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A Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks with Dandelion Optimizer Model for Breast Cancer Detection Using Histopathological Image

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Abstract

Breast cancer is one of the common and life-threatening disorders in the world, as it requires proper and timely diagnosis to enhance the survival of the patient. Conventional diagnostic tools tend to be unable to evaluate high-dimensional histopathological image data, and the data is misclassified, which can lead to delayed treatment. To overcome this, the Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks with Dandelion Optimizer (QM-SS-HP-GNN-DO) is suggested to provide effective breast cancer diagnosis. To begin with, the images obtained and used in histopathology are gathered and preprocessed by Trainable Self-Guided Filtering (T-SGF) to improve the features of interest included in the BreakHis dataset. QM-SS-HP-GNN model subsequently provides classification, and Dandelion Optimizer (DO) optimizes the network weights to enhance the accuracy of the network. Experimental performance is better with an accuracy of 99.43%, precision of 99.10%, sensitivity of 99.05%, specificity of 99.20%, and F1-score of 99.08%, showing the best results compared to existing models. Overall, the suggested model offers a well-constructed, stable, and extremely precise framework of breast cancer diagnosis, and can be adapted to other medical image-based disease detection problems.

Keywords: *Breast cancer, Histopathological images, Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks, Dandelion Optimizer, Trainable Self-Guided Filtering.*

1. INTRODUCTION

Among women all over the world, breast cancer is one of the major causes of death Miguel J. et al, (2023). The factors contributing to its occurrence are genetic, including BRCA1 and BRCA2 mutations, and non-genetic, including age, obesity, alcohol use, and a short duration of breastfeeding. The usual symptoms are breast lumps, swelling, pain, and abnormal discharge of the nipples Al-Jabbar et al, (2023). Early detection is a great way to increase the survival rates. Conventional screening procedures, which include Breast Self-Examination (BSE), Clinical Breast Examination (CBE), mammography, MRI, ultrasound, thermography, and breast-specific gamma imaging, have been used extensively Karuppasamy, A. et al, (2024). Sophisticated methods such as microwave breast imaging and focused microwave breast hyperthermia (FMBH) offer low cost, minimally invasive detection. Nevertheless, manual interpretation of complex imaging data is time-consuming, likely to be subject to human error, and involves specialized

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expertise, underscoring the necessity of automated diagnostic solutions Srikantamurthy, M.M. et al, (2023).

The detection of breast cancer based on manual interpretation of the histopathological and imaging information is a difficult task because the morphology of tumours is very complex and variable Parshionikar, S et al, (2024). Conventional approaches require high levels of expertise, and as patients keep producing more data, this may be overwhelming to medical practitioners, resulting in a diagnosis of the wrong patient or the failure to treat him/her promptly. Machine learning methods demand manual extraction of features, which is labor-intensive and cannot always extract high-dimensional, subtle patterns found in histopathological images Ahmed, M. et al, (2023). In addition, traditional diagnostic measures might fail to provide a high degree of accuracy in detecting the disease at an early stage. These shortcomings cause an urgent demand to develop automated, accurate, and efficient systems of breast cancer detection that would process high volumes in a limited amount of time, decrease human error, and aid the clinician in the early diagnosis of a patient to enhance patient outcomes Joshi, S.A. et al, (2023).

This research is motivated by the fact that there is an urgent need to improve early identification of breast cancer and reduce the degree of human error and diagnostic lag. Independent of inheriting previous machine learning models, deep learning methods, especially convolutional neural networks (CNNs), have demonstrated impressive capabilities of automatically extracting useful features from complex histopathological images. Through these advanced computing techniques, one can come up with precise, dependable, and quick breast cancer detection systems. In this paper, a deep learning-based model is proposed to classify breast cancer.

Novelty and Contributions

- The study introduces a new Quantum Mixed-State Self-Harnessing Physics-Guided Neural Network with the Dandelion Optimizer (QM-SS-HP-GNN-DO) to improve breast cancer classification using histopathological images.
- To enhance spatial consistency, reduce noise, and retain diagnostically important tissue structures, a trainable Self-Guided Filtering (T-SGF) is added as an adaptive preprocessing step.
- A quantum mixed-state attention mechanism is used to model complex and subtle feature relations within histopathological patterns.
- Physics-guided self-harnessing constraints are incorporated into the learning process to stabilize feature evolution and enhance model robustness.
- The Dandelion Optimizer is used to optimize the weight to strike a balance between exploration and exploitation to achieve faster convergence and better classification.

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In Section 2, the pertinent literature is thoroughly evaluated. The methods employed in this study are explained in detail in Section 3. The result and its ramifications are covered in Section 4. Section 5 contains personal observations and suggestions for further study.

2. LITERATURE SURVEY

In 2023, Toma et al. examined the efficacy of deep learning-based systems with transfer learning in detecting breast cancer in histopathological images. CNNs were also trained on different image processing tools to identify patterns of features and then transferred to different architectures like ResNet, ResNeXt, SENet, Dual Path Net, DenseNet, NASNet, and Wide ResNet. The method allowed detection of cancer with high accuracy levels, which helped in the early diagnosis and treatment. The use of pre-trained networks was one of the limitations because they might not be able to find all domain-specific features.

In 2023, Kausar et al. developed a rapid breast cancer (BC) detector based on AI-powered lightweight deep CNNs. The decomposition of histopathological images (HIS) was initially performed using a wavelet transform (WT) to retrieve frequency bands, and the low-frequency images were only processed using a CNN, which consisted of invertible residual blocks. The method minimized computational expenses and memory consumption and had high accuracy. Analysis of the effects of the classifiers was done. One weakness was that the WT filtering may result in poor performance when filtering high-frequency image details.

In 2025, Chikkala et al. suggested a multi-class breast cancer (BC) classification algorithm based on Bidirectional Recurrent Neural Networks (BRNN). This model has used transfer learning with a CNN-based ResNet50 backbone, Gated Recurrent Unit (GRU), residual collaborative branch, and feature fusion module. A mechanism of attention took advantage of feature representation, whereas the residual branch obtained certain pathological features. This strategy was highly classified and thus improved diagnosis and treatment planning. One of the weaknesses was that it expanded the model complexity, and therefore, it might be costly to train and infer using large computational resources.

In 2023, Maleki et al. suggested a workflow to increase the accuracy and speed of histopathological image classification with transfer learning. A set of six pretrained networks was tested to extract features, which were used as inputs in extreme gradient boosting (XGBoost) to classify. As a feature extractor, DenseNet201 was chosen and paired with XGBoost as the ultimate classifier. The method enhanced classification accuracy and efficiency at the levels of magnification. One weakness was that it used pre-trained networks that might not give complete domain-specific image properties.

2.1 Problem Statement

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Detection of breast cancer in histopathological images has been a major challenge because of the intricacy and variability of tumor structures. Manual analysis is labor-intensive, time-consuming, and subject to human error, particularly when the patient data is increasing, which may result in misdiagnosis or delay of treatment. Conventional machine learning methods demand that features be extracted manually, and this might fail to reveal fine patterns that are important in early detection. Furthermore, current diagnostic procedures are not accurate enough to have confident classification of malignant and benign tissues. This indicates the urgency of automated, accurate, and efficient deep learning-based systems to assist clinicians in diagnosing breast cancer in a timely and accurate manner.

3. PROPOSED METHODOLOGY

In this study, Quantum Mixed-State Self-Harnessing Physics-guided Neural Networks with Dandelion Optimizer (QM-SS-HP-GNN-DO) are proposed in the context of breast cancer classification. To begin with, the histopathological images are obtained using the BreakHis dataset that offers supervised breast tissue samples. T-SGF is then used to preprocess the obtained images to reduce noise, promote lateral consistency, and sharpen diagnostic-relevant structural features. Then, the discriminating features are identified and trained on the Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks (QM-SS-HP-GNN) that incorporates quantum-inspired attention and physics-guided constraints to learn robustly. Lastly, the Dandelion Optimizer (DO) is used to optimize the network weights, which guarantees successful convergence and accuracy of classification. The proposed architecture is described in Figure 1.

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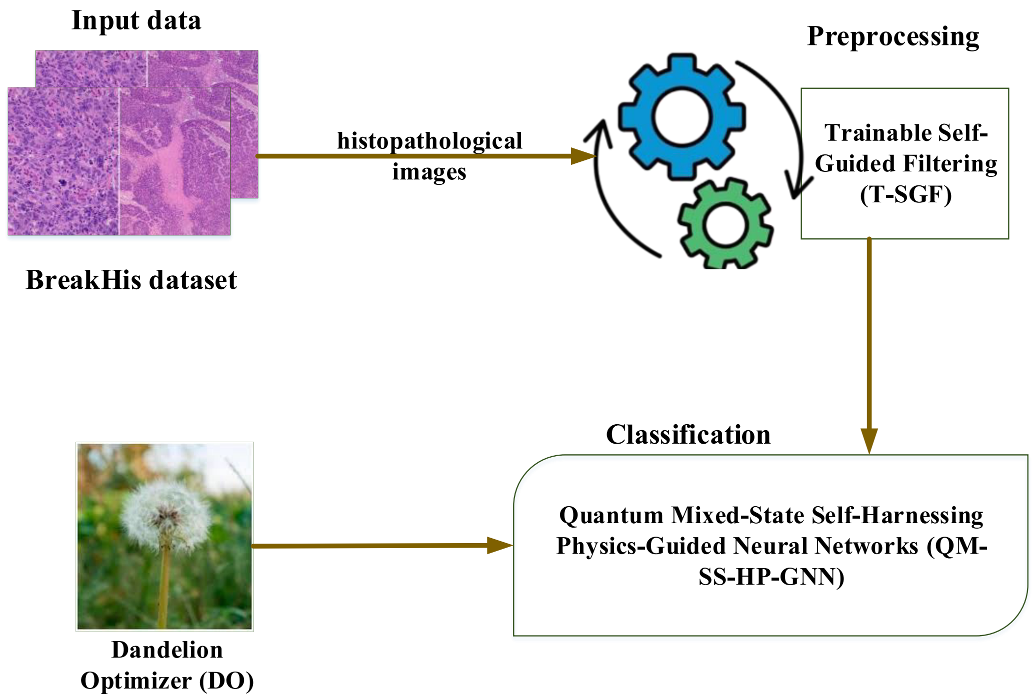

Figure 1. Proposed QM-SS-HP-GNN-DO Architecture

3.1 Data Collection

Firstly, histopathological images are sourced from the BreakHis dataset, which comprises images from different patients with breast cancer. The images acquired are diverse, comprising different cancer subtypes as well as normal tissue, all taken at varying levels of magnification, which enables intricate detail to be noted. All images are then processed.

3.2 Preprocessing using Trainable Self-Guided Filtering (T-SGF)

The image preprocessing to refine focus maps and improve spatial consistency in images is done using the T-SGF Karacan, L. et al, (2023) method. In guided filtering, a local linear model with respect to a guidance image J_j is utilized to compute the output r_j for each pixel described in equation (1).

$$r_j = b_l J_j + c_l, \qquad \forall j \in x_l \tag{1}$$

where, x_l is a local square window of radius s, J_j is a position of the pixel within x_l, b_l and c_l represent linear coefficients, and r_j is the filtered output for pixel j. The coefficients are computed as the solution of a least squares minimization problem, as given in equation (2).

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$$\min_{b_l, c_l} \sum_{j \in x_l} \left(q_j - \left(b_l J_j + c_l \right) \right)^2 + \lambda b_l^2 \tag{2}$$

Here, q_j is the input image pixel value, and λ is a regularization parameter that controls smoothness. After computing b_l and c_l for each window using a linear regression solver, the final filtered output is obtained as equation (3).

$$r_j = \bar{b}_j J_j + \bar{c}_j \tag{3}$$

where, $\bar{b}_j$ and $\bar{c}_j$ are the mean coefficients in the window surrounding pixel j. The T-SGF layer is trainable and integrated within the network, therefore model learns the optimal coefficients b_l and c_l during training. The intermediate focus map $\overline{G}$ acts as both input and guidance and is projected to a task-specific guidance map through a convolutional network block. Ensuring the spatially consistent focus map prediction, noise reduction, and refinement of boundaries. Further, the preprocessed images obtained using T-SGF are fed for classification, enhancing the accuracy and reliability of the classification model.

3.3 Classification using Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks (QM-SS-HP-GNN)

Quantum Mixed-State Self-Harnessing Physics Guided Neural Networks (QM-SS-HP-GNNs) Chen, F. et al, (2025), Hettige, K.H. et al, (2024) are applied for breast cancer diagnosis in histopathological images. In the proposed method, quantum mixed-state self-attention is combined with physics-guided learning. This combines the strength of the self-attention mechanism with the capability to learn complex feature interdependencies and ensure structured feature behavior. Classical image features are embedded in quantum states, where quantum attention is utilized for image similarity, with the help of physics-guided learning.

In the quantum mixed-state self-attention module, the similarity between the query representation and the key representation is calculated based on mixed quantum states. The attention weight between the t^{th} query and the k^{th} key can be calculated using equation (4).

$$\alpha_{t,k} = us\left(\rho_{t,r} \sigma_{k,l} \right) \tag{4}$$

Here, $\rho_{t,r}$ is referred to as the mixed state of the t^{th} query, $\sigma_{k,l}$ is denoted as the mixed state of the k^{th} query, $\alpha_{t,k}$ is the attention coefficient, and us is the trace operation, which calculates the overlap

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between two mixed states. The main reason for using this is that a mixed state contains more information than a pure state. The overlap is calculated with a probability for the state $|0\rangle$ given by equation (5) for the auxiliary bit.

$$q(|0\rangle) = \frac{1}{2} + \frac{1}{2} us(\rho_{t,r} \sigma_{k,l}) \tag{5}$$

In this case, the function $q(|0\rangle)$ symbolizes the probability and represents the direct measurement of similarity between the query and key states, used for weighing value features in the classification.

Physics-informed learning is used to guide the evolution of features according to continuation principles. The conservation of features through time is written as equation (6).

$$\frac{\partial A}{\partial u} + div\vec{G} = 0 \tag{6}$$

In which, A is the concentration of the characteristics based on histological images, $\vec{G}$ is the flux of characteristics expression characteristic transport, u is the time or depth in the network, while the div operator calculates the characteristic flux. The diffusion characteristics transmission is expressed using equation (7).

$$\frac{\partial A}{\partial u} = l\, div(\nabla A) \tag{7}$$

where, l is the diffusion coefficient that regulates the rate at which the smoothing occurs. The gradients of the concentration of the features are given by ∇A. Directional transport for the features is modeled by advection as given in equation (8).

$$\frac{\partial A}{\partial u} = -div(\vec{w}A) \tag{8}$$

Here, $\vec{w}$ represents the feature propagation speed. Such constraints lead to stability and further enable support for the accurate classification of breast cancer. In the QM-SS-HP-GNN model, combine the quantum mixed-state attention and physics-informed constraints to tackle the challenge of improving the quality of breast cancer classifications. There is quantum similarity learning to deal with complex histopathological representations, and formulations that are physically inspired to guarantee the stability of the evolution of features. Finally, the QM-SS-HP-GNN network parameters are tuned with the Dandelion Optimizer method.

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3.4 Dandelion Optimizer (DO)

The objective of the Dandelion Optimizer (DO) Zhao, S. et al, (2022) in the present work is to optimize the solution space in the QM-SS-HP-GNN weights. This is inspired by the dispersal mechanism of dandelion seeds. The DO optimizes the weights of the QM-SS-HP-GNN by simulating the behavior of how dandelion seeds spread. During the optimization, each dandelion seed corresponds to a possible set of weights for the QM-SS-HP-GNN, with the balance between global search and local search helping in its optimization.

Firstly, a set of weight vectors is randomly initialized within the pre-defined lower and upper limits. This helps create diversity in the searching space. The initialization formula for the QM-SS-HP-GNN weights is represented by equation (9).

$$\alpha_j = rand \times (upb - lob) + lob \quad (9).$$

where, α_j indicates the j^{th} candidate weight vector, upb and lob denote the upper and lower bounds of the weight vector, respectively, and $rand$ indicates a random variable between 0 and 1.

Following initialization, the fitness of each candidate solution is assessed based on the classification of the QM-SS-HP-GNN. This is achieved using the fitness function, which is expressed by equation (10).

$$fitness = \min(QM - SS - HP - GNN(\alpha)) \quad (10).$$

Here, α is the weight vector of QM-SS-HP-GNN. The fitness function is minimized by ensuring that the optimal weights for models are selected.

The fittest solution is then selected, which is referred to as the elite solution, and is used to guide the process of updating the weight vectors by taking into account the fitness values.

The adaptive weight update process is described by equation (11).

$$\alpha^{T+1} = \alpha_{elite} + levy(\lambda) \bullet \eta \bullet (\alpha_{elite} - \alpha^T \bullet \delta) \quad (11).$$

where α^T and α^{T+1} are the current and updated weight vectors, α_{elite} is the best weight vector, η is the adaptive step size, δ is the regulator for the exploitation level, and $levy(\lambda)$ is a stochastic process that promotes exploration.

During the optimization, the process involving both evaluation of the fitness function and update of the weight repeats until either the maximum number of iterations is achieved or there is little change in

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the value of the fitness function, thus obtaining convergence for an optimal weight setting on the QM-SS-HP-GNN.

4. Results

This part presents the experimental analysis of the proposed QM-SS-HP-GNN-DO model in breast cancer classification based on histopathological images. It is actually done in Python 3.9, with TensorFlow and Keras, and data processing and evaluation are done using NumPy, Pandas, and Scikit-learn. The experiments are performed under a 64-bit Windows operating system, Intel Core i7 processor (2.8 GHz), 16 GB RAM, and a 4 GB graphics card. BreakHis dataset is used to perform performance analysis. Table 1 summarizes the simulation settings of the main simulation settings.

Table 1. Simulation Parameters

Parameter	Description
Operating System	Windows 64-bit
Dataset	BreakHis
Data Type	Histopathological Images
Proposed Model	QM-SS-HP-GNN
Optimizer	Dandelion Optimizer (DO)
Epochs	100

4.1 Dataset Description

BreakHis dataset https://www.kaggle.com/datasets/ambarish/breakhis: This data set contains the histopathology images of the breast, both normal and malignant tissue regions, and was captured with contrast enhancement. It has 6327 training images and 1582 test images, including multiple types of cancer. The dataset is extensively employed to classify and segment breast cancer, which allows distinguishing between normal and cancerous areas. To evaluate the model, take 80% of the images to train the models and the remaining 20% to test generalization.

4.2 Performance Evaluation

In order to assess the effectiveness of the proposed model of QM-SS-HP-GNN-DO for the classification of breast cancer, it is implemented in the BreakHis dataset and compared with the existing models, i.e., ResNet Toma, T.A. et al, (2023), CNN Kausar, T. et al, (2023), BRNN Chikkala, R.B. et al, (2025), and XGBoost Maleki, A. et al, (2023). Various measurements are used to evaluate the performance, and they include accuracy, precision, sensitivity, specificity, F1-score, and error rate. The findings show that the proposed model is better in comparison to all other methods as it exhibits increased accuracy and balanced precision to all other measures, which means that it is robust and reliable in the accurate classification of breast cancer histopathological images.

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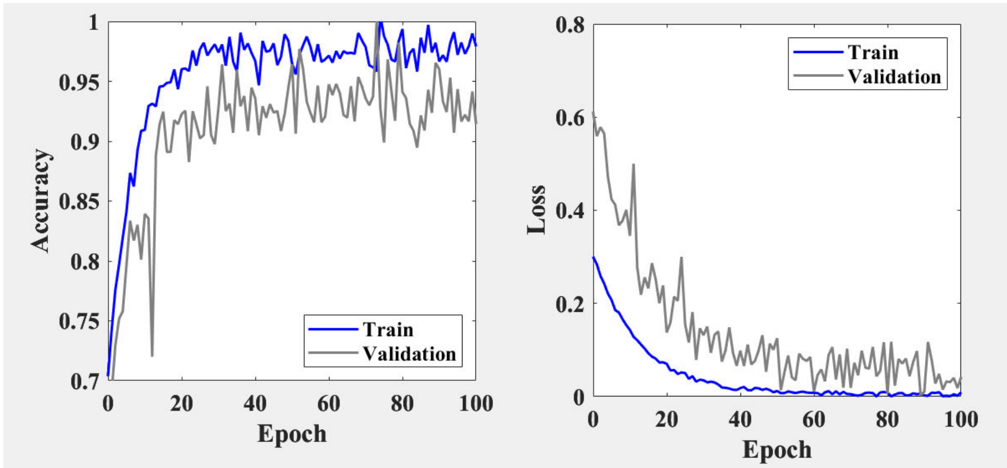

Figure 2. Training and Validation Performance of QM-SS-HP-GNN-DO

Figure 2 presents the training and validation accuracy of the proposed QM-SS-HP-GNN-DO model across 100 epochs. The training accuracy also gradually rises above 0.99, and the validation accuracy also rises and stabilizes at 0.95, which means proper learning and low levels of overfitting. The second plot depicts the respective loss curves, and both training and validation losses reduce steadily, with the training loss coming close to near zero and validation loss settling at a low value, indicating convergence and strong optimization of the model.

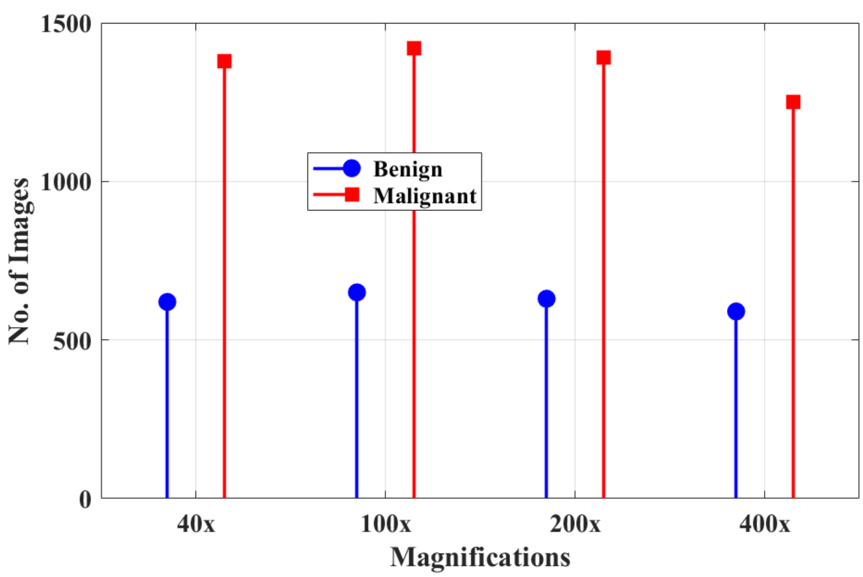

Figure 3. Distribution of Benign and Malignant Images at Different Magnifications

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Figure 3 shows the presence of benign and malignant histopathological images using four magnifications, namely, 40x, 100x, 200x, and 400x. The number of malignant images is also higher in all magnifications, but benign images are only significantly constant. This distribution underscores the disparity in the dataset and the necessity to be able to preprocess it well and train the model effectively in order to guarantee accurate classification.

Table 2. Performance Comparison of Existing Models and Proposed QM-SS-HP-GNN-DO

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	Error Rate (%)
ResNet Toma, T.A. et al, (2023)	92.15	91.50	91.20	91.80	91.30	7.85
CNN Kausar, T. et al, (2023)	90.80	90.10	89.90	90.00	90.00	9.20
BRNN Chikkala, R.B. et al, (2025)	91.50	91.00	90.80	91.10	90.90	8.50
XGBoost Maleki, A. et al, (2023)	93.20	92.80	92.50	92.90	92.65	6.80
Proposed QM-SS-HP-GNN-DO	99.43	99.10	99.05	99.20	99.08	0.57

Table 2 compares the performance of current models, including ResNet, CNN, BRNN, and XGBoost, with the proposed QM-SS-HP-GNN-DO model of breast cancer classification based on histopathological images. The proposed model has the best accuracy of 99.43, which is better than all other methods. The precision, sensitivity, specificity, and F1-score are slightly less than accuracy but are still above 99, which reflects balanced and robust performance in various evaluation measures. Only 0.57% is the error rate of the proposed model, which is much lower than that of the other models and indicates its high prediction ability and resistance to classifying breast cancer images.

5. CONCLUSION

The proposed QM-SS-HP-GNN-DO model performs exceptionally well in the classification of breast cancer based on histopathological images with an accuracy of 99.43, precision of 99.10, sensitivity of 99.05, specificity of 99.20, and an F1-score of 99.08. The combination of the Quantum Mixed-State Self-Harnessing Physics-Guided Neural Networks and the Dandelion Optimizer successfully reproduces the difficult patterns in the BreakHis dataset, promising trustworthy diagnostics. The main benefits of the model are high performance, effective weight optimization with DO, and high-dimensional data handling.

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The complex architecture will limit it by increasing computational requirements and training time. To apply the model to future work, it can be extended to multi-modal medical datasets to be able to diagnose cancer comprehensively and converted into lightweight versions to enhance computational efficiency, which would allow real-time implementation in clinical devices. These improvements may be used to extend its usefulness and enable quicker and more precise detection of breast cancer in real-world medical settings.

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