Quantum Machine Learning for Skin Cancer Classification

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Abstract: In today's world with the increasing rates of skin cancer, timely and accurate diagnosis is of utmost importance. It can greatly improve patient outcomes and lead to personalized treatment plans. Quantum computing is pushing the boundaries of technology and has the potential to solve medical problems more efficiently. Conventional machine learning techniques like deep neural networks are frequently employed for recognizing patterns in image data. However, quantum machine learning approaches are demonstrating significantly faster performance in the realm of medical image analysis. This project proposes a classification system based on Quantum Machine Learning that can classify skin lesion images into cancerous and non-cancerous classes. The publicly available Melanoma and Non-Melanoma datasets have been used to accomplish this task. This system could potentially help with early diagnosis of the disease and become a viable alternative until fully scalable quantum hardware becomes available. "In a world where skin cancer rates continue to rise, timely and accurate diagnosis is crucial for improved patient outcomes and personalized treatment plans. Quantum computing holds immense potential to address medical problems in a more efficient manner than existing classical machine learning methods. In particular, quantum machine learning methods have demonstrated faster processing speeds than classical techniques for medical image analysis. This project proposes a skin lesion classification system based on quantum machine learning, using publicly available melanoma and non-melanoma datasets. Such a system could aid in early diagnosis of the disease, and serve as a viable alternative until scalable quantum hardware becomes available."

Keywords: Quantum Machine Learning, Quantum SVM, Melanoma, Keratosis, VGG16.

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1. Introduction

Skin Cancer arises from unusual swelling of skin cells, which may be caused by a variety of factors, such as exposure to radiation, chemicals, and family history. Although there are research works that focus on the detection, identification, and classification of various skin cancers, these works are confined to the classes of Melanoma and Non-Melanoma [1]. Notable works have widened their procedures from classical machine learning [2] towards deep learning, which is a positive sign since they provide accurate results. However, there is a need to classify cancers into multiple classes, to assist specialists in giving a comprehensive diagnosis. These classes are of different types, owing to their nature, and hence Quantum Machine Learning can just provide a more efficient and suitable path towards proper classification of skin cancer lesions.

It is an undeniable fact that a magnitude of works focused on the problem of classification of skin cancer lesions via deep learning [3]. Furthermore, a handful of research works focused on expanding the classes of Melanoma and Non-Melanoma [4]. But this work focuses on developing a system that classifies skin lesions into the 5 most common classes, by leveraging Quantum Machine Learning and VGG16 frameworks. The paramount object of the work is to create a hybrid QML model that intends to train on a dataset, takes an image input, and sets it into the most appropriate class.

The 5 most common skin cancer classes are Melanoma, Nevus, Seborrheic Keratosis, Basal Cell Carcinoma, and Squamous Cell Carcinoma. Nevus, commonly known as a mole, appears as a small, pigmented spot on the skin. It typically presents as a round or oval-shaped lesion with well-defined borders. Nevus can vary in color, ranging from tan to brown, and may develop hair follicles. While most nevi are benign and pose no health risks, changes in size, shape, or color should be monitored for potential malignancy [5]. Melanoma appears as an irregular, asymmetrical lesion with undefined borders on the skin. It often exhibits variations in color, including shades of brown, black, blue, or red. Melanoma may evolve from existing moles or arise as new growth. Seborrheic keratosis manifests as raised, wart-like growths on the skin's surface, typically appearing brown, black, or tan. These lesions often have a rough or waxy texture and may vary in size and shape [6]. Basal cell carcinoma (BCC) presents as a raised, translucent, or pearly nodule on the skin, often with visible blood vessels or a central depression. BCC can cause local tissue destruction if left untreated. Early detection and prompt treatment are crucial. Squamous cell carcinoma (SCC) appears as a firm, red, scaly bump or patch on the skin, often with a crusted or ulcerated surface. It may arise from precancerous lesions or develop on sun-exposed areas like the face, ears, and hands [7].

Choosing the right treatment for skin cancer lesions involves evaluating factors like cancer type, stage, and lesion characteristics. Dermatologists carefully assess the depth, spread, and location of the lesion to determine the most appropriate approach. Treatment options vary from topical medications to surgical excision, radiation therapy, and immunotherapy, tailored to each patient's specific needs and preferences. Multidisciplinary discussions among dermatologists, oncologists, and other specialists help ensure comprehensive care and informed decision-making. The goal is to achieve optimal outcomes while minimizing side effects and preserving function and aesthetics.

The paper comprises five distinct sections for better organization and coherence. The first section shows the Introduction part. The Second section is Literature Review, focused on existing research related to our study. The third section is Methodology, which details our approach and techniques applied. The fourth section is Results and Discussion, which presents our findings In conclusion, the paper's final section provides a concise summary of the study's outcomes and outlines potential avenues for future research.

2. Literature review

Danyal Maheshwari et al. [8] reviewed quantum machine learning (QML) in biomedicine from 2013 to 2021, analyzing 3,149 articles to focus on 30 key papers that explore QML models and quantum circuits. Their study highlights the limitations and potential of these technologies, suggesting the field remains largely untapped. An optimization search technique evaluates the potential solution and frames the better solution by any of its befitting categories such as quantum-based approaches[9].

Lin Wei et al. [10] explored the integration of quantum computing with machine learning, enhancing areas like the analysis of images of the medical field, password cracking, and pattern recognition. Their review highlights quantum advancements in parameter optimization and efficiency, significantly improving on classical machine learning's challenges over the past decade.

Teck Yan Tan et al. [11] A sophisticated decision support system was created to aid in the detection of skin cancer that employs feature extraction techniques such as Grey Level Run Length Matrix and Histogram of Oriented Gradients to analyze lesion characteristics. The system uses Particle Swarm Optimization to enhance the accuracy of lesion classification by optimizing features like asymmetry, border irregularity, and color. Maria Schuld et al. [12] systematically reviewed quantum machine learning, emphasizing and promising in enhancing classical algorithms for tasks like image and speech recognition and strategy optimization, while also exploring the development of quantum learning theory.

Maxwell West et al. [13] investigated geometric quantum machine learning for image classification, showing that models equivariant to image reflections outperform traditional methods by integrating data symmetries. Quantum technology achieve more selectivity, sensitivity, robustness compared to their classical counterparts [14].

Quantum machine learning for medical image classification using quantum circuits and orthogonal neural networks, revealing the capabilities and limitations of current quantum hardware through benchmarks on retinal and chest X-ray images. Mahabubul Alam et al. [15] examined the use of Quanvolution and quantum neural networks in image classification, highlighting their roles in feature extraction and decision-making, and detailing the strengths and limitations of hybrid QML models.

Ricardo Daniel Monteiro Simoes et al. [16] analyzed quantum support vector machines and neural networks, finding they outperformed classical models by 3-7% across five datasets using various quantum feature maps. Himanshu Gupta et al. [17] evaluated deep learning and models from quantum machine learning for diabetes prognosis employing the PIMA dataset, with the deep learning model surpassing the quantum model by 1.06% in prediction accuracy.

Zhi-Peng Jiang et al. [18] improved the VGG16 model to create IVGG13, enhancing pneumonia X-ray image classification with data augmentation for over 85% accuracy, requiring less training time and resources while matching or exceeding other CNNs' performance. Douglas Rocha et al. [19] employed the VGG16 neural network to classify diabetic retinopathy in retinal images, achieving the best performance on the DDR database through comprehensive preprocessing and data augmentation.

Ville Bergholm et al. [20] introduced PennyLane, a Python 3 framework for quantum and hybrid computations, supporting qubit and continuous-variable systems and enabling gradient computation compatible with classical backpropagation for diverse quantum applications. Yunseok Kwak et al. [21] explored quantum reinforcement learning with a variational quantum circuit via PennyLane, showcasing its potential in CartPole environments. Addressing comparisons with conventional methods, aiming to aid newcomers and foreseeing future advancements.[22]

3. Methodology

Figure 1 shows the architecture proposed for the system of the skin cancer classification model.

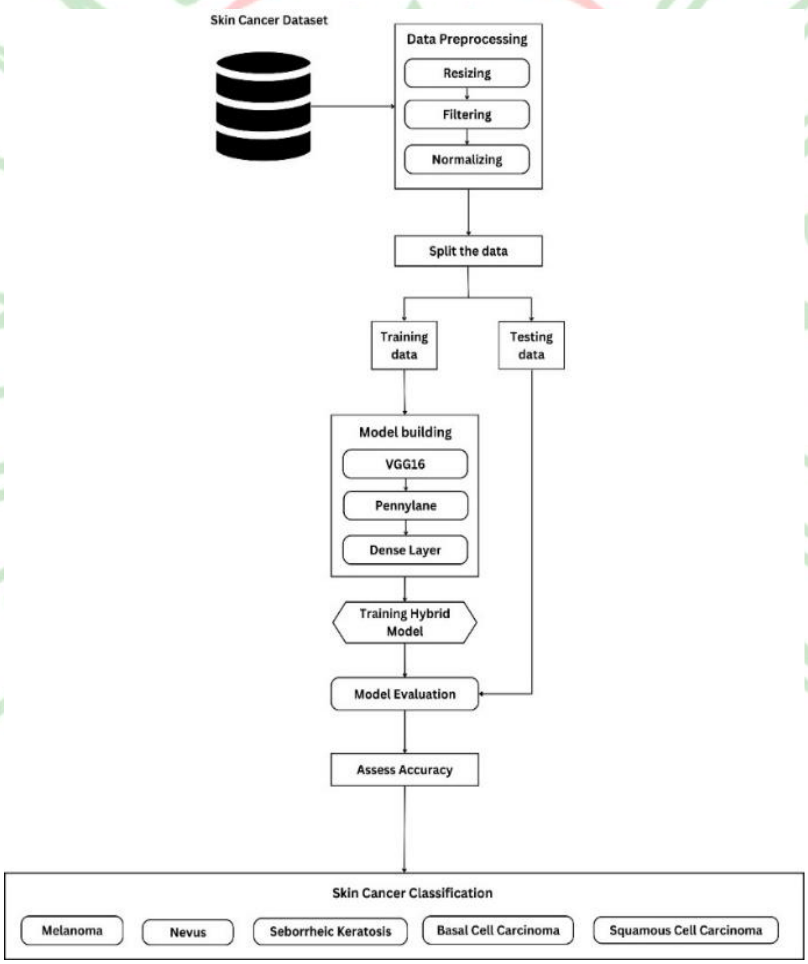

Fig 1. Process flow diagram of the proposed segmentation and classification model.

This methodology can be broadly divided into 4 major modules: Data Preprocessing, Data Splitting, Model Building, and Hybrid Model Training. Each module has been elaborated so that the entire working procedure of the classification model has been shown clearly.

3.1 Skin Cancer Dataset

For training and testing, as well as validation of the results of the model, a skin cancer dataset [23] has been selected, which consisted of more than 44000 images. Aiming towards the convenience of execution, duplicated images have been removed from the dataset, and only a total of 5000 images have to be and are been used for training objectives. The images have been selected in such a way that each of the 5 training classes is attributed with approximately 1000 images. Since the magnitude of the dataset is vast, there is scope for errors in images in the form of disturbances, foreign objects, and even human disturbances. To tackle this problem, image pre-processing techniques have been employed, which will be elaborated in the later section.

3.2 Image Preprocessing Techniques

Image preprocessing [24] is the process of preparing raw images for analysis by cleaning, transforming, and organizing them. This step is crucial for refining the quality and precision of the models in quantum machine learning and analytical tasks. Cleansing of images is highly essential especially in classification problems, since the presence of disturbances can greatly affect the performance of the classification model. Following are the pre-processing techniques employed to get the best results: Re-Sizing, Filtering, and Normalization. The mentioned image pre-processing techniques have proved themselves to be the best set of techniques, after being tested on a trial-and-error basis. These techniques have been broadly defined below:

3.2.1 Resizing

Image resizing is a technique that involves adjusting the dimensions of images to a specific size, which is essential for processing and standardizing input data. In quantum machine learning for skin cancer classification, resizing ensures that all skin lesion images are consistent in size and aspect ratio. This uniformity is crucial for the efficient processing and analysis of images by quantum models. By resizing images, the data can be more easily encoded into quantum states, enabling faster and more accurate classification. Additionally, resizing helps manage the intricacy and dimensionality of the input data, improving the model's performance and training speed in classifying skin cancer images.

3.2.2 Filtering

Filtering [25] is a technique used to remove noise and enhance features in images, which is essential for preparing data for analysis. Filtering plays a crucial role in improving image quality and focusing on the relevant aspects of skin lesion images. By applying filtering methods such as Gaussian blur or edge detection, noise can be reduced, and important features can be highlighted. This preprocessing step enhances the quality of the input data, making it easier for quantum models to process and classify skin cancer images accurately. Improved image quality allows the quantum model to focus on the critical patterns and features associated with different types of skin cancer, leading to more precise and reliable classification results.[26]

3.2.3 Normalization

Normalization [27] involves scaling data to a specific range, typically [0, 1] or [-1, 1], to ensure uniformity across different features. To classify the input images with the highest possible accuracy, normalization is essential for consistent and efficient data processing. By bringing pixel values within a standardized range, normalization reduces the influence of varying scales across images, which can otherwise skew the training and classification process.[28] This preprocessing step enhances the accuracy and reliability of the classification model, ultimately improving the detection and diagnosis of skin cancer[29]. Figure 2. Shows Ultrasound images before and after preprocessing.

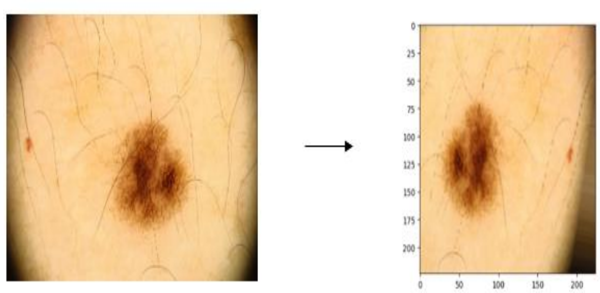

Fig 2. Ultrasound images before and after preprocessing

3.4 Data Splitting

The correct ratio of data splitting is essential for ensuring the reliability and generalization of the trained model. Data splitting typically involves dividing the dataset into three subsets: training, validation, and testing.[30] The importance of a well-balanced split lies in the following aspects: Model Training, Validation for Tuning, Model Testing, Model Representation, and Model Performance. This ratio is critical for developing a well-trained, generalized, and unbiased quantum machine-learning model for skin cancer image classification. Based on previous research works, a 70-30 ratio has been maintained between the number of training images and testing images.

3.5 Model Building

The generic definition of Model Building is "the process of designing, developing, and training a model to make predictions or decisions based on input data". It is an encapsulation of several key steps responsible for the performance of the model. These steps include choosing an appropriate model architecture, training the model on data, and evaluating its performance. For proper building of this classification model, the following are the key models incorporated, with their detailed usage.

3.5.1 Visual Geometry Group – VGG16

In algorithm 1, the process of feature extraction using the VGG16 convolutional neural network (CNN) architecture has been outlined [31]. The input is a pre-processed image, and the output consists of high-level feature representations obtained from the specified convolutional layers of the VGG16 model. The algorithm involves loading the pre-trained VGG16 model, removing the fully connected layers to retain only the convolutional layers, and freezing all layers to prevent weight updates during the feature extraction process. The input image is then passed through the VGG16 network, and feature maps are extracted from the desired convolutional layers. Finally, the algorithm returns these feature maps as high-level representations that can be leveraged for a variety of downstream tasks, including image classification or object detection.

3.5.2 Pennylane Framework

PennyLane which is a software of open source framework designed for quantum computing and quantum machine learning. It allows for the automatic differentiation of hybrid quantum-classical computations, facilitating the development and training of quantum models. PennyLane supports various quantum hardware and can integrate with classical machine learning libraries.

3.5.3 Dense Layer

In algorithm 3, an approach to image classification using dense layers [32] in a neural network has been outlined. First, a sequential model is defined, including a flattened layer to convert the input image into a 1D vector, followed by one or more dense layers with activation functions like ReLU. A final dense layer with C output neurons and softmax activation provides class probabilities. During training, the model is optimized using a loss function such as categorical cross-entropy and an optimizer for example Adam. For prediction, a new image is pre-processed, flattened, and passed through the trained model to obtain class probabilities.

3.6 Training the Hybrid QML Framework

Pennylane is a powerful open-source framework primarily designed for quantum machine learning (QML) tasks. However, its application in image classification, specifically in the context of traditional tasks related to classifying images like those executed with convolutional neural networks (CNNs), is indirect and not as direct as using classical deep learning frameworks. In image classification tasks, traditional CNNs are typically preferred due to their proven effectiveness, scalability, and efficiency in handling large-scale image datasets. These CNNs, such as VGG16 or ResNet, excel at learning hierarchical features directly from image data and have demonstrated the capability to excel in achieving state-of-the-art performance across a range of benchmark datasets.

4. Results and Discussion

This section deals with the results obtained by successfully executing the classification hybrid model, as well as the performance analysis of the results generated. Implementation of a Quantum Machine Learning algorithm on medical classification problems has never been done before, and hence, this is a novel work, which showcased attractive results, which in turn promises scope towards addressing medical challenges using quantum frameworks.

The following performance metrics have been elaborated in the later sub-sections: Model accuracy. Model Training Loss, Confusion Matrix, and Receiver Operating Characteristic (ROC) curve.

4.1 Confusion Matrix and ROC-AUC Curve

Confusion Matrix is a performance metric used to assess the accuracy of a classification model is called accuracy. It quantifies the proportion of correctly classified instances, encompassing both true positives and true negatives, relative to the total number of instances in the dataset. The confusion matrix depicted in Figure 3 represents all the instances for the 5 skin lesion classes, namely Basal Cell Carcinoma, Nevus, Melanoma, Seborrheic Keratosis, and Squamous Cell Carcinoma.

The ROC Curve serves as a graphical representation that depicts the performance of a binary classification model across various thresholds for distinguishing between positive and negative classes The following Figure 4 illustrates the ROC curve of the hybrid QML model, indicating the ROC scores of each class, labeled from 0 to 4.

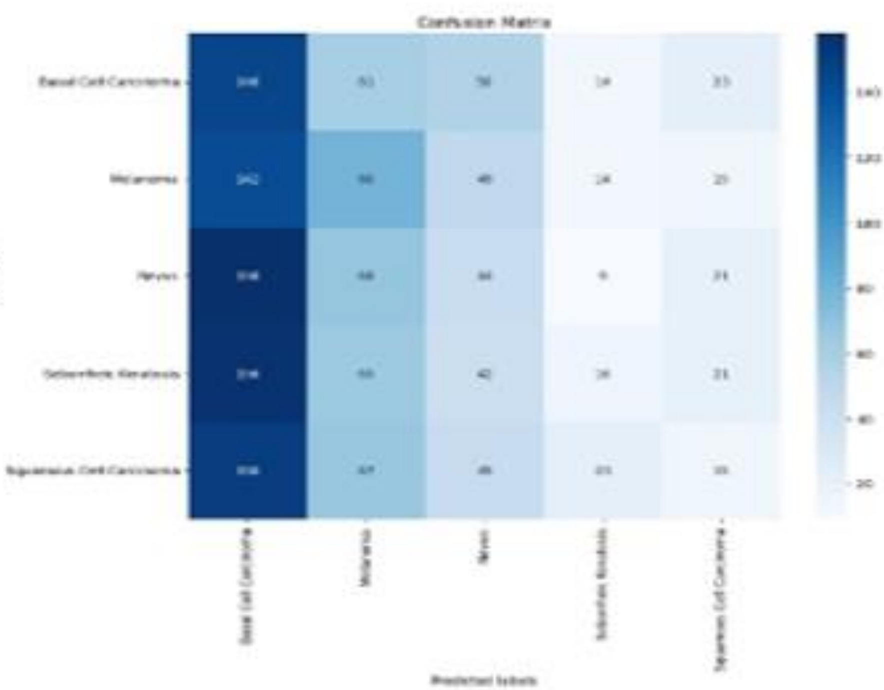

Fig 3. Confusion Matrix of QML model

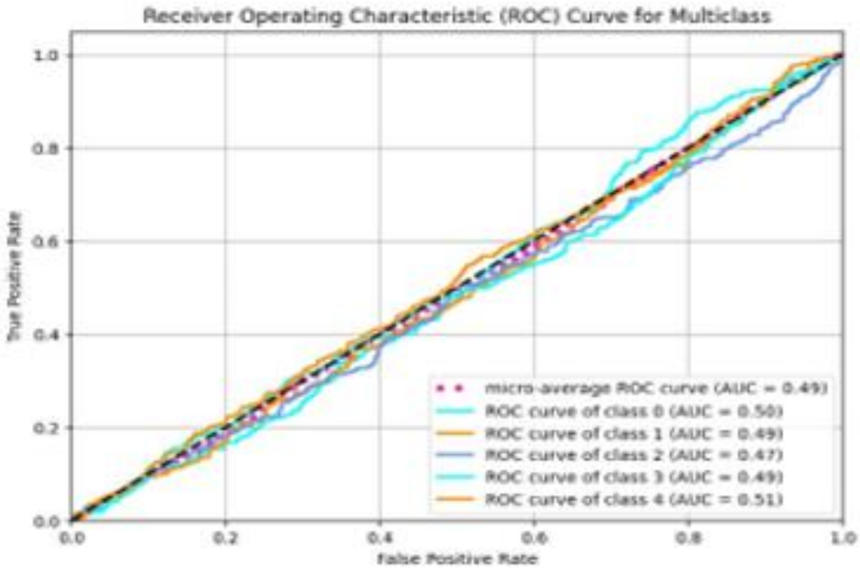

Fig 4. ROC Curve of the Hybrid Ensemble model QML model

4.2 Accuracy Curve and Loss Curve

Figures 5 and 6 represent Accuracy and Training Loss respectively. Accuracy measures the effectiveness of a classification model, whereas Training Loss is a metric used to quantify how well a model is performing on the training dataset during the learning process. Figure 5 shows that the accuracy of the classification model is at 71.11. Figure 6 indicates that the training loss of the model, after a total of 25 epochs, is 0.7123.

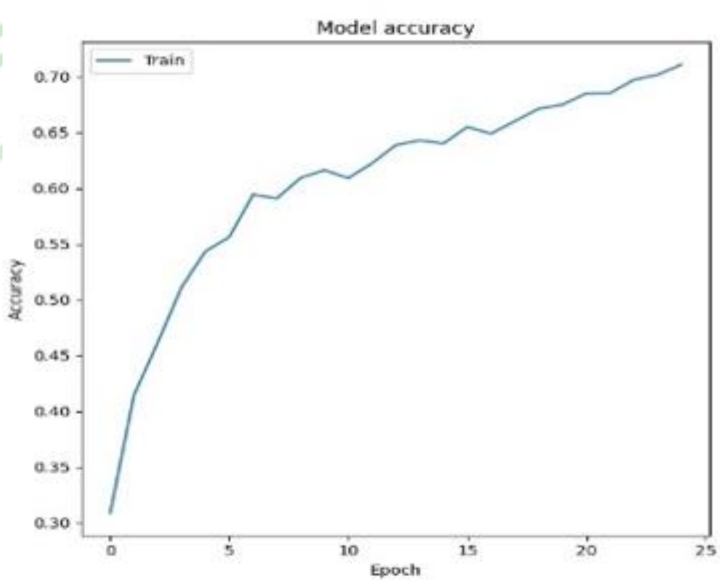

Fig 5. Accuracy curve of the hybrid QML model

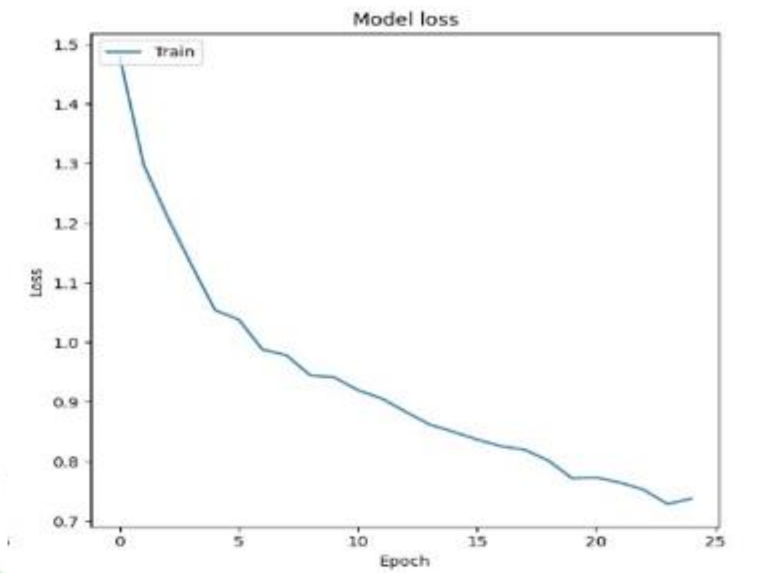

Fig 6. The model loss function of the hybrid QML model

4.3 User Interface

To create an environment for the user to look at the preprocessed image as well as to know the class his input image belongs to, there is a need for a concise Graphical User Interface (GUI). A simple Graphical User Interface consists of an Image upload prompt, Raw Input of the Image, and the skin lesion class output, as mentioned in the following Figures 7, 8 and 9.

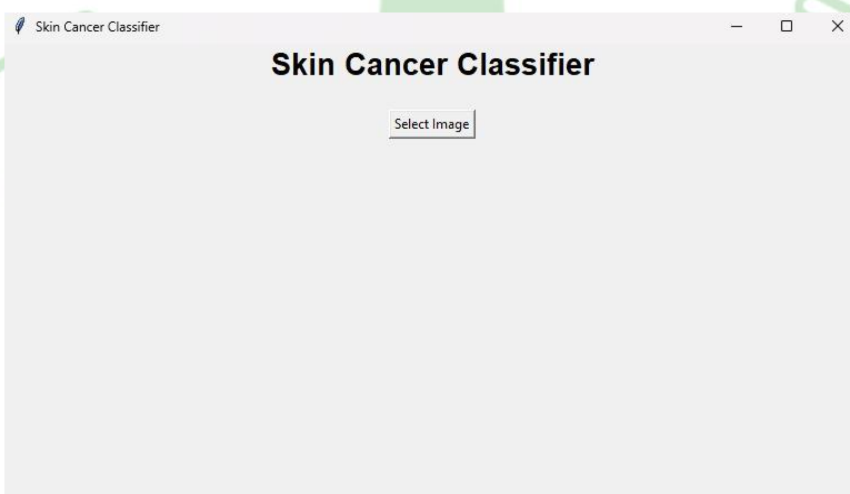

Fig7. Image Upload Prompt

Fig 8. Raw Input of the class "Basal Cell Carcinoma"

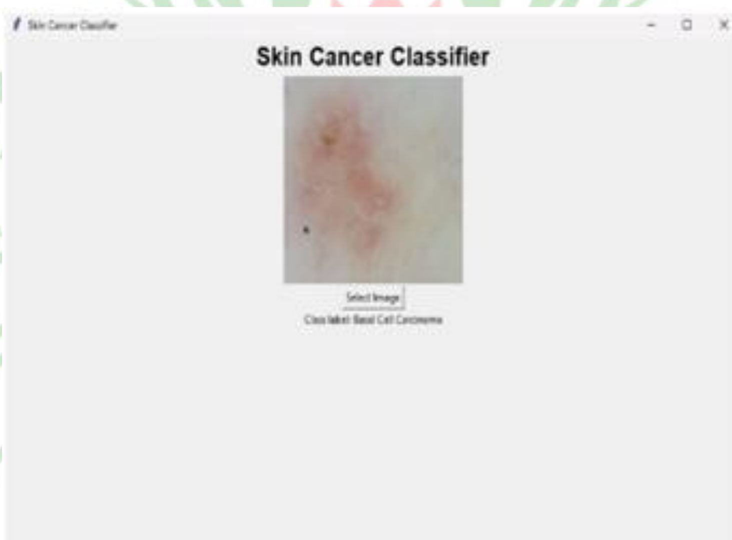

Fig 9. Image classified as "Basal Cell Carcinoma"

5. Conclusion

In conclusion, the development and implementation of a quantum machine learning (QML) hybrid model for skin cancer classification represents a significant advancement in the field of medical diagnostics. By leveraging the computational power and potential of quantum computing alongside traditional machine learning techniques, this approach has demonstrated promising results in accurately identifying different types of skin cancer with high precision and sensitivity. The hybrid model's ability to process large datasets and extract complex features from medical images has shown great potential in improving early detection rates and reducing the need for invasive diagnostic procedures. Moreover, the integration of quantum computing into medical diagnostics opens up avenues for exploring novel algorithms and computational frameworks that could further enhance the accuracy and efficiency of skin cancer classification systems.

Looking ahead, future work in this area could focus on several key aspects to advance the efficacy and applicability of QML hybrid models in skin cancer classification. Firstly, efforts should be directed towards optimizing and refining the existing hybrid model architecture to enhance its scalability and computational efficiency, ensuring its practical feasibility in real-world clinical settings. Moreover, additional research is warranted to delve deeper into the integration of advanced quantum algorithms and techniques tailored specifically for medical image analysis tasks, aiming to unlock new insights and capabilities for more accurate and reliable diagnosis of skin cancer. Moreover, collaborations between quantum computing experts, medical professionals, and data scientists will be essential for validating and refining the proposed hybrid models through rigorous experimentation and clinical trials, ultimately paving the way for their widespread adoption in healthcare practice. By addressing these challenges and opportunities, QML hybrid models hold the potential to revolutionize skin cancer diagnosis and improve patient outcomes in the future.

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