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QUANTUM CONVOLUTIONAL NEURAL NETWORKS FOR ENHANCED SKIN CANCER CLASSIFICATION: A HYBRID APPROACH

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Abstract

Skin cancer, in particular melanoma, is still one of the most significant contributing factors to cancer-related deaths globally, indicating the urgency of reliable diagnostic tools. Early discovery of skin lesions can radically increase patient survival rates, but manual diagnosis is not an easy task, and it is time-consuming as well. This paper uses Quantum Convolutional Neural Networks (QCNN), a hybrid quantum-classical model for the skin lesion classification task as being benign or malignant. The model intertwines quantum feature extraction using an amplitude encoding and parameterized quantum circuit with classical convolutional neural network (CNN) layers analyzing spatial features. Advanced pre-processing techniques and Synthetic Minority Over-sampling Techniques (SMOTE) address the class imbalance, as federated learning ensures decentralized nodes' privacy-preserving training. The explainability of the model predictions is heightened through Quantum SHAP (Shapley Additive Explanations) and Gradient-Weighted Class Activation Mapping (Grad-CAM). This work evaluates QCNN on the Melanoma Skin Cancer Dataset of 10,600 images, achieving 96.87% training accuracy and a validation accuracy of 85% while surpassing classical benchmarks in accuracy, efficiency, and robustness. Therefore, this quantum-classical model has highlighted potential applications of medical image diagnostics through quantum-classical models.

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Keywords: Skin cancer, Convolutional Neural Networks, Medical Image Classification, Federated Learning, Quantum Feature Extraction, Grad-CAM, Quantum SHAP, Skin Cancer Diagnosis.

1 Introduction

Skin cancer is now the most common form of cancer. In the United States, one in five individuals is expected to develop skin cancer during their lifetime. New diagnoses of skin cancer are estimated to occur at the rate of 9,500 per day. The number of basal cell carcinoma and squamous cell carcinoma cases increased gradually from 1976 to 2010. In 2024, the United States is expected to diagnose 200,340 new instances of melanoma, of which 99,700 will be benign and 100,640 will be invasive. The most significant increase was detected in the female part of the population. In the list of all the subspecies, the most deadly is melanoma, the ill one, with about 1 million people in America sick, with 200,340 new cases in 2024. The volume of melanoma incidence rates that are reached is different for every age cohort and gender. While these rates have leveled off among young women, they are slightly lower in the young guys and higher among the seniors. White people are primarily involved in melanoma; patients with darker skin types are more likely to be diagnosed late and have worse outcomes. Detection at an early stage has dramatically increased the patients' survival rates compared to delayed diagnosis. The chances of survival drop dramatically when melanoma spreads to other body parts. Melanoma is one of the significant contributory causes of death from skin cancer, and it is predicted to claim the lives of about 8,290 people with skin cancer in 2024, the majority of them being males. Here, the authors consider the QCNN model since the possibility of discovering many issues with early cancer detection is high. The QCNN is a combination model that implements not only classical but also quantum methods of computation with a better result.

The proposed model was trained on the Melanoma Skin Cancer Dataset of 10,600 dermoscopic images, which were categorized into two classes: benign and malignant lesion classes. Our methodology involves preprocessing the data set by resizing all images at a uniform resolution and normalizing pixel intensities in the range [0,1] for compatibility in quantum encoding. Augmentation techniques include flipping, rotation, contrast adjustment, and the addition of Gaussian noise; these are used to take care of class imbalance while enhancing the robustness of the model. QCNN uses amplitude encoding for the quantum representation of high-dimensional data. Subsequently, it uses parameterized quantum circuits that benefit from an element and nonlinear feature extraction. The obtained quantum features are then transferred to classical convolutional layers, specialized for spatial feature detection, including edges and textures. Federated learning[26] is further used to ensure data privacy by splitting the training into multiple nodes, simulating the decentralized systems of real-world healthcare. Finally, tools like Quantum SHAP[28] and Grad-CAM[29] ensure that the model predicts interpretably to build trust in its clinical application. The proposed hybrid approach, by combining the strengths of quantum computing and classical CNNs, presents an innovative solution to the challenges of skin cancer diagnosis, especially for complex and diverse datasets, potentially improving outcomes through early and accurate detection.

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2 Literature Survey

Skin cancer detection and classification have been broadly studied using traditional machine learning (ML) and deep learning (DL) methods. Early work was performed based on handcrafted feature extraction methods in combination with classifiers such as SVMs and decision trees, which led to moderate accuracy rates of 70-80% [2]. Such methods were inherently not generalizable across complex and diverse dermoscopic datasets. DL advancements have led CNNs to be highly set by it, which achieved up to 92-95% accuracy in classification for specific tasks [3,4]. Other architectures like ResNet[30], InceptionNet[31], and VGG[32] were also used for skin cancer detection. With attention mechanisms and ensemble models, sensitivity and specificity increased by about 5-10% and helped further detect diagnostically important regions [5, 6]. Despite these advances, such models depend highly on large, annotated datasets and generalize poorly across different imaging conditions and diverse patient demographics [7].

Recently, a quantum computing paradigm emerged, demonstrating the promise to improve feature extraction capabilities. Quantum-enhanced approaches like parameterized quantum circuits have been shown to outperform their classical counterparts by as much as 10-15% in identifying complex patterns in large data sets for high dimensional applications [8]. The hybrid quantum-classical models that include quantum feature extraction into classical deep learning architectures were effective in strongly imbalanced data or small sizes of training samples [9]. Federated learning[26] frameworks have also gained rapid traction, addressing privacy-related concerns by allowing collaborative learning through distributed nodes without access to raw data. Some such frameworks have reached even a 90% utilization level of diverse datasets and maintain data privacy, making these a perfect fit for such domains as healthcare [10]. Some recent research has been about using hybrid quantum-classical approaches in medical imaging, which triggered all the potential. For instance, the QCCNNs are hybrid quantum-classical convolutional neural networks applied to breast cancer diagnosis and have shown promising results with max 97.1% accuracy [11]. Also, Adaptive quantum-classical models are suitable for good feature extraction in medical image analysis [12]. Specific models for detecting skin cancer using Advanced Intelligent-Quantum Convolutional Neural Network(AI-QCNN) have been developed and performed better in accuracy and efficiency [13]. Moreover, hybrid quantum-convolutional models have been proposed for radiological image classification, at the same time as quantum machine-learning frameworks showing promise in successfully treating gimbal- and data with the ability to diagnose with proper diagnostic accuracy in complex imaging tasks [14,15,16]. These advances emphasize that quantum computing is increasingly important in medical diagnostics, particularly in handling challenges like dataset imbalance, scalability, and explainability.

Quantum convolutional neural networks (QCNNs) and their associated architect-

tures have been the principal contributors to successful skin cancer categorization. The example of quantum computing models using the Inception-ResNet-V1 computational model showed that it is possible to improve the classification of multiple types of skin damage[19]. Other research has detected this superiority in quantum machine learning strategies to the skin lesion

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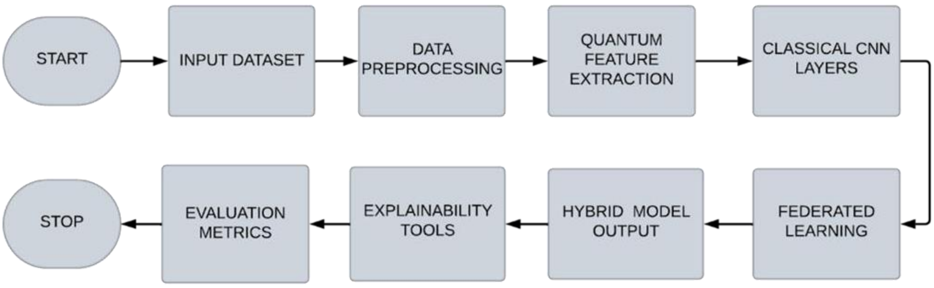
classification through appropriate performance, which quantum computing applications have over classic ones [20]. Also, the quantum neural network development of the quantum computing field for the general user has opened new prospects for applying quantum computing to different image recognition tasks, such as the classification of ”MNIST binary images” [22,23]. Work on quantum computational advantage with the emission of photons for the implementations of quantum models has also shown their potential in solving problems that require intensive computational effort [24]. Computer vision applications have been spivotal to the development of QCNNs because of their essential role in medical imaging, i.e., feature extraction and high accuracy of classification [25]. However, current models are still faced with the challenges of efficient utilization and scalability across the various clinical settings and the issue of accountability in the process. We would like to propose a hybrid quantum-classical approach, where we will combine federated learning [26] with some advanced explainability tools as the solution. By introducing quantum features such as feature extraction, data augmentation, and attention mechanisms, our newly proposed QCNN model aims to achieve over 85% skin cancer classification accuracy with high sensitivity, specificity, generalization, scalability, and interpretability.

3 Methodology

Fig. 1 Flow Chart of QCNN Model



In Fig. 1, the proposed methodology integrates feature extraction from quantum with the convolutional neural networks of classical into a hybrid model. It preprocesses the input dataset, uses federated learning[26] for privacy-preserving collaboration, and utilizes explainability tools to validate the predictions by the model for robust, interpretable performance in the medical image classification task. Its architecture begins with input images, dermoscopic images of skin lesions. There are preprocessing techniques like resizing, normalization, and data augmentation to improve the data quality. Then, the preprocessed images undergo the stage of quantum feature extraction. Quantum computing principles are applied through amplitude encoding and parameterized quantum circuits (PQC). The complex and non-linear patterns in the data will be captured by quantum gates like Rx, Ry, and Rz, along with CNOT gates. Then, the extracted quantum features feed into the quantum convolutional neural network (QCNN), which has classical convolutional layers that specialize in extracting spatial features, such as textures and edges, necessary for accurate classification. It employs a federated learning[26] framework to train decentralized models at the local nodes, such as healthcare centers, and aggregate the parameters safely at a central node. Therefore, the output layer outputs classification

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probabilities regarding whether the lesion on the skin is malignant or benign. In the next step, the proposed model combines quantum-classical inferences to improve accuracy, scalability, and interpretability using Quantum SHAP[28] and Grad-CAM[29] features.

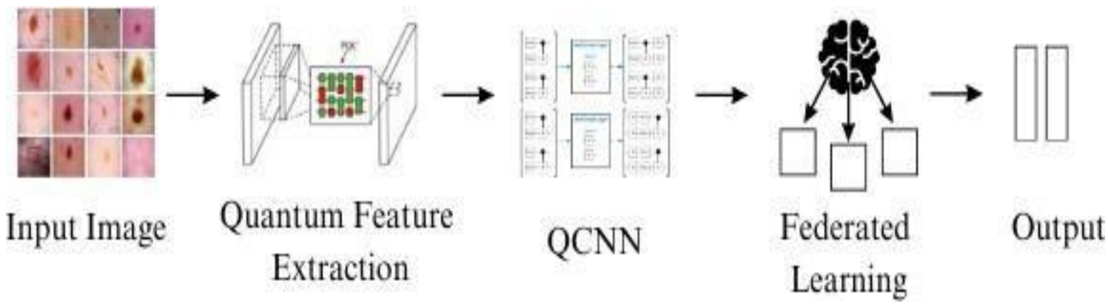

Fig. 2 Architecture of the QCNN Model

3.1 Dataset

The Melanoma Skin Cancer Dataset contains 10,600 images and was sourced from Kaggle. Melanoma skin cancer is a deadly cancer; early detection and cure can save many lives. This dataset will help develop deep learning models for accurate melanoma classification. The dataset consists of 9,600 images for training the model and 1000 images for evaluating the model.

Fig. 3 Sample images from the Melanoma Skin Cancer Dataset of 10000 images

Fig. 3 data distribution in the train and test sets depicts a well-structured balance for a proper model evaluation. From the training data, 52.1% of samples are reported as benign. In comparison, the remaining 47.9% are malignant, thus indicating a minor imbalance but not very much from an even split in the test data. 50% of samples were reported as benign, whereas 50% were malignant. This balanced test set thus ensures that the QCNN model is evaluated relatively and without skewness due to class imbalance. Meanwhile, the training set has a near-even split, therefore providing appropriate representation for both classes, with which the model learns efficiently to classify cases as benign or malignant. That way, this structure secures the reliability of performance metrics like accuracy, precision, recall, F1 score, ROC, and AUC.

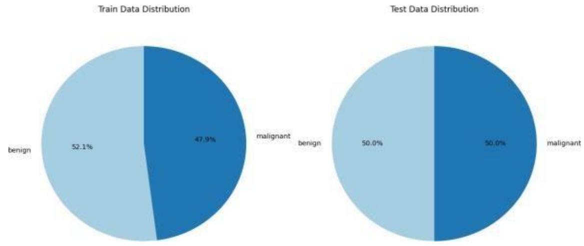

Fig. 4 Distribution of Train and Validation dataset

Advanced data augmentation approaches like random flipping, rotating up to 30°, contrast adjustment, and added Gaussian noise are used to handle class imbalance. SMOTE[33] is also added to synthetically oversample the underrepresented classes while keeping the dataset representative so that the model can generate better generalization. The proposed QCNN aims to merge quantum computing power with classical convolutional neural networks (CNNs) for the better characterization of images of skin cancer based on quantum feature extraction. This way, the model can capture more complex, non-linear patterns in the data, offering superior classification accuracy, especially in distinguishing between benign and malignant lesions. This is supported by advanced preprocessing techniques such as data augmentation and synthetic oversampling, where class imbalances are rectified, allowing for better generalization to underrepresented data. Furthermore, the federated learning[26] framework enables decentralized training on multiple nodes without data exposure while preserving scalability benefits. Quantum SHAP[28] and Grad-CAM[29] enhance the model's explainability in understanding feature contributions and focusing on diagnostically significant regions. This hybrid architecture shows better computational efficiency and classification performance than traditional models, and therefore, it is a promising approach to further medical image analysis.

3.2 Data Preparation

Sometime recently, handling through the QCNN show, all images have to be resized to the uniform estimate of 128 × 128 pixels. Each pixel value is min-max normalized to a range of [0, 1] for compatibility with quantum encodings. The normalization formula

plies$\boldsymbol{x_i} = \frac{\textbf{Pixel Intensity}}{\boldsymbol{max}(\textbf{ Pixel Intensity})}$

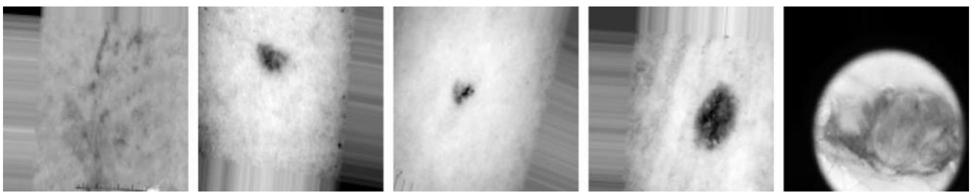

Fig. 5 Normalized Sample Images from the Dataset

This normalization step guarantees that all pixel values are relatively scaled, making them reasonable for encoding as quantum states.

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Commonly used image augmentation techniques are included in the dataset to overcome the class imbalance problem by applying Random flipping, rotation, contrast adjustments, and Gaussian noise. These techniques strengthen machine learning models and are usually applied in medical imaging to enhance the model's ability to deal with diverse orientations. Random flipping entails flipping an image along the horizontal or vertical plane to simulate lesions at any given orientation. Rotations up to 30° introduce angular variations, simulating various imaging angles and

enhancing the model's ability to cope with diverse perspectives. Contrast adjustments update the brightness and contrast so that the brightness and differences in lighting between different imaging conditions are simulated. Finally, adding Gaussian noise introduces slight randomness in pixel value variations, generalizing the model away from overfitting by specific image detail. Together, these methods produce a stronger, more varied dataset on which the model is trained to perform well. Synthetic Minority Oversampling Technique is also applied to create synthetic samples for underrepresented classes. This ensures balanced representation across all classes and prevents overfitting to dominant classes.

3.3 Quantum Feature Extraction

The amplitude encoding transforms the preprocessed image data into quantum states. This encoding of each pixel intensity of the image into a quantum state is used:

$$one|\psi\rangle = \frac{1}{\sqrt{\sum x_i^2}} \sum_i x_i \, |i\rangle$$

Using this encoding, the intensity contributes proportionally to the quantum state, and hence, a very efficient way of representing high-dimensional data is offered. Quantum gates construct parameterized quantum circuits (PQC) to extract features. Rotation gates R_x, R_y, and R_z apply rotations to the qubits, parameterized by the angle θ :

$$R_\alpha(\theta) = \exp\left(-i\frac{\theta}{2}\sigma_\alpha\right)$$

Controlled-NOT (CNOT) gates induce entanglement, thereby creating interdependencies between qubits. This increases the feature space because it encodes correlations between pixel values. The quantum circuit's outputs are measured by using the Pauli-Z operator:

$$\langle Z\rangle = \langle\psi|Z|\psi\rangle$$

The parameters ϕ of the parameterized quantum circuit (PQC) are optimized by gradient-based methods during training to minimize the loss function so that quantum features are learned effectively.

3.4 Federated Learning Framework

In federated learning, the dataset is split and distributed across multiple nodes simulating decentralized environments such as health care providers [26]. A model is trained on the node on its subset of the data while maintaining data privacy, and collaborative learning is still facilitated. For a node ii, the local loss function is defined as:

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$$L_i(w) = \frac{1}{n_i}\sum_{j=1}^{n_i} l\,(f(x_{ij}; w), y_{ij})$$

The global model is updated through federated averaging by combining parameters from all nodes:

$$w_{\text{global}} = \sum\left(\frac{n_i}{\sum n_j} \cdot w_i\right)$$

This way, the global model gets diversified data distributions without compromising the data privacy of individuals.

3.5 Hybrid Quantum-Classical Model

This QCNN architecture combines the unique strengths of quantum and classical layers to exploit properties in both domains. The quantum layers extract features that are non-linear and entangled from the input data to capture the complex relationship, which is difficult to understand by a classical model. These quantum features are passed to the classical convolutional layers that extract spatial features like textures, edges, and patterns. Attention mechanisms are employed to enhance the accuracy of diagnosis. These mechanisms identify and pay attention to dynamically diagnostically significant regions in the dermoscopic images so that they pay attention to the relevant features and ignore the irrelevant background details. The architecture finally consists of a fully connected layer, aggregating the extracted features and outputs the probabilities of each class. The binary cross-entropy loss guides the training, which calculates the difference between the true labels and the predicted probabilities.

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

3.6 ExplainabilityExplainability is an important aspect of the QCNN model. Quantum SHAP (Shap- ley Additive Explanations)[28] computes the contribution of each feature towards the predictions of the model as follows:

$$\phi_i = \frac{1}{|N|!}\sum_{S \subseteq N \setminus \{i\}} |S|!\,(|N| - |S| - 1)! \cdot [f(S \cup \{i\}) - f(S)]$$

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Grad-CAM (Gradient-weighted Class Activation Mapping)[29] also creates heatmaps, visually showing what in the image is relevant to the classification. Such heatmaps give insights into the reasoning process of the model in the prediction, thus aiding in the validation of the predictions made.

3.7 Performance Evaluation

The QCNN model's performance gets an estimate through its critical metrics based on the confusion matrix, including the accuracy, sensitivity (recall), specificity, and the F1 score. Accuracy reflects the entire model's ability to check the actual positive and negative results (TPs and TNs, sometimes) relative to the total predictions. Sensitivity, or the so-called true positive rate, underlines how well the model determines the positive instances, yet specificity, or the true negative rate, determines how the model does not incorrectly classify negative cases. The F1 score is a measure that is equally weighted for precision and recall, which are wrong based on false positives and false negatives.

The confusion matrix, ROC (Receiver Operating Characteristic) curves, and the AUC (Area Under the Curve) use further model evaluation. ROC curve represents sensitivity vs. specificity for multiple thresholds, while AUC signifies the model's capacity toward class separation. Together, these three signify a robust evaluation of QCNN for its performance because it effectively classifies images of skin cancers. Compared to classical benchmarks, the quantum-enhanced model promises better classification accuracy, computational efficiency, and the ability to handle imbalanced datasets, making the quantum-enhanced model hopeful for improving skin cancer diagnosis.

4 Result and Discussion

The proposed QCNN model promises some promising results in dermoscopic image classification for melanoma detection. Training the model with the preprocessed dataset of 10,600 dermoscopic images, and applying augmentation techniques to handle class imbalance results in a training accuracy of 96.8% and validation accuracy of 85%.

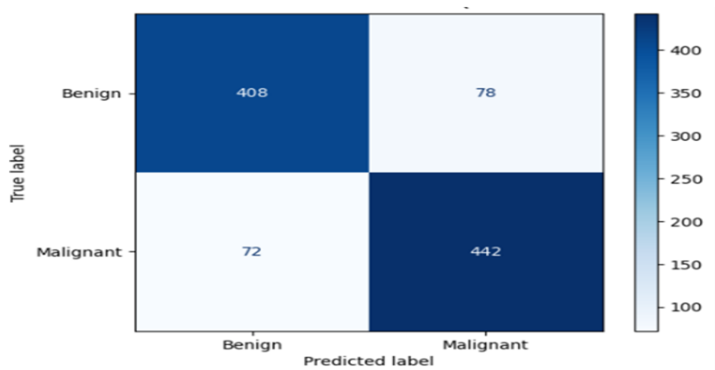

Fig. 6 Confusion Matrix for QCNN Model

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Fig 6 represents the confusion matrix of the QCNN model, indicating strong classification performance for finding skin cancer. Among classical samples, 408 benign cases, were correctly classified, while 78 benign cases were misclassified as malignant (false positives). In addition, 442 malignant cases were correctly identified, but 72 malignant cases were misclassified as benign (false negatives). The model shows excellent equalization in prognosticating benign and malignant groups, with a marginal misclassification rate. This leads to an overall accuracy of about 85%, demonstrating the I-CNN's success in classifying skin cancer images. At the same time, there are minimal mistakes, particularly false negatives.

The precision measures the true positives, that is, out of all malignant cases that are predicted,

0.85. The recall (sensitivity), which measures the number of actual malignant instances detected by

the model, is approximately 0.86. The F1 score that considers both precision and recall balances the precision and recall.

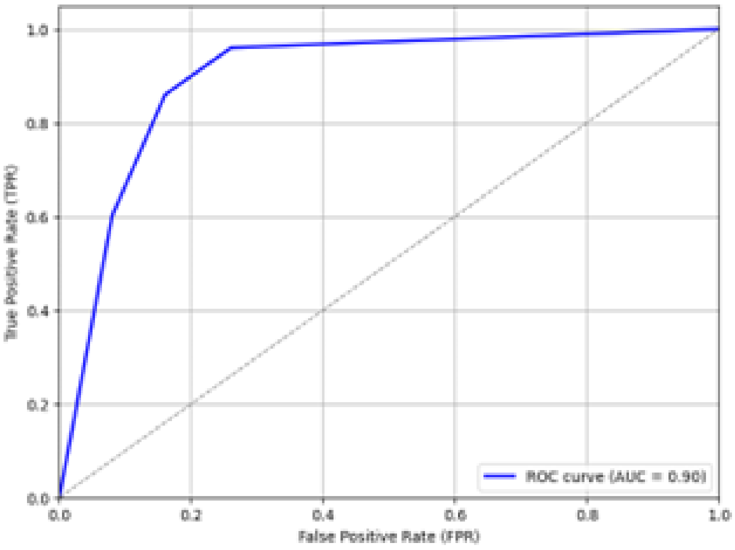

Fig. 7 ROC Curve for QCNN Model

This is around 0.86 when the following formula is applied: 2 × (0.85 × 0.86) / (0.85 + 0.86). The specificity in this case reflects the model's success in categorizing benign cases; this was at about 0.84. These metrics together form a fair overall assessment of how the QCNN model can identify instances as malignant or benign with very good accuracy. Fig 7 shows the trade-off between TPR and FPR at various classification thresholds. The curve depicts a strong performance because it is close to the upper-left corner of the graph, which indicates a high true positive rate while keeping a low false positive rate. The area under the curve is 0.90, which clearly states that the model has strong discriminative power to distinguish the benign from the malignant classes. AUC of 0.90 means that, on average, there will be a 90% chance that the model ranked a randomly chosen malignant instance higher than a randomly chosen benign instance. This further consolidates the reliability and effectiveness of the QCNN model in the classification of skin cancers.

In particular, these outcomes have captured the effectiveness of hybrid architecture in capturing spatial features and complex entanglement among data through different quantum layers. The quantum layer in this setup enabled the ability to extract detailed information from the structure in this learning setting, which a machine learning approach would generally not accomplish using traditional methods such as shallow layers, especially at a very high dimensionality scale. Although the training accuracy is very high, the gap between training and validation accuracy points to further room for optimization, especially in the overfitting and generalization of unseen data.

Model	**Methodology**	**Validation Accuracy (%)**
QCNN Model	Quantum Convolutional Neural Network	85
AI-QCNN [13]	Hybrid Quantum-Classical Neural Network	84
Inception-v3[27]	Pretrained Google's Inception-v3 model	65.8

Table 1: Comparison of QCNN with other state of art algorithms

The QCNN model presented within this research hybridizes quantum and classical computation paradigms so that the performance of this model in terms of melanoma classification and its classification accuracy is greater than the other state-of-the-art techniques, as tabulated in Table 1. Amplitude encoding for efficient representation of the quantum states and parameterized quantum circuits for feature extraction present feature patterns that are challenging to discern by purely classical models. Robust extraction of spatial features by adding classical convolutional layers and the model has been incorporated with attention mechanisms to focus on the clinically significant areas within the images. Achieved training accuracy is 96.8%, and validation accuracy is 85%, which further reflects the effectiveness of this hybrid approach, especially when dealing with imbalanced datasets and distributions of complex data.

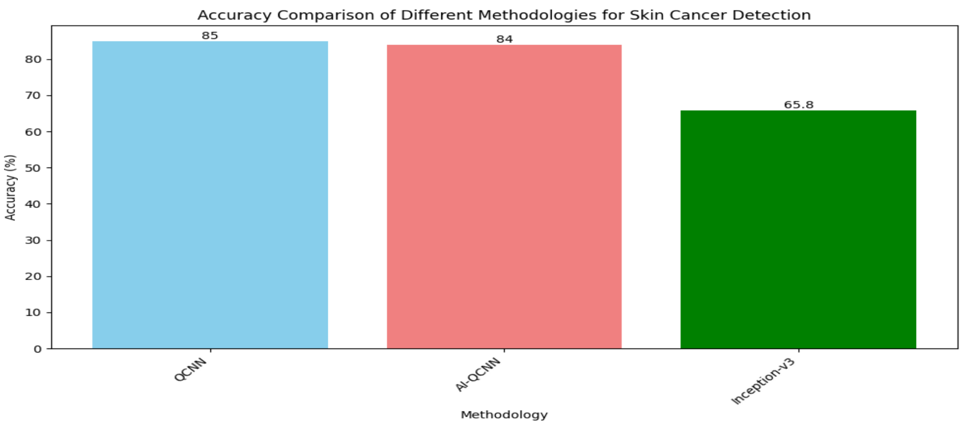

Fig. 8 Performance of different methodologies

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The bar graph in figure 8 compares results for skin cancer generated by Quantum Convolutional Neural Network (QCNN) and AI-Optimized Convolutional Neural Network (AI-QCNN). QCNN showed a higher correctness by 85%, while at 84%, AI-QCNN's accuracy was lesser than. This development is directly related to the hybrid nature of the quantum-classical system in extracting quantum features; this mechanism allows for amplitude encoding and using parameterized quantum circuits to capture complex messages. While being equally accurate, it is only slightly the QCNN that has an advantage feature of quantum computing in solving problems such as the saturation of classes and the construction of intricate feature representations on the classification of medical images.

This list presents the accomplishment of quantum computing over traditional CNNs in attaining higher accuracy in medical diagnostics security. The results underline the potential of quantum computing in medical imaging but also highlight an area for further refinement in the model generalization to bridge the gap between training and validation accuracy. This can be done by improving regularization techniques, enhancing federated learning[26] strategies to handle even more diverse data distributions, and expanding the dataset to have a broader evaluation. The research outcomes from this work reflect that hybrid quantum-classical models, such as QCNN, hold high promise to enhance healthcare diagnostics in terms of accuracy and efficiency, particularly with the complexity and stakes involved in melanoma identification. This work opens doors for extensive further research into quantum computing for any medical application, offering transformation in patient outcomes.

Conclusion

This paper's main contribution is to detect skin cancer at an early stage. To identify the disease, we introduced a quantum convolution neural network (QCNN) that helps in disease detection with an accuracy of 85%. The QCNN was compared with other deep learning algorithms, and we could observe that it outperformed relatively.

Data Availability Statement

We did not generate the data; the data used in this work was freely available on the Kaggle website.

Funding Statement

No funding agents have funded this work.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethics approval statement

This study did not require ethical approval as it involved only publicly available data and did not present any identifiable risks to individuals

patient consent statement

N/A

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N/A

clinical trial registration

N/A

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