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Breast Cancer Detection Using Local Optimization Algorithm for Deep Convolutional Neural Networks

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***Abstract*---**In this paper, breast cancer identification and grading is implemented through chitosan nanoparticles agents in cancer cells during molecular imaging through DnCNN image enhancement algorithm. However, cancer cell detection at early stage using mammogram and Tissue culture due to improper maintenance of aseptic conditions, microbial and chemical contamination. To overcome above problems, a Chitosan nanoparticle is used as agent in SEM image is obtained from cancer cell for grading of cancer. The chitosan nanoparticles based cancer cell SEM images is enhanced using Deep CNN. The enhanced images cancer detection at earlier stage and grading is obtained. The proposed Deep CNN-based classification and identification, specifically employing LOA-DNCNN for cancer cell performs better than traditional method in terms of cost and accuracy.
Keywords: *Cancer, Chitosan, Nanoparticles, SEM, LOA- DnCNN*

1. Introduction

Tumors are caused by cancer cells that impact human cells. When a tumor spreads to different body parts, it is considered malignant. Cancer cells never spread to other parts of the body when the tumor is benign. Women's rates of breast cancer have been rising recently as a result of changing lifestyles. Breast cancer can occur anywhere on the breast, but it most commonly occurs in the outermost part of the upper breast, either on the surface or deeper within the breast, and closer to the chest wall. There are 2 types of breast cancer: invasive and non-invasive. Invasive Breast cancer spread to separate organs or other tissues. Non-invasive breast cancers never metastasise from the breast lobules or milk ducts. Breast cancer cells can be seen at the molecular and cellular levels using molecular imaging. CT, UGS, and digital radiography images are never used to visualize cells or tissues—only the physical structure. Physicians can better comprehend the chemical and biological processes occurring at the cellular level in the human body thanks to molecular imaging (MI). Very little radioactive material is used to diagnose and treat syndrome during MI. In MI, radiopharmaceuticals are chemical agents that react with cells to either diagnose or cure illnesses. Images of the chemical agent reactions are seen on a computer and camera. Cancer and other diseases are treated with nuclear medicine. MI uses nonmaterial's to analyze chemical and physical properties. Imaging of cells, tissues, and organs is done using nanoparticles. Human tissues and cells interact with induced nanoparticles in the body to facilitate treatment or produce higher-resolution, more visibly displayed images.

2. Scanning Electron Microscopes

Using a scanning electron microscope, solid specimens can be imaged. A high-energy electron beam is created by SEM, directed at solid objects, and the reflected signal is converted into images. Information about the specimen, including its crystalline structure, chemical makeup, and external morphology, can be obtained from the reflected signal. Performance analyses, such as chemical compositions and qualitative or semi-quantitative determination, can be carried out at a designated location on the specimen. Thermo Fisher FEI QUANTA 250 FEG scanning electron microscope camera model number is used to take pictures and analyze material morphological studies. The instrument has a high resolution of 1.2 nm at 30 kV and operates in the voltage range of 5 kV to 30 kV. Detectors found in SEM cameras include the Gaseous Secondary Electron

Detector, Back Scattering Electron Detector, Large Field Detector, and Everhart Thornley Detector. White noise and random noise can be removed from scanning electron microscope (SEM) images of breast cancer cells using chitosan nanoparticles in order to better visualize the cancer cells.

3. Chemicals And Reagents For Preparation Of Chitosan Nanoparticles

Molecular imaging uses chitosan, sodium tripolyphosphate, and 7,12-Dimethylbenz(a) anthracene. tripolyphosphate is used as a gelatin agent in the synthesis of chitosan via ionic gelatin. After dissolving chitosan in one percent (v/v) acetic acid, it was stirred for an hour. To the chitosan dispersion, add 3 mg/ml of AB ethanol. After one hour of stirring at pH 5.0 (1M NaOH), one milligram per milliliter of tripolyphosphate was added to the chitosan ethanol extract, and magnetic stirring was used. After two hours of stirring, the resultant mixture forms encapsulated chitosan nanoparticles. Chitosan nanoparticles obtained following 45 minutes at 4°C and 10,000 rpm centrifugation. Sampled powder that has been lyophilized and kept at 4°C.

4. DNCNN Architecture

- **Architecture Design:** Design DNCNN architecture suitable for image denoising tasks. CNNs are adept at capturing intricate patterns in images.
- **Input Preprocessing:** Preprocess input mammogram images, considering factors like resizing and grayscale conversion.
- **Loss Function:** Use appropriate loss functions such as mean squared error for denoising tasks.
Lion Optimization Algorithm (LOA)
- **Solution Representation:** Represent solutions in LOA as sets of parameters for DNCNN, like filter sizes, number of layers, learning rates, or dropout rates.
- **Initialization:** Initialize a population of lions with random parameter sets for DNCNN.
- **Fitness Function:** Develop a fitness function that evaluates the performance of DNCNN with the given parameters. Metrics like accuracy, sensitivity, specificity, or AUC can be used, depending on the problem requirements.
- **Pride Formation:** Organize lions into prides based on their fitness scores. Stronger prides represent lion groups with better-performing DNCNN configurations.
- **Territorial Marking:** Each lion (solution) marks its best parameter set, indicating the optimal configuration it has found.

A. Integration of LOA with DNCNN

- **Territorial Exploration:** Lions explore the solution space by altering the parameters of DNCNN. Pride territories guide the exploration, focusing on promising areas of the parameter space.
- **Nomad Lions:** Nomad lions can be introduced to inject diversity into the search process. They explore new configurations randomly, ensuring a broad exploration of the solution space.
- **Iterations:** The algorithm iteratively refines the lion population. Lions continue exploring and marking territories and the algorithm converges as lions discover better DNCNN configurations over iterations.

B. Evaluation and Validation

- **Cross-Validation:** To evaluate the model's performance in a robust manner, apply methods such as k-fold cross-validation.
- **Testing:** Evaluate the final LOA-DNCNN model on a separate test dataset not seen during training to gauge its real-world performance accurately.

C. Hyperparameter Tuning

- **Learning Rates:** Experiment with different learning rates for DNCNN to find the optimal rate for faster convergence.

- **Filter Sizes and Network Depth:** Tune the size of filters and the depth of DNCNN layers for capturing relevant features effectively.
- **Batch Size:** Adjust batch size to balance between computational efficiency and model stability.

D. Analysis and Interpretation

- **Feature Visualization:** Use techniques like occlusion maps or class activation maps to visualize which part of mammogram images contribute most important to the model's conclusion.
- **Error Analysis:** Analyze misclassified cases to identify patterns or commonalities that the model finds challenging.

5. Results And Discussions

By combining LOA's exploration capabilities with the deep learning power of DNCNN, this hybrid approach aims to optimize the breast cancer detection process, potentially leading to more accurate and efficient diagnostic tools. Remember that this process may require thorough experimentation and validation to fine-tune the model for optimal performance. Figure.1shows the best training performance of LOA-DNCNN algorithm.

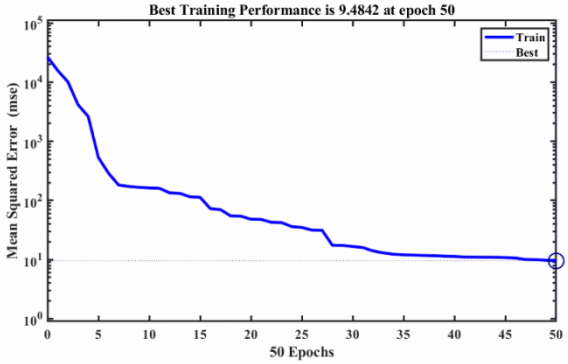

Figure 1. Training Performanceof LOA-DNCNN for breast cancer detection.

The quantity of training epochs is indicated on the x-axis. A single trip through the whole training dataset is referred to as an epoch. In order to minimize the mean squared error, the model analyses all of the training data during each epoch and modifies its weights and biases using an optimization approach (such stochastic gradient descent).The mean squared error (MSE) of the model's predictions in relation to the actual target values is shown on the y-axis. MSE is a typical loss function that is applied to regression issues. The average of the squared discrepancies between the model's predictions and the actual values is determined for each epoch by comparing the forecasts with the actual values. When the MSE is smaller, the model is doing better since its predictions are more accurate and closer to the real values. Figure.2shows the training state of LOA-DNCNN algorithm Figure.3Error histogram of LOA-DNCNN for breast cancer detection.

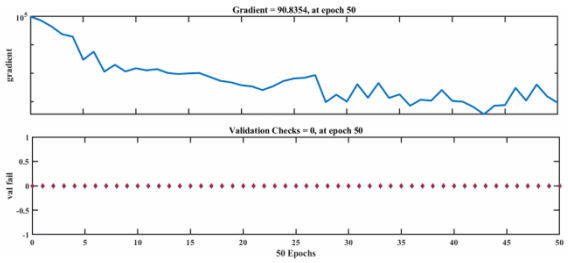

Figure 2. Training stateof LOA-DNCNN for breast cancer detection.

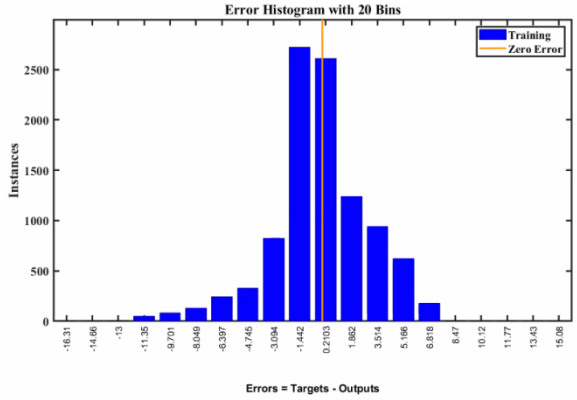

Figure 3. Error histogram of LOA-DNCNN for breast cancer detection.

The initialization of the neural network's weights and biases marks the start of training. Usually, these starting points are chosen at random. The training data is sent via the network during each training iteration, or epoch. The source data goes through layers of neurons with weighted connections. Activations are calculated using activation functions (like ReLU or Sigmoid) for each neuron in hidden layers, producing an output prediction. The output from the neural network is compared to the actual target values. The difference between expected and actual values is measured by a loss function, which might be cross-entropy loss for classification tasks or mean squared error for regression tasks. Compute the gradients of the loss with respect to the network's parameters (weights and biases) in back propagation. The amount that each parameter should be changed to minimize the loss is shown by these gradients. This step uses the chain rule of calculus to propagate the error backward through the network. With the gradients calculated, an optimization algorithm (like Stochastic Gradient Descent or its variants) updates the weights and biases of the network in the direction that reduces the loss. The size of these updates is controlled by the learning rate. The model's performance is periodically assessed using a validation dataset (not the training data), often following each epoch. This aids in tracking the model's ability to generalize to new data. Metrics such as accuracy, precision, recall, or mean squared error are calculated on the validation data to assess the model's performance. Training continues for a predefined number of epochs or until a certain condition is met (such as achieving a specific level of accuracy or loss on the validation set). Early stopping, a technique where training halts if the validation performance starts degrading, is often employed to prevent over fitting.Figure4.showsDenoised image.

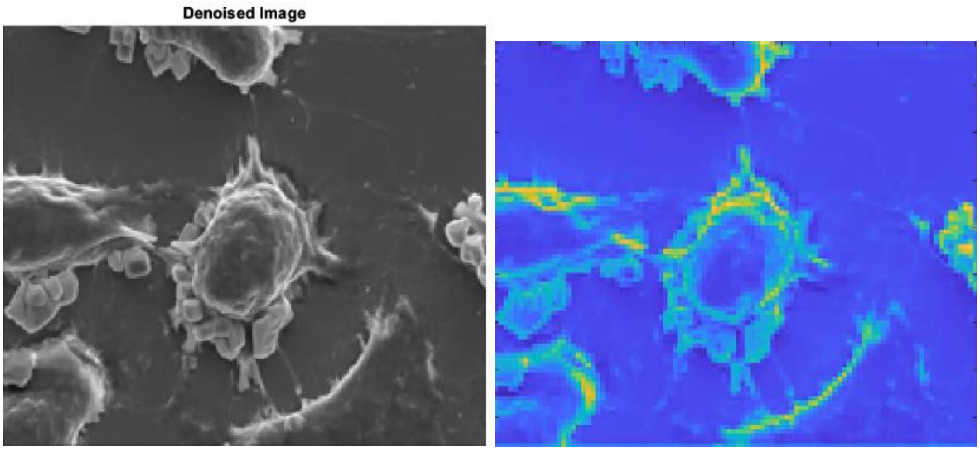

Figure 4. Denoised image of LOA-DNCNN for breast cancer detection

A denoised image refers to an image that has undergone a process to remove or reduce noise, which are unwanted variations in brightness or color that can occur during image acquisition or transmission. Noise can degrade the quality of images, making it harder to analyze or interpret them accurately. The process of

denoisingaims to enhance the visual quality of the image by removing these unwanted artifacts. Figure5.shows the regression of LOA-DNCNN for breast cancer detection.

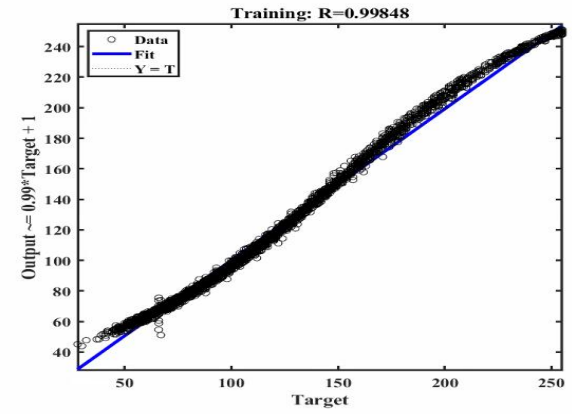

Figure 5. Regression of LOA-DNCNN for breast cancer detection

A scatter plot is a statistical plot that shows the connection between two continuous variables graphically. The pattern and intensity of the association between the variables are visualized using it. One variable (the independent variable) is represented on the x-axis and the other variable (the dependent variable) on the y-axis in a regression plot.The time series response of LOA-DNCNN for breast cancer detection is displayed in Figure 6. The error autocorrelation of LOA-DNCNN for breast cancer detection is displayed in Figure.7

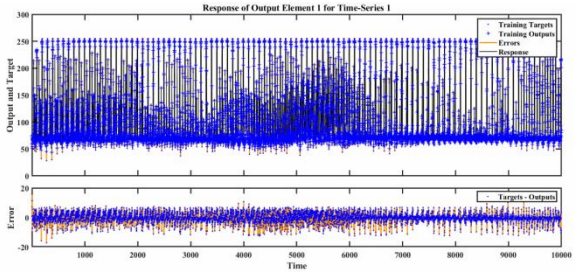

Figure 6. Time Series Response of LOA-DNCNN for breast cancer detection

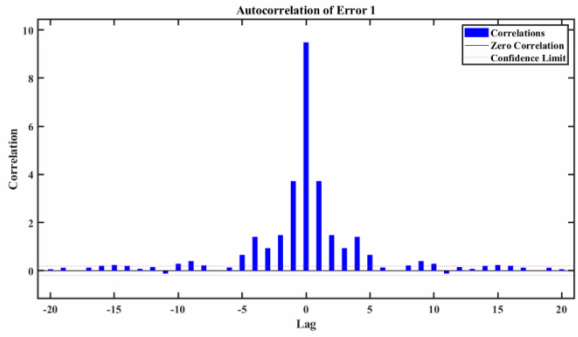

Figure 7. Error autocorrelation of LOA-DNCNN for breast cancer detection

Error autocorrelation, also known as residual autocorrelation or serial correlation, refers to the correlation between consecutive errors or residuals in a time series or regression analysis. In simpler terms, it measures whether the errors in a statistical model (or time series data) exhibit a pattern of correlation over time. Figure 8shows the of input-error cross-correlation of LOA-DNCNN for breast cancer detection.

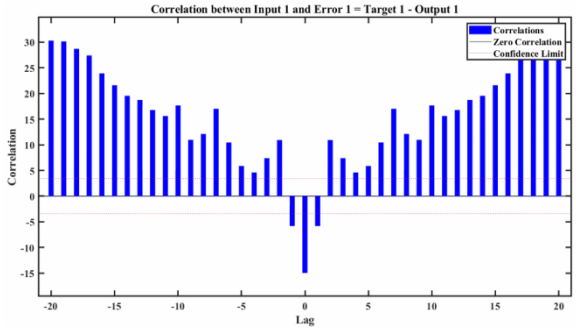

Figure 8. Input-Error Cross-Correlation of LOA-DNCNN for breast cancer detection.

6. Conclusion

From the limitations of conventional imaging methods, this study introduced the innovative Local Optimization Algorithm for Deep Convolutional Neural Networks technique, enhancing Scanning Electron Microscopy (SEM) images through perspective projection. This algorithm enabled early-stage cancer detection with remarkable accuracy, outperforming traditional methods both in terms of cost-effectiveness and precision. This technique not only provides a solution to the challenges faced in early cancer detection but also sets a new standard in the field. The collaborative optimization of molecular imaging and computational methodologies has the potential to transform cancer diagnosis globally, offering patients more accurate and timely interventions.

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