

Breast cancer detection via wavelet energy and feed-forward neural network trained by genetic algorithm

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Abstract

Enhancing the precision of breast cancer detection is the primary objective of this investigation, given its status as the most prevalent cancer among women worldwide. Timely identification of breast cancer can significantly improve the likelihood of successful diagnosis. To achieve the objective, an innovative approach is proposed that combines wavelet energy and a feedforward neural network. The method employs the genetic algorithm and undergoes 20 iterations of 10-fold cross-validation for robustness. By utilizing wavelet energy as a feature extractor and a feedforward neural network as the classifier, the method demonstrates superior performance compared to three alternative algorithms.

Keywords: breast cancer, wavelet energy, genetic algorithm

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1. Introduction

Breast cancer [1] is a fatal tumor occurring inside the breast tissue. Breast cancer remains the predominant type of invasive cancer that predominantly affects the female population, leading to a significant mortality rate of approximately 450,000 women worldwide each year [2]. The main clinical manifestations are breast mass [3], abnormal nipple areola, nipple discharge, axillary lymph node enlargement, etc. [4, 5]. Currently, the cause of breast cancer cannot be clearly determined, but researchers believe that the occurrence of breast cancer [6] is related to age, family history, long-term excessive use of exogenous estrogen and other factors [7, 8]. It enables early intervention and facilitates prompt access to appropriate medical care, leading to better prognosis and improved overall survival.

Clinical treatment of breast cancer has a variety of treatments [9], including surgical resection, radiotherapy, chemotherapy and so on [10]. Surgical resection and radiotherapy can achieve better results in local treatment, but for individuals diagnosed with advanced-stage breast cancer or distant metastasis, chemotherapy [11, 12] and biological therapy are needed to improve clinical efficacy. Before treatment, doctors can use bone scans, computed tomography (CT) [13, 14], magnetic resonance imaging (MRI) [15, 16], or

positron emission tomography (PET) [17] to reveal the location of the tumor.

Over the past few years, there has been a notable rise in the utilization of artificial intelligence (AI) in the realm of disease diagnosis [18-20]. They have made great achievements. Therefore, some researchers used artificial intelligence algorithms to detect breast cancer. In this study [21], an automated methodology using ensemble classifiers and feature weighting algorithms was proposed for the detection of breast cancer in mammography images. This study [22] utilizes computer-aided diagnosis (CAD) systems and a combination of preprocessing algorithms to improve the accuracy of mammography image interpretation and classification. Nguyen [23] employed Hu moment variant (HMI) approach to detect breast cancer. Rao [24] is the first approach to test Jaya algorithm in breast image classification. Pan [25] employed rank-based stochastic pooling to identify breast cancer image. The paper [26] introduces a 6L-CNN model serves as a binary classifier for rapid COVID-19 patient screening in chest CT images. This study [27] developed regression model through medical images to predict dental age, providing valuable insights for treatment planning according to personal dental development rather than real age.

In this research, a new method is introduced for breast cancer detection, combining the utilization of wavelet energy (WEN) and genetic algorithm (GA) to train a feedforward neural network. The proposed methodology leverages the effectiveness of WEN in extracting highly informative features, while harnessing the power of the widely employed feedforward neural network as a

robust classifier.

2. Dataset

In this research, the mini-MIAS is downloaded as the dataset [28]. The dataset used in this study comprises a total of 322 mammogram images, each with dimensions of 1024x1024 pixels. For the analysis, a random selection of 200 samples was made from the dataset, comprising 100 normal cases and 100 abnormal cases. The dataset presented in Figure 1 displays two representative samples that are included in our study.

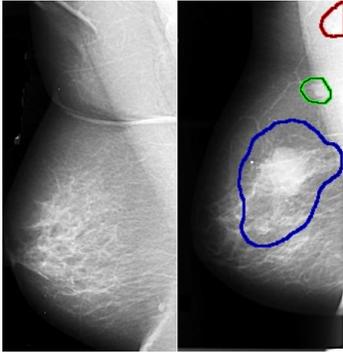


Figure 1. Two representative samples in the dataset

3. Methodology

Our method's implementation revolves around three integral components: WEN, a feedforward neural network, and the GA. Wavelet energy plays a pivotal role as a feature extractor [29, 30], extracting informative features from the breast cancer dataset. The feedforward neural network [31] serves as a robust classifier, leveraging its capability to effectively classify mammogram images as either normal or abnormal. The employment of the GA as a training algorithm harnesses its powerful global optimization capability. The integration of the wavelet energy and feedforward neural network components in our method aims to enhance the accuracy and efficiency of breast cancer detection. This combination of components forms the foundation of the approach, which strives to contribute to the early identification and improved prognosis of breast cancer cases.

3.1. Wavelet Energy

To extract comprehensive information from each binary image, the wavelet transform is employed, which allows us to obtain the wavelet coefficients of both the approximate sub-band and the detailed sub-bands at all levels of decomposition. The coefficients are used to calculate the WEN to extract the image features. At present, wavelet energy has become an instrument for successfully extracting features and has achieved good application in many fields.

The i -level horizontal, vertical and diagonal wavelet energy is defined as:

$$E_i^h = \sum_{x=1}^M \sum_{y=1}^N (H_i(x, y))^2 \quad (1.)$$

$$E_i^v = \sum_{x=1}^M \sum_{y=1}^N (V_i(x, y))^2 \quad (2.)$$

$$E_i^d = \sum_{x=1}^M \sum_{y=1}^N (D_i(x, y))^2 \quad (3.)$$

where E represents wavelet energy. These energies reflect the intensity of image detail in different directions at the i th wavelet decomposition level [32, 33]. In the methodology, employing a 3-level decomposition scheme, the ultimate extracted feature comprises the energy values derived from a total of 10 sub-bands. These sub-bands encompass a comprehensive representation of the image information. This multi-scale and multi-orientation analysis enhances the understanding of the image content, facilitating the extraction of relevant features for further analysis and interpretation. This comprehensive feature set derived from the wavelet coefficients captures essential spatial and frequency information, enabling a more robust and discriminative analysis of the mammogram images. In considering the energy values from these diverse sub-bands, our method enhances the ability to discern subtle patterns and irregularities that are indicative of potential breast cancer cases.

3.2. Feedforward Neural Network

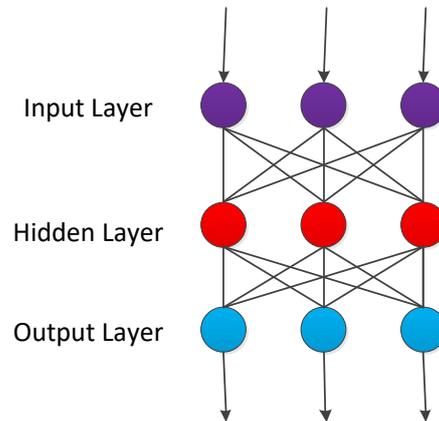


Figure 2. Architecture of the feedforward neural network

The calculated wavelet energy values discussed in Section 3.1 are utilized as inputs for the feedforward neural network, as shown in Figure 2, as presented in reference [34]. The input layer is accountable for unfolding features, the hidden layer is answerable for complex nonlinear transformation of data, and the output layer is responsible for summarizing features. All neurons in the next layer are connected to each neuron in the previous layer. The connection between the i th and j th neurons is characterized by the weight coefficient w_{ij} . The output values of x_i can be determined by equations (4) and (5) [35]:

$$x_i = f(\xi_i) \tag{4.}$$

$$\xi_i = \sum w_{ij}x_j \tag{5.}$$

where ξ_i is the potential of the i-th neuron and the function $f(\xi_i)$ is termed the transfer function [36, 37]. The relationship between ξ_i and $f(\xi_i)$ is defined as follows:

$$f(\xi_i) = \frac{1}{1 + \exp(-\xi_i)} \tag{6.}$$

The weight coefficient w_{ij} is adjusted by minimizing the squared differences between the calculated and desired output values. This process aims to minimize the objective function E , which can be calculated as:

$$E = \frac{1}{2}(x_n - x_{nac}) \tag{7.}$$

where x_n and x_{nac} are the calculated and required activities of the output neurons. We employ a back-propagation training algorithm [38, 39]. This algorithm facilitates the adjustment of the weight coefficients, as defined in formula (8) of our methodology.

$$w_{ij}^{k+1} = w_{ij}^k - \lambda \left(\frac{\partial E}{\partial w_{ij}} \right)^{(k)} \tag{8.}$$

where λ is the learning rate. The feedforward neural network [40, 41], after initialization with random weight values [42], undergoes an iterative process to optimize its performance [43].

While the information transmitted by the neurons can only be moved in the direction from input to output. There is no feedback between the layers, that is, the output of each layer does not affect other neurons in the same layer [44, 45]. In addition, the feedforward neural network possesses a straightforward architecture that has gained significant popularity and widespread adoption. This type of network demonstrates remarkable versatility.

3.3. Genetic Algorithm

The genetic algorithm [46], a renowned methodology in the realm of artificial intelligence and computer science [47], plays a crucial role as an adaptive global optimization search algorithm. It effectively computes optimal solutions to problems by simulating the genetic and evolutionary mechanisms observed in natural environments [48]. Through iterative processes, the algorithm leverages the principles of genetic inheritance, mutation, and selection to converge upon optimal outcomes.

The genetic algorithm encompasses three essential operators: selection, crossover, and mutation. These operators play crucial roles in the optimization process by selecting favorable individuals, combining their genetic information, and introducing variations to explore new solutions [49]. The fundamental concept behind the genetic algorithm lies in its iterative process of increasingly optimizing a hitch via the integration of gene crossover and mutation, ultimately leading to the discovery of the ideal solution. A graphical representation of the genetic algorithm's workflow can be observed in Figure 3.

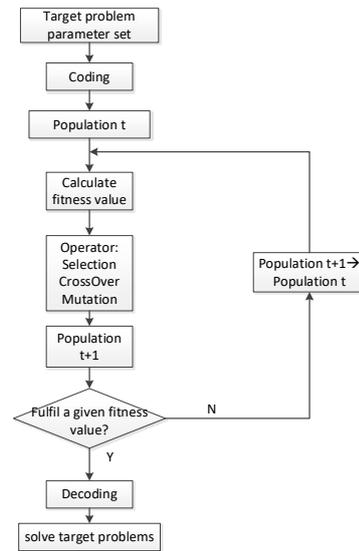


Figure 3. Genetic algorithm flow chart

Table 1 Pseudocode of GA

```

begin
t=0;
initialize P(t);
evaluate P(t);
while (Not fulfilling the fitness value) do
begin
t=t+1;
select P(t) from P(t-1);/* The selected P(t) has a higher fitness*/
recalculation P(t); /*Include Crossover and Mutation*/
evaluate P(t);
end;
end;
    
```

Different from the traditional optimization method, the genetic algorithm has the following advantages [50]: (1) The search target is a group of parameters, not a single parameter, so it has good parallelism. (2) Some scale, nonlinear and multi-peak optimal values can be solved by using objective function information. (3) The encoding of the parameter set is used, and the object function can be converted to the fitness of the code parameters, so the complexity can be reduced.

3.4. 10-fold Cross Validation

The 10-fold cross-validation technique represents a

robust approach to evaluate the accuracy and performance of models constructed using datasets [51]. This method involves dividing the dataset into ten equal-sized folds, where each fold takes turns acting as the validation set while the remaining nine folds to serve as a training set [52]. Through rotating the roles of the folds in an iterative manner, the effectiveness of the model in capturing underlying patterns and generalizing to unseen data can be assessed [53], as shown in Figure 4. Ensure the integrity and accuracy of the results, our experiment incorporates a rigorous approach by conducting 20 iterations. This averaging process provides a more reliable and representative measure of the model's performance, reducing the impact of any potential outliers or variability across individual cross-validation runs.

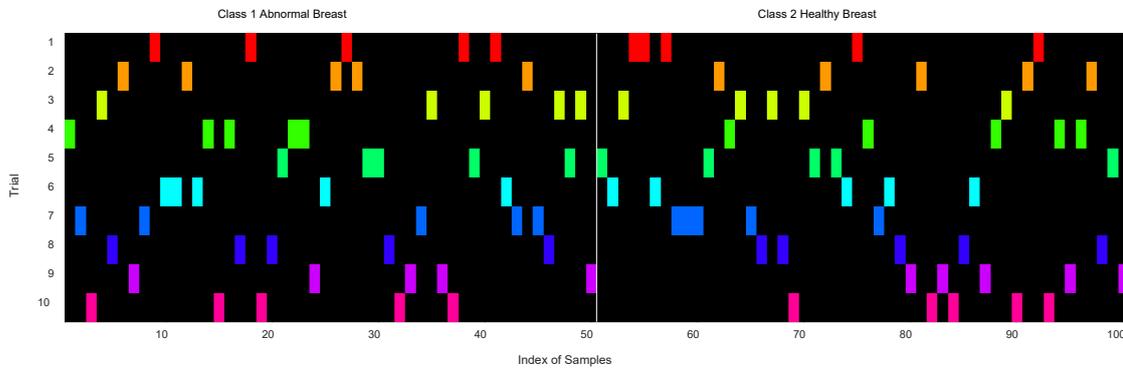


Figure 4. Illustration of one-run

While the performance of the classifier can be calculated based on sensitivity, specificity, precision, accuracy, F1-score and Matthews correlation coefficient, and these standard formulas can be achieved from the ratio of true positive(TP), true negative(TN), false positive(FP) and false negative(FN). The formula as follows:

$$\text{sensitivity} = \frac{TP}{TP + FN} \quad (9.)$$

$$\text{specificity} = \frac{TN}{FP + TN} \quad (10.)$$

$$\text{precision} = \frac{TP}{TP + FP} \quad (11.)$$

$$\text{accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (12.)$$

F1-score is defined as follow.

$$\text{F1-score} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{2TP}{2TP + FP + FN} \quad (13.)$$

Where

$$\text{recall} = \frac{TP}{TP + FN} \quad (14.)$$

Matthews correlation coefficient (MCC) is basically the correlation coefficient between the categories and predictions observed in the binary classification. It only returns a value in the range -1 to 1. Correlation coefficient 1 indicates a consistent prediction, and -1 indicates an inconsistent prediction [54].

$$\text{MCC} = \frac{TN \times TP - FN \times FP}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (15.)$$

4. Experiment results

4.1. Parameter Setting

After fine-tuning by trial-and-error method, we set the following parameters in Table 2. We use the Haar wavelet for wavelet transform and the fourth-level wavelet decomposition to get the WEN. A feedforward neural network is constructed with two hidden layers. The initial hidden layer comprises 25 neurons, while the second hidden layer consists of 10 neurons.

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The GA is employed with a crossover rate set at 0.8 and a mutation rate of 0.05.

Table 2 Parameter Setting

Parameter	Value
Wavelet	Haar
Wavelet decomposition levels	4
Number of hidden layers	2
Neurons in first hidden layer	25
Neurons in second hidden layer	10
Crossover rate	0.8
Mutation rate	0.05

4.2. Statistical Analysis

The proposed breast cancer detection method, named "WEN-FNN-GA," was implemented and evaluated through

an extensive experimental setup comprising 20 iterations of 10-fold cross-validation. For feature extraction from mammogram images, a four-level decomposition technique utilizing the Haar wavelet is adopted in this research. This approach allows for the extraction of informative features by decomposing the images into multiple scales, revealing detailed information at different levels of resolution. The obtained results are presented in Table 3, showcasing the performance of our method in terms of sensitivity, specificity, precision, accuracy, F1-score, and Matthews correlation coefficient. These six measures provide a comprehensive assessment of the method's ability to accurately classify breast cancer cases. We find a sensitivity of $83.35 \pm 2.13\%$, a specificity of $83.00 \pm 3.38\%$, a precision of $83.37 \pm 2.90\%$, an accuracy of $83.17 \pm 2.08\%$, an F1 and MCC are $83.10 \pm 1.99\%$ and 66.73 ± 4.17 respectively.

Table 3 Twenty runs of 10-fold cross validation

Run	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
1	82.00	88.00	87.42	85.00	84.38	70.46
2	84.00	86.00	85.86	85.00	84.37	70.77
3	83.00	77.00	78.41	80.00	80.56	60.24
4	85.00	82.00	82.73	83.50	83.81	67.09
5	83.00	81.00	82.20	82.00	82.03	64.79
6	79.00	80.00	79.78	79.50	79.37	59.03
7	85.00	83.00	84.19	84.00	84.28	68.53
8	85.00	84.00	84.88	84.50	84.71	69.39
9	81.00	85.00	84.53	83.00	82.49	66.38
10	81.00	84.00	83.37	82.50	82.01	65.21
11	84.00	78.00	78.99	81.00	81.00	62.76
12	82.00	82.00	82.68	82.00	81.84	64.67
13	89.00	83.00	84.32	86.00	86.52	72.25
14	84.00	81.00	81.55	82.50	82.59	65.33
15	81.00	85.00	84.66	83.00	82.45	66.46
16	86.00	89.00	88.67	87.50	87.26	75.11
17	83.00	88.00	87.49	85.50	85.03	71.30
18	82.00	80.00	80.41	81.00	81.13	62.12
19	84.00	86.00	85.90	85.00	84.64	70.48
20	84.00	78.00	79.32	81.00	81.52	62.25
Mean±SD	83.35± 2.13	83.00± 3.38	83.37± 2.90	83.17± 2.08	83.10± 1.99	66.73± 4.17

4.3. Optimal Structure of Neural Network

We set nine network configurations as below in Table 4. The nine network configurations can be divided into three groups. Each group consists of different numbers of neurons in the first hidden layer, namely 5, 15, and 25. The second hidden layer of each of the three neural networks in each group contains 5, 10, and 15 neurons respectively.

Table 4 Configuration of network structure setting

Setting	Neurons in first hidden layer	Neurons in second hidden layer
A	5	5
B	5	10
C	5	15

D	15	5
E	15	10
F	15	15
G	25	5
H	25	10
I	25	15

The performance of neural networks with different structures in the experiment is shown in Figure 5. We can observe that better performance can be obtained when the first and second hidden layers of the neural network contain 25 and 10 neurons respectively. To facilitate a convenient and intuitive comparison of the breast cancer detection methods, we have presented the comparison results graphically in Figure 5.

Table 5 Results of various setting

Setting	Sensitivity	Specificity	Precision	Accuracy	F1	MCC
A	79.40± 3.84	78.95± 3.15	79.39± 2.38	79.17± 2.09	79.18± 2.28	58.66± 4.23
B	78.90± 3.03	79.20± 2.29	79.24± 2.14	79.05± 1.91	78.92± 2.11	58.31± 3.90

C	79.50± 2.84	79.85± 2.80	80.14± 2.31	79.67± 1.69	79.63± 1.75	59.60± 3.40
D	80.60± 2.78	80.05± 2.65	80.43± 2.47	80.33± 2.10	80.33± 2.16	60.91± 4.31
E	80.45± 3.34	81.15± 2.87	81.46± 2.56	80.80± 2.10	80.72± 2.23	61.95± 4.31
F	81.70± 3.51	81.45± 2.71	81.93± 2.32	81.58± 2.13	81.50± 2.28	63.63± 4.33
G	81.70± 3.78	82.30± 1.49	82.48± 1.34	82.00± 1.89	81.80± 2.28	64.42± 3.75
H	83.35± 2.13	83.00± 3.38	83.37± 2.90	83.17± 2.08	83.10± 1.99	66.73± 4.17
I	81.50± 2.54	81.75± 3.25	82.31± 2.75	81.62± 1.87	81.61± 1.76	63.68± 3.78

(Bold means the best)

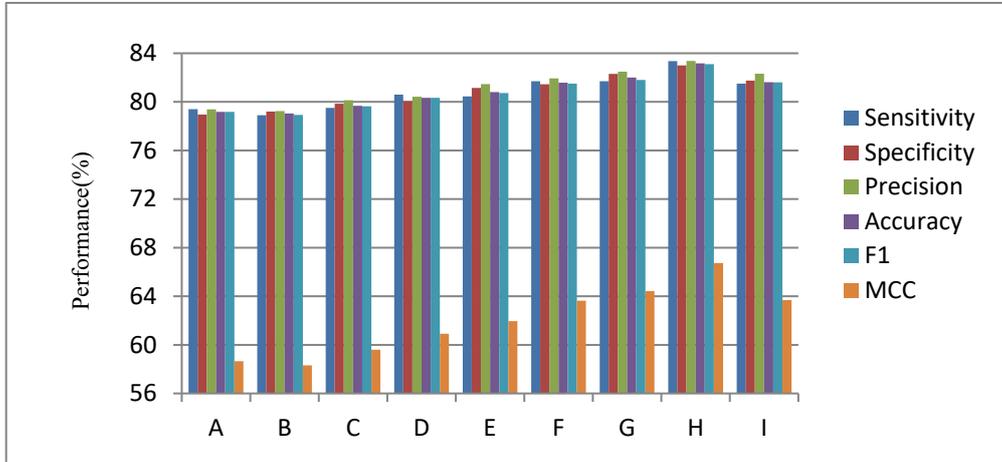


Figure 5. Comparison of structure of neural network

4.4. Comparison to State-of-the-Art Algorithms

We conducted a comprehensive comparison of our proposed method with three state-of-the-art approaches in the field of breast cancer detection: Hu moment invariant(HMI) approach[23], Support Vector Machine(SVM) Combined

with Principal Component Analysis(PCA) [55]and wavelet energy and support vector machine(SVM) [56]. The results are shown in Table 6 and Figure 6. From the point of view of accuracy, the values obtained by HMI [23], SVM+PCA [55], and WEN+SVM [56] are 73.50±1.35%, 82.85±2.21%, and 81.80±0.92% respectively. However, the accuracy of our method reaches 83.17±2.08%. Thus, it proves that our approach exceeds those three methods.

Table 6 Comparison with these State-of-the-art approaches

Approach	Sensitivity	Specificity	Precision	Accuracy
HMI [23]	73.20±2.86	73.80±4.26	n/a	73.50±1.35
SVM+PCA [55]	83.10±1.91	82.60±4.50	n/a	82.85±2.21
WEN+SVM [56]	82.60±3.78	81.00±3.16	n/a	81.80±0.92
WEN+FNN+GA (Ours)	83.35± 2.13	83.00± 3.38	83.37± 2.90	83.17± 2.08

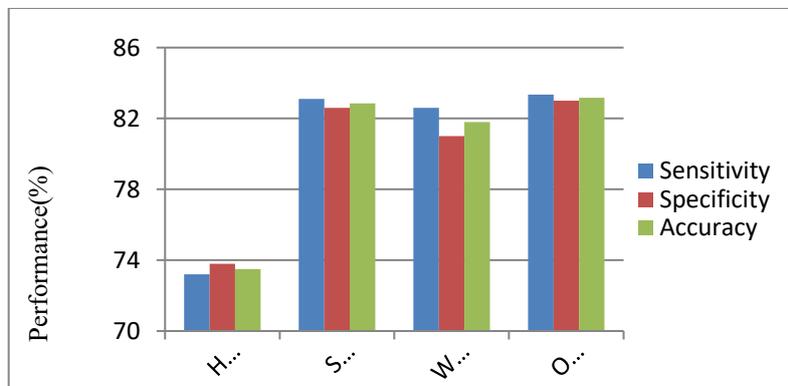


Figure 6. Comparison to State-of-the-art approaches

5. CONCLUSION

In conclusion, this study presents a novel approach using wavelet energy, feedforward neural network, and GA. The proposed method aims to improve accuracy and efficiency, particularly in early diagnosis. Experimental results support the effectiveness of the approach, outperforming existing techniques in terms of many metrics. The proposed approach holds great potential for improving patient outcomes and advancing healthcare practices. Furthermore, integrating other imaging modalities and data sources, such as molecular markers or genetic information, could enhance the overall diagnostic capability. Fusion of multiple modalities and data types may provide a more comprehensive understanding of breast cancer and improve the accuracy of detection.

Future research in breast cancer detection should focus on integrating multiple imaging modalities, exploring advanced deep learning architectures. Integration of additional imaging techniques such as ultrasound or MRI can improve detection accuracy. Advanced deep learning models offer potential for enhanced performance. Large-scale validation studies are needed to evaluate the effectiveness of proposed methods. Interpretability of the models should be improved to gain trust from clinicians. Moreover, conducting validation in real-world clinical settings is essential for practical implementation. Continual learning approaches can enable the system to adapt to evolving patterns.

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