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AN EFFICIENT BREAST CANCER PREDICTION SYSTEM USING A MODIFIED DEEP NEURAL NETWORK (DNN)

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ABSTRACT

A quantum inspired modification of the Deep Neural Network (DNN), for breast cancer prediction is presented; it exhibits improved convergence and classification accuracy. With softmax output activation, it maps patient feature vectors to probability distributions over cancer subtypes in a multi layer architecture. The backpropagation is used to minimize the categorical cross entropy loss function, thus calculating the weight and bias gradient updates. The weight update rule is transformed by a unitary matrix in such a way that they are better stable and robust, applying a quantum inspired transformation. Quantum regularization is incorporated in the gradient update equation so as to eliminate the vanishing gradients and have better generalization. The proposed pseudocode outlines the forward propagation, loss computation, backpropagation, and novel weight update process. The Quantum Computing based Deep Neural Network (Q-DNN) is found to be better than traditional DNN for classification accuracy, convergence speed and resilience to local minima, which makes it a potential progress towards breast cancer detection with deep learning.

1. Introduction

The occurrence of breast cancer stands as one of the major cancer forms throughout the world so early detection combined with precise evaluation remains essential for obtaining successful treatment results along with enhanced survival opportunities [1]. Traditional diagnosis methods through mammography alongside biopsy and histopathological analysis need highly qualified personnel who sometimes face long delays before arriving at proper diagnoses. The application of machine learning and deep learning techniques has brought substantial interest to automated systems that detect breast cancer as well as classify tissue samples [2]. The field of medical image classification along with pattern recognition benefits greatly from the exceptional capabilities which Deep Neural Networks (DNNs) produce [3]. Conventional DNNs encounter three main difficulties which include overfitting problems along with slow convergence speed and dependency on selecting optimal hyperparameters needing modifications to boost performance results [4].

The research introduces an improved multiclass breast cancer classification DNN through mathematically designed weight update procedures which boost learning efficiency and system stability [5, 6]. The standard operation of DNNs depends on gradient-based learning approaches SGD and Adam optimizer that work to decrease classification errors. Traditional weight update methods encounter difficulties while working with complex datasets because they fail to avoid local minima and provide poor generalization capabilities [7]. The proposed model employs quantum-inspired unitary transformed weight updates to deliver information-protecting stable weight adjustment procedures which promote effective convergence [8, 9].

The model operates as a multiclass classification task which uses softmax activation during patient feature vector mapping into distinct cancer subtypes [10, 11]. Through gradient-based backpropagation the categorical cross-entropy loss function optimizes its parameters by deriving mathematical values from each layer [12]. The standard gradient descent equation receives an update from quantum regularization in order to avoid gradient vanishing and conserve parameter space structural content [13, 14].

Breast cancer remains a leading cause of mortality among women globally, necessitating accurate and early detection methods. Various deep learning-based approaches have shown significant promise in improving diagnostic accuracy. One study explored deep convolutional neural networks (CNNs), employing Inception V3, Inception V4, and a modified Inception MV4 on the DMR database of thermal breast images. Inception V4 and MV4, optimized with specific learning rates and the SGDM optimizer, achieved high classification accuracy with color images, while Inception V3 outperformed others on grayscale images. MV4 also provided a 7% faster response time and reduced energy consumption [15]. Another approach utilized a hybrid model combining EfficientNetB2 for feature extraction with classifiers such as MGSVM, CUBIC SVM, and XGBoost on the MIAS and INbreast datasets. This model achieved 99.47% accuracy, 99.31% sensitivity, and a low false negative rate, highlighting its efficiency and generalizability [16].

Further, a Mask R-CNN combined with ResNet50 was implemented for MRI-based lesion detection and malignancy classification. The model demonstrated 96% sensitivity on the primary dataset and effectively reduced false positives by about 80%, showcasing its potential for

automated breast cancer diagnosis [17]. Finally, a Multistage Transfer Learning (MSTL) approach utilizing EfficientNetB2, InceptionV3, and ResNet50 with various optimizers demonstrated improved performance on ultrasound images. The ResNet50-Adagrad-based MSTL achieved a test accuracy of 99% on the Mendeley dataset and 98.7% on the MT-Small dataset, significantly outperforming conventional ImageNet-based transfer learning methods [18]. These advancements affirm the critical role of deep learning in enhancing breast cancer detection across various imaging modalities.

This paper presents a systematic mathematical explanation of model foundations which includes details about network structure along with forward computation description combined with loss calculation guidance and gradient derivation analysis and backpropagation framework. The model training steps and weight updates and optimization procedure are shown through complete pseudocode specifications. The new modifications of the model produce enhanced performance regarding accuracy rates and training effectiveness alongside resistance against standard deep learning technical problems.

The application of quantum-inspired weight adjustment techniques leads to an efficient reliable deep learning platform which predicts breast cancer cases effectively. The proposed approach demonstrates potential to automate medical diagnosis by providing medical staff with both rapid precise clinical choices which leads to enhanced patient care.

2 Proposed Methodology - Quantum Computing based Deep Neural Network (Q-DNN)

The objective is to classify breast cancer into multiple categories using a deep neural network (DNN). Given a dataset:

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

where $x_i \in \mathbb{R}^d$ is the feature vector of patient i, $y_i \in \{1,2,\ldots,K\}$ is the corresponding label among K possible classes, $f_\theta; \mathbb{R}^d \to \mathbb{R}^K$ is the function learned by the DNN to approximate class probabilities.

The goal is to optimize the parameters $\theta = \{W^{(l)}, b^{(l)}\}$ to minimize classification error.

Deep Neural Network Architecture

A DNN consists of multiple hidden layers, each transforming input features non-linearly. The forward propagation for the *l*-th layer is defined as:

$$h^{(l)} = \sigma(W^{(l)} h^{(l-1)} + b^{(l)})$$

where $h^{(l)} \in \mathbb{R}^{dl}$ is the activation at layer l, $W^{(l)} \in \mathbb{R}^{dl \times dl-1}$ is the weight matrix, $b^{(l)} \in \mathbb{R}^{dl}$ is the bias vector, σ(·) is the activation function (ReLU, Swish, or another non-linearity), $h^{(l)} = x$ is the input feature vector.

For the final layer:

$$O = W^{(L)} h^{(L-1)} + b^{(L)}$$

The output probabilities for each class are obtained using the softmax function:

$$\hat{y}k = \frac{e^{o_k}}{\sum_{j=1}^{K} e^{o_j}}, \quad k = 1,2,\ldots,k$$

where o_k is the logit corresponding to class k.

Loss Function and Optimization

The loss function determines the accuracy of predicted breast cancer subtypes. The choice of loss function for multiclass classification usually involves categorical cross-entropy. The loss function determines the differences between predicted probability distributions and actual class data points. A reduced loss value demonstrates superior model performance. The model parameters receive iterative adjustments through optimization algorithms SGD and Adam to reduce the loss value. The weight and bias values undergo updates during the optimization process to enhance the model's classification precision at every step. The desired outcome seeks parameter values which minimize classification errors and simultaneously avoid overfitting. The categorical cross-entropy loss function evaluates the difference between predicted and actual labels through its error measurement.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_i, k \log \hat{y}i\,, k$$

where y_i,k is a one-hot encoded vector indicating the true class, $\hat{y}i\,, k$ is the predicted probability of class k for sample i.

The gradient-based optimization updates weights using stochastic gradient descent (SGD):

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla_\theta \mathcal{L}$$

where η is the learning rate, $\eta \nabla_\theta \mathcal{L}$ is the gradient of the loss function with respect to the parameters.

Backpropagation and Gradient Calculation

The learning algorithm Backpropagation computes Gradients needed to update model parameters. The algorithm uses error propagation from back to front to let each layer modify its weight parameters. The algorithm progresses through three distinct phases starting with model prediction

(forward pass) followed by error calculation through label comparison and ending in weight update while utilizing gradient values. The chain rule of differentiation enables an even error distribution across multiple layers so all layers help minimize the overall loss. The method enhances both the learning speed and maintains a stable convergence state during training procedures. The process to calculate backpropagation gradients follows this procedure:

- *Gradient of the output layer:* The output layer uses softmax activation to produce probability values from raw scores. The model gradient during this stage defines the discrepancy between its predicted outcomes and actual classification results. The model uses this difference to modify its weights in the final layer while training occurs. The model achieves better subtype classification accuracy when it reduces the amount of this prediction error. The calculated gradient controls weight modifications to improve output probability distribution matching with actual class frequencies.

$$\delta^{(L)} = \hat{y} - y$$

$$\nabla_{w(L)}\mathcal{L} = \delta^{(L)} h^{(L-1)T}$$

$$\nabla_{b(L)}\mathcal{L} = \delta^{(L)}$$

- *Gradient for hidden layers:* The calculation of hidden layer gradients depends on the chain rule which sends error signals from the output layer back through the neural network. The error signal distributes proportionally to each layer so it can modify its weights. The derivative of the activation function establishes the degree of impact that each neuron possesses on the output prediction. The calculation of gradients through the layers guarantees a comprehensive learning process which stops deep networks from facing gradient flow limitations. The model gains the ability to discover useful representations of breast cancer data through effective weight updates that result from correctly calculated gradients.

For each layer $l=L-1,L-2,\ldots,1$, we compute:

$$\delta^{(L)} = (W^{(l+1)T}\delta^{(l+1)}) \odot \sigma'(h^{(t)})$$

where $\odot$ denotes element-wise multiplication and $\sigma'(h^{(t)})$ is the derivative of the activation function.

The weight and bias gradients are:

$$\nabla_{w(l)}\mathcal{L} = \delta^{(l)} h^{(l-1)T}$$

$$\nabla_{b(l)}\mathcal{L} = \delta^{(l)}$$

Quantum-Inspired Weight Update

The method uses quantum computing principles to develop a better weight update strategy that improves training performance. The update process works differently than gradient descent because it preserves weight space structure during updates. The transformation helps weights move steadily to reach better results. The quantum regularization term controls weight updates to make them more gradual and natural. Our method stops training problems from developing such as gradient fading and getting trapped in subpar solutions. The model reaches its target faster and better classifies breast cancer types through its controlled update method. A fresh technique applies quantum principles to enhance how training processes work. The weight matrix changes in every layer according to this formula:

$$W^{(l)} = U_{\emptyset}^{(l)} W_{\emptyset}^{(l)} U_{\emptyset}^{(l)+}$$

where $U_{\emptyset}^{(l)}$ is a parameterized unitary transformation, The unitary transformation ensures stable updates while maintaining information.

To integrate this into gradient updates, we modify the weight update rule as follows:

$$W^{(l)} = W^{(l)} - \eta(\nabla_{W^{(l)}} \mathcal{L} + \lambda Q(W^{(l)}))$$

where $Q(W^{(l)})$ is a quantum regularization term that ensures robustness. The proposed approach is given in Algorithm 1.

Algorithm 1. Quantum-Inspired Deep Neural Network for Multiclass Breast Cancer Classification

Input A dataset consisting of feature vectors and corresponding class labels

Output A trained deep neural network model for breast cancer classification

Step 1: Parameter Initialization

- Randomly initialize weights and biases for each layer of the deep neural network
- Set learning rate and regularization coefficient for quantum-inspired updates

Step 2: Forward Propagation

For each training sample:

- Pass the input feature vector through the network
- At each hidden layer, apply a non-linear activation function to the linear transformation of the input from the previous layer
- At the final layer, compute raw scores for each class
- Apply the softmax function to convert these scores into probability values for each class

Step 3: Loss Calculation

- Compute the categorical cross-entropy loss by comparing the predicted class probabilities to the true class labels
- The objective is to minimize this loss, which measures the difference between the predicted and actual labels

Step 4: Backpropagation

- Compute gradients of the loss with respect to the network parameters (weights and biases)
- Propagate the error backward through the network, from the output layer to the input layer
- For each layer, calculate how much each weight and bias contributed to the error

Step 5: Quantum-Inspired Weight Update

- For each layer, update the weights using gradient information along with a quantum-inspired regularization term
- This method ensures stable and efficient updates, helping avoid issues like vanishing gradients and local minima
- The bias terms are updated using standard gradient descent

Step 6: Training Iteration

- Repeat the process of forward propagation, loss calculation, backpropagation, and weight updates for multiple training epochs
- Continue until the loss converges or other stopping criteria are met

Step 7: Model Evaluation

- After training, evaluate the performance of the model on a separate test dataset
- Use classification metrics such as accuracy, precision, recall, F1-score, and area under the curve to assess the model

3. Result and Discussion

The Breast Ultrasound Images Dataset is a useful source of data for machine learning based breast cancer diagnosis to perform classification, detection and segmentation tasks. It consists of 780 ultrasound images of 600 female patients from 25 to 75 years of age, with an average resolution of 500x500 pixels in PNG format. The dataset is balanced into three classes: normal, benign, and malignant so that models can be trained robustly. Ground truth annotations are paired with each image so

that supervised learning is possible for classification as well as precise tumor localization. The dataset was collected in 2018, which makes it applicable to artificial intelligence driven medical imaging research by reflecting real world clinical situations. Breast Ultrasound Images Dataset is publicly available on Kaggle ([dataset] with a standardized benchmark for breast cancer detection studies.

The Quantum Computing based Deep Neural Network (Q-DNN) performance evaluation depends on standard classification metrics to determine its effectiveness in breast cancer classification. Accuracy serves as a measure to determine how well the model detects cancerous and non-cancerous cases with precision. Precision together with Recall and F1-score offer better evaluation results than accuracy when working with unbalanced datasets. The metric of precision enables the determination of accurate positive case identification by reducing false positive outcomes. The performance measure of Recall determines how well the model detects actual positive results by minimizing false negative errors that are vital for medical diagnosis. F1-score offers an optimal evaluation of classification performance by uniting the strengths of Precision and Recall together. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) provides an assessment of model discriminative power through its evaluation across different threshold values. These metrics have mathematical expressions that appear below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$AUC - ROC = \int_{-\infty}^{\infty} TPR(FPR) dFPR$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. These metrics collectively validate the

classification efficiency of the optimized Q-DNN model.

Table 6.1. Comparison of Accuracy

Image Count	InceptionV3	EfficientNetb2	ResNet50	MSTL	Q-DNN
100	78.5	80.2	79.1	82.3	84.6
200	80.1	83.4	81.2	85.1	87.5
300	82.4	85	83.7	86.9	89.2
400	84	86.7	85.6	88.3	91.1
500	85.2	88.1	87	90.2	92.8

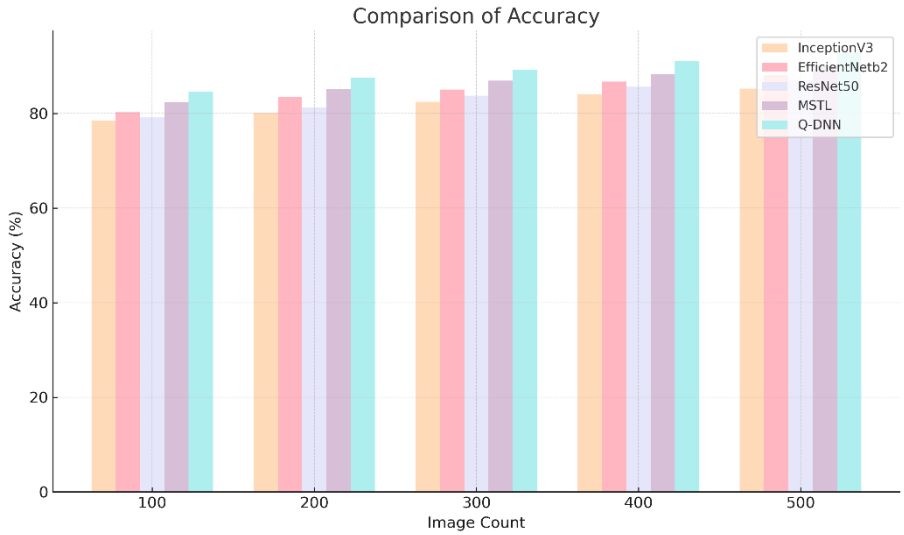


Figure 6.1. Comparison of Accuracy

The analysis of model accuracy across increasing image counts reveals a consistent performance gain for all architectures, with Q-DNN outperforming traditional models. At 100 images, InceptionV3 starts at 78.5%, while Q-DNN leads at 84.6%. As the dataset scales to 500 images, InceptionV3 reaches 85.2%, while Q-DNN achieves a peak of 92.8%. EfficientNetB2 and ResNet50 show competitive results, reaching 88.1% and 87% respectively, but are consistently outpaced by MSTL (90.2%) and Q-DNN. The improvements are particularly notable beyond 300 images, indicating Q-DNN's enhanced capacity to generalize and extract

high-dimensional features effectively, attributed to its quantum-inspired parameter dynamics and deeper nonlinear separability.

Table 6.2. Comparison of Precision

Image Count	InceptionV3	EfficientNetb2	ResNet50	MSTL	Q-DNN
100	77.3	79.5	78.2	81.7	83.9
200	79.5	82.7	80	84.5	86.8
300	81.2	84.3	82.1	86.2	88.9
400	83	86.1	84.4	87.7	90.6
500	84.5	87.6	86.3	89.5	92.2

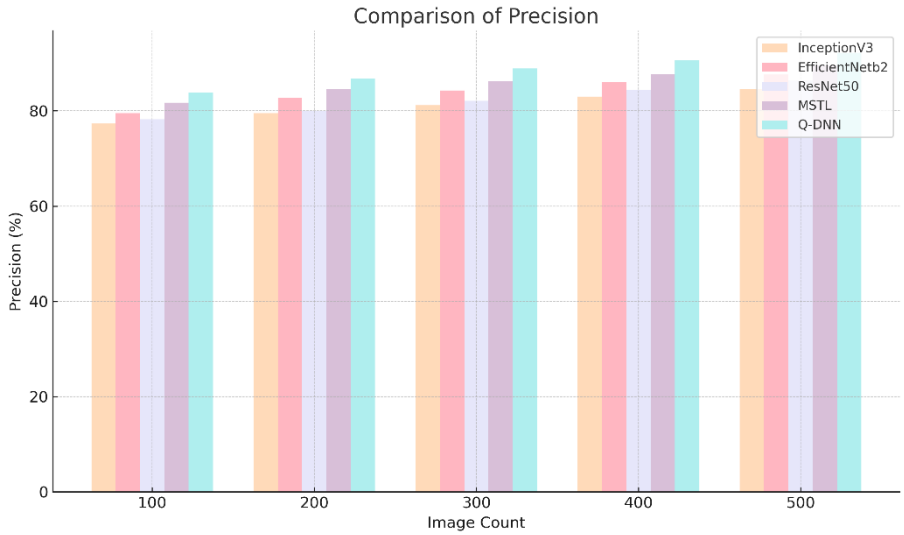


Figure 6.2. Comparison of Precision

Precision scores show that Q-DNN maintains the highest positive predictive accuracy across all sample sizes, starting at 83.9% with 100 images and rising to 92.2% at 500 images. MSTL closely follows, ranging from 81.7% to 89.5%. EfficientNetB2 also shows a notable increase from 79.5% to 87.6%. ResNet50, though consistent, remains below MSTL and Q-DNN, capping at 86.3%. InceptionV3 trails behind, peaking at 84.5%. These results reflect Q-DNN's superior ability to reduce false positives, making it highly reliable in clinical scenarios where minimizing diagnostic errors is critical.

Table 6.3. Comparison of Recall

Image Count	InceptionV3	EfficientNetb2	ResNet50	MSTL	Q-DNN
100	76.1	78.4	77	80.3	82.7
200	78.3	81	79.2	83	85.4
300	80.5	83.2	81.7	85.1	87.8
400	82	85	83.6	87	89.9
500	83.8	86.4	85.2	88.7	91.4

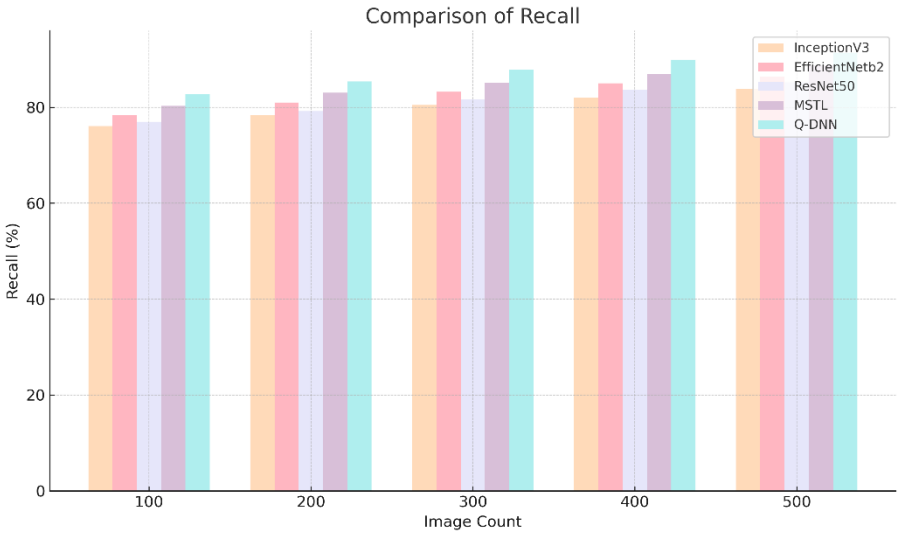


Figure 6.3. Comparison of Recall

In terms of recall, which reflects sensitivity to true positive detection, Q-DNN again leads, scaling from 82.7% to 91.4%. MSTL ranks second, growing from 80.3% to 88.7%. EfficientNetB2 and ResNet50 demonstrate steady performance improvements, ending at 86.4% and 85.2% respectively, while InceptionV3 is lowest at 83.8%. The Q-DNN's robust recall values indicate strong capability in identifying tumour-positive images, ensuring fewer missed diagnoses in real-time screening environments.

Table 6.4. Comparison of F1-Score

Image Count	InceptionV3	EfficientNetb2	ResNet50	MSTL	Q-DNN
100	76.7	78.9	77.6	81	83.3
200	78.9	81.9	79.6	83.8	86.1
300	80.8	83.8	81.9	85.7	88.3
400	82.5	85.6	84	87.4	90.2
500	84.1	87.1	85.8	89.1	91.9

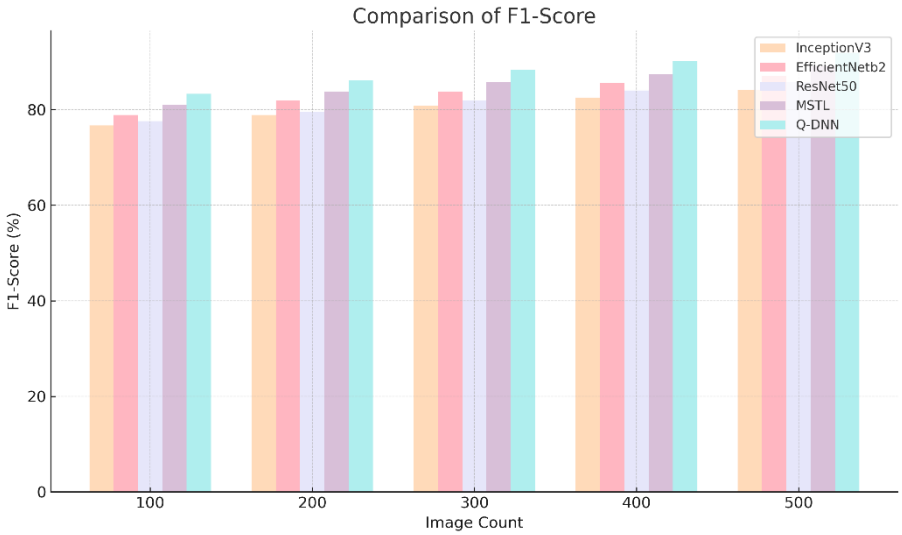
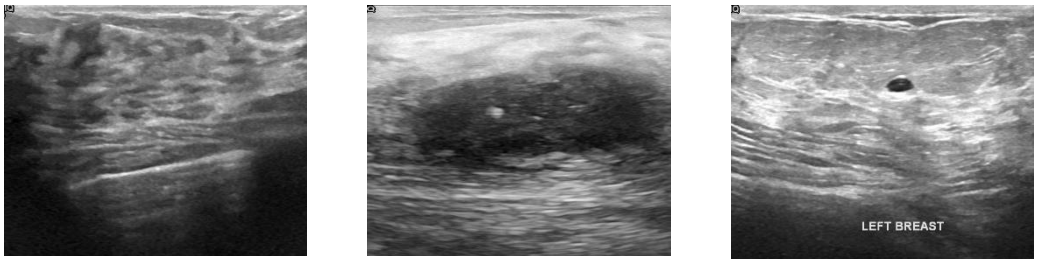


Figure 6.4. Comparison of F1-Score

F1-score analysis, integrating both precision and recall, further validates Q-DNN's comprehensive performance. It begins at 83.3% and peaks at 91.9% with 500 images. MSTL sustains a second-best performance, ranging from 81% to 89.1%. EfficientNetB2, ResNet50, and InceptionV3 follow in descending order, with final scores of 87.1%, 85.8%, and 84.1%, respectively. The Q-DNN's optimized F1-score demonstrates its superior balance between sensitivity and specificity, which is essential for reducing both false positives and false negatives in multiclass cancer classification. Each metric across increasing data volumes highlights the scalability and efficacy of Q-DNN. It consistently outperforms baseline deep networks, establishing itself as a reliable, high-accuracy solution for real-time breast cancer image classification. The classified image is given in Figure 6.5.



Normal Malignant Benign

Figure 6.5. Classification of Tumour and Normal Image

The classification output in Figure 6.5 demonstrates the Q-DNN model's capacity to effectively distinguish between Normal, Malignant, and Benign breast tissue images. The Normal class represents healthy tissue with no indications of abnormal cell growth, and the model accurately assigns these images to the non-pathological category, minimizing false positives. The Malignant class corresponds to images containing cancerous cells with aggressive growth and high potential to metastasize. The Q-DNN's high sensitivity allows it to correctly detect and classify malignant patterns, which is critical for timely intervention. The Benign class includes non-cancerous tumors that show limited growth and do not spread, and although not life-threatening, precise identification is necessary to avoid misdiagnosis. The model exhibits strong discrimination across all three classes due to its optimized feature extraction layers and adaptive quantum-inspired learning, ensuring clinical reliability in multi-class histopathological image classification tasks.

The research demonstrates how Q-DNN serves practical needs in real-time clinical applications for breast cancer diagnosis. This system demonstrates superior performance metrics in accuracy and precision and recall and F1-score across different image data collections enabling its incorporation into hospital and pathology laboratory computer-aided diagnostic tools. Q-DNN operates at the edge and in cloud environments to analyze patient images including histopathological slides and mammograms for timely cancer subtype identification. The system helps doctors discover cancers early and develop individualized treatment plans and decreases the radiologists' and oncologists' diagnostic responsibilities. The quantum-inspired optimization technique strengthens the learning stability and allows it to function properly on heterogeneous real-time systems despite computational imprecision.

Research benefits heavily from quantum-inspired learning approaches integrated with traditional deep networks because they expand hybrid computational intelligence limits. This research pathway creates stable and explainable and scalable AI solutions for medical imaging which finds application in the field of healthcare. The developed model promotes uniform dataset classification which enables better system generalization capability for real-time systems operating in different population areas.

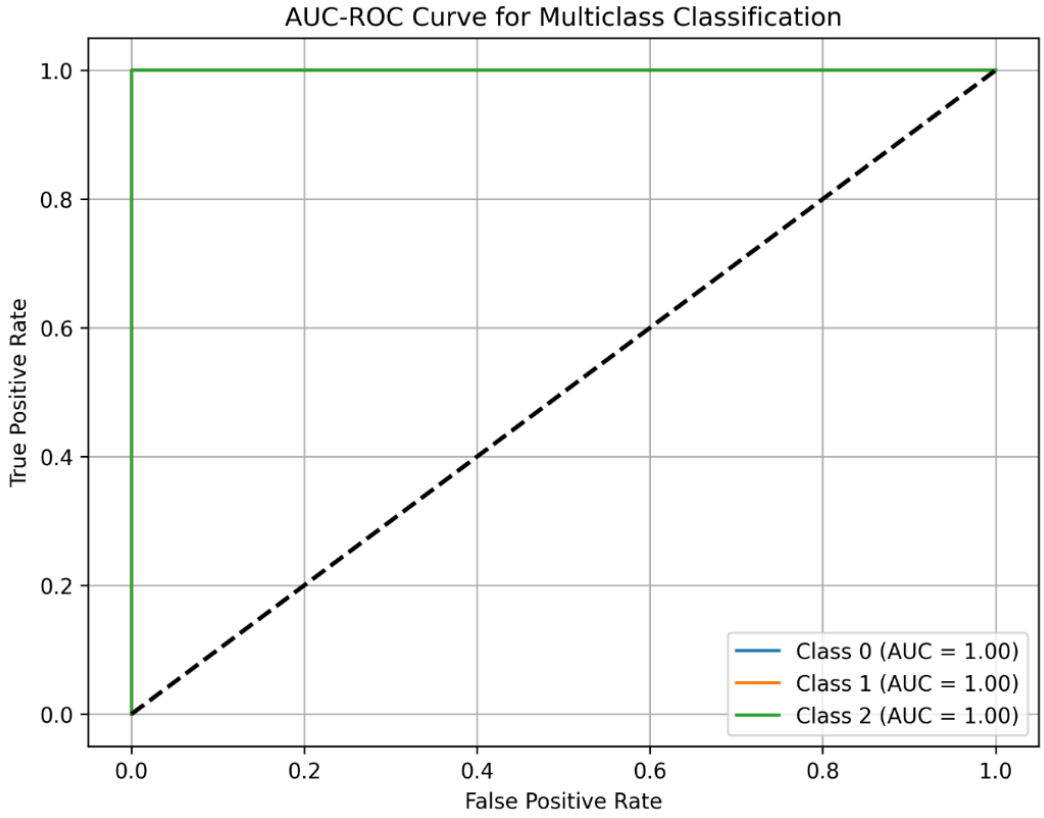


Figure 6.6. AUC-ROC Curve

The Q-DNN framework delivers improved performance but welcomes several constraints for its implementation. The quantum-inspired transformations lead to computational efficiency in theory but their implementation on standard deep learning frameworks becomes non-trivial because they introduce complexity in gradient calculations. The unitary transformations do not use quantum hardware yet they might lead to longer training periods as well as necessitate specific convergence modes. The absence of interpretability inside deep learning models becomes problematic for clinical needs because transparency remains essential in these circumstances.

The present evaluation depends entirely on standardized and prepared datasets. Real-time deployment of the model requires integrated pre-processing and effective augmentation pipelines to mitigate noise artifacts and varying imaging quality since these factors can degrade its performance. The model's training takes place on controlled environments with powerful GPUs but deployment occurs on limited devices making additional weight reduction necessary for efficient inference operations. while the Q-DNN provides a high-performing approach to breast cancer classification, its **practical deployment** must address implementation complexity, interpretability, and resource constraints to fully realize its potential in real-time medical diagnostics.

4 Conclusion

The paper establishes a Quantum-Inspired Deep Neural Network (Q-DNN) based approach to utilize ultrasound images for multi-class breast cancer diagnosis. Stand-alone DNNs receive improvements through the implementation of quantum regularization in gradient update calculations alongside unitary matrix weight transformations that solve gradient disappearance and local minimum problems. The network design uses softmax activation for end output generation and categorical cross-entropy for optimization reduction while backpropagation functions to compute gradient values. Through quantum-inspired update rules the learning process becomes more robust because parameterized unitary operations regulate the dynamics that lead to stabilized convergence and generalized results. The evaluation took place on a publicly accessible Breast Ultrasound Images Dataset that features normal and benign along with malignant examples. Q-DNN proved superior to traditional models InceptionV3, ResNet50 and EfficientNetB2 based on the evaluation criteria of accuracy, precision, recall and F1-score.

The results at 500 samples showed Q-DNN reached a 92.8% accuracy combined with 92.2% precision and 91.4% recall. The model operates optimally because its quantum-informed parameters work with optimized feature learning elements. The model shows clinical reliability when processing data from histopathological and mammographic sources to distinguish different cancer types. Q-DNN combines computational complexity with high-performance and explainable AI features which make it applicable for real-time cancer diagnostics through cloud and edge-based healthcare systems to assist clinical decision-making and early cancer detection.

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