16.25
50	16.97	15.5	32.5
75	28	40	51.2
100	38	54	69
125	47.45	67.5	88
150	59.9	86	107.5
175	72.9	102	130
200	86.5	121	150

To overcome clinical diagnosis concerns, Ge (2019) presented an alternate direction technique. The method was designed to take into account both the overall structure of the image and the individual pixel information in order to increase accuracy. However, there was no reduction in the computational complexity. To better detect brain tumours in MR images, a new two-phase multi-model was developed by Abd-Ellah et al. (2018). On the other hand, the computational cost was not reduced. An effort was made in BhaskarraoBahadure et al. (2017) to make the Berkeley wavelet transformation (BWT) simpler and more accurate. A support vector machine classifier was employed to extract useful characteristics from the segmented area. Despite the improvement in accuracy, there was no reduction in the amount of time required.. The developed model was used to classify MRI images as normal or abnormal in order to identify the brain tumour. The two-phase multi-model, on the other hand, did not improve classification accuracy. A Tripartite Generative Adversarial Network (Tripartite-GAN) was introduced in Zhao et al. (2020) to identify the tumour without using the CA injection. The Tripartite-GAN model, on the other hand, did not reduce the error rate. Wang et al. (2019) introduced a new computer-aided detection (CADe) system with the goal of decreasing clinician reading time and increasing efficiency. To identify breast tumour candidates, a phase-based approach was used on a local level. However, the time complexity was overlooked. In Cinar and Yildirim (2020), CNN, a deep learning network, was introduced for diagnosing brain tumours using MRI images. However, the planned network did not complete the pre-processing task. Varuna Shree and Kumar (2018) introduced a method for noise removal that included feature extraction and DWT-based segmentation to reduce complexity. However, the developed method did not improve the accuracy of cancer detection (Natarajan et al. 2020).

3 Methodology

An input image is subjected to a series of operations aimed at improving it through the extraction of useful information. As a result of early cancer detection, the tumour can be identified and treated. To diagnose cancer at an early stage, many researchers conducted investigations. There was, however, no improvement in either detection accuracy or time consumption. Least Mean Square Filterative Ricker Wavelet Transform Based Deep Convolutional Neural Learning (L-DCNLC) Model is presented in order to address these problems. The L-DCNLC Model's major purpose is to identify cancer more quickly and accurately. The L-DCNLC Model's architecture design is shown in Fig. 1.

Figure 1 depicts the proposed L-DCNLC Model design. Images are first extracted from the input dataset. The image quality was then improved by preprocessing by removing noisy pixels using the Least Mean Square Weiner Filtering

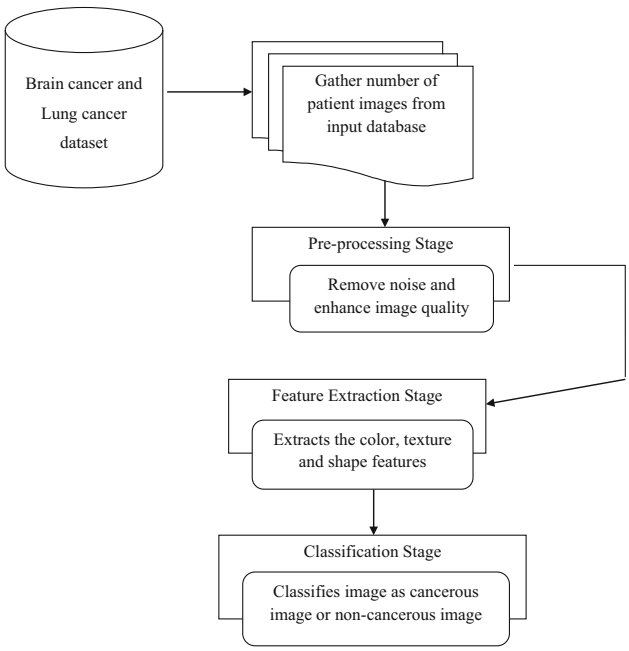


Fig. 1 Structural design of the proposed L-DCNLC Model

process. The image features are then extracted using the Continuous Ricker Wavelet Transform. Finally, the classification process is used to identify the cancerous image. The following subsection describes the detailed process of the L-DCNLC Model.

3.1 Least squares filterative deep convolutional neural learning classifier based on ricker wavelet transform

In order to reliably identify cancer, the L-DCNLC Model incorporates a fully linked max pooling deep convolutional network. Preprocessing, feature extraction, and classification are carried out through a series of processing layers within the network. The input from the previous layer is used as a foundation for the future layers. Max pooling deep convolutional networks consist of an input layer and three hidden layers plus an output layer. All of the hidden layers of a fully connected max pooling network are used to learn the input images and then turn them into an output layer. Max pooling deep convolutional networks are depicted in Fig. 2.

The diagrammatic representation of fully connected max pooling deep convolutional network is shown in Fig. 2. In designed network, neurons like nodes are linked to other layers to form an entire network. The input layer comprises the image from the database and formulated as,

$$\text{Input}(t) = \sum_{i=1}^{n} I_{\text{i}}(t)\varphi_{\text{ih}} + d \tag{1}$$

In (1), 'Input(t)' denotes an input at a specific time instant.

't', 'I i (t)' denotes the input from the dataset, and '_ih' denotes the weight between the input and the hidden layer. The letter 'd' represents bias. The input layer then sends the collected inputs to the hidden layer 1. Image preprocessing is done in this layer. The proposed L-DCNLC Model begins with preprocessing.

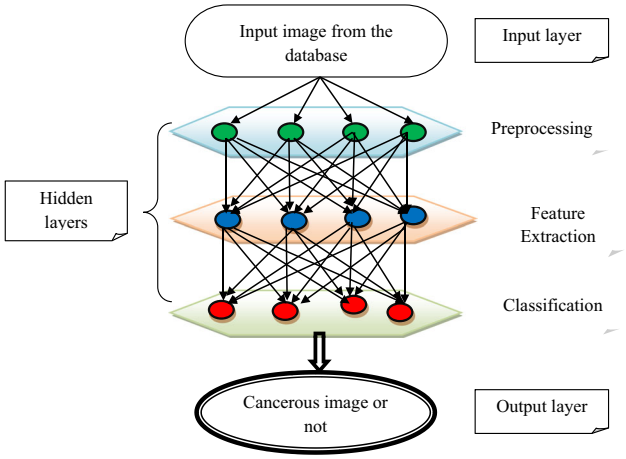


Fig. 2 Diagrammatic representation of fully connected max pooling deep convolution network

The database is used to determine the number of images. Normally, the original images are harmed by unwanted noise, which reduces image quality. The presence of noise in the input image increases the complexity of cancer detection. As a result, preprocessing is critical for improving image quality and reducing noisy pixels. For input image pre-processing, the proposed L-DCNLC Model employs the Least Mean Square Weiner Filtering (LMSWF) process. The total number of images collected is 'I 1,I 2,I 3….,I n'. LMSWF is a stochastic and statistical method for noise removal that employs inverse filtering and noise smoothing. The blur and noise in the input image are reduced by LMSWF. The orthogonality principle entails the Wiener filter is defined in the Fourier domain as

$$\text{WF}(u,v) = \frac{B(u,v)P_{\text{yy}}(u,v)}{|B(u,v)|^2 P_{\text{yy}}(u,v) + P_{\text{zz}}(u,v)} \tag{2}$$

The power spectra of the input image and noise are denoted by 'P yy (u,v)' and 'P (zz) (u,v)' in (2). The blurring filter is denoted by 'B(u,v),' and the Weiner filter is denoted by 'WF(u,v).' The preprocessed image is obtained in this manner, and thus the PSNR improves.

The preprocessed image is then sent to hidden layer 2. The feature extraction process is carried out in that layer to reduce the dimension in order to provide the interesting parts of an image.

The L-DCNLC Model decomposes the preprocessed image and generates different sub-blocks for horizontal and vertical directions using the Continuous Ricker Wavelet Transform (CRWT). Figure 3 depicts an example of an input pre-processed image.

Figure 3 describes the Ricker transform of input image. Then, the pre-processed input image is converted into single point in parameter space.

4 Performance discussion

The qualitative and quantitative performance analysis is carried out in this section.

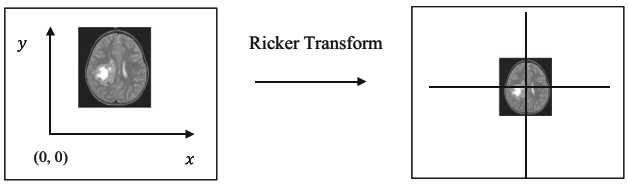
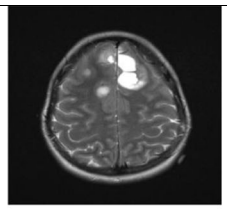
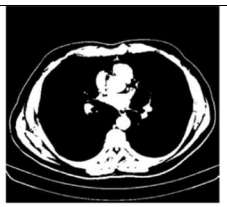
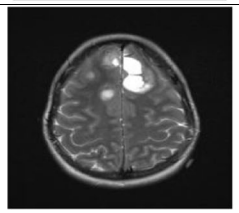
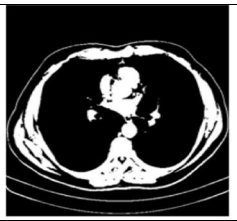
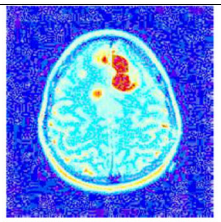
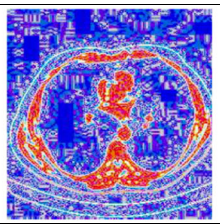
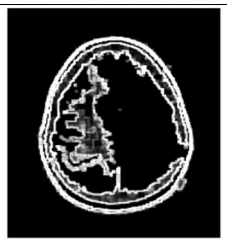
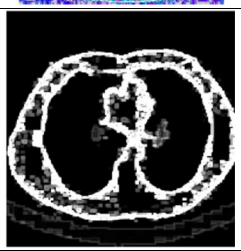
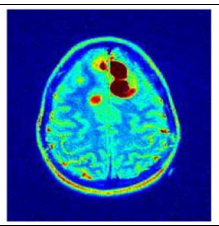
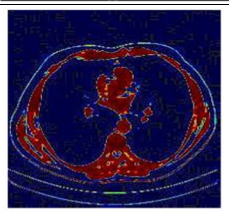
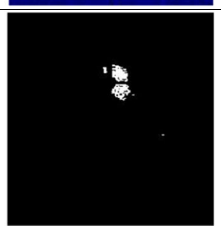
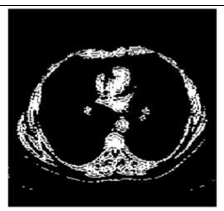


Fig. 3 Ricker transform

Fig. 4 Qualitative performance analysis of L-DCNLC model for Brain cancer dataset and Lung cancer dataset

Process	Brain cancer dataset	Lung cancer dataset
Input image		
Least Mean Square Weiner Filter based Image preprocessing		
Texture feature		
Color feature		
Shape feature		
Feature Extracted Image		
Cancer Detection		

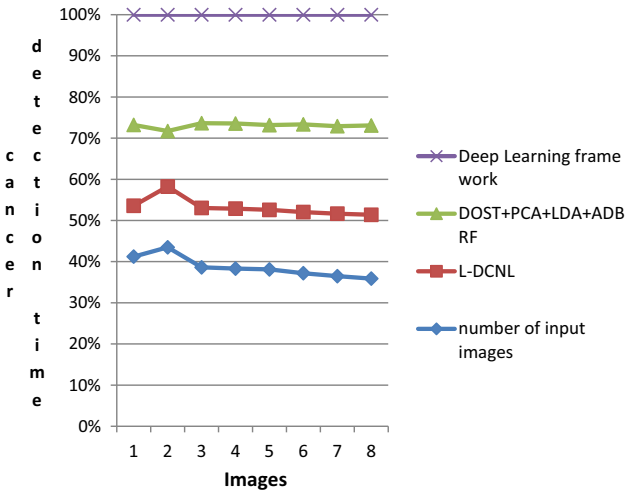


Fig. 5 Measurement of cancer detection time

The first subsection explains qualitative results analysis.The quantitative analysis is carried out using various metrics, which are discussed in the second sub-section.

4.1 Qualitative performance analysis

A qualitative analysis of the proposed L-DCNLC model is performed using two different datasets, one for brain cancer and one for lung cancer. Initially, the input MRI and CT images are obtained from the database.

The quality results for the L-DCNLC model are shown in Fig. 4. The MRI and CT images original input are taken from the database. In order to obtain a better quality picture, the least mean square weiner-based image preprocessing is performed. The image is then removed with the texture, shape and colour features. Finally, the Kulczynksi Similarity Coefficient is used to detect the cancer.

4.1.1 Cancer detection time

Cancer detection time is the time consumed by the technique to detect the normal or cancerous image. The cancer detection time is determined as,

$$\mathrm{CD_{Time}} = n * \mathrm{Time}(\text{ detecting one image}) \quad (3)$$

From (3), 'CD_{Time}' represents the cancer detection time and 'n' denotes the number of input images. The cancer detection time is computed in milliseconds (ms).

Figure 3 shows how the number of images calculated is used to analyse cancer detection time. The line graph in the image above depicts a patient's diagnosis date for brain cancer versus lung cancer. According to the three different conventional methods demonstrated above, the L-DCNLC model has the cancer detection time that is better. Because a fully connected max pooling deep convolutional network was trained using the L-DCNLC model, this is the result. Before processing, noise was removed. In addition to the colour, texture, and shape data that remains, it also includes colour, texture, and shape information. After classifying the image, the results show whether it is cancerous. Consequently, this helps to speed up the cancer detection process. The cancer detection time of the L-DCNLC model is reduced by 30% and 44% when compared to the current DOST + PCA + LDA + ADBRF (Mishra 2019) and Deep learning framework (Feng et al. 2019). When comparing L-DCNLC (Mishra 2019) and Deep learning framework (Feng et al. 2019), the lung cancer detection time of L-DCNLC (Mishra 2019) is 22% slower and Deep learning framework (Feng et al. 2019) is 33% slower.

In Fig. 5, we see that the calculation of the number of images is used to analyse cancer detection time. In the above graph, the red line represents the time when a patient was diagnosed with brain cancer, and the green line represents the time when a patient was diagnosed with lung cancer. L-DCNLC model's cancer detection time is better than the other two conventional methods demonstrated above. This is because the L-DCNLC model was used to train a fully connected max pooling deep convolutional network. The image quality was improved by removing noise before processing. And the remaining data after that includes colour, texture, and shape information. Following that, the image is classified to determine if it is cancerous. As a result, this helps to shorten the time needed to detect cancer. Compared to existing DOST + PCA + LDA + ADBRF (Mishra 2019) and Deep learning framework (Feng et al. 2019), the average cancer detection time of L-DCNLC model is reduced by 30% and 44%. The lung cancer detection time of L-DCNLC (Mishra 2019) and Deep learning framework (Feng et al. 2019) are 22% and 33% respectively, when compared to existing DOST + PCA + LDA + ADBRF (Feng et al. 2019).

5 Conclusion

Three distinct processes are introduced in this paper: preprocessing, extraction of features, and classification. After removing noise from the input image, the L-DCNLC model can accurately classify the image. Once the image has been preprocessed, the important features of the image are extracted in order to speed up the detection of cancer. Finally, the similarity coefficient is used to perform the classification process in order to detect cancer with greater accuracy and a lower error rate based on the extracted features. An MRI of the brain and a CT scan of the lungs are used to conduct the extensive experimental evaluation. The results and discussion section includes both qualitative and quantitative analysis. The quantitative results are

confirmed in terms of improved cancer detection accuracy and shorter detection times when compared to other studies.

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Data availability Data sharing not applicable.

Declarations

Conflicts of interest The authors declare that they have no conflicts of interest.

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