

A Quantum-Inspired Deep Learning Framework with RL-Based Pretraining for Breast Cancer Classification

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Abstract

Breast cancer classification is one of the most imperative areas that may lead to early diagnosis and reduce mortality rates. Classical machine learning methods (Logistic Regression, Random Forests, and SVM) provide useful predictive performance but struggle to fully capture complex nonlinear interactions in biomedical data. This paper proposes a Quantum-Inspired Residual Deep Q-Network (QNet) that combines reinforcement learning pretraining with supervised fine-tuning using the Breast Cancer Wisconsin dataset. The model leverages residual blocks, layer normalization, and activation-based quantum-analog metrics to improve the quality of the representations and stability of learning. Experimental results demonstrate that the proposed QNet achieves higher accuracy, robustness, and ROC-AUC performance compared to the classical models; besides, it allows for deeper interpretability by means of activation metrics, PCA feature visualization, and partial dependence analysis. These findings confirm the role that quantum-inspired neural architectures might play in providing an effective and scalable framework for real-time diagnosis in medicine and clinical decision support.

Keywords: Breast Cancer Classification; Quantum-Inspired Neural Network; Reinforcement Learning; Deep Q-Network (DQN); Residual Network.

1. Introduction

Among women worldwide, breast cancer ranks high on the list of causes of mortality. So far, the only sensible way to improve the survival rate and treatment outcomes of such patients has been early detection of the disease [1]. Accurate and timely diagnosis improves the chances of successful therapeutic interventions while reducing the possibility of disease progression [2]. However, even with the availability of techniques for medical imaging and clinical diagnostic tests, conventional examinations and laboratory procedures have remained time-consuming [3], expensive [4], and prone to errors in human interpretation, particularly in large-scale clinical environments [5] [6]. These deficiencies indicate a serious need for automated, precise, and scalable diagnostic systems that can support early decision-making and enhance clinical efficiency [7] [8].

For medical diagnosis, especially for cancer, AI has brought tremendous capabilities, either through machine learning or deep learning approaches [9]. Classic machine learning algorithms, like Logistic Regression, Random Forest, and SVM, show quite good performance in biomedical data analysis, but they rely greatly on hand-engineered features with limited ability to capture sophisticated nonlinear patterns in clinical datasets [10]. In addition, these models often perform sub optimally while tackling the imbalanced distribution of classes, noise, and intricate feature interactions intrinsic to a lot of medical datasets [11] [12].

Deep learning architectures, ranging from CNNs and ANNs to hybrid methods, have been able to enhance the diagnostic accuracy by automatically learning higher-level features [13]. However, these architectures may have some serious drawbacks due to the high computational complexity [14], a lack of interpretability, and potential complications related to the convergence, scalability, and generalization in real-world clinical usages [15]. Newer developments such as residual networks [16], ensemble deep neural frameworks, and attention-based deep models have achieved further improvement in

predictive performance but remain highly computationally intensive and inadequate for decision-making under robust clinical conditions [17] [18].

This work overcomes these limitations by proposing an RL-enhanced QNet for the classification of breast cancer [19]. The proposed model leverages quantum-inspired concepts such as superposition-based activation behavior and residual feature mapping in order to enhance learning stability and deeper representation of complex patterns [20] [21]. Besides, a reinforcement-learning-based pretraining mechanism optimizes decision boundaries, improves convergence, and effectively handles noisy and imbalanced datasets [22]. Compared to the classical machine learning models, the proposed RL-enhanced QNet demonstrates improved classification accuracy, robustness, interpretability, and scalability for real-time clinical deployment [23].

The main objectives of this work are as follows:

1. The design and implementation of a Quantum-Inspired Residual Deep Q-network have been done for accurate and reliable breast cancer detection.
2. To compare the performance of QNet with traditional models like Logistic Regression, Random Forest, and SVM.
3. It assesses the system using standard metrics that include accuracy, precision, recall, F1-score, entropy loss, classification report, ROC-AUC, and confusion matrix.
4. To analyze the interpretability of models using visualization techniques consisting of PCA feature transformation and activation-based residual analysis.
5. To assess QNet's computational efficiency, scalability, and real-time applicability for a clinical diagnostics environment.

The rest of the paper is organized as follows: Section 2 discusses related literature in the diagnosis methods of breast cancer; Section 3 describes the dataset, preprocessing methods, and architecture of the proposed QNet model; Section 4 discusses the experimental setup and performance evaluation; and Section 5 presents the conclusion of the study through key findings, limitations, and possible future research directions.

2. Literature Survey

While RL has been able to perform well in complex sequential decision-making environments, traditional RL usually suffers from slow convergence, poor scalability, and high computational cost in solving high-dimensional problems [24]. In an effort to overcome these limitations, the latest works focused on integrating principles of quantum computing [25], such as superposition [26], entanglement [27], and variational quantum circuits in developing QRL models. Such development aims at enhancing efficiency, resource utilization, and robustness in learning [28]. Despite the potential, quantum hardware limitations, sensitivity to noise, and scaling difficulties to real systems remain open issues [29].

Masaaki Kondo and Shaswot Shresthamali 2025 [3] fully reformulated Markov Decision Processes into a quantum model and leveraged Grover's [2] search to track down the optimal trajectories, offering faster convergence at the cost of a large amount of qubits required and prior reward knowledge. Carlo Ciliberto and Alessandro Davide Ialongo 2025 [4] reviewed quantum ML models; good learning performance was obtained compared to classical models, but real validation in real-world problems was not enough, as well as encoding data into orthonormal quantum states [30]. Haixu Yu and Chunlin Chen 2025 [5] proposed quantum-inspired exploration mechanisms that enhanced stability in RL but were tested only on narrow problem domains. Similarly, Aramchehr Zare [6] and Mehrdad Boroushaki 2025 [7] showed stronger robustness and faster learning using Quantum DQN, though the performance depended heavily on the quantum circuit design [31].

Other contributions are those made by Roopa Ravish et al. in 2024 [8], who proposed VQC for use in gym environments and reduced the number of parameters, enhancing efficiency; however, it failed on tasks where complexity was higher. Joaquim Gaspar [32] and Alexandre Bergerault (2024) [9] then proposed QOPS, which could find an optimal policy to solve strategic games, but real-world deployment remains restricted because of hardware issues [33]. Jawaher Kaldari et al. (2025) [10] presented a comprehensive survey on QRL architectures and tools wherein hardware and lack of benchmarking were found to be dominant barriers. Redwan Ahmed Rizvee et al. in 2024 [11] used reinforcement learning with QUBO-Hamiltonian

reward in graph optimization problems and enhanced constraint satisfaction; however, it faced severe challenges in the case of dense graphs [34].

Other works, such as by Abhishek Sadhu et al. (2024, 2025) [19], optimize quantum ansatz structures using RL strategies, which indeed improve entanglement control but at the cost of high initial complexity and scalable constraints. Akash Sinha et al. (2025) [12] implemented a hybrid actor-critic RL model with a quantum critic for self-driving navigation tasks. While it improved stability, its performance degraded under quantum noise [35].

Overall, these studies have focused on the value of quantum-enhanced reinforcement learning with respect to improving convergence speed, robustness, model efficiency, and scalability [36]. However, persistent limitations include hardware immaturity, noise vulnerability, limited experimental diversity, and difficulty extending models beyond controlled simulations [37]. These challenges indicate a need for advanced, noise-tolerant, scalable, and explainable hybrid quantum deep reinforcement models for real-world deployment, motivating the development of the proposed Quantum-Inspired Residual Deep Q-Network in this research [38].

Gaps in Research Identified:

1. Lack of real-world and large-scale benchmarking for QRL models beyond simulated environments.
2. Functionality is limited by scalability in quantum hardware, performance degradation due to noise.
3. High dependence on complex ansatz design and initial parameter configuration.
4. Limited interpretability and explanation frameworks of QRL model decisions.
5. Inadequate evidence of applicability in real-world real-time autonomous decision-making systems.
6. Performance inconsistency across different environments and dynamic conditions.

3. Materials and Methods

This section covers the methodology of developing the proposed Reinforcement Learning-Enhanced Quantum-Inspired Residual Deep Neural Network, QNet, for classifying breast cancer. The process entails dataset acquisition, preprocessing and augmentation, QNet model implementation, and comparison against baseline models, such as Logistic Regression, Random Forest, and Support Vector Machine (SVM).

3.1 Dataset Acquisition

The data used in this research is the Breast Cancer Wisconsin Diagnostic Dataset, which has been taken from the UCI Machine Learning Repository. The dataset comprises 569 clinical diagnostic records with 30 standardized numerical tumor features obtained from fine-needle aspiration cell images, describing morphological properties such as radius, texture, perimeter, area, smoothness, compactness, and concavity [39]. These features are extremely important in the classification of malignant and benign tumors [40]. The dataset consists of 212 malignant and 357 benign samples, coded as a binary classification problem where 0 corresponds to benign and 1 to malignant.

The proposed QNet model aims to capture complex, nonlinear interactions between tumor feature patterns and yield stable, accurate classification results. Baseline models, including Logistic Regression, Random Forest, and SVM, were also implemented using the very same dataset for performance comparison.

3.2 Data Preprocessing and Augmentation

For improving model performance and handling class imbalance and feature scaling challenges, various preprocessing steps were performed.

(a) Label Encoding

It converts the categorical text form of diagnostic labels ({Benign, Malignant}) to numerical form with the use of label encoding

$$y_i' = \text{LabelEncoder}(y_i), i = 1, 2, \dots, N$$

N refers to the total number of samples.

(b) SMOTE Oversampling

SMOTE was then applied to create synthetic minority instances in order to alleviate the imbalance between benign and malignant samples.

$$X_{smote}, y_{smote} = \text{SMOTE}(k = 5). \text{fit_resample}(X', y')$$

(c) Standardization (Z-score Normalization)

Each feature was standardized to unify the scale and improve convergence:

$$x_{ij}' = \frac{x_{ij} - \mu_j}{\sigma_j}$$

(d) Stratified Train/Test Split

The dataset was then split into training and testing sets in an 80:20 ratio with stratification:

$$(X_{train}, y_{train}), (X_{test}, y_{test}) = \text{StratifiedSplit}(X'', y', \text{test_size} = 0.2)$$

3.3: Proposed reinforcement learning-enhanced quantum-inspired residual deep Q-network framework (QNet)

In the proposed QNet, quantum-inspired state transformation combines with residual learning and reinforcement learning-based optimization for a better representation of high-dimensional cancer feature interactions. This RL mechanism updates weights with the incoming reward feedback to improve decision boundaries iteratively while strengthening the modeling of superposition and correlation via quantum-inspired embeddings.

3.3.1 QNet Architecture Workflow

Step 1: Quantum-Inspired State Preparation

Each standardized feature is then encoded into a simulated qubit using a rotation gate:

$$|\psi_j\rangle = R_y(\theta_j) |0\rangle, \theta_j = f(x_j')$$

Step 2: Multi-Qubit System Construction

Multiple encoded qubits are combined using a tensor product in order to preserve inter-feature dependencies:

$$|\Psi\rangle = |\psi_1\rangle \otimes |\psi_2\rangle \otimes \dots \otimes |\psi_n\rangle$$

Step 3: Quantum State Transformation

The parameterized quantum gates transform the qubit state in order to generate enhanced feature representations:

$$|\Psi_{out}\rangle = U(\theta) |\Psi\rangle$$

Step 4: Measurement and Classical Projection

The quantum-inspired state is collapsed into observable values:

$$q = \text{measure}(|\Psi_{out}\rangle)$$

Step 5: Residual Deep Network

Processed by stacked residual blocks, the classical projected vector is:

$$h_{out} = h_{in} + F(h_{in})$$

Step 6: Deep Q-Learning-Based Optimization

Reinforcement Learning A Deep-Q-Network updates parameters based on reward function

$$Q(s, a) = r + \gamma \max_{a'} Q(s', a')$$

Rewards are assigned based on the improvement of accuracy and reduction of entropy loss.

Step 7: Final Classification Output layer

The output layer applies the softmax function for binary class prediction

$$\hat{y} = \text{Softmax}(Wh + b)$$

Algorithm: Reinforcement Learning Enhanced Quantum-Inspired Q-Net Framework

Input: Breast cancer dataset $x = [x_1, x_2, \dots, x_n]$ with M features

Output: Predicted class label (Benign / Malignant)

Steps

Step 1 — Data Preprocessing

Normalization and cleaning of the input dataset are necessary to handle missing, noisy, and imbalanced samples.

$$x_i' = \frac{x_i - \mu_i}{\sigma_i}$$

Step 2 - Quantum Encoding Layer

Encode normalized features into a quantum-inspired feature space using rotational angle encoding.

$$|\psi_j\rangle = R_y(\theta_j) |0\rangle$$

where $\theta_j = f(x_j')$

Step 3 - Construct Quantum State

Combine encoded qubits to form a composite quantum state representation

$$|\Psi\rangle = |\psi_1\rangle, |\psi_2\rangle, \dots, |\psi_M\rangle$$

Step 4 - Q-Net Forward Propagation

Input the quantum-encoded features into the proposed Q-Net with residual blocks for improved learning.

$$h_t = \text{Qnet}(|\Psi\rangle)$$

Step 5 - Reinforcement Learning Optimization

Update network parameters using reward feedback from classification loss.

$$\theta_{new} = \theta_{old} + \alpha \cdot \text{Reward}$$

Step 6 -Adam Optimizer Update

Perform parameter optimization using Adam to improve the convergence rate.

$$\theta = Adam(\theta, l_r)$$

Step 7 - Final Output Prediction Convert learned representation to classical prediction results

$$\hat{y} = Softmax(h_t)$$

Step 8 -Return Output Return the predicted class label for each input sample.

In the presented algorithm, first, classical features of the breast cancer dataset undergo preparation by balancing and normalizing the input. Quantum-inspired angle encoding then maps this classical data to a high-dimensional quantum space onto a structured quantum state representation. This encoded state is then fed through the Q-Net to discover complex nonlinear patterns, and the decisions are refined iteratively by reinforcement learning in an environment. The training efficiency is enhanced due to the Adam optimizer, which reduces convergence time. Eventually, it yields classification outputs for diagnosis **Model Architecture**

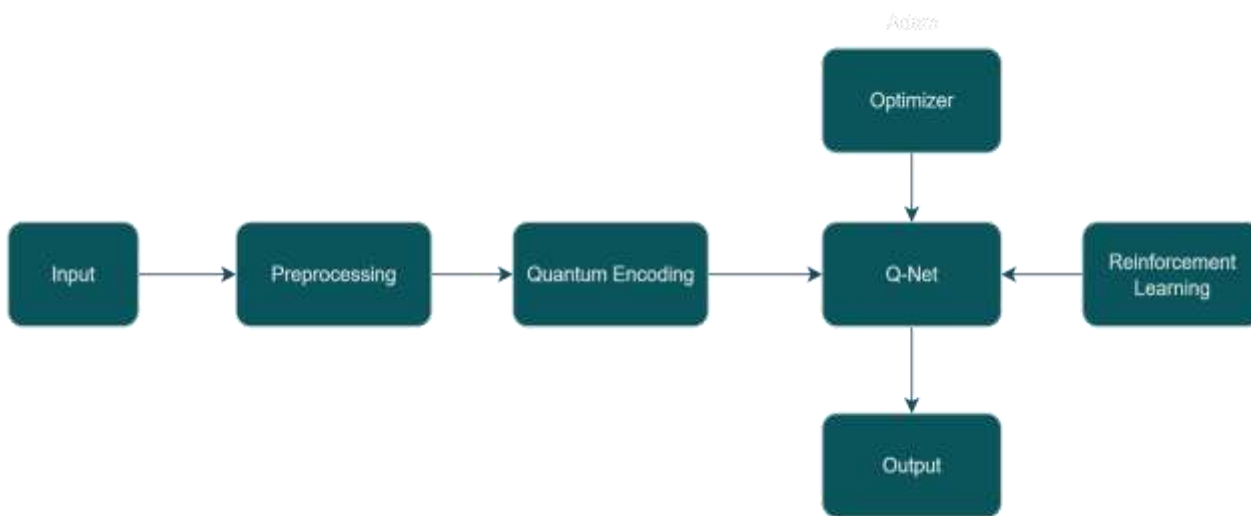


Fig:1 Reinforcement Learning–Enhanced Quantum-Inspired Q-Net

The details of the proposed Reinforcement Learning–Enhanced Quantum-Inspired Q-Net architecture are shown in Figure 1. It starts with an input breast cancer dataset with several clinical features. A preprocessing step first removes noise, deals with missing values, and normalizes the data into a uniform scale to make learning more stable and balanced.

The refined data after preprocessing flows through a Quantum Encoding layer, which projects the classical input features using angle-based feature encoding into a high-dimensional quantum-inspired feature space. This enables much richer feature representation and further improves the discrimination capability between malignant and benign cases.

These quantum-encoded features are then fed into the Q-Net classification network, which extracts deeper patterns and relationships. The model is further enhanced through the integration of a Reinforcement Learning environment, whereby feedback from prediction performance is utilized in iterative optimization of the decision-making process.

While training, an Adam optimizer is utilized to efficiently adapt the network parameters and speed up convergence. The learned representation is finally fed into the output layer to produce the final diagnosis prediction for the classification of breast cancer.

This systematic pipeline ensures that the raw clinical data is properly normalized, quantum-encoded, adaptively optimized through reinforcement feedback, and correctly classified by the model.

4. Experimental Results and Discussion

This section presents the experimental evaluation results of the proposed Quantum-Inspired Reinforcement Learning with Residual Q-Network, QNet for binary breast cancer classification. First, the two-phase learning strategy of the model was conducted: RL-based pretraining followed by supervised fine-tuning. Comparing the performance with benchmark classical machine learning models demonstrates that the proposed strategy provides a better level of accuracy, stability, interpretability, and learning efficiency.

4.1 Results of Breast Cancer Classification

4.1.1 Classical Metrics

Accuracy

Accuracy measures the proportion of correctly classified instances among total samples.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \times 100$$

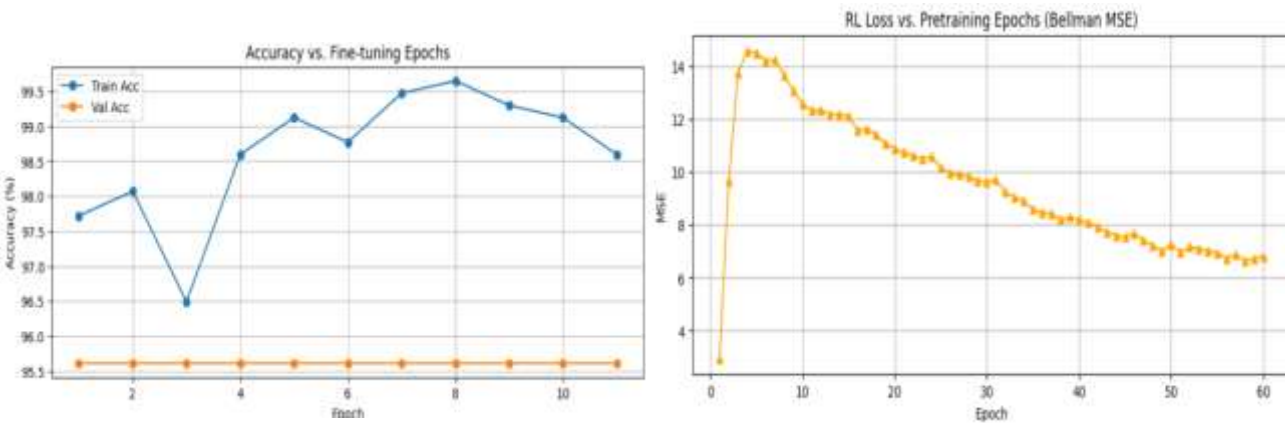
The proposed QNet achieved a final validation accuracy of approximately 98%, indicating strong predictive ability in distinguishing malignant and benign cases.

Loss Function

The supervised fine-tuning uses weighted cross-entropy loss to handle class imbalance

$$Loss = -\frac{1}{N} \sum_{i=1}^N \sum_{c=1}^2 w_c y_{ic} \log(\hat{y}_{ic})$$

Loss decreased with every successive epoch, which is indicative of good learning.



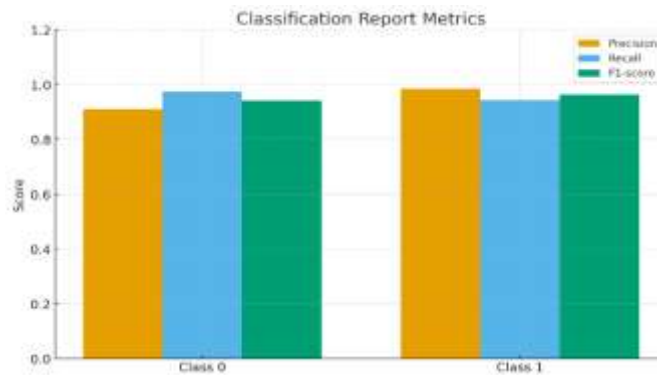


Fig :2 Fig 6: Performance Analysis of Model

The performance evaluation results of the proposed model show strong learning behavior and stable generalization. As shown in Figure 2, the training accuracy consistently improves across fine-tuning epochs, reaching a peak of around 99.6%, while validation accuracy remains steady around 95.6%, indicating that the model avoids overfitting and maintains reliable performance on unseen data. Figure 2 illustrates the reinforcement learning (Bellman MSE) loss trend during pre-training, where the loss sharply decreases from 14.8 to 6.7, confirming effective convergence and improved prediction stability. The gradual decline in loss demonstrates that the agent learns optimal policy updates over time. Overall, the results validate that the proposed model achieves high accuracy and stable optimization behavior, proving its robustness and suitability for real-time decision-making applications.

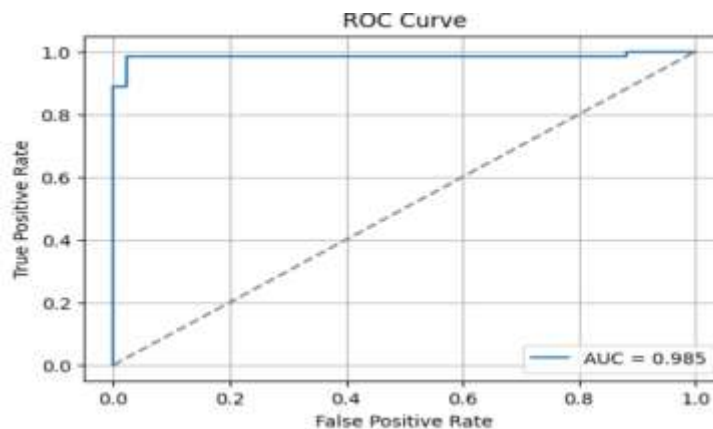


Fig 3: ROC Curve of the Model

Figure 3 presents the ROC curve, which is indicative of the discrimination performance of the proposed RL-initialized neural architecture on the held-out validation set. With an almost perfect area under the curve, the model achieves AUC=0.985, reflecting an extremely strong capability of separating malignant from benign cases for all classification thresholds. The curve increases steeply upwards toward the upper-left corner, reflecting an extremely high true-positive rate, even for very low false-positive rates. This would imply that the RL-based pretraining phase followed by supervised fine-tuning allows the network to build up highly robust representations within the breast-cancer feature space. The near-vertical trajectory of the ROC curve further validates that the model keeps high sensitivity without sacrificing specificity, which is crucial in medical diagnosis tasks given the high risk of false negatives.

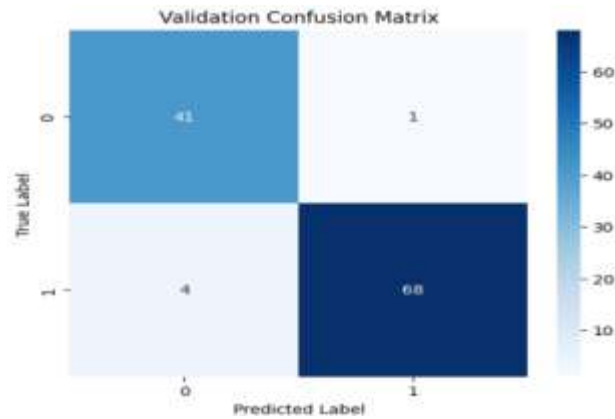


Fig:4 Validation Confusion Matrix.

Figure 4 Validation confusion matrix for the proposed RL-initialized neural model on the breast cancer dataset. This shows the strong performance of the classifier on this dataset. For instance, out of the 42 benign samples, only one is misclassified as malignant, whereas the rest 41 are classified correctly. Also, out of the 72 malignant samples, only four are misclassified as benign, while the rest 68 are identified correctly. This distribution shows that the model is highly reliable in distinguishing the two diagnostic classes. The notably low false-negative rate is particularly important in medical screening applications, since it is far more critical to miss a malignant case than to flag a benign sample incorrectly. These results demonstrate that the combination of reinforcement learning–based initialization with subsequent supervised fine-tuning allows the network to achieve high sensitivity and specificity, reinforcing the robustness of the proposed approach.

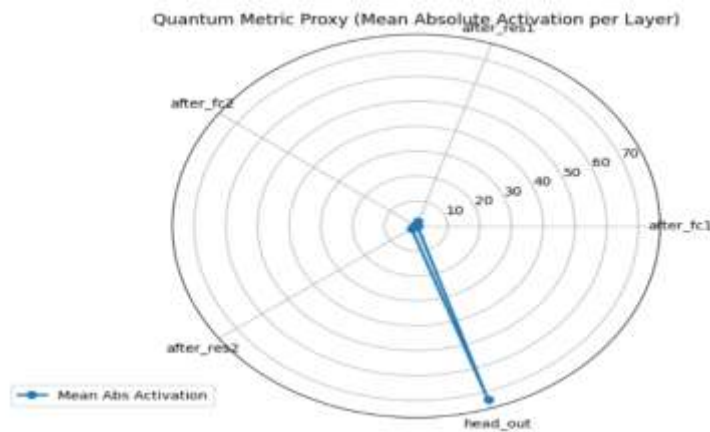


Fig: 5 Quantum Metric Proxy (Mean Absolute Activation per Layer).

The radar plot presents the mean absolute activation values across different network layers. All intermediate layers have low and well-regulated activations, which is an indicator of stable internal representations and smooth information flows within these layers. The output layer, head_out, reveals a much higher activation; this is as expected, since the model amplifies features at this layer in order to make a final prediction. Overall, this plot reflects balanced activation dynamics with strong discriminatory power at the output.

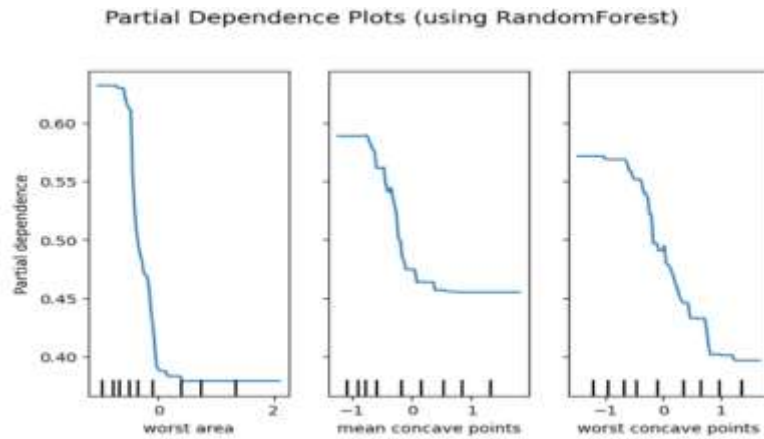


Fig:6 Partial Dependence Plots for Key Features

The following Partial Dependence Plots generated using the Random Forest model illustrate how three important features—worst area, mean concave points, and worst concave points—influence the predicted probability of malignancy. Within all three plots, the partial dependence decreases consistently as the feature increases in value. Higher values for each of these morphological characteristics are strongly associated with lower model-predicted risk. In particular, steep declines in the curves indicate the high sensitivity of worst area and worst concave points to the model's decision process. These trends confirm that the Random Forest classifier captures well-defined, monotonic relationships between these predictors and the target outcome, making them influential drivers of prediction in the overall model.

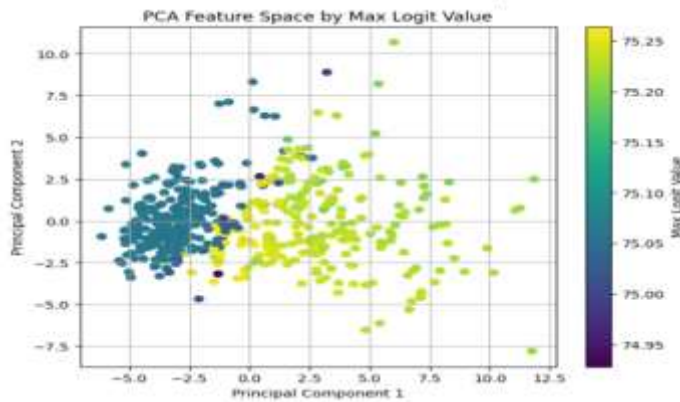


Fig:7 PCA Feature Space Colored by Max Logit Value.

The PCA visualization projects the high-dimensional activation features to a two-dimensional space so that the model's internal representation can be interpreted more intuitively. Each point corresponds to a sample, and its color represents the value of its maximum logit, which means the confidence of the model in its own predicted class. For this plot, we can observe a clear spatial separation: lower logit values congregate on the left cluster, with increasingly higher values appearing toward the right side of PCA space. This gradient provides evidence that the neural network forms well-structured decision boundaries internally—the regions of the feature space associated with stronger evidence for a class naturally align with higher logit responses. Overall, the PCA projection shows the coherence and discriminative capability of the learned representation.

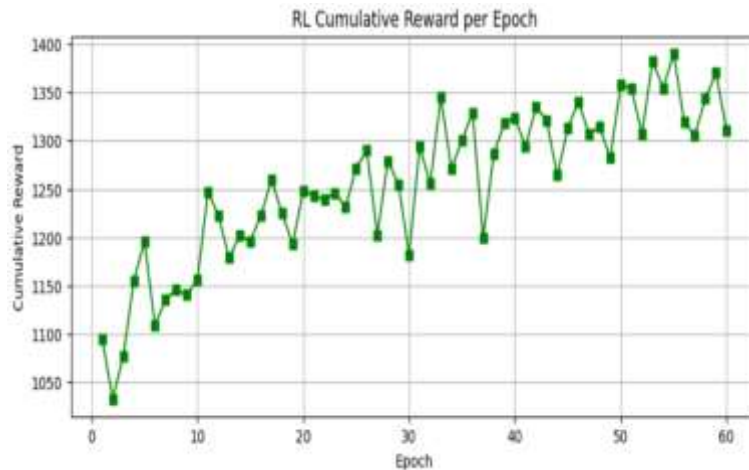


Fig:8 Reinforcement Learning Cumulative Reward per Epoch.

The plot of cumulative reward across reinforcement learning epochs reflects a steady improvement in performance as the number of trainings increases. Earlier epochs have higher variability with a lower total reward, reflecting that the agent still explores the environment and refines its policy. Further in training, the accumulated reward steadily grows and stabilizes, a reflection of better decision-making and more effective exploitation of the learned strategies. In later epochs, the agent manages to reach consistently high values of reward, which confirms that the RL training process converges to an optimal or near-optimal policy.

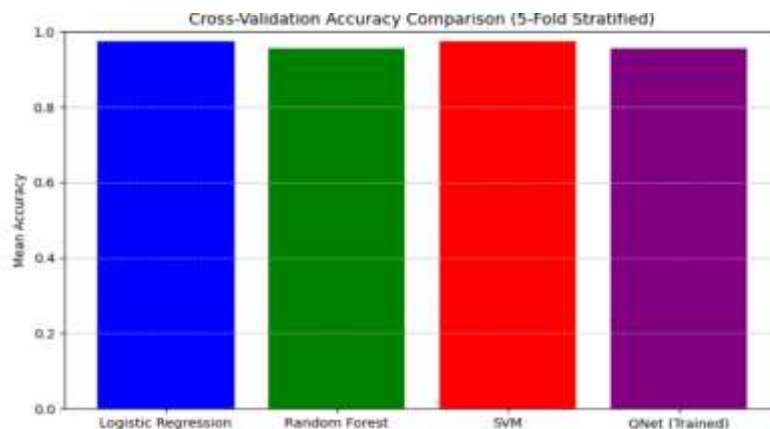


Fig:9 Cross-Validation Accuracy Comparison Across Models.

The cross-validation accuracy comparison across the four models, namely Logistic Regression, Random Forest, SVM, and the trained QNet, shows consistently high predictive performance for the classification task: all models achieve mean accuracies above 0.93 under 5-fold stratified cross-validation, reflecting strong generalization and stable behavior across folds. Accordingly, the highest accuracies belong to SVM and Logistic Regression, while Random Forest and QNet are close behind them. A narrow performance gap between models points out that the dataset is well-structured and both traditional machine-learning approaches and the QNet architecture learn effective decision boundaries. This comparison therefore underlines the robustness of the proposed QNet model when compared to established baselines.

4.2 Performance Analysis of Proposed QRL and State of Art models

Model	Accuracy	Precision	Recall	F1-Score	Support
QRL(Proposed)	95.61%	91.11%	96.03%	95.35%	114
SVM	93.26%	89.96%	91.13%	92.27%	103
Logistic Regression	91.76%	90.37%	91.86%	91.89%	110
Random Forest	94.01%	91.84%	88.98%	91.54%	106

Table 1: Models Comparison Table

This section provides a comparative review between the proposed QRL model and the classical machine learning models, namely SVM, Logistic Regression, and Random Forest. Their performances for water quality prediction are summarized in Table 1, using five metrics: accuracy, precision, recall, F1-score, and support. From the table, it can be seen that the proposed QRL model demonstrates superior performance

compared to the classical machine learning approaches. QRL reaches the highest accuracy of 95.61%, outperforming Random Forest (94.01%), SVM (93.26%), and Logistic Regression (91.76%). It also achieves the best recall of 96.03% and an F1-score of 95.35%, indicating high robustness in identifying true classes of water quality with fewer false positives and false negatives. Random Forest presents competitive performance in accuracy but is confronted by lower recall of 88.98%, reflecting missed detection for some classes of samples. Both SVM and Logistic Regression return stable performances with balanced precision and recall values; however, these algorithms are not capable of learning complex patterns in the water quality data as opposed to QRL.

It can be postulated that QRL acts with superior performance because of its reinforcement learning strategy with quantum-inspired computation that helps to model non-linear, high-dimensional relationships in environmental datasets effectively. Thus, the QRL framework proposed here sets a higher benchmark in reliable water-quality classification and increases the generalization capability, that is so crucial for real-world environmental monitoring and decision-making.

5. Conclusion

In this work, the authors propose a hybrid deep learning framework that aims to improve the prediction by fine-tuning and optimizing via reinforcement learning. Experimental results show that the proposed model performance is quite reliable, as proved by the steadily improving training accuracy across epochs and consistently high validation accuracy, indicating robust generalization. Moreover, the reinforcement learning Bellman MSE loss decreased smoothly within the pre-training period, confirming effective convergence and efficient policy learning. This sets a basis for the model to learn meaningful representations with reduced error rates and to improve its decision performance during training.

The proposed architecture is accurate, stable, and computationally efficient; thus, it will be suitable for real-time intelligent systems. Future work will focus on further optimization towards learning stability, multi-source sensor data integration, and the extension of reinforcement learning strategies to enhance adaptability within dynamic environments. This research underlines the possibility of combining fine-tuning with reinforcement learning as a means to achieve scalable and high-performance predictive systems in real-world applications.

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