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Quantum Enhanced Hybrid Face Recognition Using MultiGate-Quantum Convolutional Neural Network (MG-QCNN)

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Abstract: Face recognition has become an essential biometric technology for applications such as security monitoring, user authentication, and intelligent surveillance systems. Conventional approaches based on deep neural networks, particularly convolution-based architectures, provide high recognition performance but often demand considerable computational resources and extended training durations as network complexity increases. To overcome these challenges, Quantum Machine Learning (QML) utilizes quantum computing concepts, including quantum superposition and entangled states, to achieve efficient feature representation and processing. This paper presents a Hybrid Quantum-Classical Face Recognition System built on a Multi-Gate Quantum Convolutional Neural Network (MG-QCNN). The proposed framework employs a 4-qubit variational quantum circuit that incorporates R_Y state encoding together with R_X, R_Z, and CNOT quantum operations to extract discriminative facial representations. In addition, a structural ablation analysis is conducted to investigate the influence of individual quantum components on the overall recognition capability of the model.

To enhance spatial feature learning and classification performance, several classical neural network layers, namely convolution, batch normalization, max-pooling, dropout, and fully connected layers, are integrated after the quantum feature extraction stage. Within the hybrid framework, the quantum circuit is responsible for generating meaningful feature representations, whereas the classical neural network performs feature refinement and final identity classification. The framework is further combined with the DeepFace verification approach to perform facial similarity analysis and identity verification. Moreover, an Open-Set Face Recognition mechanism is incorporated to determine if an input facial image corresponds to a registered identity or represents an unseen individual. This capability increases system reliability and supports accurate unknown-person identification.

The effectiveness of the proposed framework is validated using the ORL and Yale face datasets. The obtained experimental findings indicate that the complete MG-QCNN architecture achieves superior performance compared with reduced quantum configurations, emphasizing the significance of multigate quantum operations and entanglement strategies. The developed hybrid model attains an accuracy of 99.17% on the ORL dataset and 97.80% on the Yale dataset. Furthermore, the application of data augmentation techniques enhances the model's capability to capture diverse facial characteristics and minimizes overfitting, particularly when training data are limited. Overall, the developed hybrid quantum-classical framework offers accurate face recognition, efficient feature extraction, and dependable unknown-person identification, making it a promising solution for next-generation secure biometric systems.

Keywords: Quantum Machine Learning, Face Recognition, MG-QCNN, Hybrid Quantum-Classical Learning, DeepFace Verification, Open-Set Recognition, ORL Dataset, Yale Dataset.

I. INTRODUCTION

Among various biometric identification techniques, face recognition has emerged as a prominent technology for modern security and authentication systems. It plays a significant role in surveillance applications, attendance management, banking services, identity verification, and intelligent access control systems. The primary objective of a face recognition system is to automatically identify or verify an individual using distinctive facial characteristics.

Early face recognition methods, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Eigenfaces, and Fisherfaces, mainly relied on handcrafted feature extraction and statistical learning approaches. Although these methods require relatively low computational resources, their recognition performance often deteriorates when facial images exhibit variations in illumination, facial expressions, pose, noise, or occlusions. Consequently, achieving robust and reliable face recognition in real-world environments remains a challenging research problem.

Recent progress in Artificial Intelligence (AI) and deep learning technologies has considerably improved the efficiency and performance of face recognition systems. Among the various deep learning approaches, Convolutional Neural Networks (CNNs) have gained widespread attention because of their capability to automatically extract multi-level facial features directly from image data. Several advanced frameworks, including FaceNet, VGGFace, ArcFace, and DeepFace, have demonstrated remarkable recognition performance on benchmark datasets. Despite these achievements, deep learning approaches often depend on extensive training datasets, significant computational resources, and long training durations, which may restrict their applicability in resource-constrained environments.

The emergence of quantum computing has created new opportunities for developing advanced machine learning and pattern recognition systems. In contrast to conventional computing systems that operate using binary digits, quantum computing utilizes quantum bits, commonly referred to as qubits. By exploiting quantum phenomena such as superposition and entanglement, qubits are capable of existing in multiple states simultaneously, enabling highly efficient information processing. Owing to these properties, quantum computing has attracted considerable interest in areas including optimization, cryptography, artificial intelligence, image analysis, and machine learning. Quantum Machine Learning (QML) represents an interdisciplinary field that merges quantum information processing with machine learning algorithms to improve learning efficiency and computational capability. Through the use of quantum phenomena, including superposition, entanglement, and parameterized quantum gate operations, QML methods can model intricate data relationships that are often difficult to capture using traditional techniques. In recent years, considerable attention has been directed toward integrating quantum methods with deep neural networks to overcome the limitations of classical learning approaches and to improve visual recognition tasks.

A notable advancement in quantum deep learning is the development of Quantum Convolutional Neural Networks (QCNNs), where parameterized quantum circuits are designed by adopting the principles of convolutional neural networks. In these architectures, quantum operations are responsible for extracting meaningful representations while the network retains the learning characteristics of conventional neural models. Previous studies have reported encouraging results for QCNNs in image analysis, classification tasks, and intelligent pattern recognition applications.

The MG-QCNN framework improves traditional QCNN models by employing multiple quantum gates and entanglement strategies to achieve more effective quantum feature extraction. The incorporation of multiple quantum gate operations enables richer feature learning and improves the model's capability to capture complex facial patterns. Moreover, entanglement mechanisms facilitate improved learning of relationships among facial characteristics, leading to enhanced feature representation and recognition performance.

Although quantum feature extraction provides significant advantages, combining quantum and classical learning techniques can further improve system performance. Consequently, Hybrid Quantum-Classical Learning has emerged as an attractive solution in which quantum layers perform feature extraction while classical neural networks conduct feature refinement and classification. This integration benefits from the computational advantages of quantum computing while maintaining the stability and learning capability of classical deep learning architectures.

Apart from classification accuracy, practical face recognition systems also require dependable face verification and the ability to identify previously unseen individuals. DeepFace has become one of the most widely adopted frameworks for facial verification and similarity measurement. By comparing facial embeddings and evaluating similarity scores, DeepFace provides reliable face matching capabilities. Integrating DeepFace with hybrid quantum-classical models can therefore improve recognition reliability and reduce false recognition rates.

Most existing recognition frameworks follow a closed-set setting in which every testing sample is assumed to correspond to an identity observed during training. In practical scenarios, however, systems frequently encounter previously unseen individuals. Open-Set Face Recognition overcomes this limitation by enabling simultaneous recognition of known identities and detection of unknown persons. This functionality is particularly valuable in security systems, surveillance applications, and biometric authentication environments.

To address the aforementioned challenges, this work presents a hybrid face recognition framework that integrates a Multi-Gate Quantum Convolutional Neural Network (MG-QCNN) with classical deep learning techniques.

The proposed approach employs a four-qubit variational circuit for quantum feature extraction and utilizes CNN layers for feature refinement and final classification. The quantum module consists of R_Y state encoding, R_X and R_Z rotational transformations, and CNOT-based entanglement operations to derive informative facial representations. Furthermore, DeepFace-based verification and an Open-Set Recognition strategy are incorporated to improve identity validation and unknown-person detection. The effectiveness of the proposed method is assessed using the ORL and Yale benchmark datasets, which contain significant variations in illumination and facial expressions. Experimental findings demonstrate that the hybrid MG-QCNN architecture achieves high recognition accuracy while maintaining efficient feature extraction and classification capabilities. The combination of multigate quantum operations, entanglement mechanisms, classical CNN learning, DeepFace verification, and open-set recognition offers an effective and scalable solution for next-generation biometric face recognition applications.

II. RELATED WORK

A. Quantum Machine Learning and Quantum Convolutional Neural Networks

Extending earlier QCNN architectures, Zhu et al. [1] proposed a Multi-Gate Quantum Convolutional Neural Network (MG-QCNN) specifically designed for facial recognition applications. Their framework employed multiple quantum gate operations together with entanglement strategies to enhance the quality of feature extraction. Several reduced quantum configurations, including R_X Reduction, R_Z Reduction, and No Entanglement models, were investigated to determine the contribution of individual quantum components. The obtained results revealed that the full MG-QCNN model achieved better recognition performance than the reduced quantum variants.

Quantum Machine Learning (QML) has recently emerged as a rapidly developing research domain that combines principles of quantum information processing with machine learning algorithms to achieve improved computational efficiency and data representation. Schuld et al. [2] explained that quantum phenomena, including superposition and entangled quantum states, can significantly improve learning efficiency and facilitate the processing of complex and high-dimensional data. The combination of quantum computing techniques with artificial intelligence methods has therefore created new possibilities for addressing difficult pattern recognition and classification tasks.

An important contribution to this field was made by Cong et al., who proposed the concept of Quantum Convolutional Neural Networks (QCNNs). [3], who proposed a quantum-inspired counterpart of conventional convolutional neural networks for feature extraction and classification tasks. These architectures utilize parameterized quantum circuits, entanglement mechanisms, and quantum pooling operations to extract meaningful representations from input data. Experimental investigations demonstrated that these architectures can reduce computational requirements while maintaining competitive classification performance. Because of these advantages, QCNN-based approaches have attracted growing interest in image analysis, pattern recognition, and face recognition applications.

B. Deep Learning Based Face Recognition

Face recognition technology has undergone remarkable progress due to the rapid evolution of deep learning methodologies. LeCun et al. [5] introduced Convolutional Neural Networks (CNNs), which later became one of the most successful approaches for automated feature extraction and image classification tasks. CNN architectures can automatically derive multi-level facial features directly from raw image inputs.

Several deep learning-based face recognition frameworks have further enhanced recognition capabilities. Schroff et al. [6] proposed FaceNet, which learns discriminative facial embeddings for face verification and recognition tasks. Similarly, Parkhi et al. [7] showed that very deep convolutional neural networks can substantially improve recognition performance under different facial expressions and imaging conditions. Deng et al. [13] introduced ArcFace, which reported highly competitive recognition performance by employing an angular margin-based feature learning strategy.

Several advanced neural network models, such as AlexNet [9], VGGNet [10], Inception [11], ResNet [12], and DenseNet [14], have significantly contributed to progress in computer vision and recognition tasks. These architectures demonstrated the capability of deep neural networks to effectively manage complex facial variations and large-scale recognition problems, thereby significantly improving the performance of modern face recognition systems.

C. Hybrid Quantum-Classical Learning Models

Although deep learning approaches have achieved impressive recognition performance, they usually depend on substantial computational resources and extensive training data.

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To overcome these challenges, To address these limitations, various studies have explored architectures that combine quantum feature extraction techniques with conventional neural network learning strategies.

Henderson et al. [4] proposed a learning framework in which quantum circuits are integrated with classical deep neural network layers to form a hybrid quantum-classical architecture. Their findings showed that combining quantum processing with classical learning methods can produce better feature representations and improved classification results. Such hybrid models exploit the computational advantages of quantum processing while preserving the robustness and scalability of classical neural network architectures.

Recent investigations suggest that hybrid quantum-classical systems can achieve more efficient feature extraction, improved recognition performance, and enhanced learning capability when compared with conventional machine learning techniques. Owing to these advantages, hybrid architectures have emerged as promising solutions for intelligent biometric recognition and related pattern analysis applications.

D. Open-Set Face Recognition and Research Gap

Most traditional face recognition approaches are designed under a closed-set assumption in which all test identities are expected to be known during training, where every testing identity is assumed to belong to the set of individuals used during training. However, practical biometric applications require the capability to recognize both previously seen and unseen individuals. DeepFace [14] and several modern face recognition frameworks have significantly improved facial verification through deep feature learning and similarity-based matching techniques.

Despite the considerable progress achieved in quantum machine learning and face recognition research, several challenges remain unresolved. A large portion of existing research mainly focuses on enhancing recognition accuracy within closed-set classification scenarios. Comparatively less attention has been devoted to combining MG-QCNN-based feature extraction with DeepFace verification and Open-Set Face Recognition mechanisms for reliable unknown-person detection. Furthermore, integrated frameworks that simultaneously incorporate quantum feature extraction, classical CNN classification, facial verification, and open-set recognition are still relatively limited in the existing literature.

To address the identified research gaps, the present work develops a hybrid face recognition framework that combines MG-QCNN-based quantum feature extraction with classical CNN learning. The developed system integrates quantum feature learning, DeepFace-based identity verification, and open-set recognition techniques within a unified framework. enabling reliable recognition of registered identities together with efficient detection of previously unseen individuals in practical biometric applications.

III. METHODOLOGY

The proposed Hybrid Quantum-Classical Face Recognition System consists of eight major phases: (1)Dataset Loading, (2)Image Preprocessing and Augmentation, (3)Dataset Splitting, (4)MG-QCNN Based Quantum Feature Extraction, (5)Hybrid CNN Classification, (6)Model Training and Evaluation, (7)DeepFace Verification, and (8)Open-Set Face Recognition. The framework integrates quantum computing principles with classical deep learning techniques to improve facial feature extraction, recognition accuracy, and unknown person detection.

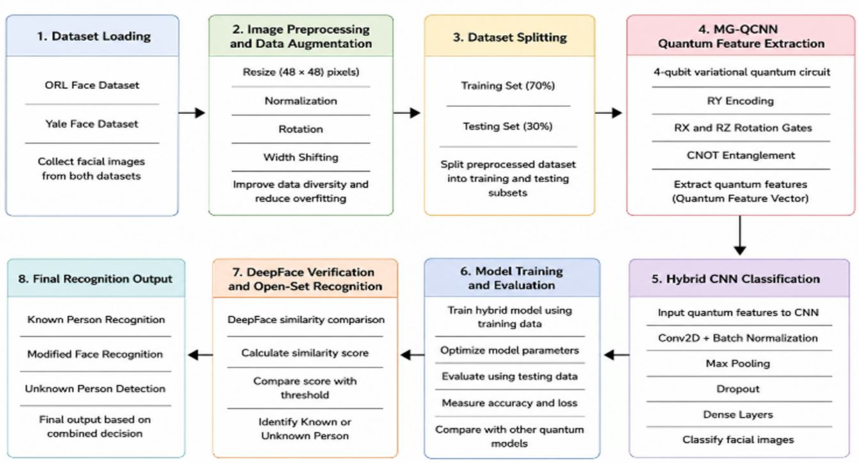

Fig. 1 Workflow of the Proposed Hybrid MG-QCNN Face Recognition System

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A. Dataset Loading

The proposed framework employs the ORL and Yale face datasets for model training and performance evaluation. The ORL dataset consists of facial images from several individuals exhibiting differences in facial expressions and appearance characteristics, whereas the Yale dataset contains images acquired under varying illumination conditions. Utilizing these benchmark datasets enables a comprehensive assessment of the generalization capability, robustness, and adaptability of the proposed face recognition framework.

B. Image Preprocessing and Data Augmentation

Before feature extraction, all input images undergo a preprocessing stage to improve data quality and learning effectiveness. The facial images are resized to a resolution of **48 × 48 pixels** and normalized to achieve consistent pixel intensity values. To enhance dataset variability and minimize the possibility of overfitting, data augmentation methods including image rotation and horizontal width shifting are employed. These preprocessing operations assist the model in learning robust facial representations under diverse image variations and environmental conditions.

C. Dataset Splitting

Following preprocessing, the dataset is partitioned into separate training and testing sets. Approximately **70%** of the images are allocated for model training, while the remaining **30%** are reserved for testing and performance evaluation. This partitioning strategy enables an unbiased assessment of the proposed model and ensures that its recognition capability is evaluated using previously unseen facial samples.

D. MG-QCNN Quantum Feature Extraction

The proposed Multi-Gate Quantum Convolutional Neural Network (MG-QCNN) extracts facial representations through a four-qubit variational quantum circuit. Initially, facial information is mapped into quantum states using R_Y state encoding. Subsequently, R_X and R_Z rotation gates are applied to perform quantum feature transformations, while CNOT operations establish entanglement among the qubits.

The multigate quantum design enhances the representation of facial information and facilitates the learning of complex relationships among facial features. The resulting quantum feature vectors are then transferred to the classical CNN component for further feature refinement and classification.

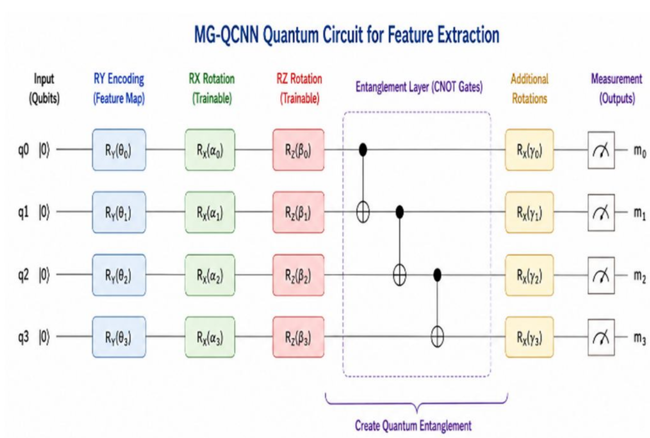

Fig. 2. MG-QCNN Circuit for Quantum Feature Extraction

E. Hybrid Quantum Classical CNN Classification

The extracted quantum features are integrated with classical Convolutional Neural Network (CNN) layers. The CNN architecture consists of Conv2D, Batch Normalization, Max Pooling, Dropout, and Dense layers. These layers refine the extracted features and perform facial classification.

The hybrid architecture combines the advantages of quantum feature extraction and classical deep learning, resulting in improved recognition performance and efficient learning capability.

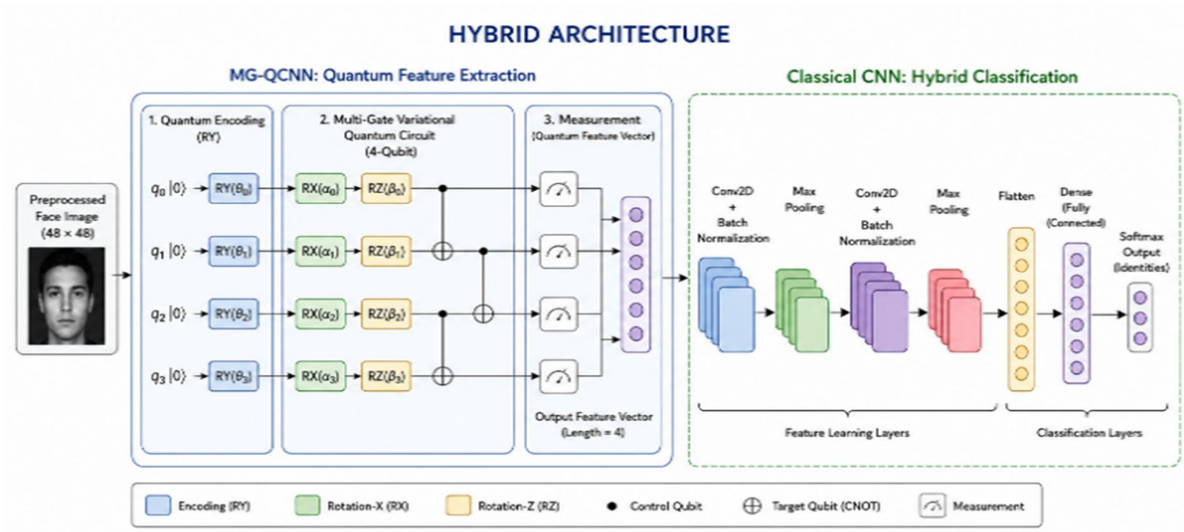

Fig. 3. Hybrid Architecture of the Proposed System

F. *Model Training and Evaluation*

The hybrid model is trained using labeled facial images from the training dataset. During training, optimization algorithms adjust model parameters to minimize classification loss and improve prediction accuracy. The trained model is evaluated using testing images from both datasets.

Performance evaluation is carried out using recognition accuracy and loss values. Experimental analysis is also performed to compare the complete MG-QCNN model with reduced quantum architectures and non-entanglement models.

G. *DeepFace Verification and Open-Set Recognition*

To improve recognition reliability, DeepFace verification is integrated into the framework. DeepFace performs facial similarity comparison between the input image and reference dataset images. This additional verification layer strengthens face matching performance and reduces false recognition.

The proposed system further supports Open-Set Face Recognition. The similarity score obtained through DeepFace verification is compared with a predefined threshold value. If the similarity exceeds the threshold, the face is identified as a Known Person; otherwise, it is classified as an Unknown Person. This mechanism enables reliable unknown person detection and improves the applicability of the system in real-world biometric security environments.

H. *Final Recognition Output*

The final output of the proposed framework is generated based on the combined decision of MG-QCNN feature extraction, CNN classification, DeepFace verification, and Open-Set Recognition. The system produces one of the Known Person Recognition or Modified Face Recognition or Unknown Person Detection

The proposed hybrid framework provides accurate face recognition, efficient quantum feature extraction, and reliable unknown person detection for secure biometric applications.

IV. RESULTS AND DISCUSSION

A. *Experimental Setup*

The developed Hybrid Quantum-Classical Face Recognition framework was implemented in Python and experimentally validated using the ORL and Yale face datasets. The proposed MG-QCNN architecture was combined with classical CNN layers to accomplish effective facial feature extraction and image classification tasks. Several preprocessing operations, including image resizing, normalization, rotation, and width shifting, were employed to enhance image quality and improve the generalization capability of the model. In addition, data augmentation techniques were applied to minimize overfitting and increase model robustness under diverse imaging conditions.

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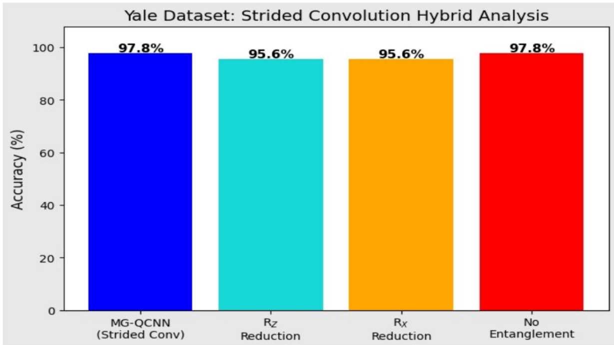
For experimental evaluation, the dataset was separated into independent training and testing subsets to ensure an unbiased assessment of model performance. Quantum feature extraction was performed using multiple quantum gate operations and entanglement mechanisms, whereas the classical CNN component was responsible for learning higher-level facial representations and generating the final classification results. DeepFace verification was further integrated to measure facial similarity between input and reference images, thereby providing an additional level of identity verification.

Moreover, an Open-Set Recognition mechanism was incorporated to differentiate between individuals present in the training dataset and previously unseen persons. The proposed framework was evaluated under multiple experimental scenarios, including known-person recognition, modified-face recognition, and unknown-person detection. Experimental observations obtained from both the ORL and Yale datasets demonstrate that the developed hybrid quantum-classical framework achieves accurate, reliable, and robust face recognition performance under variations in facial expressions, illumination conditions, and image characteristics.

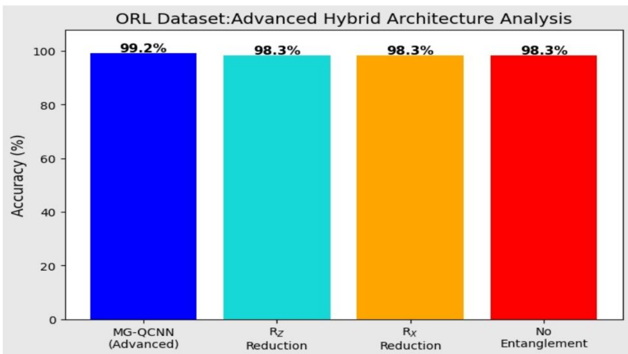
B. *Yale Dataset Results*



4.2 Yale Dataset Results

Fig. 4.2 represents the recognition results obtained using the Yale Face Dataset**.** The dataset contains facial images captured under different illumination conditions and facial expressions, making it suitable for evaluating the robustness of the proposed Hybrid MG-QCNN Face Recognition System. The model successfully extracted discriminative facial features through quantum feature extraction and classical CNN learning mechanisms. Despite variations in lighting intensity,the system maintained consistent recognition performance and accurately classified the facial images. The integration of quantum gates and entanglement operations helped capture complex facial patterns, while the CNN layers improved feature refinement and classification accuracy. The experimental results demonstrate that the proposed framework is robust against illumination variations and provides reliable face recognition performance under challenging image conditions. These outcomes validate the effectiveness of the hybrid quantum-classical architecture for real-world biometric recognition applications.

C. *ORL Dataset Results*



4.3 ORL Dataset Results

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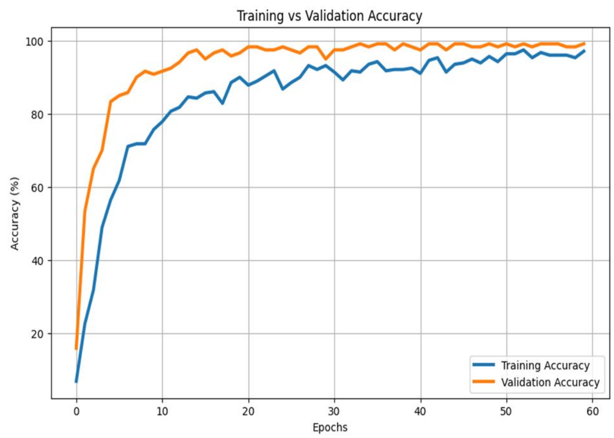
Fig. 4.3 presents the face recognition results obtained from experiments conducted on the ORL Face Dataset. This dataset includes several facial images of the same individuals collected under different facial expressions, pose changes, and imaging conditions, making it an appropriate benchmark for assessing the robustness and generalization capability of the developed Hybrid MG-QCNN Face Recognition framework. The proposed MG-QCNN model effectively generated informative facial representations through quantum-based feature extraction, while the classical CNN component further refined these features for accurate classification. The developed framework successfully recognized the individuals present in the dataset and delivered consistent classification performance. The experimental findings indicate that the proposed hybrid architecture can effectively learn complex facial characteristics and maintain stable recognition behavior under different facial variations and imaging conditions. The combination of quantum feature extraction and classical deep learning techniques significantly enhanced the overall identification capability of the framework. These observations demonstrate that the developed approach is suitable for biometric identification systems and intelligent face recognition applications operating in practical environments.

D. Training and Validation Accuracy Analysis



4.4 Training and Validation Accuracy Analysis

Fig. 4.4 presents the training and validation accuracy curves of the developed Hybrid MG-QCNN Face Recognition framework during the learning phase. The graph illustrates the progressive improvement in classification accuracy over successive training epochs. During the initial epochs, the accuracy values were comparatively low because the model had only begun learning discriminative facial representations from the training data. As the training process continued, both training and validation accuracies increased gradually, indicating effective feature extraction and improved classification capability.

The MG-QCNN component generated quantum-enhanced facial representations, whereas the classical CNN layers further refined these features to achieve accurate classification results. Throughout the training process, the validation accuracy exhibited a trend similar to that of the training accuracy, suggesting strong generalization capability and consistent learning behavior. The relatively small gap between the two curves indicates that the proposed model experienced minimal overfitting and maintained stable performance.

The obtained experimental findings demonstrate that the developed hybrid quantum-classical framework can effectively learn discriminative facial characteristics and achieve high recognition performance. The steady increase in accuracy across the training epochs further verifies the effectiveness of integrating MG-QCNN with classical CNN layers for intelligent face recognition tasks.

Moreover, both accuracy curves reached a stable convergence after several training epochs, indicating successful learning of the underlying facial patterns present in the dataset. The strong validation performance also shows that the proposed model can accurately classify previously unseen facial images, thereby confirming the reliability and robustness of the developed hybrid framework.

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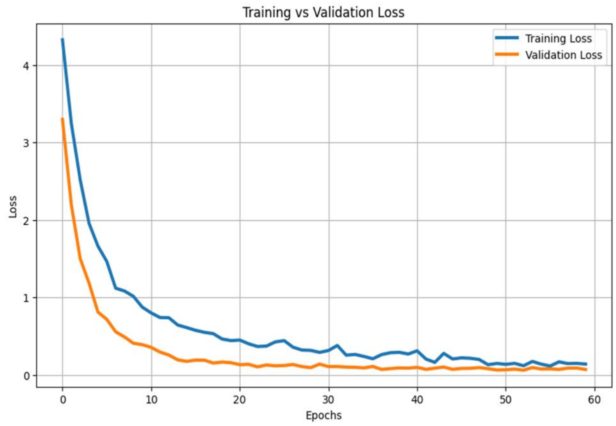
E. Training and Validation Loss Analysis



4.5 Training and Validation Loss Analysis

Fig. 4.5 illustrates the training and validation loss curves of the proposed Hybrid MG-QCNN Face Recognition System. The graph shows the reduction in classification error as the training process progressed over multiple epochs. Initially, the loss values were higher because the model parameters were randomly initialized and the network had limited knowledge of facial patterns. As training continued, both training and validation loss gradually decreased, indicating successful optimization and effective learning of facial features. The decreasing loss trend demonstrates that the model was able to minimize classification errors and improve recognition capability. The validation loss followed a pattern similar to the training loss, showing stable convergence and reliable learning behavior.

The absence of large fluctuations between training and validation loss suggests that the model maintained good generalization performance and avoided severe overfitting. These results confirm that the proposed hybrid MG-QCNN framework effectively optimizes feature extraction and classification processes, resulting in accurate and reliable face recognition performance.

F. Performance Analysis

The performance of the proposed Hybrid Quantum-Classical Face Recognition System was thoroughly evaluated using different quantum model configurations on both the ORL Face Dataset and Yale Face Dataset. To analyze the contribution of quantum operations in the recognition process, four different architectures were tested, namely MG-QCNN, R_Z Reduction, R_X Reduction, and No Entanglement models. The objective of this analysis was to study the impact of quantum gates and entanglement operations on facial feature extraction and recognition performance.

Experimental results obtained from both datasets indicate that the complete MG-QCNN architecture consistently achieved the highest recognition accuracy among all tested models. The MG-QCNN model utilizes multiple quantum gates, including R_X and R_Z rotational gates, together with quantum entanglement operations, allowing the network to learn complex facial representations more effectively. As a result, the model was able to extract highly discriminative facial features and improve overall classification performance.

The R_Z Reduction model, which removes a portion of the quantum rotational operations, achieved slightly lower recognition accuracy compared to the complete MG-QCNN architecture. Similarly, the R_X Reduction model showed a small decrease in performance due to the reduced quantum feature learning capability. These observations indicate that both R_X and R_Z quantum gates play an important role in generating meaningful facial feature representations within the quantum circuit.

The No Entanglement model produced the lowest performance among the evaluated architectures. In this configuration, the entanglement connections between qubits were removed, limiting the ability of the quantum circuit to learn complex relationships among facial features. The decrease in recognition accuracy demonstrates the significance of quantum entanglement in enhancing feature extraction capability and improving classification performance.

The comparative evaluation clearly shows that the integration of multiple quantum gates and entanglement operations contributes significantly to the success of the proposed face recognition framework.

The experimental findings confirm that quantum-enhanced feature extraction provides better facial representation compared to reduced quantum architectures. Furthermore, the hybrid integration of MG-QCNN with classical CNN layers enables efficient learning, stable convergence, and high recognition accuracy across different facial conditions.

Overall, the performance analysis validates the effectiveness of the proposed Hybrid MG-QCNN architecture for advanced face recognition applications. The results demonstrate that the combination of quantum computing principles and classical deep learning techniques can improve recognition capability, enhance feature learning, and provide reliable performance for real-world biometric authentication and intelligent surveillance systems.

G. Recognition Analysis

The proposed Hybrid MG-QCNN Face Recognition System was extensively evaluated under different recognition scenarios to analyze its effectiveness, robustness, and practical applicability. The recognition process involved image preprocessing, quantum feature extraction using the MG-QCNN architecture, classical CNN-based classification, and similarity-based verification. The objective of this analysis was to determine the system's ability to accurately recognize known individuals, handle facial variations, and distinguish unknown persons in open-set environments.

During the evaluation, the system successfully recognized facial images belonging to individuals present in the training dataset. The MG-QCNN model effectively extracted discriminative facial features through multi-gate quantum operations and entanglement mechanisms, while the classical

CNN layers refined these features for accurate classification. The generated feature representations enabled reliable matching between the input image and the corresponding reference identity, resulting in high-confidence recognition performance.

To evaluate robustness, the model was also tested under varying image conditions, including changes in facial expressions, illumination levels, and minor appearance modifications. The hybrid quantum-classical architecture maintained stable recognition performance and successfully captured essential facial characteristics despite these variations. The combination of quantum feature extraction and deep learning based classification helped preserve important facial information, thereby improving recognition reliability under challenging conditions.

Furthermore, the Open-Set Recognition mechanism was employed to analyze the system's capability to detect unknown individuals. Facial images that were not included in the training dataset were processed and compared with the stored facial representations. The system utilized similarity-based verification and threshold analysis to determine whether the input image belonged to a registered individual. When the similarity score remained below the predefined threshold value, the system correctly classified the input as an unknown person and prevented incorrect identity assignment. The overall recognition analysis demonstrates that the proposed Hybrid MG-QCNN framework provides accurate, reliable, and secure face recognition performance. The integration of quantum feature extraction, classical CNN learning, and open-set recognition significantly enhances the system's ability to recognize known individuals while effectively detecting unknown persons. These results confirm the suitability of the proposed architecture for real-world biometric authentication, intelligent surveillance, access control, and advanced face recognition applications.

H. Discussion

The outcomes obtained from the ORL and Yale face datasets verify the capability of the developed Hybrid MG-QCNN framework in achieving dependable and precise face recognition performance. The integration of Multi-Gate Quantum Convolutional Neural Networks with conventional CNN layers enabled effective extraction of facial characteristics and improved the overall classification process. By combining quantum computing concepts with deep learning techniques, the framework achieved better recognition performance and stable learning behavior.

The experiments conducted on the Yale dataset demonstrated that the proposed system can effectively manage changes in illumination and facial expressions without significant degradation in performance. Likewise, the results obtained from the ORL dataset revealed that the framework can correctly identify individuals even under variations in facial pose and image conditions. These findings suggest that the proposed approach can learn robust and discriminative facial representations suitable for practical environments.

Analysis of the training process indicated stable and consistent learning behavior. The training and validation accuracy curves increased progressively across epochs, reflecting successful feature learning and improved classification ability. In addition, the relatively small gap between the two accuracy curves indicates strong generalization capability and minimal overfitting. Similarly, the training and validation loss values decreased steadily during optimization, confirming stable convergence of the proposed model.

The comparative analysis further emphasized the significance of quantum operations in improving recognition performance. The complete MG-QCNN model outperformed the R_Z Reduction, R_X Reduction, and No Entanglement variants, demonstrating the contribution of multigate quantum operations and entanglement strategies toward enhanced feature extraction and classification accuracy. These observations highlight the benefits of quantum-enhanced learning for intelligent face recognition systems.

In summary, the proposed Hybrid MG-QCNN architecture offers an efficient and reliable solution for advanced biometric recognition applications. The combination of quantum feature extraction and classical deep learning techniques improves recognition capability while maintaining computational efficiency. The encouraging results indicate that hybrid quantum-classical approaches have strong potential for future applications in biometric authentication, surveillance systems, access control, and emerging quantum machine learning technologies.

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

The present study developed a Hybrid Quantum-Classical Face Recognition framework based on a Multi-Gate Quantum Convolutional Neural Network (MG-QCNN) to perform facial identification and verification tasks. The proposed approach integrates quantum-driven feature extraction with classical convolutional neural network learning to generate effective facial representations and accurate classification results. The effectiveness of the framework was examined using the ORL and Yale benchmark datasets containing variations in lighting conditions, facial expressions, and appearance changes.

The experimental findings revealed that the proposed system could successfully learn discriminative facial characteristics and maintain reliable recognition performance under diverse image conditions. The hybrid architecture accurately identified enrolled individuals and remained robust even when moderate modifications were introduced into facial images. Furthermore, integrating the DeepFace verification module improved similarity evaluation and increased the reliability of the recognition process.

An important aspect of this work is the implementation of an Open-Set Recognition mechanism that enables the system to distinguish between known identities and previously unseen individuals. The experimental outcomes showed that the framework accurately recognized registered users while effectively detecting faces that were not included in the training data. This capability increases the practical usefulness of the proposed approach in biometric authentication, intelligent surveillance, and security-oriented applications.

In conclusion, the developed MG-QCNN-based system provides an efficient and dependable solution for advanced face recognition applications. The integration of quantum computing concepts with deep learning methodologies demonstrates the promise of hybrid quantum-classical frameworks for solving complex biometric recognition problems and offers a strong foundation for future research in quantum machine learning and intelligent recognition systems.

B. Future Scope

Further research can investigate the performance of the proposed framework on larger and more challenging datasets, including LFW and Extended Yale B, to improve its adaptability and generalization ability in real-world scenarios. The design of more advanced hybrid quantum-classical models and improved quantum feature extraction strategies may further increase recognition capability.

The framework can also be adapted for practical applications such as smart surveillance, automated attendance systems, secure access control, and biometric authentication solutions. Integration with edge devices, IoT platforms, and intelligent camera systems could support faster and more efficient deployment.

Another potential research direction involves implementing the MG-QCNN architecture on real quantum computing hardware to study its behavior in practical quantum environments. Future studies may also explore optimized quantum circuits, alternative entanglement techniques, and advanced quantum neural network models to improve both recognition performance and computational efficiency.

Moreover, the development of an interactive user interface and monitoring dashboard can provide real-time recognition visualization, reporting, and system administration capabilities. As quantum technologies continue to evolve, hybrid quantum-classical face recognition frameworks are expected to become an important component of next-generation secure biometric systems.

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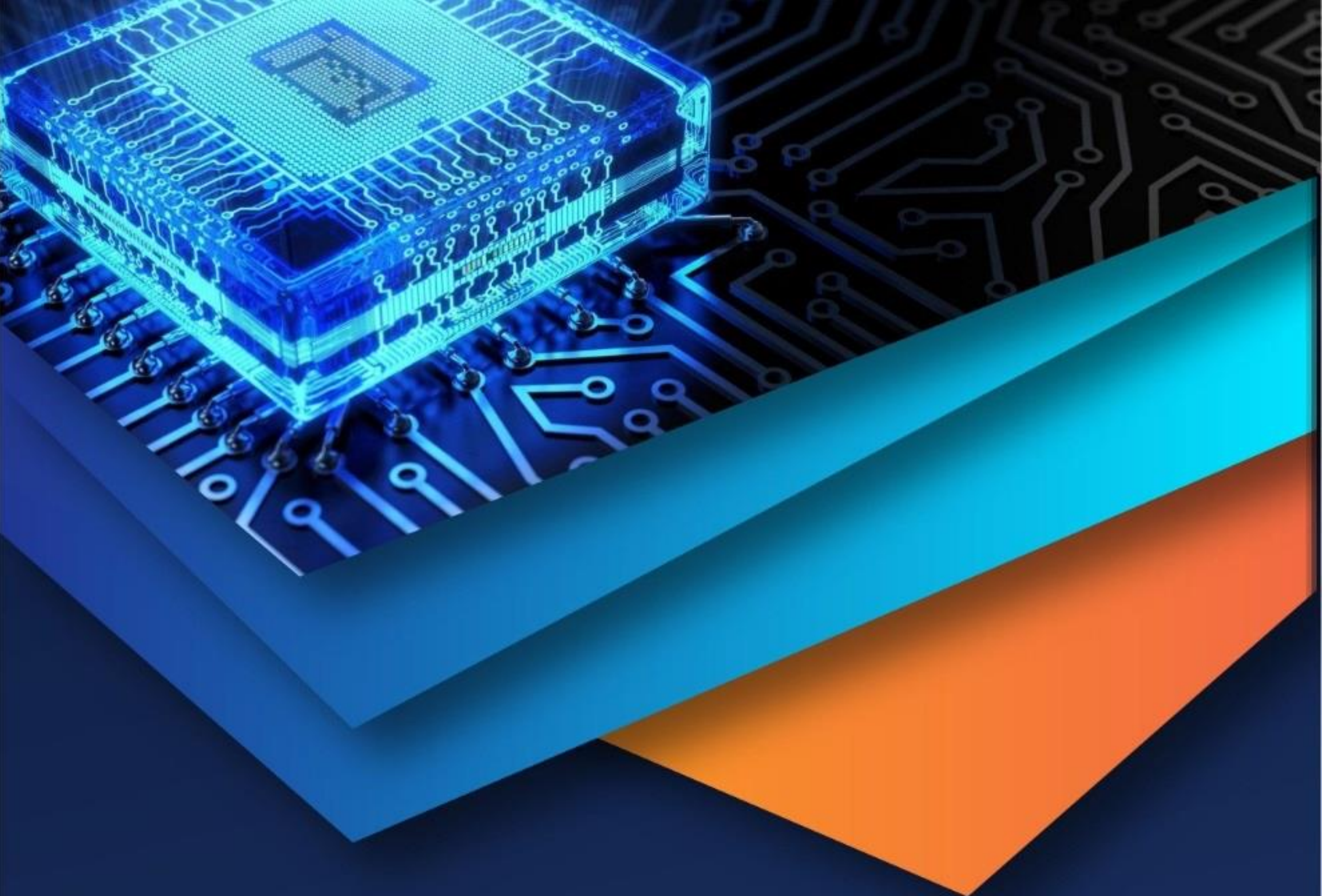

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