Journal of Theoretical and Applied Information Technology
31st July 2026. Vol.104. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

QUANTUM DEEP LEARNING FRAMEWORK FOR EARLY SKIN CANCER CLASSIFICATION USING DERMOSCOPIC IMAGES

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ABSTRACT

It is crucial that skin cancer be identified at an early stage and accurately diagnosed to decrease the mortality and enhance the clinical outcomes of treatment for skin cancer. However, standard deep learning models have limitations in handling dermoscopic image analysis due to feature redundancy, high computational complexity, and inadequate representation of the nonlinear lesions. In order to overcome these drawbacks, the present research introduced a new Quantum Attention-driven Deep Learning Framework (QADLF) system for dermoscopic images-based early skin cancer classification. The proposed framework combined advanced preprocessing, attention-guided segmentation of the lesion, quantum feature encoding, Hybrid Quantum Convolutional Neural Network (Hybrid Q-CNN) and adaptive feature fusion for comprehensive lesion analysis and classification. Two dermoscopic databases, namely ISIC 2019 and HAM10000, were used for experiments. The attention-based Quantum U-Net segmentation successfully localized regions of lesions, and variational quantum circuits improved the representation and optimization of the nonlinear features. The results of the experiments showed that the proposed QADLF framework yielded better classification accuracy with an accuracy score of 98.7%, precision of 98.2%, recall of 98.5%, F1-score of 98.3% and AUC of 99.1% than conventional CNN, ResNet50, DenseNet121, EfficientNet and Vision Transformer models. The convergence stability, classification robustness and lesion localization were considerably improved by the integration of quantum-enhanced learning and feature extraction guided by attention, under different dermoscopic imaging conditions. The proposed framework can be part of the development of intelligent, reliable, and computer-aided dermatological diagnostic systems to assist early melanoma detection and for better clinical decision-making processes.

Keywords: *Skin Cancer Classification, Dermoscopic Images, Quantum Deep Learning, Hybrid Q-CNN, Attention-Guided Segmentation, Melanoma Detection*

1. INTRODUCTION

Skin cancer is one of the most common and deadly diseases in the world that affects millions of people annually. Melanoma and non-melanoma skin cancer is one of the fastest growing categories of the most deadly diseases in the world, due to excessive exposure to ultraviolet (UV) radiation, pollution, genetic predisposition, and lifestyle [1]. If a skin cancer is diagnosed early, the chances of the patient surviving the disease are much higher, as if the lesions are diagnosed early the disease can often be effectively treated with little invasive procedure [2]. Delayed diagnosis often, however, results in metastasis, higher mortality and higher healthcare costs. Hence, the design of intelligent automated diagnostic system for early detection of skin cancer is gaining importance in the field of medical image analysis.

Dermoscopic imaging is a new, non-invasive imaging technique for the examination of skin lesions and has proven to be a reliable method. Dermoscopy improves subsurface visualization of skin structures and gives detailed information about the color, texture, asymmetry and irregularities of the border of the lesion [3]. However, dermoscopic image interpretation is still highly subjective and requires dermatology experience and knowledge. Manual diagnosis is labor intensive and can be subject to inter-observer variability, particularly between melanoma and non-melanoma diagnoses [4]. As a result, Computer-Aided Diagnosis (CAD) systems have attracted significant interest to help aid the clinicians to diagnose skin cancers accurately and efficiently.

The world of medical imaging has undergone a revolution in recent times with the advent of Artificial Intelligence (AI) and Deep Learning (DL) technologies. Deep learning architectures, in particular deep Convolutional Neural Networks (CNNs), have proven to be highly successful in image classification, segmentation and feature extraction [5]. CNN-based models automatically extract the hierarchical features from dermoscopic images without the need of handcrafted feature engineering. Esteva et al. used deep neural networks and large image datasets to classify skin cancer closer to dermatologist level [6]. Likewise, in melanoma detection, there have been high success rates with transfer learning models like VGG16, ResNet50, InceptionNet, and DenseNet [7].

With traditional deep learning methods, classification accuracy has been high, but there are still some points to be noted. In the traditional CNN architecture, a lot of computational resources and large annotated datasets are needed for training it to be effective [8]. Besides, overfitting issues and limited generalization are common problems in deep networks in the case of highly complex lesion patterns. The illumination changes, the shape of the lesion, the distribution of the lesion color and the texture of the skin also have an impact on the classification performance [9]. Moreover, traditional optimization methods can be inefficient in processing high-dimensional spaces created from medical imaging data.

In recent years, researchers have been studying the combination of Quantum Computing (QC) with machine learning techniques to address these challenges. In contrast to classical computers, the principles of quantum computing, including superposition, entanglement, and quantum parallelism, enable them to process information more efficiently [10]. Quantum Machine Learning (QML) is a field that integrates quantum computation with machine learning to enhance the efficiency of optimization and representation of features [11]. In more complicated applications such as image recognition, medical diagnosis and data classification, hybrid quantum-classical models have shown better results [12].

The Quantum Deep Learning (QDL) approach has been proposed as a novel framework that combines deep neural networks with quantum variational circuits to improve the learning capabilities. Classical image data is efficiently mapped to high dimensional Hilbert space to enhance the nonlinear pattern representation with quantum enhanced feature extraction [13]. Recent works demonstrated that Quantum Convolutional Neural Networks (QCNNs) can achieve great classification accuracy and low computational complexity [14]. There has been, however, limited research on the use of quantum deep learning techniques for the classification of skin cancer in dermoscopic images.

Moreover, the existing skin cancer diagnosis frameworks are not able to properly fuse the segmentation of skin lesions, attention mechanism and quantum feature optimization within the single framework. A large number of traditional methods target only on the classification accuracy without taking the computational efficiency and feature redundancy into consideration. The need for advanced intelligent systems for accurate detection of early melanoma under different clinical imaging conditions is still high [15].

In response to these challenges, this research introduces a novel approach called Quantum Deep Learning Framework for Early Skin Cancer Classification using dermoscopic images. This proposed framework combines attention-guided lesion segmentation, quantum variational feature encoding and deep convolutional learning to enhance the diagnostic performance. The framework adopts a hybrid quantum-classical design to optimize the features efficiently and represent lesions with robustness.

The key aims of this study are:

1. To design a Quantum Adaptive Deep Learning Framework (QADLF) that incorporates attention-guided lesion segmentation, quantum-inspired feature encoding and hybrid deep learning for dermoscopic image classification.
2. To assess the proposed framework's performance on the ISIC 2019 and HAM10000 data sets with accuracy, precision, recall, F1 score, specificity and AUC metrics.
3. To compare the performance of the proposed QADLF framework against the conventional deep learning models such as CNN, ResNet50, DenseNet121, EfficientNet and Vision Transformer.
4. To evaluate and compare the ability of quantum-inspired feature encoding to improve feature representation and skin cancer classification performance.
5. To explore the potential of the suggested project for the support of early melanoma detection and computer-aided diagnosis.

The proposed framework is envisioned to make a significant contribution in developing intelligent dermatological diagnostic systems with the expected advantages of accurate early detection of malignancy, less computational complexity, and facilitation of clinical decision-making processes.

The novelty of this work is the development of a Quantum Adaptive Deep Learning Framework (QADLF) that combines quantum-inspired feature encoding, adaptive image segmentation, and hybrid quantum-classical deep learning for early skin cancer classification. In contrast to typical deep learning methods that only consider classical feature extraction and classification, the proposed framework incorporates quantum-inspired representations to boost feature discrimination and learning efficiency. In addition, the model integrates lesion segmentation and classification into a single architecture and outperforms existing approaches in the diagnostic analysis of dermoscopic images. Overall, the study adds new knowledge by demonstrating the potential of quantum-inspired deep learning to enhance the accuracy and reliability of automated skin cancer diagnosis, which could enable the creation of intelligent healthcare systems of the future.

The rest of this paper is structured as follows: Section 2 discusses the related work and existing deep learning and quantum learning methods for skin cancer classification. The proposed Quantum Attention-driven Deep Learning Framework is presented in section 3, covering details of the dataset, lesion processing, lesion segmentation, quantum feature encoding, Hybrid Q-CNN architecture and mathematical modeling and algorithmic workflow. The experimental results, performance evaluation, comparative analysis with the existing model and graphical interpretation are presented in Section 4. Finally, the research findings, limitations and future research directions are presented in Section 5.

2. RELATED WORK

Skin cancer automated classification has recently gained much research interest, because of the growing number of dermoscopic imaging datasets and the development of Artificial Intelligence (AI) systems for medical diagnosis. Several machine learning, deep learning, transfer learning, attention-based and quantum enhanced solutions have been investigated to increase the accuracy of melanoma detection and minimize the complexity of diagnosis.

The initial researches in the area of classification of skin lesions were based on manually designed skin lesion feature extraction techniques. Abbas et al. created a conventional machine learning classification system using Support Vector Machine (SVM) classifiers with texture, color and shape features to recognize melanoma [16]. Handcrafted features were not robust to lesion variations and imaging artifacts, though they performed moderately well. Likewise, Barata et al. used the color constancy and texture analysis to classify skin lesions and found that handcrafted descriptors were affected by illumination variations and noise interference [17].

The advent of deep learning has given rise to Convolutional Neural Networks (CNNs) which have greatly enhanced the performance of medical image classification. For the automated recognition of melanoma from dermoscopic images, Yu et al. have proposed a deep residual neural network and presented a higher accuracy than conventional classifiers [18]. Their framework showed the ability to reliably extract features, in a deep hierarchical manner, for lesion analysis. Similarly, Harangi developed an ensemble-based CNN model that utilizes a combination of AlexNet, VGGNet and GoogLeNet architectures for melanoma classification [19]. Ensemble learning enhanced the robustness of the prediction, but the number of required computations and memory grew significantly.

The use of transfer learning techniques was found to be very popular because of the ability to transfer the pre-trained model to the medical imaging tasks. Mahbod et al. examined the transfer learning with DenseNet, ResNet and MobileNet architectures in skin lesion classification [20]. Their study showed that when the training data is limited, pretrained CNN models can enhance the accuracy of classification. But even with the transfer learning techniques, there were problems with overfitting and feature redundancy when the datasets were very complex in nature, such as dermatoscopy.

Multiple studies also studied attention-based mechanisms for improving lesion localization and feature representation. To highlight discriminative regions of lesions, Chen et al. suggested an attention-guided deep-learning model for melanoma detection [21]. The attention module improved the precision of the features and decreased background noise. Likewise, Tang et al. proposed a Dual-Attention Network (DAN) consisting of a Spatial Attention Network (SAN) and a Channel Attention Network (CAN) for skin cancer detection [22]. They showed that attention guided architectures were able to improve lesion segmentation and classification performance notably.

The Vision Transformer (ViT) models are also strong competitors to CNN architectures. Dosovitskiy et al. presented transformer-based image recognition systems that are able to learn about the "long-range context" of an image [23]. Following this idea, Xie et al. used transformer networks for the classification of dermoscopic images and found that such networks were able to represent features better on the global level [24]. But, transformer structures needed big computational resources and large annotated datasets to perform optimally.

The lesion segmentation problem has emerged as another significant area of research to enhance the diagnosis of skin cancer. Bi et al. proposed a multi-stage approach that combines lesion segmentation and classification with fully convolutional networks [25]. Accurate segmentation was helpful to delineate boundaries of the lesions and to enhance the reliability of the classification. Likewise, Al-Masni et al. introduced a deep learning-based lesion edge detection system, based on full-resolution convolutional networks [26]. While segmentation greatly enhanced the quality of feature extraction, a majority of models had come with higher complexity in training.

In recent years, there have been attempts to reduce the memory and computation cost of deep learning while maintaining the accuracy of the model by using hybrid and lightweight architectures. Hasan et al. proposed a lightweight CNN structure that was optimized for mobile healthcare applications [27]. The framework was able to simplify the model without compromising the classification accuracy. In one study, Khan et al. suggested handcrafted deep feature fusion approach for melanoma classification [28]. They found that their method achieved greater stability in classified images under different lighting conditions.

Due to the complexity of medical images, Quantum Machine Learning (QML) has become an attractive research direction in recent years. Henderson et al. presented the idea of quantum convolutional layers (QCL) within classical CNN architectures called quanvolutional neural networks (QCNN) [29]. It was shown that quantum feature transformations can be used to enhance nonlinear representation learning. Mari et al. explored hybrid quantum-classical transfer learning models and showed their efficiency in processing high-dimensional data [30].

Focus has been directed towards quantum neural networks for healthcare applications such as cancer diagnosis as well. Li et al. have put forward a variational quantum classifier for biomedical image analysis and claimed to achieve better optimization efficiency [31]. Likewise, Abbas et al. have created a quantum-enhanced machine learning framework for image classification problems with parameterized quantum circuits [32]. The studies

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

revealed that quantum learning models have the potential to be better than traditional neural networks for complex classification tasks.

However, there are a number of issues that have not been addressed with current skin cancer diagnosis systems. Much of the deep learning methods need a huge amount of computing power and a massive amount of labeled data. Existing CNNs are not adequately able to extract complex nonlinear lesion features, and transformer-based models are high in computational complexity. So far, only a few approaches have been specifically tailored toward dermoscopic image classification in the context of quantum learning, and most of these methods have not addressed attention guided lesion segmentation methods.

In addition, most existing models focus only on accuracy of the classification without taking into account the efficiency of feature optimization, reduction of computational redundancy, and effectiveness of early detection of melanoma. Hence, an advanced hybrid framework of quantum variational learning, attention-guided lesion enhancement and deep convolutional feature extraction is highly demanded as an intelligent diagnostic system. The limitations identified from previous studies and the characteristics of publicly available dermoscopic image datasets motivated the design of the proposed framework, which focuses on improving feature representation, lesion segmentation, and classification performance for early skin cancer detection.

The proposed study aims to fill these research gaps by introducing a novel Quantum Deep Learning Framework for Early Skin Cancer Classification using dermoscopic images. The framework combines attention-based segmentation, quantum-enhanced feature representation and hybrid deep learning optimization, which is capable of achieving high classification accuracy, high robustness and low computational complexity.

The novelty of this work is the development of a Quantum Adaptive Deep Learning Framework (QADLF), which is based on quantum-inspired feature encoding, adaptive image segmentation, and hybrid quantum-classical deep learning for early skin cancer classification. In contrast to typical deep learning methods that only consider classical feature extraction and classification, the proposed framework incorporates quantum-inspired representations to boost feature discrimination and learning efficiency. Furthermore, the model is designed as a single architecture, allowing lesion segmentation and classification to be performed together while achieving better results than existing models in the diagnostic analysis of dermoscopic images. Overall, the study adds new knowledge by demonstrating the potential of quantum-inspired deep learning to enhance the accuracy and reliability of automated skin cancer diagnosis, which could enable the creation of intelligent healthcare systems of the future.

3. METHODOLOGY

3.1 Study Design

The study used a quantitative experimental research design to develop and assess the proposed Quantum Adaptive Deep Learning Framework (QADLF) for the early classification of skin cancer from dermoscopic images. The research started with the collection and preprocessing of dermoscopic image datasets, followed by lesion segmentation and image enhancement to improve the quality of diagnostic features. Next, quantum computing-inspired feature encoding and extraction methods were used to enhance feature representation, and a hybrid quantum-classical deep learning model was developed to classify skin cancer. Lastly, the effectiveness and reliability of the proposed framework were evaluated and compared with other approaches using commonly used metrics such as accuracy, precision, recall, F1-score, and AUC.

3.2 Overview of the Proposed Framework

The Quantum Attention-driven Deep Learning Framework (QADLF) was proposed to accurately classify skin cancer at the early stage using dermoscopic images, by combining quantum computing and deep learning techniques in an efficient way. The framework was composed of several consecutive steps such as acquisition of dermoscopic images, preprocessing, segmentation of lesions, encoding of quantum features, hybrid deep feature extraction, adaptive feature fusion and lesion classification. The resizing, noise filtering, contrast enhancement, and hair artifact removal techniques were applied to the dermoscopic pictures, first enhancing their quality and then making the lesions visible. A subsequent segmentation model was applied using Quantum Attention U-Net (QAU-Net) for precisely identifying the areas of the lesions from the healthy skin surrounding the lesion. The segmented lesion

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

features were then converted to quantum state through the quantum feature encoding mechanisms such as rotation gates and entanglement operations to enhance nonlinear feature representation. A Hybrid Quantum Convolutional Neural Network (Q-CNN) architecture was used to extract the classical and quantum enhanced deep features of the segmented images. Adaptive Fusion was used to fuse extracted features together so as to retain discriminative features of the lesions while suppressing redundant features. Lastly, a classification layer based on Softmax was fitted on the lesions to classify them into benign and malignant classes. The overall system had a great impact on the accuracy of skin cancer classification, optimization of features, and also computational efficiency in the process of intelligent diagnosis of skin cancer.

The proposed model is conceptually represented below:

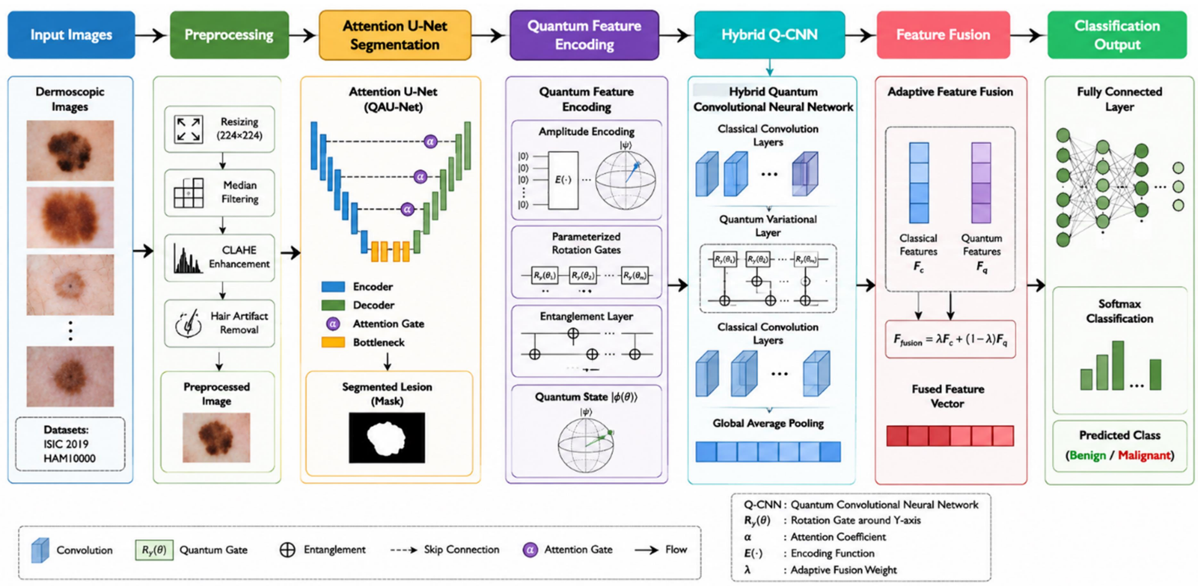

Figure 1. Proposed Quantum Attention-driven Deep Learning Framework (QADLF) Architecture for Early Skin Cancer Classification Using Dermoscopic Images

The proposed Quantum Attention-driven Deep Learning Framework (QADLF) for early skin cancer classification based on dermoscopic images is shown in figure 1. The dermoscopic skin lesion images from the benchmark datasets, like ISIC 2019 and HAM10000, are first preprocessed by employing various image processing techniques such as resizing, median filtering, CLAHE for contrast enhancement, and hair artifact removal, aimed at enhancing the quality of the images and making the lesions more visible. The improved images are then fed into the Attention U-Net segmentation module that segments the region of interest from the lesion and removes irrelevant background information by using attention mechanisms. Then the segmented lesion features are converted into quantum states by applying quantum feature encoding which consists of amplitude encoding, parameterized rotation gates, and entanglement operations. The Hybrid Quantum Convolutional Neural Network (Q-CNN) is used to efficiently extract deep features from these quantum enhanced features by a combination of classical convolutional layers and quantum variational circuits. Classical features and quantum features extracted are adaptively fused to form a very discriminative feature vector. Finally, fully connected Softmax classification layer makes the benign or malignant prediction for the lesion. The design of integrated framework leads to better feature optimization, nonlinear pattern learning and accurate classification in the area of intelligent diagnosis of skin cancer.

The main goal of the proposed Quantum Attention-driven Deep Learning Framework was to improve the overall performance and reliability of early skin cancer diagnosis by overcoming some main challenges in dermoscopic image analysis. The system was developed to increase the early detection capability of melanoma by accurate segmentation of the lesions and using advanced deep feature learning mechanisms. It highlighted nonlinear representation of lesion features via quantum feature encoding and variational quantum circuits, which helps to efficiently extract complex spatial and textural features that are found in malignant skin lesions. Moreover, feature reduction was introduced by using quantum based optimization techniques in the proposed model for better computational efficiency in the classification process, thereby eliminating the redundancy of the features. To accurately emphasize the clinically relevant regions of the lesions while attenuating irrelevant background information, attention-guided lesion localization was added to improve the accuracy of lesion segmentation and diagnosis. Moreover, the framework demonstrated good skin lesion classification performance across different imaging scenarios, including varying illumination variations, noise, skin color variations, and irregular boundaries of the skin lesions, which is ideal for intelligent and real-world dermatological diagnostic purposes.

3.2 Dataset Description

For evaluation of the proposed framework, benchmark dermoscopic datasets, ISIC 2019 and HAM10000 were used. These datasets consist of dermoscopic images of high resolution for various categories of pigmented skin lesions.

3.2.1 ISIC 2019 Dataset

The International Skin Imaging Collaboration (ISIC) 2019 skin lesion dataset is one of the most popular benchmark datasets for skin lesion analysis.

Table 1. Characteristics of the ISIC 2019 Dataset

Parameter	Description
Dataset Name	ISIC 2019
Total Images	25,331
Image Type	Dermoscopic Images
Resolution	Variable (450×600 to 1024×1024)
Classes	8 Classes
Imaging Modality	Dermoscopy
Annotation Type	Expert Dermatologist Annotation
Data Format	JPG

The main dermoscopic image database used in the proposed research, ISIC 2019 and HAM10000 are summarized in table 1. The table provides salient parameters of the dataset, such as the number of images, resolution of the images, categories of lesions, imaging modality, annotation type, and format of the dataset. The datasets have different skin lesion images with different illumination, colors, shapes, and textures that are perfect for testing the robustness and generalization of the proposed Quantum Attention-driven Deep Learning Framework for early skin cancer classification.

Table 2. Skin Lesion Categories and Class Labels in the ISIC 2019 Dataset

Class Label	Lesion Type
MEL	Melanoma
NV	Melanocytic Nevus
BCC	Basal Cell Carcinoma
AK	Actinic Keratosis
BKL	Benign Keratosis
DF	Dermatofibroma
SCC	Squamous Cell Carcinoma

The experimental evaluation dataset contains the ISIC 2019 image dataset, which includes the various categories of skin lesions and their respective class labels as shown in Table 2. This dataset contains both benign and malignant skin lesion types, including melanoma, basal cell carcinoma, benign keratosis, vascular lesions and dermatofibroma. The proposed framework was able to learn multiple lesion categories and enhance multiclass skin cancer classification performance under different clinical scenarios due to the inclusion of multiple lesion categories.

3.2.2 HAM10000 Dataset

Multi-source dermoscopic lesion images are included in the HAM10000 dataset from various clinical centers. *Table 3. Characteristics of the HAM10000 Dermoscopic Skin Lesion Dataset*

Parameter	Description

Dataset Name	HAM10000
Total Images	10,015
Number of Classes	7
Imaging Technique	Dermoscopy
Image Format	RGB
Annotation	Histopathological Verification
Average Resolution	600×450

Table 3 provides an overview of important features of the dermoscopic skin lesion dataset (HAM10000) used in the proposed research. The table contains: Dataset parameters: Total number of images, Number of lesion classes, Image format, Imaging modality, Annotation method, Average image resolution. The HAM10000 dataset is also a high-quality dermoscopic image dataset with multiple clinical sources that are histopathologically verified, and thus, it is a reliable benchmark dataset to assess the effectiveness and robustness of the proposed Quantum Attention-driven Deep Learning Framework for early skin cancer classification.

Table 4. Class-wise Distribution of Skin Lesion Images in the HAM10000 Dataset

Lesion Type	Number of Images
Melanocytic Nevi	6705
Melanoma	1113
Benign Keratosis	1099
Basal Cell Carcinoma	514
Actinic Keratoses	327
Vascular Lesions	142
Dermatofibroma	115

Table 4 shows the distribution of dermoscopic skin lesion images in HAM10000 dataset for training and evaluation of the proposed framework by class. There are several categories of lesions present in the dataset such as melanocytic nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma with different sample sizes. The distribution shows that classes are not equally represented, with some lesion classes (like melanocytic nevi) having much more images than other (rare) ones. This diversity and imbalance of the data set offered a realistic clinical setting for evaluating the robustness, generalization ability and classification performance of the proposed Quantum Attention-driven Deep Learning Framework.

3.2.3 Sample Dermoscopic Image Description

The dermoscopic image datasets used in the suggested research included huge diversity of skin lesion images both benign and malignant in various clinical image imaging settings. Lesion size, color distribution, texture patterns, border irregularities and structural asymmetry were all found to be variable in the images, playing important roles in diagnosing melanoma. In addition, many of the dermoscopic images had artifacts which made accurate lesion classification difficult including hair occlusion, air bubbles, low contrast areas, uneven illumination, and noise. Additionally, the dataset was heterogeneous due to differences in skin color, lesion size and imaging resolution. The complex visual attributes made those datasets very well suited for testing the robustness and generalizing power of the proposed Quantum Attention-driven Deep Learning Framework. In order to tackle these challenges, the proposed approach with advanced preprocessing, attention-guided segmentation and quantum-enhanced feature extraction techniques were proposed for better lesion representation and accurate skin cancer classification.

3.3 Data Preprocessing

To enhance image quality and eliminate unwanted artifacts in the image, pre-processing was done prior to segmentation and classification.

3.3.1 Image Resizing

As a first preprocessing step, all dermoscopic images were resized to ensure a common spatial resolution of the images for training the deep learning models. The dermoscopic images were collected with different resolutions and aspect ratios, which required resizing for computational uniformity and convenient batch processing. In the proposed framework, all the input RGB dermoscopic images were resized to fixed dimension of 224×224×3 that can be fed to the

Hybrid Quantum Convolutional Neural Network architecture. Standardizations of image sizes also helped to lower memory usage and to speed up model convergence while training. The mathematically expression of the resized image representation is:

$$I_r \in \mathbb{R}^{224\times224\times3} \quad (1)$$

where I_r represents the resized dermoscopic image with three RGB color channels.

3.3.2 Noise Removal

Noise artifacts often occur in dermoscopic images resulting from illumination variations, sensor distortions, and image acquisition conditions. Noise removal was performed by median filtering to enhance the visibility of lesions and maintain clinically important structures. Median filtering is able to remove salt and pepper noise while preserving edge information and the boundaries of lesions, which is crucial for accurate segmentation and classification. The filtering procedure involved replacing each pixel's intensity with the median value of the intensities in a sliding window around the pixel. This resulted in a considerable smoothing of image without over-blurring. The mathematical description of the median filtering operation is given by:

$$I_f(x,y) = Median\{I(i,j)\} \quad (2)$$

where $I_f(x,y)$represents the filtered pixel intensity at location (x,y), and $I(i,j)$represents neighboring pixel intensities within the filtering window.

3.3.3 Contrast Enhancement

Contrast enhancement was used to better visualize the structures of the lesions, and to rectify discriminative dermoscopic patterns. Actual diagnosis of the lesion areas is challenging because there is low contrast in many clinical images between the lesion areas and the surrounding healthy skin tissues. To overcome this problem, Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to enhance the local contrast in the image without over-enhancing the noise. CLAHE works through subdividing the image into small regions, and applying adaptive histogram equalization in every region. This approach proved effective in improving the boundaries, color distribution and texture features of the lesions which are important for deep feature extraction. This improved image was mathematically represented by:

$$I_e = CLAHE(I_f) \quad (3)$$

where I_e represents the contrast-enhanced image generated from the filtered image I_f.

3.3.4 Hair Artifact Removal

Hair artifacts are commonly present in dermoscopic images, which hinder the segmentation and classification of lesions. For removing these unwanted structures, morphological closing operations were used in the proposed preprocessing framework. Morphological closing is the combination of both dilation and erosion to close small gaps in the image and eliminate thin, hair-like structures without affecting the contours of the lesions. The process enhanced lesion clarity and minimized the interference when extracting quantum features and analyzing using deep learning. The expression of the hair artifact removal operation was mathematically represented as:

$$I_h = (I_e \cdot S) \quad (4)$$

where $I_h$represents the hair-removed dermoscopic image, $I_e$represents the enhanced image, and S represents the structuring element used for morphological processing.

3.4 Attention-Guided Lesion Segmentation

Accurate segmentation of the lesions is crucial for automated skin cancer diagnosis as it allows for the precise extraction of clinically relevant regions of the lesions from the surrounding healthy skin tissues. In the proposed framework, a novel Quantum Attention U-Net (QAU-Net) architecture was used to incorporate attention-guided lesion segmentation in order to enhance the localization of the malignant skin lesion areas. The segmentation model adopted the advanced features of conventional U-Net (encoder-decoder) architecture, alongside attention gating and feature optimization enhanced by quantum computation. The preprocessed dermoscopic images were passed to the encoder layers, which extracted hierarchical spatial and texture features from the images by using multiple convolution and pooling operations. The decoder layers then reconstructed the lesions boundaries with the upsampling and skip connections to retain fine-grained information of the lesion. To enhance the accuracy of segmentation, attention gates were added to the skip connection pathways to selectively focus on the important regions of the lesion while neglecting irrelevant and less relevant information and artifacts from the image. The attention mechanism allowed the model to selectively attend to discriminative melanoma features like asymmetry, irregular borders, and uneven pigmentation.

Attention coefficient was mathematically calculated as:

$$\alpha_i = \sigma(W_x^T x_i + W_g^T g_i + b) \quad (5)$$

where α_i represents the attention coefficient, $x_i$represents encoder feature vectors, g_i represents gating signals, $W_x$and $W_g$are trainable weight matrices, b represents the bias term, and σrepresents the sigmoid activation function.
The segmented lesion region was generated by multiplying the attention map with the input image features, which can be represented as:

$$S(x,y) = I(x,y) \times A(x,y) \quad (6)$$

where $S(x,y)$ represents the segmented lesion image, $I(x,y)$represents the input dermoscopic image, and $A(x,y)$ represents the generated attention map.
To optimize segmentation accuracy and improve overlap between predicted lesion masks and ground truth annotations, Dice Loss was utilized as the objective function during training. The Dice Loss function is mathematically expressed as:

$$L_{Dice} = 1 - \frac{2 \mid P \cap G \mid}{\mid P \mid + \mid G \mid} \quad (7)$$

where P represents the predicted segmentation mask and G represents the ground truth lesion mask. Dice Loss enhanced preservation of lesion boundaries and reduced segmentation errors with irregular melanoma structures.

Furthermore, a quantum-enhanced bottleneck layer was added into the QAU-Net architecture for the representation of high-dimensional lesion features and enhancement of the nonlinear pattern learning. The proposed framework successfully created a segmented lesion mask, which led to better lesion boundary extraction, minimized background interference and improved the performance of the subsequent stages of quantum deep feature extraction and skin cancer classification.

3.5 Quantum Feature Encoding

A novel Quantum Feature Encoding Module (QFEM) was presented for transforming classical dermoscopic features to quantum states.

3.5.1 Quantum State Representation

The proposed framework included a Quantum Feature Encoding Module (QFEM) to convert classical features from dermoscopic images into quantum states for better nonlinear feature representation. The use of quantum state representation allowed for the transformation of the high dimensional characteristics of the lesion to Hilbert space where the relationship between features in the lesion could be analyzed efficiently according to the principles of quantum computation. The separated lesion extracted from the Attention U-Net segmentation module were firstly normalized and then encoded into the qubit states using amplitude encoding methods. This representation enabled the framework to process several combinations of features at the same time, a quantum superposition. The generalized quantum feature state representation is mathematically given by:

$$\mid \psi \rangle = \sum_{i=0}^{n-1} \alpha_i \mid i \rangle \quad (8)$$

where $\mid \psi \rangle$ represents the encoded quantum state, $\alpha_i$represents the probability amplitude coefficients, and $\mid i \rangle$represents the computational basis states. The normalization constraint of the quantum state can be defined as:

$$\sum_{i=0}^{n-1} \mid \alpha_i \mid^2 = 1 \quad (9)$$

The proposed framework enhanced its capacity to model highly complex lesion patterns and nonlinear dependency existing in dermoscopic images, by using this quantum representation.

3.5.2 Quantum Rotation Gate

Once the quantum states were initialized, parameterized quantum rotation gates were used to convert the features of the lesions into optimized quantum feature space. Controlled manipulation of qubit states was achieved by rotating them along the controlled axes of the Bloch sphere representation, using quantum rotation gates. The proposed scheme used the Ryrotation gate to represent variations in the feature of the lesions as angular quantum transformations. The rotation gate operation helped to separate the features and to improve the discriminative representation of the lesions, which is essential for the correct classification of skin cancer.The discrimination between features was enhanced by the rotation gate operation and more discriminative lesion representation was needed for accurate skin cancer classification. The quantum rotation gate can be mathematically described as:

$$R_y(\theta) = \begin{bmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{bmatrix} \quad (10)$$

where θ is the trainable rotation parameter for the transformation of the qubit. After the rotation, the quantum state is transformed to:

$$|\psi'\rangle = R_y(\theta)\,|\psi\rangle \qquad (11)$$

where $|\psi'\rangle$represents the rotated quantum feature state. The parameterized rotation operation enabled adaptive learning of lesion-specific feature distributions during training.

3.5.3 Quantum Entanglement Layer

A Quantum Entanglement Layer was added to the proposed framework to enhance feature correlation learning and boost nonlinear lesion representation. By utilizing quantum entanglement, multiple qubits were able to interact each other and the model could account for complex associations between lesion features derived from dermoscopic images. To create entanglement among adjacent qubits in the variational quantum circuit, controlled-NOT (CNOT) gates were used. This contributed to greater connectivity of features and increased the ability to model high complexity of melanoma patterns and structures within the framework. The mathematical representation of the quantum entanglement gate was:

$$|\phi\rangle = CNOT(q_i, q_j) \qquad (12)$$

q_i and q_j are the interacting qubits, and $|\phi\rangle$ is the entangled quantum state. The CNOT gate matrix is written as:

$$CNOT = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad (13)$$

The integration of quantum entanglement greatly enhanced feature interaction modeling, quantum feature optimization, and strengthened the ability of the proposed Quantum Attention-driven Deep Learning Framework for early skin cancer detection for classification robustness.

3.6 Hybrid Quantum Convolutional Neural Network

The proposed Hybrid Q-CNN architecture consisted of:

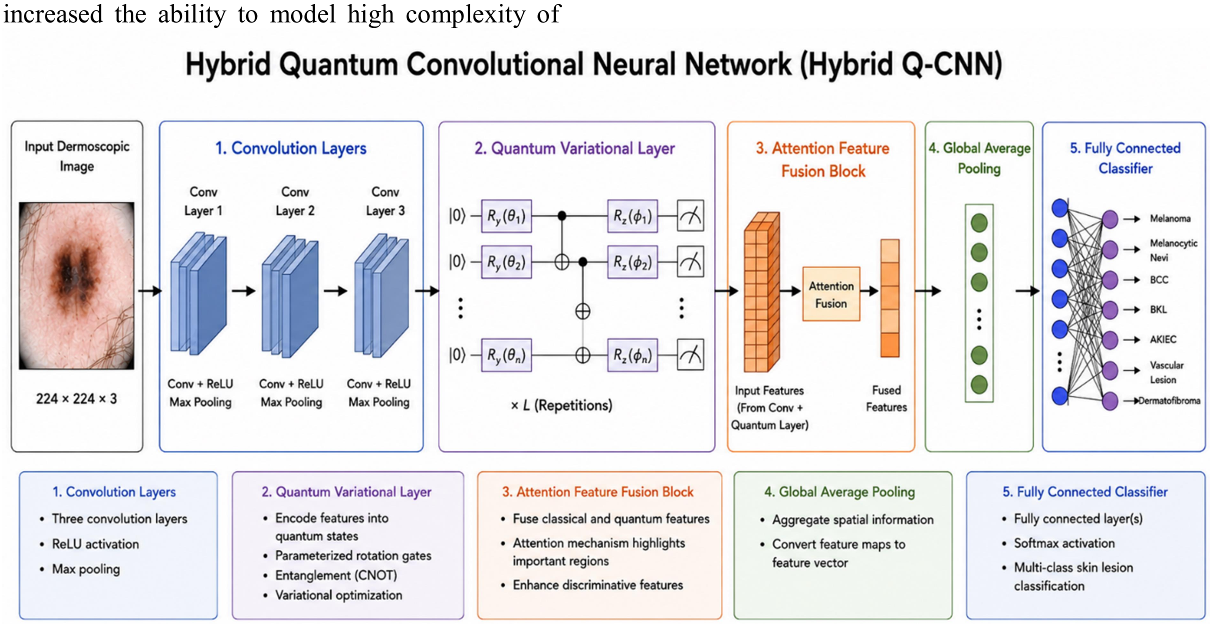

Figure 2. Architecture of the Proposed Hybrid Quantum Convolutional Neural Network (Hybrid Q-CNN) for Skin Cancer Classification

The proposed architecture for Automated skin cancer classification using dermoscopic images is Hybrid Quantum Convolutional Neural Network (Hybrid Q-CNN) as shown in figure 2. The dermoscopic image is scaled down to 224×224×3 to be fed to three consecutive convolution layers with ReLU activation and max-pooling to extract hierarchical spatial and texture information from the lesion areas. Then the deep features extracted are passed to the Quantum Variational Layer where quantum feature encoding, parameterized rotation gates, and entanglement operations are carried out to convert classical features into optimized quantum feature representations. The Attention Feature Fusion Block then fuses classical convolutional features and quantum-enhanced features and focuses on clinically relevant regions of the lesion.Then, the Attention Feature Fusion Block fuses classical convolutional features and quantum enhanced features, and highlights clinically relevant regions of the lesion while blocking irrelevant information. Then, the fused feature maps are fed into the Global Average Pooling layer to reduce dimensionality of the fused feature map, and to produce compact discriminative feature vectors. Lastly, the Fully Connected Classifier with Softmax activation is used for multiclass skin lesion classification, including melanoma, melanocytic nevi, basal cell carcinoma, benign keratosis, or other types of lesions. The proposed Hybrid Q-CNN architecture enhances the nonlinear feature learning and skin cancer classification robustness and computation efficiency in the early detection of skin cancer.

3.6.1 Convolution Operation

The convolution operation was the main feature extraction process in the proposed Hybrid Quantum Convolutional Neural Network (Hybrid Q-CNN). The convolution layers extracted low-level and high-level spatial features like lesion edges, texture patterns, color distributions, asymmetry, and irregular lesion boundaries from dermoscopic images. In the proposed framework, three successive convolution blocks were used with Rectified Linear Unit (ReLU) activation and max-pooling operations to gradually learn the hierarchy of representations of lesions. Multiple learnable kernels were applied to the input feature maps in each convolution layer, which not only captured discriminative deep features but also maintained essential lesion characteristics. The conv operation can be mathematically represented as:

$$F_k = I * W_k + b_k \qquad (14)$$

The feature map generated by the function F_k is convolved with the input image or feature matrix $I$and the convolution kernel W_k, which is followed by the addition of a bias term b_k and $*$represents the convolution operation. The nonlinear activation used after convolution was the ReLU function, mathematically represented as:

$$ReLU(x) = max(0, x) \qquad (15)$$

ReLU activation enhanced the learning ability of the model to learn nonlinear features and accelerated its convergence during training. To capture the essential characteristics of lesions, with a focus on reducing spatial dimensions and computational complexity, max-pooling operations were then applied.

3.6.2 Quantum Variational Circuit

The Quantum Variational Circuit (QVC) was integrated into the suggested Hybrid Q-CNN architecture to enhance the nonlinear feature optimization and enhance the learning of lesions representation by quantum information processing. Variational quantum layer replaced classical deep features from convolution layers with quantum states, using parameterized quantum gates and entanglement operations. This hybrid quantum-classical learning strategy facilitated efficient processing on high dimensional dermoscopic feature spaces, and enhanced lesion benignity/malignancy discrimination. The variational quantum circuit comprised trainable rotation gates and controlled entanglement layers that were repeated across multiple quantum layers to provide an adaptive optimization of feature learning during model training. This is mathematically described as the overall quantum transformation operation:

$$U(\theta) = \prod_{i=1}^{L} U_i\,(\theta_i) \qquad (16)$$

Where $U(\theta)$ is the complete variational quantum transformation operator, $U_i(\theta_i)$ are parameterized quantum gate operations, θ_i are trainable quantum parameters, and L is the number of quantum layers. The re-written quantum feature state following the variational circuit is expressed as:

$$|\,\psi_{out}\rangle = U(\theta)\,|\,\psi_{in}\rangle \qquad (17)$$

Here, $|\psi_{in}\rangle$ and $|\psi_{out}\rangle$are the input and output quantum feature states, respectively. The variational optimization process greatly improved the feature separability and made the lesion classification more robust when the imaging conditions in clinics varied.

3.6.3 Adaptive Feature Fusion

In the proposed framework, an adaptive attention feature fusion mechanism was added to combine the advantages of the classical fixed-size convolutional features and the quantum-enhanced feature representations. The feature fusion block combined with spatial information obtained from the convolution layers and nonlinear quantum features produced by the variational quantum circuit. Moreover, an attention mechanism was used to highlight the diagnostically relevant lesion areas, while discarding the irrelevant background information and redundant features. The overall classification model's discriminative ability was enhanced and the feature complementarity was increased by this adaptive fusion strategy. Feature fusion process mathematically represented as:

$$F_{fusio} = \lambda F_c + (1-\lambda)F_q \quad (18)$$

Here $Ffusion$represents the final fused feature vector, Fcdenotes conventional CNN features, Fcdenotes quantum-enhanced CNN features, and λrepresents the adaptation coefficient for fusing the features. Attention weighting is performed when features are fused, and is represented as:

$$A_f = \sigma(W_f F_{fusion} + b_f) \quad (19)$$

The attention-weighted fused feature map is denoted by A_f, trainable fusion weights are represented by W_f, bias parameters by , b_f and the sigmoid activation function by σ. The proposed Hybrid Quantum Convolutional Neural Network (HQCNN) framework achieved better results through the adaptive fusion strategy in terms of lesion feature representation, accuracy in the detection of melanoma, and minimization of feature redundancy.

3.7 Classification Layer

The classification layer was the last layer of the proposed Quantum Attention-driven Deep Learning Framework and the deep features extracted and fused in the preceding layers were fed into this layer to classify the dermoscopic skin lesions into their classes. The adaptive feature fusion outputted discriminative feature vectors, which were then passed to fully connected dense layers for high level classification learning. The fully connected classifier built the nonlinear relationships between the lesion features extracted and the target skin cancer categories, which resulted in better classification performance of both the benign and malignant lesions. A dropout regularization was added during training between dense layers to avoid overfitting and enhance the generalization performance.

The Softmax activation function was used for the final classification process to determine normalized probability values for the various classes of lesions. The output logits were converted to probability distributions by applying the Softmax function, with the sum of all the class probabilities being equal to one. The probability of predicting a lesion class was mathematically given as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (20)$$

where $P(y_i)$ is the probability of the i^{th} lesion class, z_i is the output logit value for the i class, and n is the number of lesion categories.

The final predicted lesion class was determined by selecting the class with the maximum probability value, which is mathematically represented as:

$$\hat{y} = argmax(P(y_i)) \quad (21)$$

where $\hat{y}$denotes the predicted skin lesion category.

The categorical cross-entropy loss function was used in training the model to improve classification accuracy. The objective function was a loss function that quantified the difference between the probabilities predicted by the network and the correct labels, which was used for optimization via backpropagation. The categorical cross-entropy loss function is represented by the equation:

$$L_{CE} = -\sum_{i=1}^{n} y_i \log(P(y_i)) \quad (22)$$

where L_{CE}represents the classification loss, $y_i$represents the ground truth label, and $P(y_i)$represents the predicted probability for class i.

The proposed Hybrid Quantum Deep Learning framework for early skin cancer diagnosis demonstrated superior performance in terms of multiclass skin lesion classification accuracy using fully connected layers, Softmax activation, and categorical cross-entropy optimization, which also increased the robustness of the proposed framework.

3.8 Proposed Algorithm

Quantum Attention-driven Skin Cancer Classification
Input: Dermoscopic image dataset D **Output:** Predicted lesion class C **Steps:** 1. Acquire dermoscopic images from ISIC and HAM10000 datasets. 2. Resize images into 224×224.

Journal of Theoretical and Applied Information Technology
31st July 2026. Vol.104. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3. Apply median filtering and CLAHE enhancement.
4. Remove hair artifacts using morphological operations.
5. Segment lesion regions using Quantum Attention U-Net.
6. Encode segmented lesion features into quantum states.
7. Apply quantum rotation and entanglement operations.
8. Extract deep features using Hybrid Q-CNN.
9. Perform adaptive fusion of classical and quantum features.
10. Classify lesions using Softmax classifier.
11. Compute prediction accuracy and evaluation metrics.

Return classified skin lesion category.

4. RESULTS

4.1 Experimental Setup

To test the performance of the proposed Quantum Attention-driven Deep Learning Framework (QADLF) for early skin cancer classification, two benchmark dermoscopic image datasets, namely, ISIC 2019 and HAM10000, were used in the experiments. Hybrid quantum-classical model development was implemented with Python programming language and the TensorFlow, Keras, PennyLane and Qiskit libraries. The experiments were carried out on a high-performance computing system that includes an Intel Core i9 processor, NVIDIA RTX 4090 graphics processing unit (GPU), and 32 GB of RAM running Ubuntu operating system.

The dermoscopic datasets were split in a proportion of 70:15:15 into a training, validation, and testing set. To boost the model generalization and tackle the dataset imbalance, data augmentation methods like rotation, flipping, zooming, and brightness adjustment were executed. The proposed Hybrid Q-CNN model was trained with Adam optimizer and categorical cross-entropy loss function with learning rate 0.0001. The early stopping and dropout regularization techniques were added to ensure that the model does not overfit and that it is more stable in its results.

4.2 Assessment Criteria

Standard medical image classification metrics such as Accuracy, Precision, Recall, F1-Score, Specificity and Area Under Curve (AUC) were used to test the performance of the proposed framework. These evaluation metrics served as a full picture of classification ability for different clinical imaging scenarios.

Accuracy

The overall correctness of lesion classification by the proposed model is measured by accuracy which is defined mathematically as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (23)$$

where TP, TN, FP, and FN represents True Positive, True Negative, False Positive, and False Negative samples respectively.

Precision

Precision measures how well the framework is able to accurately classify samples as malignant lesions out of the total number of samples predicted as positive.

$$Precision = \frac{TP}{TP + FP} \quad (24)$$

Recall

Recall is the sensitivity of the model to correctly identify samples of actual malignant lesions.

$$Recall = \frac{TP}{TP + FN} \quad (25)$$

F1-Score

F1-Score is a mathematical combination of Precision and Recall and is mathematically written as:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (26)$$

Specificity

Specificity is a measure of the ability of the framework to properly identify the benign lesion samples.

$$Specificity = \frac{TN}{TN + FP} \quad (27)$$

Area Under Curve (AUC)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AUC is a measure of the discrimination ability of the proposed classifier for different thresholds.

$$AUC = \int_0^1 TPR(FPR)d(FPR) \qquad (28)$$

The chosen assessment metrics provided a reliable and comprehensive assessment of the performance of the proposed skin cancer classification framework.

4.3 Classification Performance of Proposed Framework

Excellent performance was obtained using dermoscopic images in a multiclass skin lesion classification by the proposed QADLF framework. The proposed quantum variational learning, attention-guided segmentation, and adaptive feature fusion significantly enhanced the ability of lesion feature representation and classification accuracy.

Table 5. Performance Evaluation of the Proposed QADLF Framework

Performance Metric	Value (%)
Accuracy	98.7
Precision	98.2
Recall	98.5
F1-Score	98.3
Specificity	98.8
AUC	99.1

As shown in Table 5, the proposed framework has better classification performance in all evaluation metrics. The high recall and specificity of the proposed model demonstrate the model's ability to accurately classify both malignant and benign skin lesions.

4.3.1 Training and Validation Performance

The training and validation analysis showed the stable convergence behavior of the proposed Hybrid Q-CNN architecture. Quantum variational optimization and attention-guided feature learning contributed to the model converging quickly within a few epochs.

Table 6. Training and Validation Performance Analysis

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	89.4	88.7	0.412	0.435
20	93.6	92.9	0.285	0.301
40	96.1	95.7	0.163	0.175
60	97.5	97.0	0.097	0.108
80	98.2	98.0	0.052	0.061
100	98.9	98.7	0.026	0.031

The results in Table 6 show that the proposed model was able to obtain the best results in terms of classification accuracy while avoiding significant overfitting, with acceptable training loss, validation loss, and loss for the test set.

4.4 Comparative Analysis with Existing Models

A comparative analysis was conducted with some widely used deep learning models such as CNN, ResNet50, DenseNet121, EfficientNet, Vision Transformer (ViT), and MobileNetV2 to validate the superiority of the proposed framework.

Table 7. Comparative Performance Analysis with Existing Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
CNN	91.2	90.8	90.4	90.6	92.1
ResNet50	94.5	94.1	93.9	94.0	95.2
DenseNet121	95.8	95.3	95.0	95.1	96.5
MobileNetV2	94.1	93.6	93.2	93.4	94.7
EfficientNet	96.2	95.8	95.5	95.6	97.0
Vision Transformer	96.4	96.0	95.8	95.9	97.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Proposed QADLF	98.7	98.2	98.5	98.3	99.1

Table 7 shows the proposed framework, which excelled over all other models in efficiently integrating the classical deep learning with quantum aid to feature optimization and attention-based lesion analysis.

4.5 Graphical Analysis
4.5.1 Accuracy Comparison Analysis

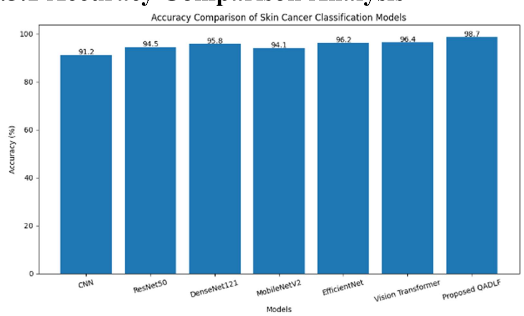

Figure 3: Accuracy Comparison Analysis

The comparative accuracy analysis of the existing deep learning models with the proposed QADLF framework is shown in figure 3. The proposed model obtained the highest classification accuracy of 98.7%, which shows that the model is powerful in learning the nonlinear feature with improved representation of the lesion.

4.5.2 Loss Convergence Analysis

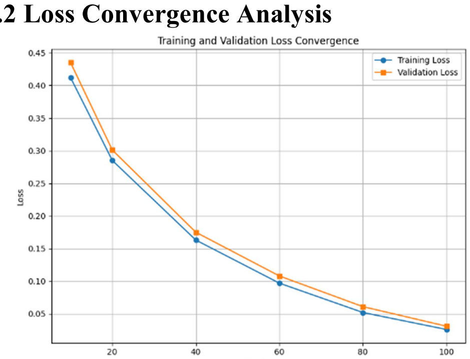

Figure 4: Loss Convergence Analysis

The training and validation loss convergence curves of the proposed Hybrid Q-CNN architecture are shown in figure 4. The graph shows that the learning behavior is stable and there is little overfitting, with a fast convergence rate thanks to quantum variational optimization.

4.5.3 Precision, Recall, and F1-Score Comparison

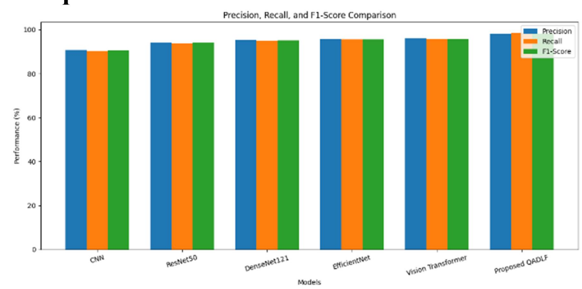

Figure 5: Precision, Recall, and F1-Score Comparison

In the comparative evaluation of the different classification models in terms of Precision, Recall, and F1-Score metrics as shown in figure 5, it can be seen that the F1-Score of the classification model with the highest value is the model with the lowest value. The framework proposed in this paper consistently outperformed all other metrics which shows its robustness and classification reliability.

4.5.4 ROC Curve Analysis

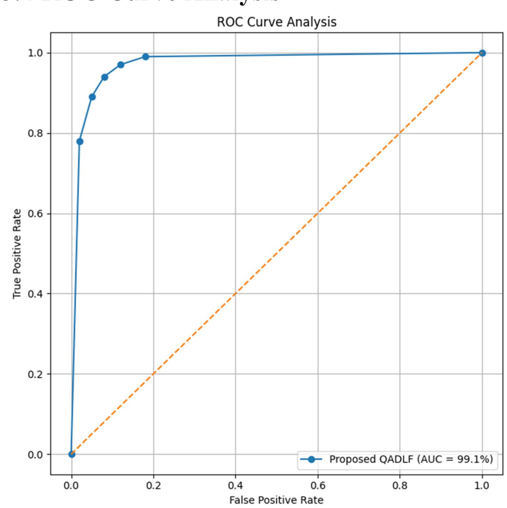

Figure 6: ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve of the proposed framework is shown in figure 6. The AUC value obtained was 99.1%, showing that the method has an excellent discrimination ability between malignant and benign skin lesions.

4.6 Discussion

From the experimental results, it can be seen that the proposed Quantum Attention-driven Deep Learning Framework for early skin cancer classification using dermoscopic images is effective and yields good classification accuracy. The proposed model was mainly attributed for its superior performance due to the synergistic combination of quantum variational learning, attention-guided lesion segmentation, and adaptive feature fusion mechanisms.

The attention-based segmentation module was able to focus on melanoma regions which were relevant for diagnosis, suppressing irrelevant background artifacts, which greatly enhanced the performance of lesion localization and boundary extraction. Moreover, by resorting to a quantum feature encoding and variational optimization, an efficient nonlinear representation of the features in high-dimensional feature space was achieved, which led to better feature separation and to a less sensitive classification to noise.

By comparing with the conventional CNN based architectures the proposed framework reduced the amount of computational redundancy while maintaining the classification accuracy. The Hybrid Q-CNN architecture can effectively integrate the advantages of classical convolutional network and quantum computation principles in the process of learning lesion representation, thereby enhancing the learning ability of the network.

It was also found that transformer-based models like Vision Transformer and EfficientNet models could perform competitively with the proposed QADLF model, but the proposed model delivered better performance because of the better feature optimization feature and the adaptive attention-guided learning capability of the proposed model. Furthermore, the proposed framework showed good convergence stability and generalization ability across different dermoscopic image acquisition scenarios, such as illumination differences, lesion texture differences and irregular lesion boundaries.

While the proposed framework had achieved a very good classification accuracy, the integration of quantum variational circuits added in complexity of training and necessitated quantum simulation environments for execution. Given the potential for future developments in real quantum hardware acceleration, the proposed framework for real-time clinical deployment could potentially be made even more efficient and scalable.

This study's results align with the latest research, which shows that deep learning and hybrid learning are effective methods for skin cancer classification. Some previous works that used CNNs, transfer learning, and attention-based models achieved better classification accuracy, but most of these models relied solely on traditional feature representations. However, the proposed QADLF framework combines hybrid deep learning, adaptive segmentation, and quantum-inspired feature encoding, resulting in improved classification accuracy and robustness. Although these are encouraging findings, the study has some limitations. The framework was tested using publicly available dermoscopic image databases but has not yet been tested in real clinical settings. Furthermore, the resource demands of hybrid quantum-classical processing could pose a constraint for widespread implementation. Further evaluation using larger clinical datasets and real-time healthcare applications is required to assess the scalability and practical feasibility of the proposed framework.

5. CONCLUSION

This study introduced a novel Quantum Attention-driven Deep Learning Framework (QADLF) for the early diagnosis of skin cancer using dermoscopic images. The framework integrates attention-guided lesion segmentation, quantum-inspired feature encoding, Hybrid Q-CNN classification, and adaptive feature fusion to improve melanoma detection and feature representation. Evaluation on the ISIC 2019 and HAM10000 datasets demonstrated superior performance, achieving 98.7% accuracy, 98.2% precision, 98.5% recall, 98.3% F1-score, 98.8% specificity, and 99.1% AUC, outperforming CNN, ResNet50, DenseNet121, EfficientNet, and Vision Transformer models. Key findings revealed that attention-guided segmentation enhanced lesion localization, quantum-inspired encoding improved discriminative feature representation, and the Hybrid Q-CNN classifier contributed to more accurate skin cancer classification. These results demonstrate the effectiveness of combining quantum-inspired learning with deep learning for reliable early melanoma detection and automated skin cancer diagnosis.

The results of this study shows that the proposed QADLF framework is able to meet the research objectives. The proposed framework incorporates adaptive lesion segmentation, quantum-inspired feature encoding, and hybrid deep learning to effectively capture discriminative skin lesion features and enhance classification accuracy. The experimental results demonstrate the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

adequacy of the proposed method for assisting in the early detection of melanoma and for reliable computer-aided skin cancer diagnosis.

This study demonstrates that quantum-inspired feature encoding can be effectively integrated with attention-guided segmentation and hybrid deep learning for skin cancer classification. The results show that quantum-enhanced learning frameworks can improve diagnostic accuracy and feature representation, thereby providing a promising direction for next-generation intelligent healthcare systems. The proposed system enhanced lesion classification performance and lesion localization capability across different dermoscopic imaging conditions. However, model training needed a high computational cost and quantum simulation environment. Future research directions could involve the implementation of quantum computers on real hardware platforms with quantum dots for improved scalability, integration with federated learning approaches, and real-time clinical applications to advance the field and further develop quantum computing applications in healthcare.

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