KARYA ILHAM PUBLISHING
CONNECTING MINDS, BRIDGING IDEAS, INSPIRING READERS

Journal of Advanced Research in Computing and Applications

Journal homepage:
https://karyailham.com.my/index.php/arca/index
ISSN: 2462-1927

Quantum Deep Learning Strategies for Facial Feature Extraction Based on Quantum Image Representation

Rayane Chadli[1], Suzan J. Obaiys[1,*]

[1] Department of Computer System & Technology, Faculty of Computer Science and Information Technology, Universiti Malaya, Kuala Lumpur, 50603, Malaysia

ARTICLE INFO

Article history:
Received 10 February 2026
Received in revised form 30 May 2026
Accepted 2 June 2026
Available online 1 September 2026

Keywords:
Facial recognition; image representation; quantum machine learning; feature extraction; feature fusion; principal component analysis; hybrid learning

ABSTRACT

Facial recognition has become one of the most widely implemented biometric technologies, with applications ranging from identity authentication to human-computer interaction. Despite the remarkable performance under controlled conditions, recognition accuracy degrades significantly in unconstrained environments because of variations in illumination, pose, facial expression, and background complexity. However, current facial recognition research remains subject to several limitations. First, most studies are evaluated primarily on controlled or semi-constrained benchmarks, resulting in limited evidence of robustness under fully unconstrained real-world conditions. Second, the integration of quantum image processing techniques into facial recognition pipelines remains scarce, despite the considerable advances in quantum image processing. Finally, existing studies primarily investigate image representation and feature extraction independently, leaving their interaction within facial recognition pipelines largely unexplored. A dual-branch hybrid framework is proposed that integrates quantum image representation with classical and quantum-based feature extraction. The framework employs two quantum encoding methods, followed by feature fusion and Principal Component Analysis (PCA)-based dimensionality reduction. The resulting feature representations are evaluated using both classical and quantum machine learning classifiers. The proposed hybrid feature combinations achieved up to 81.96% recognition accuracy on the in-the-wild dataset while maintaining competitive performance on the controlled dataset. These results demonstrate the practical value of hybrid classical–quantum facial recognition frameworks and provide a foundation for future quantum machine learning research in computer vision.

1. Introduction

Face recognition is one of the most widely adopted biometric technologies in computer vision. It has emerged as one of the most prominent applications of image analysis [16], with widespread applications in biometric authentication, surveillance, and social media. Consequently, achieving robust facial recognition under unconstrained real-world conditions has become increasingly

* *Corresponding author.*
E-mail address: chadli.rayanechadli@gmail.com

important for reliable identity recognition. In recent years, deep learning have significantly contributed to the advancement of facial recognition systems, enabling models to learn facial features with high accuracy. Furthermore, deep learning models have achieved near-perfect performance under controlled conditions [19].

Despite recent advancements in computer vision, facial recognition systems often struggle in real-world applications due to environmental constraints. These challenges include, but are not limited to, variations in pose, illumination, facial expressions, appearance variations, and background complexity [19]. These limitations often lead to significant performance degradation compared with controlled conditions. While deep learning models have improved the performance and robustness of facial recognition, they are still susceptible to environmental variations. These weaknesses greatly limit their reliability in real-world applications. Consequently, developing a framework capable of maintaining high accuracy regardless of the environment remains a challenge.

Recent research has explored various approaches and different frameworks to improve face recognition performance, including classical handcrafted descriptors, deep learning models, and feature fusion techniques [3,12,17]. While these approaches significantly improved the overall accuracy, several limitations remain. First, most of the existing studies are evaluated using controlled or semi-controlled datasets, providing limited evidence of robustness in unconstrained real-world applications, as can be inferred from [12,20]. Second, although quantum computing has achieved significant breakthroughs in image processing and representation [2,18], as well as advancements in quantum machine learning, their integration into facial recognition pipelines has remained limited [15,18]. Finally, existing research focuses on improving either image representation or feature extraction methods independently, based on the evidence presented in [9,10,12,13,21], while the interaction between the two has been comparatively underexplored, with limited understanding of their influence on overall system performance.

To address these limitations, this paper proposes a dual-branch hybrid face recognition framework that integrates quantum image representation with quantum-based and classical feature extraction. The proposed framework combines multiple feature representations through feature fusion, followed by Principal Component Analysis (PCA)-based dimensionality reduction. The resulting feature representations are then evaluated using classical and quantum machine learning (QML) classifiers. The main contributions of this work are as follows:

Developing unified robust hybrid framework, with competitive accuracy on controlled and uncontrolled benchmark datasets. The framework integrates quantum image representation with classical and quantum-based feature extraction

A systematic investigation of the interaction between quantum image representation and quantum-based feature extraction within the pipeline. A comprehensive experimental evaluation on various environmental conditions.

2. Related Work

2.1 Classical Feature Extraction

Before the emergence of deep learning-based methods, classical handcrafted feature extraction techniques were dominant in face recognition systems. These descriptors can be categorized into two main groups: local and global feature extraction methods. Global descriptors represent the entire image with a single feature vector, while local descriptors characterize distinctive image regions through multiple local feature vectors extracted from key points or local neighborhoods. Representative methods include Histogram of Oriented Gradients (HOG), GIST, Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT) [7,10,12,21]. Handcrafted descriptors have been widely employed in face recognition systems due to their computational efficiency, simplicity, and interpretability. However, these descriptors are susceptible to environmental variations, including changes in pose, illumination, facial expression, and occlusion.

Histogram of Oriented Gradients (HOG) represents facial images as gradient orientation histograms, which makes it effective for analysing edges and contrasts of facial images, making it effective for capturing edge and contour information such as upright and well-aligned faces. HOG is computationally efficient and performs well for well-aligned faces especially under stable imaging conditions. However, its performance significantly deteriorates when subjected to pose variations, illumination changes, and image rotations [10].

Local Binary Patterns (LBP) is an efficient visual descriptor used in computer vision for texture classification and facial recognition. It operates by comparing the intensity value of the center pixel with its neighboring pixels and encoding the resulting pattern into a binary representation. LBP is simple, lightweight, and can effectively detect the textures within images. However, it is extremely sensitive to illumination changes and varies with rotation [21].

Scale-Invariant Feature Transform (SIFT) is a computer vision algorithm that detects keypoints and extracts distinctive local features from images. It remains effective even when images are rotated or resized, making it suitable for object recognition and image matching. However, it is optimized for 2D object matching. Human faces are 3D, deformable, and non-rigid objects; thus, they are not invariant to 3D pose variations and out-of-plane rotations [7].

Overall, classical feature extraction techniques are computationally efficient, easy to implement, and interpretable, making them suitable for face recognition in controlled environments. Nevertheless, their performance significantly degrades in an unconstrained environment, thus motivating the adoption of deep learning-based feature extraction methods.

2.2 Deep Learning Feature Extraction

Deep learning is a subset of machine learning that uses multi-layered neural networks to automatically extract and learn patterns from raw data without explicit human intervention. In digital image processing, Convolutional Neural Networks (CNNs) are widely employed as specialized deep learning algorithms. They automatically process raw images and detect, isolate, and extract the most important characteristics into a compact numerical vector. Deep learning feature extraction emerged as a replacement for handcrafted descriptors because it is data-driven and does not rely on specialized equations.

AlexNet is a deep Convolutional Neural Network (CNN) introduced in 2012 for image classification. It is an 8-layer neural network that won the ImageNet Large Scale Visual Recognition Challenge by a large margin, demonstrating the effectiveness of deep learning for computer vision. It has a high feature extraction capability, and it can be efficiently adapted to new tasks through transfer learning using pre-trained weights. However, it requires significant computational power, large training data, and achieves lower classification performance on many benchmark datasets [4].

In summary, deep learning models automatically learn patterns from raw images, are capable of learning both linear and non-linear features, and produce highly discriminative feature representations. However, they require a larger dataset, higher computational power, and are more sensitive to real-world variations compared to handcrafted methods [4,6].

While deep learning provides powerful feature representations, no single feature extraction method is capable of capturing every aspect of facial information. Therefore, this study combines deep learning features with handcrafted and quantum-inspired features through feature fusion to improve the robustness and recognition performance across controlled and unconstrained environments.

2.3 Feature Fusion

Feature fusion is the process of combining multiple feature representations into a single, more informative, and general feature vector [14]. Since single-feature representations often fail to capture the full complexity of visual data, feature fusion has emerged as an effective strategy for integrating complementary information extracted by different feature extraction methods. Moreover, different feature extractors capture different facial characteristics [17].

Direct concatenation is the most basic and straightforward feature fusion technique, which combines multiple feature vectors into a single higher-dimensional feature representation. It is simple, preserves information from every feature extractor, and easy to implement. However, it introduces redundancy, increased computational complexity, results in a substantial increase in feature dimensionality, and requires dimensionality reduction [8].

Although direct concatenation effectively integrates complementary facial representations, the resulting feature vectors are often high-dimensional and contain redundant information. Thus, dimensionality reduction techniques such as Principal Component Analysis (PCA) are often applied before classification. This strategy is adopted in the proposed framework.

2.4 Quantum Image Representation

Quantum Image Representation (QIR) is the process of encoding classical image information into quantum states allowing images to be processed within a quantum computing framework. QIR maps pixel intensities onto quantum bits (qubits) while preserving spatial location information. There are different QIR models, each employing distinct encoding strategies. However, most QIR methods offer the potential advantages of quantum parallelism, compact information encoding, and the exploitation of quantum phenomena such as superposition and entanglement [2].

Quantum Probability Image Processing (QPIE) encodes pixel intensities into qubit states using a probability-derived approach. The probability amplitudes represent normalized pixel intensities [1]. This model requires the least number of qubits compared to other methods such as FRQI and NEQR. However, pixel values are stored in the state amplitude. This makes it unsuitable for both facial recognition and image retrieval [18].

While QIPE is an efficient quantum representation, it fails to encode spectral and phase information. Therefore, the proposed framework extends QIPE through the Quantum Image Interpolation Processing (QIIP), thereby making it more suitable for quantum feature extraction techniques by introducing nonlinear Fourier phase transformation.

3. Proposed Hybrid Facial Recognition Framework

3.1 Overall Framework

Figure 1 shows the proposed framework. It begins by receiving the input images, followed by a face detection and cropping algorithm, which isolate the facial regions. The cropped face is processed through two parallel branches (dual-branch): A classical image branch, where the features are extracted using AlexNet, HOG, and LBP, and a quantum image representation branch, where the image is encoded into quantum representations, where the features are extracted using Quantum Fourier Spectral Descriptor (QFSD) and quantum-inspired features descriptor. The two types of features are merged through feature fusion process into a single feature vector subsequently reduced using Principal Component Analysis (PCA) to remove redundancy and decrease dimensionality. Finally, the reduced features are classified using both classical machine learning classifiers and quantum machine learning (QML) classifier.

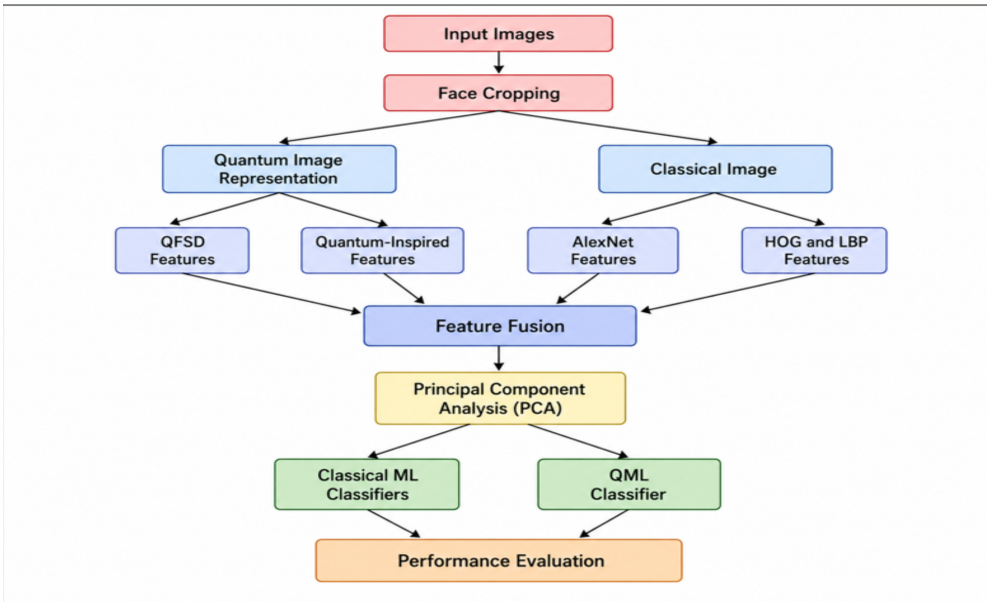

Fig. 1. Proposed hybrid facial recognition pipeline

3.2 Quantum-Inspired Image Processing (QIIP)

Classical image representations are highly incompatible with quantum algorithms. They are designed for classical processing and cannot be directly used by quantum image processing and quantum machine learning methods. In contrast, QIPE provides a bridge between classical images and their quantum representations. Furthermore, it can be implemented on classical computers while preserving key quantum-inspired principles.

However, QIPE encodes pixel intensities into amplitude qubits, which discards phase information of the image. Therefore, The proposed Quantum Image Interpolation Processing (QIIP) representation transforms the input image into a complex-valued representation using a nonlinear phase shift in the Fourier frequency domain.

First, the grayscale image is normalized using the Quantum Image Probability Encoding (QIPE) [1]:

$$|I_{QIPE} >= \sum_{x,y} \sqrt{\frac{I(x,y)}{\sum_{x,y} I(x,y)}} |x, y > \qquad (3.1)$$

where I(x,y) represents the pixel intensity at position (x,y).
The encoded image is then transformed [11] using a unitary Fourier phase operator:

$$QIIP(image) = U\big|I_{QIPE} >= F^{-1}DF\big|I_{QIPE} > \qquad (3.2)$$

where F denotes the Fast Fourier Transform matrix and D is a diagonal phase modulation operator defined as

$$D(u,v) = \mathrm{e}^{-\mathrm{j}\tau\sin\left(10(\mathrm{u}^2+\mathrm{v}^2\right)} \tag{3.3}$$

Thus, the final QIIP representation is obtained as

$$|I_{QIIP}\rangle = U|I_{\mathrm{QIPE}}\rangle \tag{3.4}$$

This transformation preserves spectral information while introducing complex-valued phase representations that enhance robustness to illumination and structural variations.

3.3 Feature Extraction

3.3.1 Classical feature extractions

AlexNet, HOG, and LBP were selected to be implemented in the proposed pipeline because they are complementary feature extraction techniques. AlexNet extracts high-level representations, HOG captures edges and gradients, while LBP describes local texture patterns.

3.3.2 Quantum feature extractions

Quantum Fourier Spectral Descriptor (QFSD)

The Quantum Fourier Spectral Descriptor (QFSD) extracts spectral information from the QIIP representation using magnitude and phase analysis. Although the Quantum Fourier Transform is generally more complex than its classical counterpart [5,22], the proposed image representation allows the analysis to be performed using the conventional Fast Fourier Transform (FFT). Thus, the magnitude and phase spectra are defined as

$$Q(u,v) = |I_{\mathrm{QIIP}}(u,v)| \tag{3.5}$$
$$\Phi(u,v) = arg\left(\mathrm{I}_{\mathrm{QIIP}}(u,v)\right) \tag{3.6}$$

with the radial and angular partitions defined as

$$r = \frac{\sqrt{(x-\mathrm{x_c})^2+(y-\mathrm{y_c})^2}}{\mathrm{r_{max}}} \tag{3.7}$$
$$\theta = \frac{atan2(y-\mathrm{y_c}, x-\mathrm{x_c})+\pi}{2\pi} \tag{3.8}$$

For each radial and angular region, statistical descriptors including the mean and standard deviation are extracted from both magnitude and phase spectra. The global spectral energy is computed as

$$E_{\mathrm{Q}} = \sum Q(u,v)^2 \tag{3.9}$$

The spectral entropy is defined as

$$\mathrm{H_Q} = -\sum p(u,v)\log(p(u,v)) \tag{3.10}$$

Where

$$p(u,v) = \frac{Q(u,v)}{\sum Q(u,v)} \tag{3.11}$$

The final descriptor vector is obtained by concatenating all radial, angular, energy, and entropy features.

Quantum-Inspired Feature Extraction

The quantum-inspired feature extraction method encodes local image patches into simulated quantum states using parametrized rotation gates.
Each normalized pixel intensity is encoded using a rotation around the Y-axis:

$$\mathrm{R_Y}(\theta_\mathrm{i}) = \mathrm{R_Y}(\pi x_i) \tag{3.12}$$

Where x_i is the normalized pixel intensity.

Entanglement between neighboring qubits is introduced using controlled-NOT (CNOT) operations:

$$CX(\mathrm{q_i}, \mathrm{q_{i+1}}) \tag{3.13}$$

The generated quantum state is represented as

$$|\Psi\rangle = U(x)|0\rangle^{\otimes n} \tag{3.14}$$

Expectation-like probability differences are then extracted as feature descriptors from the simulated quantum state amplitudes.

3.4 Feature Fusion and Dimensionality Reduction
3.4.1 Feature fusion

Feature fusion is employed to integrate complementary information from numerous feature extractor techniques (hand-crafted, deep learning-based, and quantum-based), which enhances the representational capability of the vector of features. In the proposed framework, direct concatenation is adopted, which allows the framework to merge all the features together without losing data due to preprocessing. This approach ensures flexibility and deeper insights into the performance of each descriptor.

3.4.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is employed after feature fusion to reduce the dimensionality of the feature vector. This step removes correlated and redundant information, thus reducing the computational complexity and memory usage while preserving the most informative characteristics of the data. This stage improves computational efficiency while maintaining the discriminative information required for accurate facial recognition.

3.5 Classification Pipeline
3.5.1 Classical Machine Learning

The feature vectors are then classified using several machine learning models, including Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), K-Nearest Neighbors (KNN), and Multilayer Perceptron (MLP). The best-performing models were selected based on the overall evaluation metrics.

3.5.2 Quantum Machine Learning

A quantum-inspired neural network is employed as the QML classifier. The model is based on a single-hidden-layer neural network in which the activation function and loss function are modified using quantum-inspired formulations. This allows the neural network to emulate quantum-inspired learning on classical computing hardware. The QML classifier was incorporated to evaluate the effectiveness of the proposed feature representations within both classical and quantum-inspired learning paradigms.

4 Experimental Setup
4.1 Datasets

The proposed framework was evaluated on two benchmark datasets representing controlled and unconstrained facial recognition scenarios. The controlled dataset was used to evaluate recognition performance under ideal conditions, whereas the in-the-wild dataset was employed to assess the robustness of the proposed framework under realistic environmental variations. Table 1 summarizes the main characteristics of both datasets.

Table 1
Summary of the benchmark datasets

Property	Controlled Dataset	In-the-Wild Dataset
Number of images	698	2,509
Number of subjects	50	31
Environment	Controlled laboratory	Unconstrained real-world
Pose	Limited variation	Large variation
Illumination	Uniform	Variable
Facial expression	Limited	Diverse
Background	Uniform	Complex
Purpose	Ideal-condition evaluation	Robustness evaluation

4.2 Experimental Protocol

All images were first subjected to face detection and cropping, followed by greyscale conversion and resizing to 224×224 pixels to provide a standardized input for all feature extraction methods.

The preprocessed images were then processed through two parallel branches. The first branch directly processed the classical images using AlexNet, HOG, and LBP feature extractors. The second branch transformed the images into the proposed Quantum Image Interpolation Processing (QIIP), from which features were extracted using Quantum Fourier Spectral Descriptor (QFSD) and quantum-inspired features extraction method.

The extracted descriptors were merged using direct feature concatenation before applying PCA to reduce dimensionality and remove redundancy. Finally, the reduced feature vectors were classified using both classical and quantum machine learning models.

The same experimental protocol was applied to both benchmark datasets to ensure a fair performance comparison.

Table 2
Experimental configuration

Parameter	Configuration
Face preprocessing	Face detection and cropping
Image format	Grayscale
Image size	224×224
Classical features	AlexNet, HOG, LBP
Quantum representation	QIIP
Quantum features	QFSD, Quantum-inspired
Feature fusion	Direct concatenation
Dimensionality reduction	PCA
Classical classifiers	SVM, RF, LR, KNN, MLP
Quantum classifier (QML)	Quantum-inspired neural network

5. Results and Discussion

5.1 Controlled Dataset Results

The proposed framework was first evaluated on the controlled dataset to assess the effectiveness of the proposed feature extraction methods under ideal imaging conditions.

Table 3
Top-performing feature extraction combinations on the controlled dataset

Feature Extraction Combination	Accuracy (%)
AlexNet	98.10
AlexNet + LBP + QFSD	96.19
AlexNet + LBP + Quantum-Inspired	96.19
AlexNet + Quantum-Inspired	96.19
AlexNet + HOG + QFSD + Quantum-Inspired	96.19
AlexNet + LBP	95.24
QFSD	95.24
AlexNet + HOG + LBP + Quantum-Inspired	95.24
AlexNet + QFSD	94.29
HOG + LBP + QFSD + Quantum-Inspired	94.29

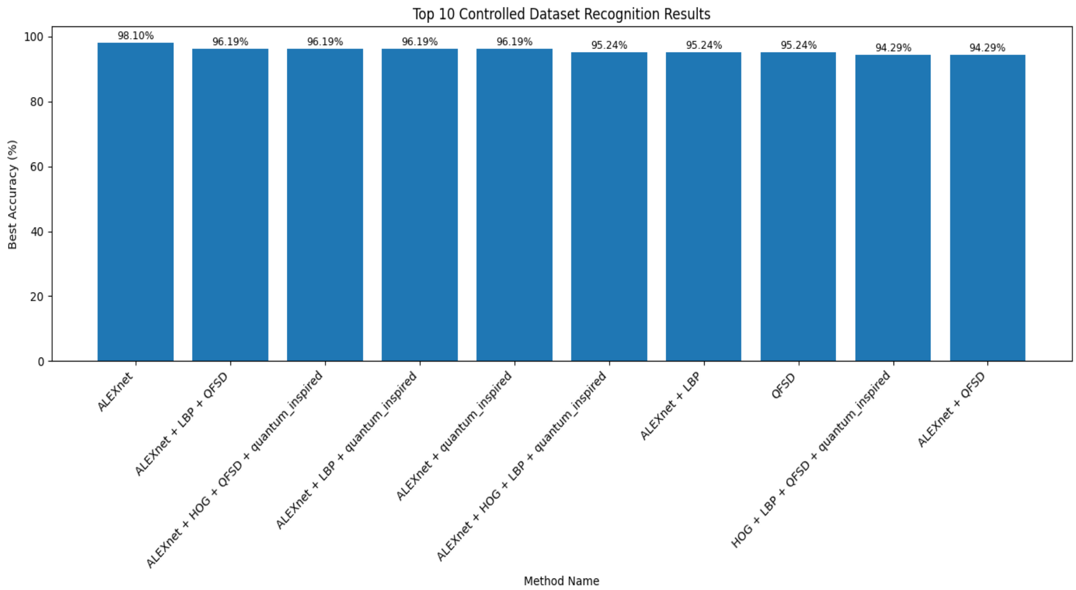

Fig. 2. Top-feature extraction combinations on the controlled dataset

The main contribution of this work is the quantum Fourier spectral descriptor and quantum-inspired feature extraction framework. From Table 3, it can be observed that both contributions achieved competitive stand-alone performance on the controlled dataset. In particular, the QFSD achieved an accuracy of 95.24%, while most hybrid combinations achieved above 90%. AlexNet outperformed the proposed methods with an accuracy of 98.10%.

From Table 3, it can be seen that introducing the hybrid pipeline degrades the accuracy by around 2%. That is because in controlled environment, the feature redundancy is high, since AlexNet successfully captures the discriminative facial features due to controlled imaging conditions. However, hybrid pipelines remain highly competitive even in controlled conditions.

5.2 Uncontrolled Dataset Results

The proposed framework was subsequently evaluated on the in-the-wild dataset to assess robustness under unconstrained imaging conditions.

Table 4
Top-performing feature extraction combinations on the uncontrolled dataset

Feature Extraction Combination	Accuracy (%)
AlexNet + HOG + QFSD + Quantum-Inspired	81.96
AlexNet + HOG + LBP + QFSD + Quantum-Inspired	81.17
AlexNet + HOG + QFSD	79.05
AlexNet + HOG + LBP + Quantum-Inspired	78.78
AlexNet + HOG + LBP	78.51
AlexNet + HOG + LBP + QFSD	78.51
AlexNet + HOG + Quantum-Inspired	77.45
AlexNet + HOG	76.13
AlexNet + LBP + Quantum-Inspired	74.27
HOG + LBP + Quantum-Inspired	74.27

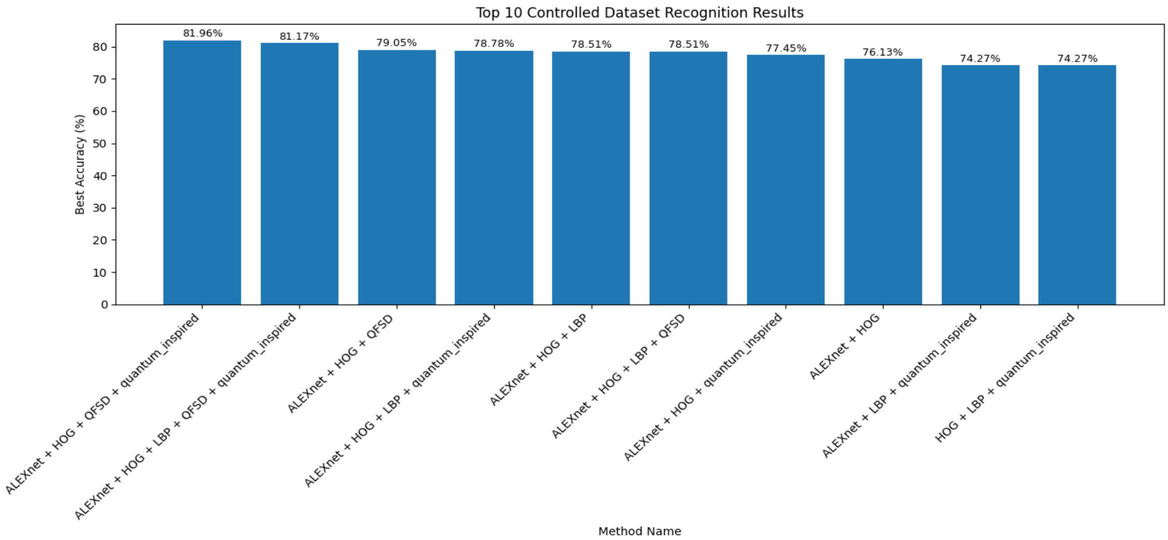

Fig. 3. Top-performing feature extraction combinations on the uncontrolled dataset

From Table 4, it can be observed that the hybrid framework achieved the highest recognition accuracy, whereas the best combination of classical methods ranked only eighth. Specifically, the combination of AlexNet and HOG achieved an accuracy of 76.13%, while AlexNet and HOG individually attained accuracies of 66.05% and 68.44%, respectively. Although this observation is beyond the primary scope of this study, it suggests that AlexNet and HOG provide complementary facial representations.

Furthermore, the results demonstrate that combining the proposed quantum-inspired methods with classical feature extraction techniques is considerably more effective than employing either approach independently. The best-performing hybrid framework, consisting of AlexNet, HOG, QFSD, and Quantum-Inspired features, achieved an accuracy of 81.96%, indicating that these feature extraction methods are highly compatible and complementary.

It is also important to note that the uncontrolled dataset contains substantial real-world variability, including differences in hairstyle, facial hair, illumination, facial pose, and image resolution. Despite these challenging conditions, the proposed hybrid framework maintained superior recognition performance, demonstrating its robustness in unconstrained environments.

The improvement observed on the uncontrolled dataset contrasts with the controlled dataset suggests that the proposed quantum-based feature extraction methods contribute primarily under challenging imaging conditions rather than ideal laboratory settings.

5.3 QML Performance

Tables 5 and 6 summarize the performance of the QML classifier, which uses 11 qubits. Figure 4 shows a steadily decreasing loss with minimal oscillations, indicating stable optimization during training. However, after 50 epochs, the best accuracy was around 34% in controlled environment, indicating that the QML classifier successfully learns meaningful patterns from the proposed feature representations.

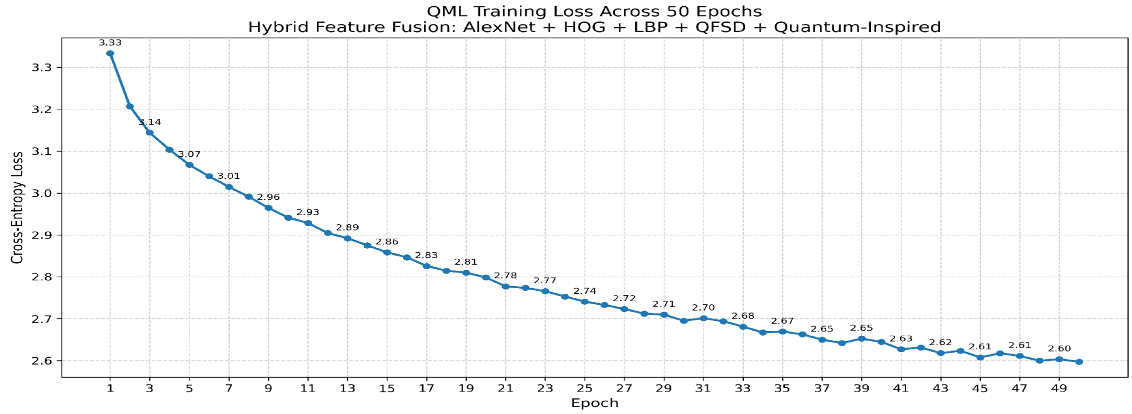

Fig. 4. QML loss function

Table 5
QML results on the controlled dataset

Feature Extraction Combination	Original Features	PCA Features	Qubits	Accuracy (%)
AlexNet + QFSD	4162	556	11	34.29
AlexNet + QFSD + Quantum-Inspired	5186	556	11	33.57
AlexNet + LBP	4106	556	11	32.14
LBP + QFSD	76	76	11	31.43
AlexNet + LBP + QFSD + Quantum-Inspired	5196	556	11	31.43

Table 6
QML results on the uncontrolled dataset

Feature Extraction Combination	Original Features	PCA Features	Qubits	Accuracy (%)
AlexNet + LBP	4106	1600	11	18.33
AlexNet	4096	1600	11	17.93
AlexNet + QFSD	4162	1600	11	14.74

While QML classifier achieved lower recognition accuracy than the classical machine learning models, it can be observed from Figure 4 that the model is converging and is slowly learning the patterns from the feature vectors. This shows that the quantum-based methods are compatible with QML and provide a foundation for future investigation using more advanced quantum learning architectures.

5.4 Discussion

The experimental results demonstrated that the proposed framework achieved a competitive facial recognition performance under both controlled and in-the-wild conditions. While the controlled dataset achieved much higher accuracies due to the stable environment, the hybrid framework achieved the highest recognition accuracy among all evaluated methods under unconstrained conditions. Therefore, the results indicate that the integration of the quantum approaches with classical feature extraction techniques has significantly improved the performance and robustness of facial recognition in real-world variability. Quantum machine learning classifier has demonstrated that it successfully learned meaningful patterns from the proposed feature representations. However, the limitations of high computational complexity and a limited number of qubits ultimately led to achieving a much lower accuracy compared to classical machine learning approaches. Finally, the experiment revealed that coupling feature fusion with PCA does not always lead to improvement of the performance, and under certain conditions, it would lead to a degradation of the performance metrics. This behavior is likely attributable to feature redundancy or incompatibility among certain feature representations, thus may negatively affect the dimensionality reduction and classification stages.

The contrast between the controlled and in-the-wild datasets suggests that the proposed quantum-inspired feature extraction methods primarily enhance robustness under challenging imaging conditions.

6. Limitations

Although the proposed framework achieved competitive performance in both controlled and uncontrolled environments, several limitations still remain. First, direct feature fusion significantly increases dimensionality, requiring PCA to eliminate redundancy. Second, the quantum machine learning (QML) implementation was heavily constrained by the limited number of qubits and computational resources. Finally, the proposed framework was evaluated on two benchmark facial recognition datasets, and additional validation on larger and more diverse datasets would further assess its generalization capability.

7. Conclusion

This paper proposed a hybrid facial recognition framework that integrates classical and quantum-based feature extraction techniques through Quantum Image Interpolation Processing (QIIP). The framework combines classical and quantum descriptors using direct feature fusion, then processed through Principal Component Analysis (PCA) before classification.

The results of the experiments on both benchmark datasets demonstrated that the proposed framework achieved competitive recognition performance. While AlexNet achieved the highest accuracy in controlled conditions, the proposed framework obtained the best performance under unconstrained environments, showcasing a significant improvement of robustness against real-world variations. Finally, the QML classifier successfully learned meaningful feature representations. However, its recognition accuracy remained below that of the classical machine learning models.

Overall, the results demonstrate the capability of quantum-based feature descriptors to complement classical descriptors in real-world applications, especially in unconstrained environments.

Acknowledgment
This research was supported by the Universiti Malaya Translational Research Grant (UM TRG) under Grant No. TRG0019-2025.

References

[1] Alwan, Nawres A., Suzan J. Obaiys, Nadia MG Al-Saidi, Nurul Fazmidar Binti Mohd Noor, and Yeliz Karaca. "Multilayered quantum computing and simulation system for enhanced image representation of HSI based Fourier transform and adjacency matrix." *Scientific Reports* 15, no. 1 (2025): 40286.

[2] Alwan, Nawres A., Nadia MG Al-Saidi, Suzan J. Obaiys, Nurul Fazmidar Binti Mohd Noor, and Musheer Ahmad. "A comprehensive review on classification of quantum image representations." *Archives of Computational Methods in Engineering* 33, no. 3 (2026): 3123-3181. https://doi.org/10.1007/s11831-025-10369-7.

[3] Bajpai, Supriya, Gargi Mishra, Rachna Jain, Deepak Kumar Jain, Dharmender Saini, and Amir Hussain. "RI-L1Approx: A novel Resnet-Inception-based Fast L1-approximation method for face recognition." *Neurocomputing* 613 (2025): 128708. https://doi.org/10.1016/j.neucom.2024.128708.

[4] Barbhuiya, Abul Abbas, Ram Kumar Karsh, and Rahul Jain. "CNN based feature extraction and classification for sign language." *Multimedia Tools and Applications* 80, no. 2 (2021): 3051-3069.https://doi.org/10.1007/s11042-020-09829-y.

[5] Barros, Tomás, Pablo Álvarez, Bárbara Vidal, and Mauricio Solar. "A review on quantum Fourier transform: T. Barros et al." *Quantum Information Processing* 25, no. 2 (2026): 41.

[6] Cansiz, Berke, Coskuvar Utkan Kilinc, and Gorkem Serbes. "Deep learning-driven feature engineering for lung disease classification through electrical impedance tomography imaging." *Biomedical signal processing and control* 100 (2025): 107124. https://doi.org/10.1016/j.bspc.2024.107124.

[7] Chang, Zheng, and Yong Luo. "Construction of Graphic Creative Feature Extraction and Recognition System based on SIFT Algorithm." In *2025 4th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, pp. 1-6. IEEE, 2025.https://doi.org/10.1109/ICDCECE65353.2025.11035685.

[8] Dehbozorgi, Pegah, Oleg Ryabchykov, and Thomas W. Bocklitz. "A comparative study of statistical, radiomics, and deep learning feature extraction techniques for medical image classification in optical and radiological modalities." *Computers in biology and medicine* 187 (2025): 109768 https://doi.org/10.1016/j.compbiomed.2025.109768.

[9] Easom-McCaldin, Philip, Ahmed Bouridane, Ammar Belatreche, Richard Jiang, and Somaya Al-Maadeed. "Efficient quantum image classification using single qubit encoding." *IEEE Transactions on Neural Networks and Learning Systems* 35, no. 2 (2022): 1472-1486. https://doi.org/10.1109/TNNLS.2022.3179354.

[10] Hamzah, Ali Safaa, and Saad S. Hreshee. "A Scalable Face Recognition Framework: Integrating HOG Features, PCA, and CNN for Offline and Web-Based Systems." *International Journal of Intelligent Engineering & Systems* 18, no. 2 (2025): 372.https://doi.org/10.22266/ijies2025.0331.28.

[11] Hu, Yingying, Dayong Lu, Qianqian Zhang, and Meiyu Xu. "Quantum image representations based on density matrices in open quantum systems." *EPJ Quantum Technology* 11, no. 1 (2024): 28.

[12] Jarullah, Thoalfeqar G., Ahmad Saeed Mohammad, Musab TS Al-Kaltakchi, and Jabir Alshehabi Al-Ani. "Intelligent face recognition: Comprehensive feature extraction methods for holistic face analysis and modalities." *Signals* 6, no. 3 (2025): 49. https://doi.org/10.3390/signals6030049.

[13] Jung, Chanyong, Gihyun Kwon, and Jong Chul Ye. "Patch-wise graph contrastive learning for image translation." In *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 12, pp. 13013-13021. 2024.

[14] Khan, Saif Ur Rehman. "Multi-level feature fusion network for kidney disease detection." *Computers in Biology and Medicine* 191 (2025): 110214. https://doi.org/10.1016/j.compbiomed.2025.110214.

[15] Kharsa, Ruba, Ahmed Bouridane, and Abbes Amira. "Advances in quantum machine learning and deep learning for image classification: A survey." *Neurocomputing* 560 (2023): 126843. https://doi.org/10.1016/j.neucom.2023.126843.

[16] Kishore, Saritha, and SCS PHG. "MKB,"Evaluation of deep learning methods in face recognition: Datasets, metrics, and results,"." *International Journal on Science and Technology (IJSAT)* 16, no. 4 (2025): 1-9.

[17] Li, Zhengji, Fazhan Xiong, Boyun Huang, Meihui Li, Xi Xiao, Yingrui Ji, Jiacheng Xie, Aokun Liang, and Hao Xu. "Mgd-yolo: An enhanced road defect detection algorithm based on multi-scale attention feature fusion." *Computers, Materials & Continua* 84, no. 3 (2025): 5613-5635. https://doi.org/10.32604/cmc.2025.066188.

[18] Parigi, Marco, Mehran Khosrojerdi, Filippo Caruso, and Leonardo Banchi. "Analysis of quantum image representations for supervised classification." *AVS Quantum Science* 8, no. 1 (2026).https://arxiv.org/abs/2507.22039.

[19] Haq, Mahmood Ul, Muhammad Athar Javed Sethi, Sadique Ahmad, Naveed Ahmad, Muhammad Shahid Anwar, and Alpamis Kutlimuratov. "A Comprehensive Review of Face Detection/Recognition Algorithms and Competitive Datasets to Optimize Machine Vision." *Comput. Mater. Continua* 84, no. 1 (2025): 1-24. https://doi.org/10.32604/cmc.2025.063341.

[20] Wang, Xinya. 2023. "Analysis of Face Recognition Technology Based on Deep Learning." Proceedings of the 5th International Conference on Computing and Data Science. https://doi.org/10.54254/2755-2721/22/20231226.

[21] Yallamandaiah, S., and N. Purnachand. "A novel face recognition technique using Convolutional Neural Network, HOG, and histogram of LBP features." In *2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP)*, pp. 1-5. IEEE, 2022.https://doi.org/10.1109/AISP53593.2022.9760679.

[22] Zhang, Ze Yu, and Weibo Gao. "Quantum Fourier Transform for Image Processing." *arXiv preprint arXiv:2305.05953* (2023).