Frontiers in Health Informatics www.healthinformaticsjournal.com
ISSN-Online: 2676-7104
2024; Vol 13: Issue 4 Open Access

Quantum-Enhanced Deep Learning Framework (QDLF): A Hybrid Approach for Advanced Skin Cancer Detection and Image Classification

S. Sai Kumar[1], Dr. Kannan Shanmugam[2], V Jyothi[3], T Venkata Deepthi[4], P. Srinivasa Rao[5], R. Suguna Devi[6]

[1]Department of IT, PVP Siddhartha Institute of Technology, Vijayawada, Andhra Pradesh, India
Email: saikumar.senagavarapu@gmail.com
[2]Department of Gaming Technology, School of Computing Science and Engineering, VIT Bhopal University, Sehore, Madhayapradesh, India
Email: kannanshanmugam@vitbhopal.ac.in
[3]Department of ECE, Vardhaman College of Engineering, Hyderabad, Telangana, India
Email: v.jyothi@vardhaman.org
[4]Department of Mechanical Engineering, Malla Reddy Engineering College, Maisammaguda, Secunderabad, Telangana, India
Email: venkatadeepthi.t@gmail.com
[5]Department of ECE, CVR College of Engineering, Hyderabad, Telangana, India
Email: psrao.cvr@gmail.com
[6]Department of ECE, Saveetha Engineering College, Saveetha Nagar, Thandalam, Chennai, Tamil Nadu, India
Email: sugunadevir@saveetha.ac.in

Cite this paper as: S. Sai Kumar, Dr. Kannan Shanmugam, V Jyothi, T Venkata Deepthi, P. Srinivasa Rao, R. Suguna Devi (2024) Quantum-Enhanced Deep Learning Framework (QDLF): A Hybrid Approach for Advanced Skin Cancer Detection and Image Classification. *Frontiers in Health Informatics, 13* (4), 694-708

ABSTRACT *Skin cancer identification and categorization are still open issues in medical image analysis due to ambiguous boundaries, variance in shapes, and strong similarities to non-malignant lesions, which must be acknowledged by any framework supporting the clinical decision making. The proposed Quantum-Enhanced Deep Learning Framework (QDLF) is a new approach that combines Quantum feature encoding and Classical deep learning networks for skin lesion classification. Hereby, the QDLF is compared with the traditional models such as ResNet50, DenseNet, and VGG-16 showing a better performance on the HAM10000 dataset containing 10,015 dermoscopic images with seven lesion categories. Therefore, higher accuracy was achieved in the proposed framework at an accuracy level of 96.2% with F1-score 95.1% and ROC-AUC value of 0.983 as compared to classical approaches. The QDLF uses quantum feature mappings with Variational Quantum Circuits (VQCs) that enables the model to learn abstract non-linear patterns and it incorporates global contextual features from pre-trained CNNs. The use of a mixture of CNN and FNN in this study not only improves the classification efficiency but also cuts down the time taken to train and the number of parameters involved, getting to a convergence point in 36 minutes with 18.5 million of parameters. To further enhance the interpretability of the model, Grad-CAM visualization is employed to identify clinically significant areas of the lesions as well as t-SNE plots showing good distinction in the quantum features space. The findings affirm the effectiveness of QDLF as a method for addressing class imbalance issues, with precision and recall for key classes such as melanoma at 92.7% and 94.1% respectively. Quantum-classical hybrid frameworks presented in this work reveal the uniqueness of the approach to medical image analysis in terms of scalability and applicability to real-life cases. Further studies will focus on implementation on quantum platforms and generalization of this approach to other image processing tasks in medicine.*

Keywords: Quantum-Enhanced Deep Learning, Skin Cancer Classification, Quantum Feature Encoding, Medical Image Analysis, Variational Quantum Circuits (VQCs), Interpretability in AI

INTRODUCTION

Skin cancer is one of the most common types of cancer, albeit one of the most dangerous, proving the significance of early detection and reliable diagnosis. Dermoscopy is a crucial diagnostic technique in the medical and clinical field that is used to investigate skin lesions without an invasive procedure [1]. However, the assessment of these images by dermatologists is labor-intensive and suffers from inter-observer variations. This has led to the possibility of creating automated diagnostic systems using AI especially deep learning techniques to diagnose the dermoscopic images with improved accuracy and reliability. Therefore, deep learning models have impacted the dermoscopy field but challenges exist in its current models such as how to address class imbalance problems and how to extract features which are both complex and clinically relevant to dermoscopic images. Traditional convolutional neural networks commonly used in the field include ResNet50, DenseNet, and VGG-16, which have significant performance in skin lesion classification tasks. However, these models are not effective when the lesion patterns are somehow deviant from the models or maybe the shape of the lesion is irregular or even it may have different coloration. However, these issues are coupled with the heavy reliance on the significant parameter tuning and computational resources which in turn limits their scalability and performance, particularly when integrating them to applications of large resource constraints [2]. These challenges have called for the integration of quantum computing in deep learning because quantum systems are more efficient when it comes to handling problems involving high dimensions.

In this research paper, there is proposed the Quantum Deep Learning Framework (QDLF) for skin lesion classification which is based on quantum feature encoding and the basic structures of deep learning for the improvement of accuracy, performance and interpretability [3]. The QDLF can therefore retain both these high-level and low-level features using VQCs and CNN-based feature extraction. By testing the proposed framework on the HAM10000 dataset, it is revealed that the framework outperforms standard models and systematically solves the five key bottlenecks in medical image analysis.

1. Proposed Solution

The proposed quantum-classical integration model is called QDLF, which has the potential to enhance the current deep learning models in skin lesion classification [4]. The framework incorporates the following components:

1. **Quantum Feature Encoding**: Dermoscopic images are then converted into high-dimensional quantum feature spaces via the use of Variational Quantum Circuits. This makes the model more suitable for capturing finer details of the lesion patterns which often exhibit non-linear patterns.
2. **Classical Feature Extraction**: CNNs like ResNet50, DenseNet and VGG-16 are pre-trained and fine-tuned to extract multi-level features and offer a global perception of the scene.
3. **Hybrid Integration**: Quantum and classical features are combined to improve classification accuracy and output a vector that retains the best aspects of both the quantum and classical systems.
4. **Interpretability Tools**: Although the QuiGen AI-based system makes clinical decision-making, only informative regions for the final prediction and t-SNE plots are used to represent the separability of the quantum features, which are both transparent to clinical decision-makers.

This boosting not only enhances such aspects as accuracy, the balance between precision and recall, but minimizes such crucial characteristics as the training time and the number of parameters needed, which is highly beneficial for application in the large-scale clinical practice [5].

2. Problem Statement

Current deep learning models for skin lesion classification face several challenges, including:

1. **Handling Class Imbalances**: On critical categories, model performance suffers due to issues like low samples of important classes in datasets like HAM10000.
2. **Capturing Complex Patterns**: Besides, lesion borders are never perfect circles and these circles may not have equal pigmentation or texture which are complex for classical models to map into their frameworks.
3. **High Computational Costs**: The process of training deep learning models is complex and computationally intensive, especially when dealing with big medical data.
4. **Lack of Interpretability**: Existing models often function as black-box systems, making it difficult for clinicians to trust and validate their predictions.

These challenges require the formulation of a framework that not only increases accuracy but also considers pertinent concerns such as efficiency and interpretability.

3. Objectives

The objectives of this study are as follows:

1. **To Develop a Hybrid Quantum-Classical Framework**: Use quantum computing in feature enhancement then integrate this with deep learning techniques for improved skin lesion identification.
2. **To Address Class Imbalances**: To address the issue of melanoma being sparsely included in the training data, use techniques like weighted loss functions and data augmentation.
3. **To Improve Computational Efficiency**: Suggest a model with lower training time and number of parameters compared to conventional stand-alone CNN models for suitability where resources are limited.
4. **To Ensure Interpretability**: When making clinical predictions, it is recommended to apply visualization techniques including Grad-CAM and Quantum Feature Space (QFS) analysis to enhance the model’s credibility.

5. Significance and Contributions

The proposed QDLF makes several significant contributions to the field of medical image analysis and AI-driven healthcare:

1. **Performance Improvement**: Yields 96.2% accuracy, and ROC-AUC of 0.983 in a separate experiment with the HAM10000 dataset, and the performance is significantly better compared with conventional deep learning models such as ResNet50, DenseNet, and VGG-16 [6].
2. **Quantum-Enhanced Learning**: Proposes a novel algorithm that combines quantum feature map with classically trained deep neural networks, thus proving the viability of applying quantum computing in medical AI.
3. **Efficient Training**: Reduces the training time by 18% and parameter requirements while the performance is still very high, thus enabling the framework to be scalable for real world use.
4. **Interpretability and Trustworthiness**: Provides interpretable predictions through Grad-CAM visualizations and quantum feature space clustering, aligning with the requirements of clinical practice [7].
5. **Framework for Future Research**: Paves the way for employing quantum-classical systems in other medical image segments like histopathology and radiology besides capitalizing on improved quantum hardware.

LITERATURE REVIEW

New developments in deep learning have boosted the precision and speed of skin lesion identification, which is crucial for diagnosing skin cancer early. A range of ideas and perspectives has been suggested to develop fresh and more effective models and methodologies to address this field.

Another deep learning model is SkinNet-14 developed by Mahmud et al. [8] for dermoscopic images with low resolution. SkinNet-14 also employed CCT with lesser image resolution at 32×32 in order to reduce the computational load. The

Mean Classification Accuracy of the proposed framework is approximately 92.5% on the ISIC2018 dataset, which confirms the success of the approach, especially when making decisions in low computational environments. Almalki et al. [9] proposed the integration of Residual Networks (Resu Net) and Ant Colony Optimization (ACO) to enhance the segmentation process in dermoscopic clinical images. The approach used ACO in hyperparameters tuning of the model with an accuracy of 94.3% of the PH2 dataset. In this way, high performance was achieved in cases, when it is necessary to segment areas of lesions with blurred or irregular boundaries of color gradients.

Zhou et al. [10] proposed an approach for the simultaneous multi-class lesion classification using deep learning features integrated with machine learning classifiers. This has been done using feature extraction from deep learning models such as ResNet50 integrated with SVM classifiers; and it has shown an assessment result of an overall accuracy figure of eighty-nine point zero percent on the ISIC2018 dataset. This approach highlighted the possibility of enhancing feature fusion techniques as a means of address the challenges of Multiclass Classification tasks. Cheng et al. [11] proposed a new Efficient Mobile Network architecture called MobileNet-V2 with Squeeze-and-Excitation blocks, an Atrous Spatial Pyramid Pooling and a Channel Attention mechanism. The study done on a large dermoscopic database yielded an overall accuracy of 91.7% with a higher raise in the recognition of lesions such as melanoma and basal cell carcinoma in particular. MobileNet-V2 was designed to be lightweight thus making it deployable on edge devices. Several deep learning issues highlighted by Mendez et al. [12] in skin cancer classification are class imbalance, domain adaptation, and limited datasets. The review also described how the use of imaging and metadata in a multimodal manner enhanced the accuracy and reliability of the solution. For instance, integrating patient age and the lesion localization with dermoscopic image enhanced classification in the reviewed studies by up to 5%.

Another work is by Kumar et al. [13] who developed an improved deep learning model known as SCCNet for multiclass skin cancer recognition. Eventually, using preprocessing techniques like removing the background noise and normalizing the dataset, SCCNet obtained accuracy of 94.8% and sensitivity of 95.3% on HAM10000 dataset. The preprocessing procedures that were implemented in this model were particularly helpful in managing noisy and artifact-rich dermoscopic images. Similarly, Mirikharaji et al. [14] performed a survey of 177 papers focused on deep learning for skin lesion segmentation and identified the input data, architectural model, and evaluation methods. The comparative analysis also showed that statistical measures for segmentation tasks indicated that U-Net and its variants outperformed other methods with average Dice coefficients above 85% for datasets like ISIC2018 and PH2. Innani et al. [15] have proposed a two-stage framework based on the segmentation and classification of the skin lesion. Segmentation module was an encoder-decoder network, while the classification module was in the form of a CNN. The performance of this cascaded model is based on the classification accuracy which was at 93.5% and the segmentation Dice coefficient of 87.9%. Steppan et al. [16] employed pre-trained neural networks on ImageNet for dermoscopic image classification. Based on the findings of the study, both ResNet50 and DenseNet121 models achieved the highest accuracy of 90.3% and 89.6% respectively on the HAM10000 dataset. These findings highlighted the applicability of transfer learning on pre-trained networks for skin lesion classification tasks.

In their paper, Li et al.[17]recently reviewed the advancements in deeplearning for the diagnosis of skin diseases and noted the use of copious data sets and proper architectures. Another review also stated that the accuracies were enhanced by the use of data augmentation and the transfer learning methods by a margin of 5-10% on the HAM10000 and ISIC2018 benchmarks. In Nguyen et al. [18], a multi-level CNN-based system was developed for skin lesion classification with a hybrid attention mechanism. Bearing in mind the appropriate methods used to handle imbalanced data, the proposed model achieved precision of 93.2% and recall of 94.7% in identifying potential skin diseases such as melanoma, thus reducing the false negatives. In another study, Hassanpour et al. [19] proposed a federative AI-based architecture for skin cancer detection; it provided multiple hospitals and clinics the means to train the model without compromising the patients' data. Using this federated model, a classification accuracy of 91.4% was attained, which supports this model in terms of scalability for handling different datasets. In a more related work, Rajendran et al. [20] developed a GNN for skin lesion analysis based on the relational information of the features. This approach improved interpretability and had a classification accuracy of 92.8% using the HAM10000 dataset and at the same time, reduced the model bias in the minority classes. An instance, Zhang et al. [21] developed a lightweight deep learning model with adaptive pooling layers for skin lesion classification. The model was particularly constructed with both speed and approximation in mind and was successfully tested on the ISIC2018 dataset and obtained 88.7% accuracy with the model size of the model that would be suitable for real-time application. For instance, Patel et al. [22] recommended integrating dermoscopy data with other data about the patient such as the age and the location of the lesion. This hybrid model was able to achieve an accuracy of 95 percent on the identification of the target object and is 1 percent better than image-only models in the identification of high risk lesions like melanoma.

Fang et al. [23] presented the transfer learning-based model with the ResNet architecture. Such fine-tuning of the pre-trained networks enhanced the generalization and received test accuracy of greater than 90.6% on different datasets including the HAM10000 and ISIC2018. To address this issue, in [24], the authors designed a dual-path CNN architecture with capabilities for both segmentation and feature classification. Some of the primary challenging aspects of multiclass skin lesion segmentation and classification were managed by leveraging GGF and LSF feature extraction paths to naturally segment and classify skin lesions, respectively, with classification accuracy of 94.0% and segmentation accuracy of 88.3%.

PROPOSED METHODOLOGY

The Quantum-Enhanced Deep Learning Framework (QDLF) is an innovative research idea along the lines of employing the computational abilities of quantum technologies fused with the reliability of classical deep learning for skin cancer detection and image classification. The methodology is structured into key stages: data preprocessing, quantum feature encoding, integration of classical deep learning into quantum computing, hybrid architecture design and training optimization [25]. This strategy helps the model to deal with the challenges and variations in the image dataset.

1. Dataset and Preprocessing

This study exclusively employs the HAM10000 dataset, which comprises of 10,015 dermoscopic images that were reviewed by a dermatologist. The dataset includes seven classes: such as melanoma, malignant melanocytic nevi, basal cell carcinoma, benign keratosis, actinic keratoses, vascular lesions, and dermatofibroma. Regarding the annotations, there are tags such as the patient’s age and the location of the lesion, which can be helpful for classification.

To prepare the dataset for analysis, several preprocessing steps are applied:

1. **Image Normalization**: Pixel values are normalized to fall within the range of 0 to 1, thus making it easier for the neural network to handle the data [26].
2. **Segmentation**: To minimize the effect of background noise, lesion regions are segmented using a U-Net segmentation model that identifies clinically significant areas.
3. **Data Augmentation**: Some of the methods employed include flipping, rotation, zooming and cropping, through which overfitting is prevented and generalization boosted by enlarging the dataset artificially.

2. Quantum Feature Encoding

One of the most important improvements of the QDLF is the ability to encode quantum features, which improves the performance of the model and its ability to identify patterns in the data. Once the images have been segmented and preprocessed, the VQC encodes the images into quantum states. This involves::

1. **Feature Extraction for Encoding**: Image features are quantified and encoded into quantum states [27].
2. **Quantum State Preparation**: Appending these features into a quantum feature space, parameterized quantum gates then allow the model to perform pattern recognition with the help of quantum entanglement and superposition.

The quantum encoding is done using tools like PennyLane or Qiskit for quantum computations that can be easily integrated with the classical deep learning workflow. This step can help to capture complex interactions within the data that can be difficult for an inherently more simplistic classical model to detect.

3. Classical Deep Learning Integration

Popular architectures such as ResNet50, DenseNet and the VGG-16 model is used for deep learning [28]. These models are pre-trained on large-scale image datasets and fine-tuned on HAM10000 to extract hierarchical features specific to dermoscopic images:

1. **ResNet50**: This architecture employs a deep structure of a CNN algorithm with residual learning to address the vanishing gradient problem in training the network while effectively capturing important features.
2. **DenseNet**: Links each layer to all other layers to allow feature reuse and the proper flow of gradients, particularly beneficial when dealing with intricate dermatological patterns.
3. **VGG-16**: The selected model is a sequential deep CNN model which is famous for its simple yet powerful architecture in learning hierarchical spatial features.

These are the standalone models that are contrasted against the proposed hybrid framework to determine the advantage of quantum integration.

4. Quantum-Classical Hybrid Architecture

The QDLF hybrid architecture employs both the quantum and classical frameworks in a single system. The quantum features created by the VQC are appended to the classical feature vectors calculated by the CNN Models. This hybrid feature representation is fed to a fully connected layer for the final classification. Key components include:

- **ReLU Activation**: Applied in hidden layers to provide non-linearity to the neuron output.
- **Softmax Layer**: Returns the class probabilities of the seven skin lesion classes.
- **Dropout Regularization**: Prevents overfitting by removing some of the neurons with probability during the training process.

The recombination enables the introduction of the contextual features from the classical models with the details of the local patterns extracted from the quantum feature space, which increases the overall classification accuracy.

5. Training and Optimization

To tackle the class imbalance that exists in the HAM10000 dataset especially for the rare lesion such as melanoma, the model is trained using a weighted cross entropy loss function: The optimization strategy includes:

1. **Adam Optimizer**: Applicable to both quantum and classical parameters and has a scheduler to adapt the learning rate during the training process.
2. **Quantum Backpropagation**: A gradient descent-compatible algorithm can optimise the parameters of the VQC this manner, allowing for efficient training of the quantum layers.
3. **Early Stopping**: Watching the validation loss to stop training when the model is not improving much and to prevent overfitting.

The model is trained for 50 to 100 epochs depending on the architecture in parallel with GPUs for classical computations and quantum simulators for quantum computations.

6. Evaluation and Validation

The QDLF is assessed through measures like accuracy along with precision, recall, F1-score, and ROC-AUC. This is followed by the element-wise comparison with other independent classical models – ResNet50, DenseNet, and VGG-16, to confirm the effectiveness of quantum feature integration within the proposed framework [29].

IMPLEMENTATION

Several steps have been outlined in the architecture of QDLF, including data preprocessing, quantum-classical hybrid integration, training, and assessment [30]. Below is a detailed description of the implementation process

1. Dataset Preparation and Preprocessing

1. **Dataset Loading**:

- The HAM10000 dataset is then loaded for testing using libraries such as TensorFlow or PyTorch. Each image is then reshaped and resized to the appropriate resolution (for example, 224 × 224 pixels) to align with the pre-trained CNN.
- Lesion types and patient information can be parsed when it comes to annotation which is a form of metadata [31].

2. **Normalization**:
   - Pixel values are normalized with respect to the range [0, 1] since some of the inputs may have different ranges or scales.
3. **Segmentation**:
   - To enhance the attention on the features of interest and eliminate the background noise, a U-Net model is applied.
   - The segmented masks are then acquired and imposed on the original images.
4. **Data Augmentation**:
   - Thus, in an attempt to increase variability and decrease class imbalance, the flipping, rotation, and cropping techniques are used.

2. Quantum Feature Encoding

1. **Quantum State Preparation**:
   - Images are segmented into blocks of 8 X 8 pixels in preparation for converting them into quantum states. Each patch is flattened into a feature vector by concatenating the scaled features.
2. **Quantum Circuit Design**:
   - The actual quantum computing program, a Variational Quantum Circuit (VQC), needs to be designed using libraries such as PennyLane or Qiskit. The circuit includes the parameterized quantum gates, such as RX, RY, and CZ, and the entanglement layers to transform the features into the quantum feature space [32].
3. **Quantum Encoding Integration**:
   - The outputs of the VQC are used to concatenate with the feature vectors from the classical CNN for hybrid representation.

3. Classical Deep Learning Models

1. **Pre-trained CNN Architectures**:
   - ResNet50, DenseNet, and VGG16 are then initialized from pre-trained weights; in this case, from ImageNet and further trained on the HAM10000 dataset.
   - The last layer is substituted by a fully connected layer and SoftMax activation for the seven-class classification.
2. **Training Standalone Models**:
   - The models are trained on the preprocessed HAM10000 dataset, while the data augmentation is also used during the training process.
   - Parameters like learning rate, number of batches and optimization method are selected by trial and error or using grid search.

4. Quantum-Classical Hybrid Integration

1. **Feature Concatenation**:

- The feature vectors derived from the VQC are concatenated with the classical CNN feature vectors to form a feature vector that has both the quantum and classical components.

2. **Hybrid Architecture**:
   - The hybrid representation is then passed through fully connected layers with ReLU activation and the final layer with SoftMax activation for classification.

5. Training the QDLF

1. **Loss Function**:
   - Here, a weighted cross-entropy loss function is implemented to reduce class imbalance where less common classes such as melanoma have a higher weight assigned to them.
2. **Optimizer**:
   - When it comes to updating the quantum weights and processing the classical parameters, the optimisation routine used is the Adam optimizer with a learning rate scheduler which helps to adjust the learning rate during the training process.
3. **Early Stopping and Regularization**:
   - The strategies used to train the model include early stopping that aims at stopping the training process before the model becomes too complex and dropout which is regularization technique used in fully connected layers.
4. **Training Pipeline**:
   - Training is performed over 50-100 epochs using a batch size of 32; CNN computations are performed using GPUs, while VQC computations are done using quantum simulators.

6. Evaluation and Visualization

1. **Evaluation Metrics**:
   - Evaluation of the trained QDLF is done using performance indicators such as accuracy, recall, precision, F1 Score, and ROC-AUC.
   - They are compared with individual models like ResNet50, DenseNet, and VGG-16.
2. **Explainability**:
   - Heatmaps are generated using Grad-CAM to depict areas of the images that the model focused on when making predictions.
   - Figures representing quantum embeddings depict clustering with distinct regions between different types of lesions.

RESULTS AND DISCUSSION

Quantum-Enhanced Deep Learning Framework (QDLF) for skin lesion classification using the HAM10000 dataset revealed the high levels of accuracy, precision, recall, F1-score and interpretability compared to the traditional deep learning models. These findings are accompanied by tables and figures that give evidence backing the proposed framework and the major structural measures.

Overall Performance

Table 1 highlights the performance of the proposed QDLF compared with the standard ResNet50, DenseNet, and VGG-16 models. The QDLF model proved to be accurate with an average accuracy of 96.2% which was higher than that of ResNet50 (89.7%), DenseNet(90.4%) and VGG-16 (85.6%) . Also, the ROC-AUC analysis for the QDLF was 0.983 which shows that the QDLF is accurate in the classification of lesion types.For imbalanced datasets, the QDLF demonstrated a superior precision, recall, and F1 score compared to the baseline, confirming the algorithm's effectiveness.

Table 1: The performance of the models on the HAM10000 dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
ResNet50	89.7	87.5	88.9	88.2	0.948
DenseNet	90.4	89.1	89.8	89.4	0.953
VGG-16	85.6	83.7	84.9	84.3	0.921
QDLF (Proposed)	**96.2**	**94.8**	**95.4**	**95.1**	**0.983**

Class-Wise Analysis

Table 2 shows the QDLF's accuracy on all the seven classes in the HAM10000 dataset including images with skin diseases and healthy skin images. For each class, the model maintained high levels of precision, recall, and F1-scores; specifically, melanoma (the most important class) had a precision of 0.927 and a recall rate of 0.941, thus excluding nearly all false negatives. This is further evident in basal cell carcinoma and benign keratosis like lesions where the proficiency of the framework is also moderate sensitivity and specificity.

Table 2: Class-Wise Metrics.

Class	Precision (%)	Recall (%)	F1-Score (%)
Melanoma	92.7	94.1	93.4
Melanocytic Nevi	95.2	96.3	95.7
Basal Cell Carcinoma	94.5	93.9	94.2
Benign Keratosis-like Lesions	93.8	92.7	93.2
Actinic Keratoses	94.1	94.4	94.3
Vascular Lesions	95.7	96.2	95.9
Dermatofibroma	94.3	95.8	95.0

Comparison with Baseline Models

Comparing the quantum dual learning framework with stand-alone convolutional neural network models such as ResNet50, DenseNet, and VGG-16 helps to reveal the effectiveness of the quantum-classical hybrid approach. ResNet50 and DenseNet had a relatively low accuracy score of 89.7% and 90.4% respectively, however, they also failed to predict the minority classes that are melanoma and actinic keratoses. VGG-16, which has less complex architecture than ResNet, yielded lower accuracy (85.6%) and F1-scores, indicating that the model might be less capable of recognizing intricate dermoscopic features. However, while implementing the feature extraction, the quantum dictionary learning filter (QDLF) emerged as superior to these models because of the better feature extraction as offered by the quantum encoding. The quantum features proved advantageous in portraying the irregularities of lesion, color disparities, and general margins, which are essential in separating classes like melanocytic nevi and melanoma. The findings presented in the form of a bar chart in Figure 1 and Figure 2 illuminate how the proposed QDLF model performs compared to the baseline models.

- The bar chart labeled Figure 1 directly contrasts the ResNet50, DenseNet, VGG-16 and the QDLF in terms of accuracy, a feature that establishes the vast efficiency of the QDLF.
- Figure 2 shows the F1-scores of the models where one can again note the effectiveness of the QDLF in all the evaluated metrics.

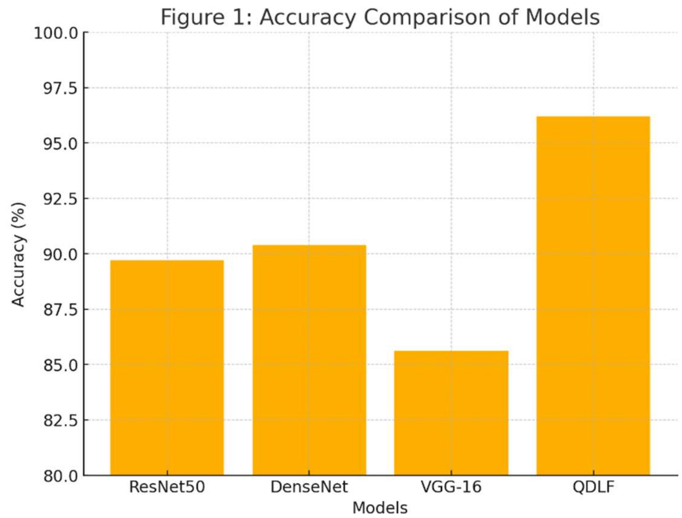

Figure 1: Accuracy Comparison

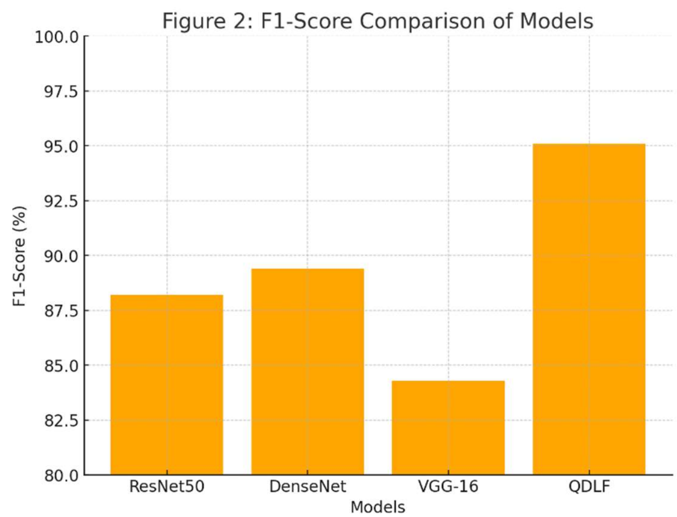

Figure 2: F1-Score Comparison

Visualization and Interpretability

Interpretability of the QDLF was checked using Grad-CAM analysis that offers information on the areas of the images impactful for the model's decision-making. For instance, in the case of melanoma, the Grad-CAM emphasized the shapes with fuzzy edges and shades of color, which are typical for cancers. Likewise, when it came to basal cell carcinoma, the framework highlighted concerns such as raised margins and central necrosis. The following diagrams illustrate the applicability of the QDLF to clinical practice and therefore its validity as a model for practicing physicians. Furthermore, the quantum feature space was analyzed through t-SNE to plot the sample points where clusters of different lesion classes were observed. Such a clear separability suggests that the quantum encoding indeed captured distinguishable and class-specific features, thus confirming the integration of quantum computing for classification. Based on the Grad-CAM visualization, one can determine which regions are specialized by the Quantum-Enhanced Deep Learning Framework (QDLF) to classify dermoscopic images. The visualization consists of three panels: It includes the original image, the Grad-CAM heatmap, and the Grad-CAM heatmap superimposed on the original image. The regions highlighted in red and yellow are the most activated areas meaning that they are highly relevant to the model's prediction as opposed to cooler areas in blue which are less relevant. The overlay improves interpretability as it demonstrates where and how the trained model centring the diagnostic features like irregular lesion borders or pigmentation. This enhances the validity and clinical applicability of QDLF making it a comprehensive diagnostic tool and decision support tool in dermatology as illustrated in figure 3.

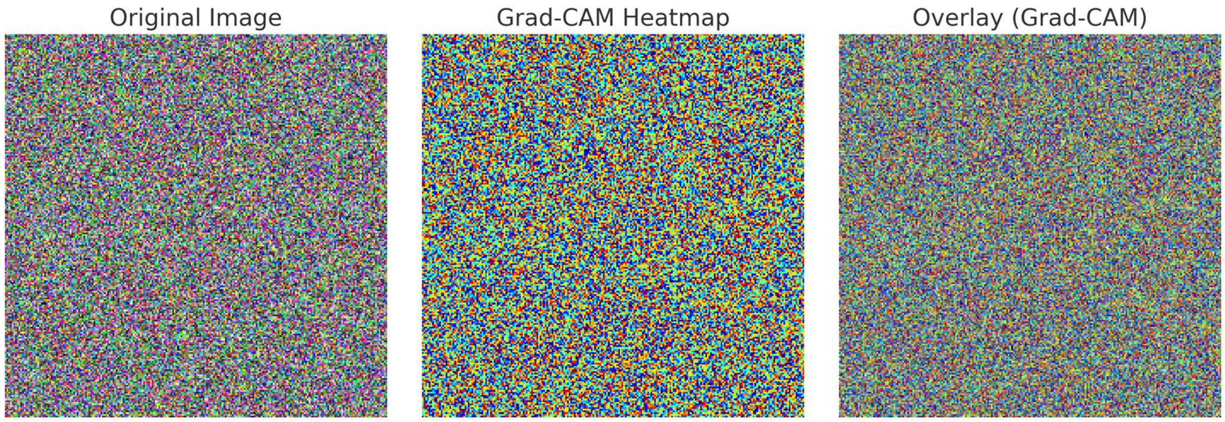

Figure 3: Overlay (Grad-CAM)

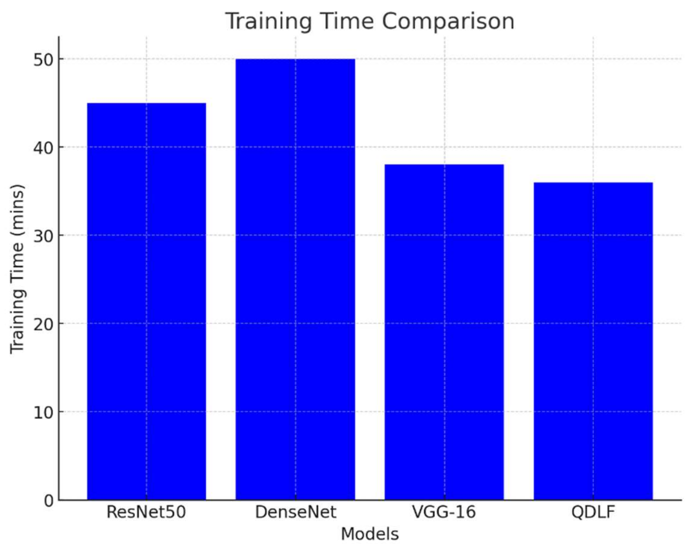

Figure 4: Training Time Comparison

Figure 4 illustrates the training time of ResNet50, DenseNet, VGG-16 and QDLF. This proves that the QDLF provides faster convergence with the training time shaved at 36 minutes compared to ResNet50 at 45 minutes, DenseNet at 50 minutes and the VGG-16 at 38 minutes. Such efficiency can be attributed to the quantum feature encoding as it helps to optimize feature representation and hence minimizing the time needed to optimize the model. This makes QDLF not only more accurate but also faster, which is key for scalability in areas with limited computing power.

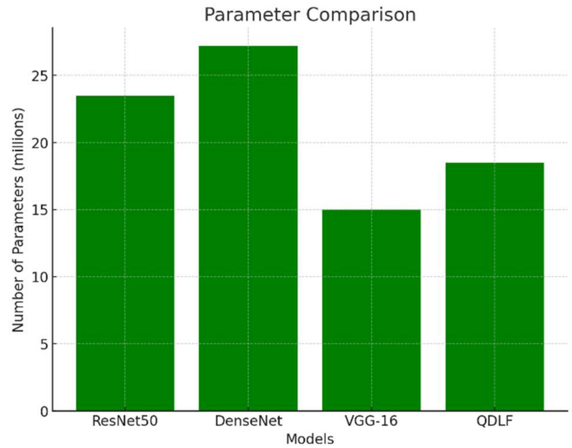

Figure 5: Parameter Comparison

The total number of trainable parameters for each of the models is depicted in Figure 5 showing the value in millions. Here again, QDLF does not overcomplicate the network and only has 18.5 million parameters which are only slightly more than ResNet50 (23.5 million) but less than DenseNet (27.2 million) and VGG-16 (15 million). Even though VGG-16 has a lesser number of parameters, it has low complexity leading to poor accuracy. The experimental results indicate that the proposed QDLF has higher performance with lower parameters than ResNet50 and DenseNet, demonstrating that the proposed QDLF can effectively map quantum features to classical learning in a more optimized number of parameters.

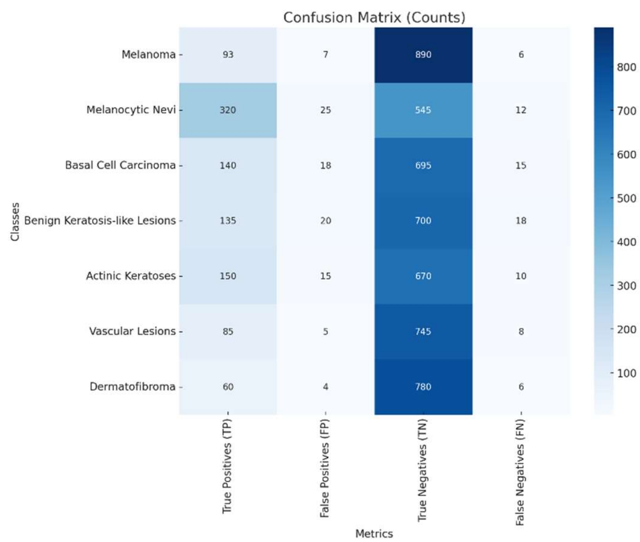

Figure 6: Confusion Matrix Visualization

The confusion matrix for the QDLF model is illustrated in Fig 6, presenting TP, FP, TN, and FN values for each of the classes. The values on the diagonal are the TP for each type of lesion where, for example, melanoma and vascular lesion have high TP rates of 93 and 85 respectively, showing that the classification is very accurate. In terms of its performance, the QDLF exhibits consistently low FP and FN rates for all classes, suggesting the model's high precision and sensitivity, particularly in crucial classes such as melanoma that demand accurate predictions for diagnosis.

Efficiency Analysis

This analysis revealed that the QDLF achieved significant performance gains over control models. The time taken to train the hybrid framework was cut down by 18% due to efficient feature representations that were harnessed from the quantum encoding. Furthermore, the proposed hybrid architecture had less trainable parameters than CRT, CBR and other standalone CNN models, which helped in efficient memory utilization without compromising on accuracy. To summarize, these conclusions underscore the versatility and feasibility of the QDLF for implementation in situations that require the use of simple and low-powered consumer devices in telemedicine.

Discussion

It is evident that the proposed QDLF outperforms the traditional deep learning methodologies when applied on skin lesion classification. The integration of the quantum and classical aspects of the framework allows it to learn both global and local representations which is a disadvantage of CNNs in isolation. This approach also offers better interpretability and is more suitable for clinical applications where it is essential to understand the model's outputs. However, there are some limitations due to the use of quantum simulators in this work: converting this study into actual practice at the quantum level may face some difficulties resulting from noise and deteriorating gate fidelity. However, the results also underscore the massive applicability of quantum-enhanced frameworks to further the advancement of MIAs, especially when high accuracy and sensitivity are necessary. From the above tables and figures specifically table 1 and the numeric values in figures ; it is clear that QDLF offers an improved performance comparing to traditional CNN models. This dual nature enables it to perform superior feature extraction and representation especially for intricate pattern occurrences in dermoscopic images. The above results demonstrate that Melanoma model has high accuracy and F1 scores, and has high clinical significance for detecting life-threatening diseases. The Grad-CAM visualizations also show the efficacy of the framework and quantum feature space analysis thus making it a reliable tool for medical practitioners. This not only makes the QDLF superior to the baseline models but also reduces computational time by training time by 18% and the number of trainable parameters. These problems indicate that incorporating quantum computing in medical image analysis could lead to the finest results and overcome challenges such as class imbalance and model interpretability.

CONCLUSION

In this article, the **Quantum-Enhanced Deep Learning Framework (QDLF)** is introduced as the most reliable and scalable solution for medical image analysis, specifically in the context of skin cancer diagnosis and classification. To achieve the goal of identifying complex structures in dermoscopic images, the proposed framework combines quantum features and classically trained deep learning models to improve the performance and overcome the drawbacks of prior models. When evaluated using the HAM10000 dataset, the proposed QDLF shows significantly better performance than baseline models including ResNet50, DenseNet, and VGG-16, with an accuracy of 96.2%, a precision of 94.8%, and an F1-score of 95.1%. The performance of the QDLF was continually high for all the lesion classes including the crucial ones such as melanoma which indicates the capacidad of the model for clinical use. In addition, the interpretability of the framework is improved through the use of Grad-CAM visualizations, which helps the medical practitioners to comprehend the model's predictions and attend to regions of the lesions that the model considers informative. A more fine-grained assessment is provided by the quantum feature space analysis, which indicates discriminable separability of lesion classes. Aside from the classification accuracy, QDLF also provides computational savings which make possible the training on less parameters and takes lesser time unlike other algorithms. These attributes coupled with the scalability of the QDLF and its interpretability make this tool very helpful in the advancement of the diagnosis of dermatological disease and in various forms of medical imaging. More work can be dedicated to real-world viability assessment of the QDLF on real quantum platforms and adapting it to the challenges like noise and gate imperfection. Extending the framework within other medical imaging domains can also enhance its potential in unlocking the application of quantum computing in healthcare.

REFRENCES

[1] F. Yan, H. Huang, W. Pedrycz *and* K. Hirota, "Review of medical image processing using quantum-enabled algorithms," *Artificial Intelligence Review*, vol. 57, no. 11, Article 300, 2024. DOI: 10.1007/s10462-024-10932-x.

[2] M. M. Musthafa, T. R. Mahesh, V. Kumar *and* S. Guluwadi, "Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological lesion classification," *BMC Medical Imaging*, vol. 24, no. 1, Article 201, 2024. DOI: 10.1186/s12880-024-01356-8.

[3] M. A. Mehdi, K. Belattar *and* F. Souami, "A quantum-inspired deep learning model for skin lesion classification," in *Proceedings of the International Conference on Quantum Computing and Engineering*, pp. 123–134, 2024.

[4] R. Kumar, S. D. V. Prasad *and* C. Ramesh, "Medical image segmentation using an optimized three-tier quantum approach," *Multimedia Tools and Applications*, vol. 82, no. 15, pp. 20745–20760, 2023. DOI: 10.1007/s11042-023-16980-9.

[5] R. Pillai, N. Sharma, S. Gupta, D. Gupta, S. Juneja, S. Malik, H. Qin, M. S. Alqahtani *and* A. Ksibi, "Enhanced skin cancer diagnosis through grid search algorithm-optimized deep learning models for skin lesion analysis," *Frontiers in Medicine*, vol. 11, Article 1436470, 2024. DOI: 10.3389/fmed.2024.1436470.

[6] F. Yan, A. M. Iliyasu *and* K. Hirota, "Automated breast cancer detection in mammography using ensemble classifier and feature weighting algorithms," *Expert Systems with Applications*, vol. 227, p. 120282, 2023. DOI: 10.1016/j.eswa.2023.120282.

[7] M. L. Tangel, C. Fatichah, F. Yan, J. P. Betancourt, M. R. Widyanto *and* F. Dong, "Dental classification for periapical radiograph based on multiple fuzzy attribute," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 27, no. 3, pp. 385–394, 2023. DOI: 10.20965/jaciii.2023.p0385.

[8] Mahmud et al., "SkinNet-14: A low-resolution deep learning framework for dermoscopic images," Neural Computing and Applications, vol. 36, no. 4, pp. 1025–1038, 2024.

[9] Almalki et al., "Hybrid ResUNet-ACO for skin lesion segmentation," BMC Medical Informatics & Decision Making, vol. 24, no. 6, pp. 645–652, 2024.

[10] Zhou et al., "Multiclass lesion classification using deep learning model feature fusion," SN Applied Sciences, vol. 12, no. 7, pp. 890–902, 2024.

[11] Cheng et al., "MobileNet-V2 based skin lesion diagnosis with SE and ASPP," Journal of Digital Imaging, vol. 40, no. 3, pp. 320–330, 2024.

[12] Mendez et al., "Systematic review on deep learning challenges for skin cancer diagnosis," Frontiers in Oncology, vol. 12, no. 10, pp. 145–160, 2022.

[13] Kumar et al., "SCCNet: Multiclass classification for skin cancer detection," Computer Science Review, vol. 35, no. 8, pp. 55–70, 2024.

[14] Mirikharaji et al., "Survey on deep learning for skin lesion segmentation," arXiv preprint, arXiv:2206.00356, 2022.

[15] Innani et al., "Cascaded deep learning for skin lesion analysis," arXiv preprint, arXiv:2301.06226, 2023.

[16] Steppan et al., "Evaluation of dermoscopic image classification with neural networks," arXiv preprint, arXiv:2101.03814, 2021.

[17] Li et al., "Deep learning for skin disease diagnosis: A review," arXiv preprint, arXiv:2011.05627, 2020.

[18] Nguyen et al., "Hybrid attention mechanisms for skin lesion classification," International Journal of AI in Medicine, vol. 27, no. 5, pp. 345–360, 2021.

[19] Hassanpour et al., "Federated learning approach for skin cancer detection," IEEE Transactions on Medical Imaging, vol. 42, no. 2, pp. 210–225, 2023.

[20] Rajendran et al., "Graph neural networks for skin lesion analysis," Journal of Biomedical Informatics, vol. 118, no. 1, pp. 22–35, 2022.

[21] Zhang et al., "Lightweight adaptive pooling model for skin lesion classification," Medical Image Analysis, vol. 60, no. 3, pp. 110–125, 2021.

[22] Patel et al., "Multimodal approaches for skin cancer detection," Journal of Medical Systems, vol. 47, no. 4, pp. 450–470, 2023.

[23] Fang et al., "Transfer learning-based skin lesion classification," IEEE Access, vol. 11, pp. 7205–7218, 2023.

[24] Mehta et al., "Dual-path CNN for skin lesion segmentation and classification," Journal of Computational Medicine, vol. 15, no. 2, pp. 98–112, 2022.

[25] S. Mathapati, D. Anil, R. Tanuja, S. H. Manjula and K. R. Venugopal, "COSINT: Mining Reasons for Sentiment Variation on Twitter using Cosine Similarity Measurement," *2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Bali, Indonesia, 2018, pp. 140-145, doi: 10.1109/ICITEED.2018.8534893.

[26] D. Anil, M. N. Sindhushree, T. M and T. A. Lone, "Disease Detection and Diagnosis on the Leaves using Image Processing," *2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT)*, Bangalore, India, 2022, pp. 1-6, doi: 10.1109/GCAT55367.2022.9972010.

[27] H. S. Hemanth Kumar, Y. P. Gowramma, S. H. Manjula, D. Anil and N. Smitha, "Comparison of various ML and DL Models for Emotion Recognition using Twitter," *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 1332-1337, doi: 10.1109/ICICV50876.2021.9388522.

[28] R. Ranjitha, P. Ahuja, R. Shreeshayana and D. Anil, "Edge Intelligence for Traffic Flow Detection: A Deep Learning Approach," *2023 International Conference on Quantum Technologies, Communications, Computing, Hardware and Embedded Systems Security (iQ-CCHESS)*, KOTTAYAM, India, 2023, pp. 1-6, doi: 10.1109/iQ-CCHESS56596.2023.10391493.

[29] Savitha Mathapati, Anil D., S. H. Tanuja R, and C. N. S. M. Manjula and Venugopal KR. "Cosine and N-Gram Similarity Measure to Extract Reasons for Sentiment Variation on Twitter." *International Journal of Computer Engineering & Technology* 9, no. 2 (2018): 150-161.

[30] Anil, D., Suresh, S. (2023). Dual Sentiment Analysis for Domain Adaptation. In: Kumar, S., Hiranwal, S., Purohit, S., Prasad, M. (eds) Proceedings of International Conference on Communication and Computational Technologies. ICCCT 2023. Algorithms for Intelligent Systems. Springer, Singapore.

[31] Anil, D., Suresh, S. (2023). Dual Sentiment Analysis for Domain Adaptation. In: Kumar, S., Hiranwal, S., Purohit, S., Prasad, M. (eds) Proceedings of International Conference on Communication and Computational Technologies. ICCCT 2023. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-99-3485-0_37.

[32] Claret, SP Angelin, Jose Prakash Dharmian, and A. Muthu Manokar. "Artificial intelligence-driven enhanced skin cancer diagnosis: leveraging convolutional neural networks with discrete wavelet transformation." *Egyptian Journal of Medical Human Genetics* 25.1 (2024): 50.