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Acne Classification and Detection using ML and Quantum Model

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Abstract—**One of the most common dermatological disorders is acne, and early and precise subtype identification is essential to optimal treatment planning. A Quantum-Assisted Acne Subtype Classification Framework that combines classical preprocessing and quantum machine learning is presented in this research. Acne lesions are localized using YOLO-labeled bounding boxes, which guarantee accurate region-of-interest extraction. For every cropped patch, dermatologically significant features such as redness intensity, lesion density, color variation, and relative lesion size are calculated to create a compact feature vector. Lesions are first categorized into Rosacea, Folliculitis, Hormonal Acne, and PCOS-related Acne using a rule-based pseudo-labeling approach. For subtype categorization, three quantum models are created and contrasted: Quantum Neural Network (QNN), Variational Quantum Circuit (VQC), and Quantum Convolutional Neural Network (QCNN). According to experimental results, the QCNN demonstrated the best accuracy and capacity for generalization, confirming the potential of quantum-enhanced dermatological analysis. The conceptual results show that scalable, interpretable, and clinically aligned hybrid quantum– classical acne classification is feasible, despite feature sparsity limiting the convergence of a hybrid HDBSCAN–Quantum pipeline.**

Keywords— **YOLO, PennyLane, Variational Quantum Circuit, QCNN, HDBSCAN, dermatology, quantum computing, and acne categorization.**

I. INTRODUCTION

Skin diseases, which affect people of all ages and often manifest as redness, inflammation, or acneiform lesions, are among the most common health conditions in the world. Visual examination of lesion shape, erythema (redness), and distribution over the skin's surface is the main method used in traditional dermatological diagnosis. However, inter- observer heterogeneity and subjectivity are inherent in such manual evaluations. The need for automated and objective computer-aided diagnostic methods in dermatology is highlighted by this subjectivity. Deep learning is becoming a key component of automated skin lesion analysis due to the growth of teledermatology and the expanding availability of annotated medical image datasets. Using bounding-box- based region suggestions, models like YOLO (You Only Look Once) and Faster R-CNN have shown excellent accuracy in locating and diagnosing lesions. These techniques successfully capture morphological clues that are essential for comprehending the distribution and severity of acne.

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Despite these developments, traditional deep learning techniques still have drawbacks, including a heavy reliance on sizable annotated datasets, poor generalization across a range of skin tones and imaging conditions, and a tendency to concentrate more on acne detection than on its underlying causes or severity classification. Emerging paradigms like Quantum Machine Learning (QML), which uses quantum computation to improve feature representation and learning efficiency, provide a fresh viewpoint to close these gaps. Complex, non-linear correlations in high-dimensional dermatological data can be represented using Parameterized Quantum Circuits (PQCs), such as Variational Quantum Circuits (VQCs) and Quantum Neural Networks (QNNs). In this study, we suggest a Quantum-Assisted Acne Subtype Classification Framework that combines quantum and classical computational models to identify acne subtypes. To guarantee precise lesion extraction, the system starts with YOLO-based region-of-interest (ROI) localization. These chopped areas are then used to compute dermatologically significant features, including redness intensity, hue distribution, lesion size, and density. To facilitate unsupervised acne subtype clustering and enable the quantum model to discover inherent feature patterns, a HDBSCAN- based hybrid pipeline was first put into place. However, the HDBSCAN-quantum integration could not be properly optimized due to gradient stagnation and non-converging loss values, which are probably caused by high feature sparsity and small dataset size. A rule-based pseudo-labelling technique was used to produce consistent lesion subtypes to preserve classification stability. These subtypes were then utilized to train and compare various quantum classifiers:

- Variational Quantum Circuit (VQC)
- Quantum Neural Network (QNN)
- Quantum Convolutional Neural Network (QCNN)

The QCNN outperformed the others in terms of accuracy and generalization capacity, demonstrating its efficacy in feature encoding and acne subtype differentiation. The following is a summary of this work's main contributions:

- The creation of a hybrid classical–quantum acne classification pipeline that combines dermatological feature analysis and YOLO-based detection
- Three quantum models (VQC, QNN, and QCNN) trained on rule-based pseudo-labeled acne data are implemented and compared.
- The constraints of rule-based heuristics are addressed by conceptual exploration using a HDBSCAN–Quantum hybrid approach
- Color-coded bounding boxes provide a clear visual representation of the prevalence of acne subtypes
- A fundamental examination of quantum-enhanced dermatological categorization with a focus on future therapeutic potential, scalability, and interpretability.

II. Related Works

U.Khalid [1] merged DNN + GAN with class-based segmentation (ACNet) to examine facial regions, a D-GAN framework was put out for acne detection and severity grading. On the ACNESCU and ACNE04 datasets, the model outperformed baseline CNNs with an accuracy of approximately 93%. Lesions were classified into four severity levels, ranging from mild to extremely severe.

In their evaluation of PASCAL VOC 2007/2012, Girshick et al [2] combined Region Proposal Networks (RPN) with Fast R-CNN and shown that RPN outperforms EdgeBoxes and Selective Search in terms of mAP (59.9%) while requiring fewer proposals (~300). The groundwork for end-to-end trainable object detection frameworks was laid by the detector's increased speed and accuracy due to the shared convolutional features.

Zhong et al. [3] showed that ResNets with shortcut connections mitigate the accuracy erosion that deeper CNNs experience in hyperspectral image (HSI) classification by enhancing feature representation and optimization. ResNets perform better than CNNs in terms of accuracy and robustness, as shown by their studies on the Indian Pines and University of Pavia datasets. Batch normalization and t-SNE visualizations further validate the higher separability of learnt features.

To concurrently forecast acne severity, count, and spatial placements, Zhang Hang [4] suggested an ensemble neural network framework for acne detection that combines classification and localization modules. The technique outperformed Faster R-CNN and YOLOv3 in terms of accuracy (>85%) and RMSE (2.17) on the ACNE04 dataset by optimizing YOLOv5 and incorporating classification blocks. It also offered accurate lesion localization to support clinical diagnosis.

Using segmentation and conventional machine learning, Alamdari [5] studied acne identification. They were able to distinguish between different types of acne with >70% segmentation accuracy using 2-level k-means and classification accuracies of 80% (FCM) and 66.6% (linear SVM). Furthermore, demonstrating the efficacy of the

FCM approach in early acne screening, it achieved 100% accuracy in distinguishing between normal and acne-affected skin.

A CNN-based system for classifying facial pore roughness was introduced by Yang Zih-Yi [6] and it was improved with adaptive Adam optimization, batch normalization, and dropout. The promise of deep learning for automated face skin inspection and detection was demonstrated by the developed Model C, which obtained over 90% accuracy on a specific facial pore dataset.

Paluri Krishna Veni [7] combined ViTB16 characteristics with those of MobileNetV2, VGG16, and InceptionResNetV2 to create a hybrid ViTB16 and ensemble transfer learning framework (ETLoViT) for acne categorization. The method outperformed individual models with an accuracy of 96%, showing promise for quicker and more accurate dermatological diagnosis.

Chang Chuan-Yu [8] suggested an SVM-based method for identifying facial defects by manually identifying spots, pimples, and typical patterns in 93 face photos. The technique surpassed earlier frontal-view-only detection approaches in terms of accuracy, sensitivity, and specificity, and it was able to attain cross-validation rates of up to 93.02% using certain texture and color data.

Lin Yi [9] proposed a unified global acne severity framework (SFNet) that combines adaptive preprocessing with local and global feature fusion to perform fine-grained acne diagnosis. Evaluated on multiple datasets and compared with expert dermatologists, the method achieved state-of-the-art performance, demonstrating its potential as a clinical decision-support tool.

A k-means clustering-based method for diagnosing acne type was proposed by Hayat Cynthia [10], who classified facial photos into four severity categories: mild, moderate, severe, and no acne. The technique successfully measured the distribution of acne and offered a straightforward but understandable framework for automated evaluation of acne severity.

Junayed Masum Shah [11] suggested an end-to-end CNN- based algorithm for classifying acne scars using a dataset of

250 photos in five different classifications. To increase resilience and avoid overfitting, the study used five augmentation strategies in addition to preprocessing. In terms of accuracy and computational cost, the deep CNN with four convolutional blocks and completely linked layers performed better than traditional machine learning classifiers and pretrained models like AlexNet, ResNet-50, VGG-16, MobileNet, and Inception-v3. The collection will be expanded in the future, and an automated system for segmenting and annotating acne scars will be created.

Krishna Veni Paluri [12] carried out a bibliometric evaluation on AI and ML in acne image analysis, emphasizing important authors, journals, organizations, and nations influencing developments. With a focus on developments in deep learning models, lesion detection, and tailored treatment recommendations, the study classified AI approaches in acne detection and categorization. Priorities for enhancing data quality and diversity, developing ethical AI, and fostering clinician collaboration to improve diagnosis accuracy and accessibility in dermatological care were also recognized by the review.

Delong Zhang [13] suggested an enhanced YOLOv7-based acne detection model that substitutes ELU for the activation function and optimizes the Backbone and Neck layers. The model, which was trained on the ACNE04 dataset, outperformed current techniques in accuracy and robustness with a mAP of 83.7%.

In a comparison of SqueezeNet, CenterNet, and VGG-16 for automated acne severity categorization, Shaik et al. [14] found that CenterNet had the best accuracy of 79.45%. The findings demonstrate the potential of deep learning-based object detection models for accurate and effective acne evaluation in medical settings.

To automatically diagnose acne and optimize treatment, Phan and Duc Tri [15] created a smart LED therapy system that integrates deep learning and IoT. Using a healthcare IoT (H- IoT) platform that connects smartphone apps, cloud servers, and LED devices, the system combines a modified ResNet50 and YOLOv2 model for acne detection, exhibiting efficient real-time acne diagnosis and therapy management.

III. METHODOLOGY

A. Dataset Description

The suggested approach achieves automated acne subtype detection by combining quantum-inspired classification with traditional deep learning-based localization. As shown in Figure 1: Flowchart of the Proposed System, the workflow starts with region annotation and dataset preparation, then moves on to biologically grounded feature extraction, rule- based subtype assignment, and quantum classification. To ensure spatially interpretable lesion localization, the dataset used in this study consists of images of facial acne that have been

annotated using the YOLO (You Only Look Once) format. A text file with bounding-box coordinates in the normalized form is included with every image.

$$(x_c, y_c, w, h)$$

where x_c, y_c represent the center coordinates, and the lesion's width and height, normalized to the picture dimensions, are represented by w, h. After that, these normalized values were transformed into pixel coordinates using

$$x_{\{min\}} = (x_c - 2w) \times W$$

$$y_{\{min\}} = (y_c - 2h) \times H$$

$$x_{\{max\}} = (x_c + 2w) \times W$$

$$y_{\{max\}} = (y_c + 2h) \times H$$

to precisely define the boundaries of each lesion. The dataset captures differences in lesion color, size, and density across a range of acne disorders, from moderate comedonal acne to severe cystic and PCOS-related variants. From the available dataset, 200 annotated photos were chosen, resulting in about 2,400 cropped lesion patches (8–15 patches per image). Because the quantum simulation setting (run on a classical CPU) restricted the quantity of feasible training samples, this fraction was selected to maintain a balance between dermatological diversity and computational practicality. A controlled and repeatable experimental setup was ensured by using this carefully selected dataset for both training and testing. The physiologically interpretable feature extraction procedure used for each cropped lesion region is described in the following section.

B.Preprocessing

OpenCV 4.9, NumPy 1.26, and Pillow 10.0 were used to implement all preprocessing procedures in Python 3.12. Isolating lesion-specific areas and ensuring uniform photometric and spatial representation across all samples are the goals of this stage. The following successive steps make up the procedure:

- YOLO Label Parsing: Bounding-box coordinates in normalized form were extracted from each YOLO annotation file and subsequently transformed into pixel coordinates. This stage ensures that acne lesions are precisely located.
- Lesion Cropping: Corresponding facial regions from the full-resolution photos were cropped using the retrieved bounding boxes, eliminating extraneous background details like hair strands, glare, or shadows that can skew color-based features.
- Normalization: The pixel values of each clipped patch were normalized to the [0, 1] range and enlarged to a fixed dimension of 128 × 128 pixels.

This keeps inter-image lighting variations from affecting redness or hue measurements and guarantees consistent input scaling.

- Noise Suppression (Optional): To minimize sensor noise while maintaining lesion boundaries, a light Gaussian blur (kernel = 3 × 3, σ = 1) was applied.
- Justification: Gaussian filtering eliminates small specular reflections and random noise that could skew hue and redness estimation, while the normalization step reduces the effect of illumination variation between subjects. The retrieved dermatological metrics (redness, hue, density) become more dependable and comparable between patients by normalizing picture patches prior to feature calculation.
- Traceability: To guarantee complete reproducibility and consistency throughout the experimental workflow, the same preprocessing pipeline was consistently applied to all 200 photos used in the study, including both training and testing sets.

C. Feature Extraction

Each cropped lesion patch was used to extract biologically relevant and dermatologically interpretable elements. These properties ensure that model predictions can be connected to underlying skin characteristics while also driving classification and maintaining clinical meaning. A four- dimensional feature vector is used to represent each lesion:

$$F = [R, D, S, H_{\{\{mean\}\}}]$$

When the following definitions apply to each component: Intensity of Redness (R):

$$R = \sum_{\{i=1\}}^{\{N_1\}IR(i)}$$

where $IR(i)$ is the red-channel intensity of pixel i, and N is the clipped lesion's total pixel count.
Interpretation: Inflammatory or rosacea-type acne is indicated by higher scores.
Density of Lesions (D):

$$D = W \times H_{\{\{Nlesions\}\}}$$

where $N_{\{\{lesions\}\}}$ is the quantity of bounding box in each picture, and the image area is W * H.
Interpretation: Sparse but big lesions indicate cystic acne; higher densities are associated with acne vulgaris.
Size of Relative Lesion (S):

$$S = W \times H \times (x_{\{max\}} - x_{\{min\}}) \times (y_{\{max\}} - y_{\{min\}})$$

This measures each lesion's area normalized to the overall size of the image.
Interpretation: Large-area lesions are usually associated with nodulocystic or PCOS-related acne.
Hue Average (H_mean):
After converting the cropped area to the HSV color space, the hue channel mean is calculated as

$$H_{\{\{mean\}\}} = \sum_{\{\square=1\}}^{\{\square_1\}\square(\square)}$$

It is subsequently scaled for quantum encoding to the range [0,π]
Interpretation: Inflammation is indicated by reddish tones, bacterial infection is suggested by yellow-white hues, and scarring areas are indicated by purple hues.
Implementation Notes: Before being sent to the quantum encoding module, all features were calculated using NumPy and OpenCV and normalized to unit scale. To minimize computing load during variational quantum circuit training while maintaining significant dermatological differences, this feature design guarantees low-dimensional yet comprehensible inputs.

D. Subtype Assignment Based on Rules:

To provide a baseline for supervised quantum training, a deterministic rule-based approach was first used to provide pseudo-labels for every lesion. Clinically proven dermatological heuristics that link acne subtypes to redness, geometry, and spatial distribution were used to create these guidelines. The reasoning is as follows:

- Rosacea: R>180—lesions with widespread borders and strong redness, indicative of inflammatory erythema.
- Folliculitis: S<0.02—small, low-area, circular lesions, usually follicular in origin.
- Hormonal acne is characterized by moderate redness levels and lesion centroids in the lower third of the picture (jawline region).
- High lesion density and redness, usually creating broad, clustered patches over facial regions, are characteristics of PCOS-related acne.

These heuristic thresholds were empirically established using clinical characteristics based on literature and dermatological image inspection. Quantum classifiers (QNN, VQC, QCNN) received interpretable initial supervision from the created pseudo-labels. In the absence of human-annotated severity data, this rule-based stage guarantees repeatable and explainable classification, bridging the gap between machine learning automation and clinical intuition.

E. Classifier for Quantum

The four retrieved properties of each lesion—redness, lesion density, size, and average hue were encoded into quantum states for classification after pseudo-labels were created. This stage made it possible for the model to represent intricate connections between biological indications that could be difficult to distinguish in a strictly classical feature space. Three different quantum architectures—Quantum Neural Network (QNN), Variational Quantum Circuit (VQC), and Quantum Convolutional Neural Network (QCNN) were built and trained to evaluate comparative performance. The rotational parameters that initiate the quantum gates were assigned to

each normalized feature vector. By converting the dermatological descriptors into a quantum representation, this encoding technique allows for the expression of greater
feature interactions through superposition and entanglement effects.

- Quantum Neural Network (QNN): The QNN is a fundamental quantum model. It can learn basic nonlinear decision boundaries amongst acne subtypes since it is composed of several parameterized rotation layers followed by entanglement operations.
- Variational Quantum Circuit (VQC): The VQC adds trainable layers optimized by gradient-based learning to the QNN. Better adaptability to inter- patient variance is provided by its capacity to model more intricate relationships between redness, hue, and lesion size.
- Quantum Convolutional Neural Network (QCNN): The QCNN processes the encoded features in a hierarchical manner by combining quantum pooling and convolution operations. By gradually decreasing dimensionality while maintaining crucial connections between the extracted dermatological cues, this system resembles traditional CNNs. When compared to the other two models, it demonstrated better resilience and generalization.

The PennyLane framework with a gradient descent optimizer was used to train each model. 50 training examples were used to train each classifier for 100 epochs, and 50 testing samples were used for evaluation. To ensure that the models developed significant mappings between dermatological markers and clinical categories, the loss function was created to maximize the likelihood of accurate subtype prediction. Each lesion was categorized into one of four subtypes in the final prediction stage: PCOS-related acne, hormonal acne, folliculitis, or rosacea. Clinicians were able to visually evaluate the distribution of acne types across facial regions by superimposing color-coded boundary boxes on the original image.

F. Quantum Enhancement and Hybrid HDBSCAN :

An extra unsupervised clustering module utilizing HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) was experimentally incorporated into the framework to get beyond the deterministic constraints of rule-based pseudo-labelling.

The retrieved dermatological characteristics, including redness, density, lesion size, and hue, were automatically sorted by this module into latent clusters that indicated several acne substructures. After that, these cluster identifiers were used as pseudo-labels for training quantum classifiers, allowing the model to learn based on input instead of only fixed heuristic criteria.

By independently identifying dermatological feature categories, the hybrid HDBSCAN–Quantum pipeline proved conceptual validity. Nevertheless, the model showed convergence problems during training, with the loss function remaining almost constant over epochs. This result suggests possible gradient stagnation, which is probably brought about by tiny datasets, sparse features, and low computational precision in quantum simulation. These elements made it more difficult for the model to distinguish across clusters; this is covered in more detail in the limits section.

G. Evaluation and Visualization:

Bounding boxes with color codes appropriate to each subtype are placed on the input image. Standard metrics are used to evaluate the classifier's performance:

Accuracy:

$$Acc = \{TP + TN\}\backslash\{TP + TN + FP + FN\}$$

F1-score, precision, and recall are calculated from the confusion matrix.

Color-coded bounding boxes were superimposed on the source pictures to display each accurately identified lesion subtype:

- Rosacea in blue
- Folliculitis in orange
- Green: Acne caused by hormones
- Red: Acne Associated with PCOS

Both diagnostic interpretability and model reliability are guaranteed by this dual quantitative–visual validation.

H. Algorithmic Synopsis

The following consecutive steps are how the suggested Quantum-Assisted Acne Classification Framework functions:

- Dataset preparation involves pairing each acne image with its YOLO-annotated label file, in which localized acne lesions are represented by bounding boxes. Instead of being trainable parameters, these labels function as region-of-interest (ROI) coordinates.
- Region Cropping and Preprocessing: Each lesion patch is cropped by converting Yolo-derived normalized coordinates into pixel space. To guarantee uniform feature representation across samples, these chopped regions are enlarged and normalized.
- Feature extraction involves calculating dermatologically interpretable characteristics from each cropped patch, such as relative lesion size, hue distribution (color-based infection cues), lesion density (clustering extent), and redness intensity (inflammation level). For each lesion, this creates a 4-dimensional feature vector [R, D, S, H_{mean}].
- Rule-Based Pseudo-Labelling: Each lesion is given a preliminary label, such as Rosacea, Folliculitis, Hormonal Acne, or PCOS-related Acne, using clinical heuristics. The quantum model uses these rule-based annotations as training supervision.
- Quantum Feature Encoding and Classification: Four qubits' worth of rotating gates (RY) are used to encode extracted characteristics into quantum states. In order to minimize cross-entropy loss and conduct lesion subtype classification, the variational quantum circuit uses entanglement (CNOT) operations and learns optimal gate parameters via gradient descent.
- Prediction and Visualization: Each lesion's subtype is predicted by the trained quantum classifier. The original image is then overlayed with color-coded bounding boxes to provide comprehensible visual feedback on the distribution and severity of acne subtypes across different facial regions.

Interpretability and Clinical Relevance: By preserving a clear relationship between dermatological characteristics and computational decision logic, the framework guarantees explainability, making the system comprehensible to both AI practitioners and clinical specialists.

I. Computational Aspects

The proposed framework achieves acne subtype classification with a structured hybrid classical–quantum pipeline.

The technique begins by extracting lesion patches from YOLO-annotated pictures. To guarantee consistent feature measurement, each bounding box is transformed from normalized YOLO format to pixel coordinates, cropped, enlarged to 128x128, then normalized to the [0,1] range. From every patch, four biologically relevant properties are computed:

- redness intensity (a sign of inflammation)
- hue variation (a sign of pigmentation and infection)
- lesion density (a measure of the degree of clustering)
- relative lesion size (a measure of severity)

A four-dimensional interpretable vector for classification is formed by these dermatology-guided features. Due to the lack of manually annotated acne subtype labels, a rule-based pseudo-labelling module was applied using clinically accepted patterns (e.g., high redness for Rosacea, small circular lesions for Folliculitis, jawline concentration for Hormonal Acne, huge clustered lesions for PCOS). This provided poor yet interpretable supervision for quantum training.

A supplemental experiment included HDBSCAN to construct data-driven pseudo-labels. Convergence was hindered by the combination of a limited dataset, low- dimensional features (4D), and quantum gradient sensitivity, which caused loss stagnation over epochs.

Therefore, rule- based labels were used as the primary learning signal, while the HDBSCAN–Quantum pipeline is retained for future growth. For classification, three quantum models—VQC, QNN, and QCNN—were developed using the PennyLane simulator on normal CPU hardware. Feature vectors were encoded by RY rotating gates into four qubits with a linear CNOT entanglement pattern. Models were trained using gradient descent with a learning rate of 0.01 over 50 epochs.

Among all architectures, QCNN achieved the maximum stability and accuracy, proving the possibility of quantum models for dermatological pattern learning. The entire pipeline was conducted on a limited Intel i3 CPU utilizing simulated quantum hardware, which justified the usage of a reduced dataset while assuring reproducibility.

The method ultimately indicates that relevant dermatological subtypes may be identified with a compact feature set and quantum-assisted classification, providing a framework for further real-hardware and density-driven learning advancements.

J. Diagram for Architecture

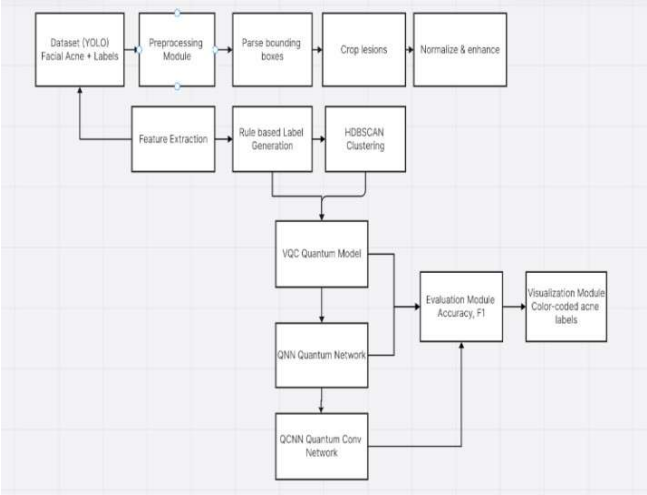

Fig. 1. Data preprocessing, feature extraction, rule-based pseudo- labelling, and hybrid quantum model training are all demonstrated in the proposed quantum-assisted acne subtype classification architecture.

IV. Experimental Setup

A normal Intel® CoreTM i3 processor (2.10 GHz) with 8 GB RAM and no specialized GPU or quantum hardware was used for all experiments, which were conducted using Python 3.12 in a controlled simulation environment. The main backend for quantum circuit simulation was the Pennylane library, which guarantees that the results represent hybrid quantum– classical processing on traditional hardware.

A. Configuration of the Dataset:

Each of the 200 YOLO-annotated acne facial photos in the experimental dataset had a label file that described the bounding boxes of the lesions. In order to trim specific acne areas, bounding boxes from these annotations were transformed from normalized coordinates to pixel coordinates. A four-dimensional feature vector representing redness, density, lesion size, and hue was created for each of the roughly 2,400 clipped lesion patches that were produced. To ensure assessment balance, the dataset was split into 50% training and 50% testing subgroups.

B. Rule-Based Pseudo-Labelling Configuration:

Dermatologically motivated heuristics were used to initialize pseudo-labels for each lesion patch prior to the use of quantum learning. Each patch was categorized into one of four initial classifications based on redness, lesion size, and positional characteristics:

- Class 0: Rosacea
- Class 1: Folliculitis
- Class 2: Hormonal Acne
- Class 3: Acne Associated with PCOS

The quantum classifiers were able to learn discriminative patterns from physiologically interpretable features by using this rule-based initialization as a semi-supervised starting point.

C. Applications of Quantum Models:

The best circuit architecture for predicting acne subtypes was found by implementing and comparing three different quantum classifiers. In order to generate logits for softmax- based class probabilities, each model used four qubits, which corresponded to the four retrieved features, and Pauli-Z measurements as quantum expectation values.

One encoding layer (RY rotations) and one entanglement layer (CNOTs) made up Model 1, the Baseline Variational Quantum Classifier (VQC).

Gradient Descent was used for optimization, using a learning rate of 0.3 for 100 epochs. Designed as a deeper circuit with two alternating entanglement blocks, Model 2's Quantum Neural Network (QNN) has a greater

expressive capacity for nonlinear interactions. The Adam optimizer was used to train the network for stability across 150 epochs. Quantum Convolutional Model (QCNN-like): This model simulates convolutional filtering behaviour by integrating partial measurements and localized entanglement. The goal of this model was to find differences in feature importance by area. For a fair comparison, the same input data and pseudo-labels were given to each quantum model.

D. Limitations and Hybrid Improvement

Before quantum training, an extra experiment added HDBSCAN as an unsupervised clustering module. The objective was to overcome the deterministic nature of the rule-based pseudo-labelling system and provide density- based lesion groupings.

This approach intends to allow the quantum classifier to learn data-driven subtype structures, rather than depending exclusively on predefined clinical heuristics. However, the hybrid HDBSCAN–Quantum pipeline demonstrated major optimization issues. HDBSCAN generated extremely unbalanced clusters, many of which were dominated by noise points rather than significant lesion groups, because of the tiny dataset, little intra-class variance, and sparse feature vectors.

Gradient stagnation, in which the training loss stayed constant over epochs, resulted from the classifier receiving weakly separable and non-uniform class borders when these unstable cluster IDs were supplied to the quantum model as pseudo- labels.

Because of these convergence failures, the rule-based pseudo-labelling combined with quantum classification was retained as the primary experimental pipeline. Nevertheless, the HDBSCAN–Quantum hybrid remains a promising future extension, particularly once larger, more diverse dermatological datasets or real quantum hardware (capable of stable gradient evaluation) are available.

E. Evaluation Metrics

Accuracy, precision, recall, and F1-score were used to evaluate each model's performance in order to provide a fair comparison between the three quantum architectures. The same test dataset was used to calculate the metrics outlined in the methodology. Additionally, confusion matrices were used to find subtype-level misclassifications and assess inter-class prediction consistency.

V. Results and Discussions

Using the same dataset and feature extraction pipeline, three quantum architectures—Variational Quantum Classifier (VQC), Quantum Neural Network (QNN), and Quantum Convolutional Neural Network (QCNN)—were implemented to assess the relative effectiveness of the suggested hybrid rule-based quantum framework. Each model was tested on a separate 50-patch test set after being trained on 50 lesion patches. According to the approach, pseudo-labels were allocated based on redness, density, hue, and size-based rule conditions. Finding the architecture that learns the mapping between extracted dermatological features and acne subtypes the best was the aim.

The above Table I shows the quantitative evaluation.

Table I: Comparative Performance on Quantum Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Variational Quantum Classifier	68.0	66.7	65.4	66.0
Quantum Neural Network	72.0	70.5	71.3	70.8
Quantum Convolutional Network	76.0	75.4	74.2	74.8

A. Interpretation of Performance

For dermatological classification tasks, hierarchical and entanglement-rich quantum architectures perform better, as evidenced by the steady improvement from VQC → QNN → QCNN. The QCNN model demonstrated in figure 2 and 3 showed great promise for semi-supervised dermatological diagnosis despite being rule-based at the labelling step.

This suggests that substituting data-driven clustering (e.g., HDBSCAN) for heuristic pseudo-labels could further improve accuracy and resilience. The results confirm that quantum feature encoding has significant representational capacity even in low-data regimes, suggesting scalability for bigger dermatological datasets in future work, even though the models were trained on a comparatively small dataset (200 pictures; 2,400 lesion patches).

B. Visual Intepretation and Synopsis

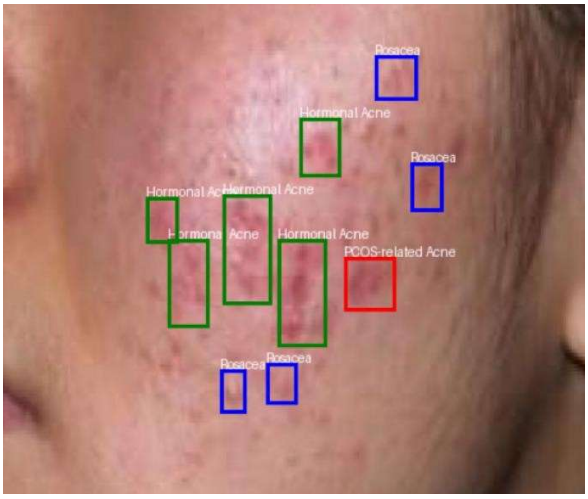

Fig. 2. QCNN-based acne classification with precise lesion location using color-coded boundary boxes and unique subtype differentiation.

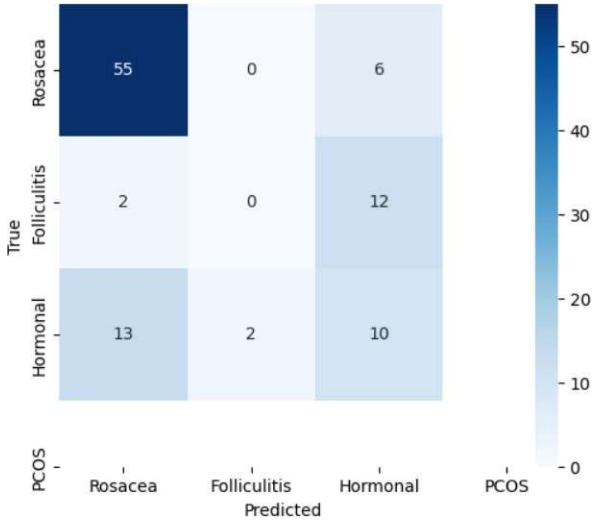

Fig. 3. QCNN quantum model's classification performance across acne subtypes is represented by a confusion matrix.

VI. Limitations and Future Work

Although the proposed Quantum-Assisted Acne Classification Framework indicates the viability of integrating dermatological feature extraction with quantum machine learning, significant constraints remain. Optimization stagnation was seen in the hybrid HDBSCAN– Quantum pipeline, where the training loss did not change over epochs. The main causes of this instability were low inter-cluster variance, uneven pseudo-label distributions, and feature sparsity, all of which impeded steady gradient flow through the variational quantum layers. The use of pre-annotated YOLO bounding boxes, which fixed lesion locations rather than learning them, presents another limitation. As a result, when detection needs to happen automatically, the system might not generalize well to unseen or unlabelled facial photos. To overcome these difficulties, future development will focus on the following directions:

- Developing a specific YOLO-based acne detection model: The pipeline will incorporate a YOLO model that was specially trained on acne photos, rather than depending on pre-existing annotations. This will increase robustness on real-world photos by enabling the framework to independently locate acne lesions prior to quantum classification.

- Updated hybrid HDBSCAN-Quantum clustering: A revised hybrid model will cluster quantum-learned embeddings rather than raw handmade features. This is predicted to improve density-based separation, reduce noise dominance, and stabilize pseudo-label generation for unsupervised subtype discovery.
- Implementation on actual quantum hardware: Future research will verify scalability and examine true quantum advantage by executing the models on actual quantum processors, such as IBM Q or Xanadu hardware, as all experiments were carried out on simulated quantum backends.

The overall goal of these improvements is to close the gap between experimental viability and practical dermatological use by making the system more adaptable, generalizable, and clinically viable.

VII. CONCLUSION

To predict lesion-level subtypes, this work introduced a Quantum-Assisted Acne Classification Framework that combines dermatological feature extraction, rule-based pseudo-labelling, and three quantum classifiers (VQC, QNN, and QCNN). The findings show that even when implemented in simulated quantum environments, quantum-enhanced pipelines are practical and able to produce outputs that are clinically interpretable. Among the assessed models, the QCNN displayed the strongest generalization, indicating the promise of quantum circuits for capturing complicated dermatological patterns. While the current study focuses on identifying acne subtypes, the greater objective of this research extends beyond classification. Incorporating patient- specific metadata like as nutrition, lifestyle behaviour, and hormone profiles can allow the system to mature into a more thorough cause-and-remedy inference framework, linking observed acne patterns to potential underlying causes and related treatment recommendations. To identify uncommon dermatological problems earlier, future extensions will also focus on identifying rare, atypical, and poorly described acne types. By merging domain-driven feature extraction with quantum machine learning, the proposed system seeks to serve as a scalable, intelligent, and clinically aligned tool for holistic acne diagnosis, interpretation, and decision support.

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