Facial Recognition by Using Ensemble and Network of Quantum Convolutional Neural Network

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Abstract. The use of Quantum Convolutional Neural Networks (QCNNs) is a promising technique for image classification, leveraging the principles of quantum parallelism and entanglement. Network of Quantum Neural Networks (N-QCNN) is introduced as a quantum AI technique that incorporates both quantum and traditional AI techniques. In this work, a new ensemble N-QCNN model is introduced that incorporates QCNN and SVM to enhance face recognition and classification performance, particularly on small datasets. As an application of this model, 48x48 pixel grayscale facial images are processed by using the well-known Yale Face dataset and a patch-based amplitude encoding scheme. In this approach, each module utilizes a unique quantum circuit design to extract distinct image features. In this two-layer model, the first layer utilized a set of three parallel QCNNs while the second layer utilized three parallel SVMs. Hence, the quantum derived features in the first layer are fed into a set of classical SVMs for classification. The final prediction of the model relied on the majority voting mechanism among the three modules, which includes a tie breaking rule for a conclusive outcome. We tested the proposed model on a partial and full Yale Face dataset; the test accuracy of the model resulted in 95.27% accuracy on a subset of 7 subjects to test the effectiveness of the model on a partial dataset. The performance remained robust when the testing was extended onto the entire dataset, with an accuracy of 80% attainment on all 15 subjects. These results highlight the effectiveness of this newly introduced ensemble-based N-QCNN models during multiclass facial image classification even when the dataset has a limited size.

Keywords: Quantum Convolutional Neural Networks, Quantum Machine Learning, Support Vector Machine, Ensemble Learning, Face Recognition.

1 Introduction

Face recognition has evolved from a specialized field of computer science to a broad and revolutionary technology that is now integrated throughout our modern life. Its applications are vast and critical, ranging from national security systems that identify threats in public spaces to seamless user authentication that unlocks our personal devices. In forensics, law enforcement and cybersecurity, the ability to accurately and efficiently identify individuals from digital images is paramount. As our world becomes increasingly digitized, the demand for automated recognition systems that are not only fast and accurate but also robust and secure continues to grow, driving innovation in the field.

For years, the dominant force in this innovation has been classical machine learning, particularly the advent of Convolutional Neural Networks (CNNs). CNNs have revolutionized computer vision by demonstrating an unparalleled ability to learn hierarchical features directly from pixel data. This has led to the state-of-the-art performance on the face recognition abilities of such approaches, surpassing human capabilities in many controlled environments. However, the availability of large, labeled datasets for training and substantial processing capacity, usually in the form of high-end GPUs, are two key requirements for the success of these traditional deep learning models. These requirements can be challenging to overcome in real-life small dataset applications and classical models can still struggle with the curse of dimensionality when processing extremely high-resolution image data.

It is at the intersection of opportunity and limitation that Quantum Artificial Intelligence and the associated computing techniques emerge as a new frontier. Quantum Machine Learning provides a fundamentally new method of computation by utilizing the concepts of superposition and entanglement found in quantum mechanics. The theoretical foundations of this field have been established through pioneering works on variational quantum algorithms [11], parameterized quantum circuits as machine learning models [13] and the quest for effective quantum neural network architecture [14]. These developments have led to various quantum learning approaches including quantum perceptrons [15], quantum-enhanced machine learning [17,18] and quantum Boltzmann machines [19], each contributing to our understanding of quantum computational advantages in machine learning tasks [20]. Quantum algorithms have the potential to process vast, high-dimensional feature spaces with an efficiency that is theoretically unattainable for the classical computers by utilizing exponential processing power [33]. This capability is particularly promising for image recognition and a single image represents a massive amount of data in such a setting. Furthermore, the principles of quantum information can offer inherent security advantages. The development of quantum biometrics could lead to recognition systems where facial data is encoded in quantum states, making it inherently resistant to classical eavesdropping and duplication, thereby addressing some of the most pressing and security concerns associated with current facial recognition technologies [5].

The exploration of quantum algorithms for face and image recognition has already yielded a diverse and promising body of research. Foundational work demonstrated the viability of a Quantum Neural Network (QNN) combined with classical Principal Component Analysis (PCA) to achieve high accuracy on limited size databases, establishing and an early proof-of-concept for hybrid systems [8]. Building on this, researchers have developed more sophisticated architectures tailored to the constraints of current hardware. The multigate QCNN (MG-QCNN), for example, was specifically designed to be efficient on Noisy Intermediate-Scale Quantum (NISQ) devices, using only a few qubits to outperform classical CNNs on benchmark face datasets [5]. Similarly, variational quantum deep neural networks (VQDNN) have been proposed to handle various scales of image recognition, showing faster convergence and better accuracy than classical networks on certain tasks [10].

Traditional machine learning has taken advantage of ensemble technique's integration with CNN by modulating the face regions [2]. The trend towards hybrid quantum-classical systems is particularly prominent, leveraging the strengths of both worlds. In the related domain of Facial Emotion Recognition (FER), researchers have achieved state-of-the-art accuracy by integrating quantum convolutional layers into established deep learning models like ResNet [3]. Others have taken a different hybrid approach, using quantum inspired optimization algorithms like the Quantum Gazelle Optimization Algorithm (QGOA) to enhance the feature selection process for classical deep learning pipelines [9]. The utility of quantum enhanced methods has been demonstrated across a range of applications beyond recognition, including the development of novel QCNN circuits for classifying complex medical X-ray images [7], the creation of frameworks for broad biomedical image processing enhancements [4] and the design of quantum enhanced models for highly efficient medical image compression [6]. Looking towards a fully quantum future, conceptual protocols have even been proposed that combine quantum imaging techniques like ghost imaging with quantum machine learning algorithms to create an end-to-end quantum recognition system with a significant theoretical speed advantage [1].

While these studies highlight the power of specific quantum models and various hybrid integrations, the strategy combining multiple, diverse quantum architectures into a single, robust ensemble remains a less explored but powerful frontier. This paper introduces a novel ensemble of QCNNs specifically for the task of multiclass facial recognition, with a focus on achieving high performance on small, challenging datasets such as the Yale Face Dataset [35] that classical models often struggle to attain strong accuracy results due to the limitations. Building on the previously introduced theoretical work on the Network of QCNNs (N-QCNN) [34], the proposed methodology in this work provides a practical implementation of this concept with the entire quantum circuits treated as modular, interchangeable subnetworks. We integrate the well-established classical strategy of ensemble learning with distinct, purpose-built quantum circuit architectures to create a powerful hybrid system. In regard to enhancing image processing, this work presents a practical and scalable pipeline with each one of the three QCNNs in the ensemble features of N-QCNN with the unique circuitry design we utilized to extract diverse quantum features. These features are then processed by independent classical Support Vector Machines (SVMs) and a final prediction is determined through a majority voting mechanism with a confidence-based tiebreaker.

In the next section, the methodological framework followed is explained with the system overview and data processing, quantum ensemble circuitry design and the nature of hybrid training and classification deployed for the N-QCNN we present in this work. The third section focuses on the experimental setup design and evaluation of the approach followed by the specific N-QCNN design on the Yale Face Dataset. The fourth section is designed to discuss the approach followed and the last section is reserved for conclusion and future work.

2 Methodology

The application of the new approach utilized in this work relies on the strengths of traditional and quantum AI techniques that we briefly explain next before details of the specific study outlined for the rest of the section.

The following are the combinations of N-QCNN introduced in [34]:

- QCNN Subnetwork Design
- Quantum Subnetwork Design
- Quantum-Qubit Subnetwork Design
- Hybrid Quantum-Traditional Subnetwork Design
- Fully Mixed Subnetworks

Noting the different infrastructures of N-QCNN designs to be explained in this section, the specific selection depends on specific applications of the problem and the network needed to be designed. The general N-QCNN design can have a variety of mixed network elements that include traditional and quantum AI techniques.

- **QCNN Subnetworks.** This design of N-QCNN uses quantum subnetworks formed by only QCNNs. The number of QCNN at each layer can be different with at n different layers. This design is specific to this case. Each QCNN would have a variable depth itself.
- **Quantum-Qubit Subnetwork Design.** This specific design of the subnetwork consists of each layer containing a mix of QCNNs and qubits, therefore the subnetwork design has variability. This specific subnetwork design can be useful in applications when special quantum computing cases require qubits in some parts of the layer and QCNN in some other cases.
- **Hybrid Quantum-Traditional Method Subnetwork Design.** Quantum

computing has been used in conjunction with classical machine learning methods focusing only on binary classification ins the literature [38-42], and such approaches were tested on large data sets with objects or numbers binary classification. The hybrid quantum-traditional method's subnetwork design consists of layers that are made up of a mixture of traditional models and QCNNs at each layer with the subnetworks once again having a variable design unlike other methods introduced in the literature. Fully Mixed Subnetwork Design

- **Full-mix N-QCNN Method.** This subnetwork design consists of a mix of quantum AI methods, qubits, and traditional AI methods at each layer.

2.1 System Overview and Data Processing

The Core of our system is an ensemble of three independent QCNN circuits. This hybrid model was trained and tested on the Yale Face Dataset. For preprocessing, all facial images were initially converted to grayscale and resized to 48x48 from 340x243 pixels. Each image was then divided into non-overlapping 2x2 patches, forming the input for the quantum circuits. Each 2x2 patch was encoded into four qubits using angle encoding scheme implemented with R_Y gates. This process translates the classical pixel information into a quantum state ready for processing.

2.2 Quantum Ensemble Circuit Design

The design of our three distinct QCNN architecture builds upon established quantum machine learning principles. The parameterized quantum circuit employed in each architecture follow the framework established for quantum machine learning models [13], utilizing variational approaches similar to those demonstrated in quantum optimization [11]. The circuit designs incorporate quantum learning principles [16] and leverage the expressive power of parameterized quantum circuits [20] to ensure diverse feature extraction capabilities. To enhance the model's resilience and ensure the extraction of diverse features, we designed three distinct QCNN architectures that ran in parallel. This architectural redundancy helps mitigate the risk of barren plateau that is a common challenge in training variational quantum circuits. Each circuit contributes complementary perspectives to the feature extraction process. The three architectures are defined as follows:

- **QCNN-1.** This circuit employs a rotationally entangled structure. After the initial R_Y encoding, the convolutional layers are parameterized using R_Y and R_Z gates. Pooling operations are executed with CRX gates and entanglement is introduced via a circular ring of CNOT gates connecting the qubits.

- **QCNN-2.** This design integrates Hadamard gates at the encoding stage to create a richer superposition. To simulate deeper entanglement interactions, the circuit incorporated CCX (Toffoli) gates, adding conditional complexity. Pooling is managed by CRZ gates, and the final measurements are optimized to extract relevant multi-qubit correlations.
- **QCNN-3.** This architecture emphasizes a layered convolutional design with a separated and chained parameterized rotation. Pooling is performed using CRZ and CRY gates and the circuit is structured to permit controlled entanglement. A key feature of this design is its efficiency, achieved by maintaining a low parameter count.

A detailed diagram of the QCNN-2 architecture, highlighting its use of complex entanglement and specific gate operations, is provided in Fig. 1.

2.3 Hybrid Training and Classification

Each one of the three QCNN circuits were trained independently using the optimizer on a simulated quantum backend. Post training, each circuit processes the patches of an image to produce an output expectation value that collectively forms a high-dimensional feature vector unique to that image. These quantum derived feature vectors were then used to train a dedicated classical SVM for each of the three QCNNs, completing the hybrid pipeline.

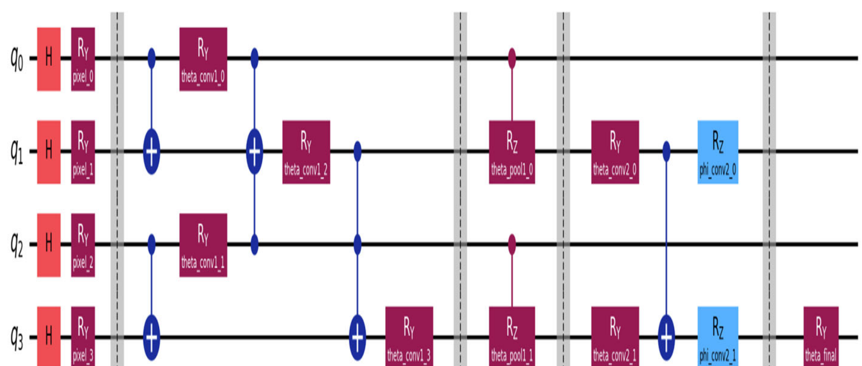

Fig. 1. Quantum circuit diagram for the QCNN-2 architecture.

The final classification decision of the N-QCNN is made by the ensemble. The primary strategy is a majority voting mechanism based on the predictions from the three individual SVMs. In the case of a numerical tie, a confidence-based tiebreaker is triggered. This secondary rule uses the output probabilities from each SVM, selecting the classification with the highest confidence score. This ensures the ensemble's final prediction reflects both majority consensus and the model's certainty.

The complete pipeline, from data input through the parallel quantum circuits and their corresponding SVMs to the final ensemble output is demonstrated in Fig. 2. This figure illustrates how the components described throughout this methodology integrate into a cohesive system.

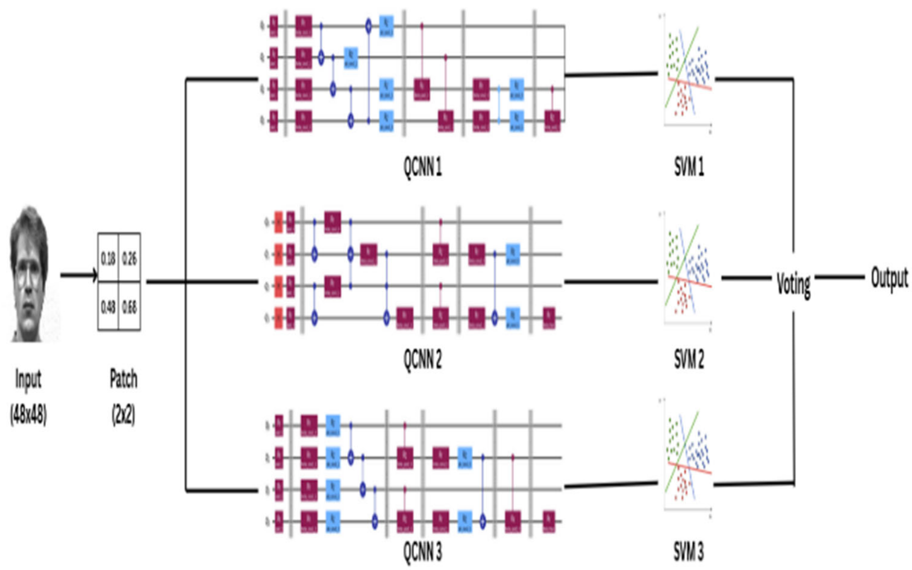

Fig. 2. High-level architecture of the proposed ensemble model.

3 Experimental Setup and Numerical Evaluation

3.1 Experimental Setup

All experiments were conducted using python leveraging Qiskit for simulator for quantum circuit simulation. Our model was evaluated on the Yale Face Dataset under two conditions: a 7-class subset evaluation to test the performance of the technique on a limited set and the full image data set consisting of 15 classes. Prior to model's input feature feeding, image data was preprocessed by resizing to 48x48 grayscale pixels. Each image was then deconstructed into 576 non-overlapping 2x2 patches. For quantum encoding, pixel values were normalized to the interval $[0, 2\pi]$ to serve as the angle parameter for the R_Y rotation gates.

Our hybrid architecture comprises an ensemble of three distinct 4-qubit QCNNs with each QCNN trained independently using COBYLA optimizer [36]. The measurement scheme was tailored to the classification complexity in which for the 7-class task, a 2-qubit measurement was used to compute an expectation value sufficient for distinguishing between fewer classes. In contrast, for the full dataset with 15-class task, three qubits were measured to capture higher-dimensional correlations, enabling more nuanced class separation required for the increased number of categories. For the classical components, a SVM with a Radial Basis Function (RBF) kernel was trained on the feature vectors extracted from each one of the corresponding QCNN.

The quantum circuits were executed on the Qiskit Aer Simulator [37]. To balance accuracy with computational demand, the number of shots for each circuit measurement was set to 1024. For both experiments, the dataset was partitioned on a per subject basis, allocating 8 images for training and 3 images for testing.

3.2 Results Evaluation

In the initial 7-class experiment, our proposed ensemble model achieved an outstanding overall test accuracy of 95.27%. This high level of performance, achieved with a limited training set of only 56 images, underscores the powerful and efficient feature extraction capabilities of the QCNN ensemble on the Yale Face Dataset. A class-wise analysis showed near perfect precision and recall for most subjects, conforming the model's ability to learn highly distinct and separable features in a less complex environment.

To evaluate scalability, the model was tested on the full 15 class dataset. In this scenario, the model achieved a robust test accuracy of 80%. An analysis of the per-class metrics reveals a high degree of performance variance. The model perfectly identified seven of the fifteen subjects achieving an F1-score of 1.00, demonstrating its strength in creating separable feature spaces for distinct subjects. However, it exhibited significant difficulty with few of the classes, particularly for class 14 that attained an F1-score of 0.33, indicating that the feature-space separation becomes more challenging for subjects with more subtle visual differences. This 80% accuracy, despite the variance, is a strong result that validates the general scalability of ensemble architecture. It shows that the model maintains robust overall performance even as the classification complexity doubles. In terms of computational resources, the 7-class execution environment, highlighting the high overhead cost of the simulation and motivating future work on native quantum hardware for improved efficiency.

4 Discussion

Our results demonstrate that a thoughtfully architected ensemble of Network of QCNNs can achieve high accuracy on image classification tasks, even with datasets of limited size. The success of our model, particularly in the 7-class (95.27%) and 15-class (80.00%) scenarios, can be directly attributed to the ensemble approach. By using distinct circuit structures for each QCNN taking place in N-QCNN, we enabled the extraction of diverse and complementary quantum features as a crucial approach for the overall accuracy and robustness of the final classification.

This work serves as a practical validation of the theoretical N-QCNN framework, applying it to real-world use cases such as facial image classification. Given the limited literature work on quantum-based facial image classification, this work provides the evidence of N-QCNN theoretical framework's success in the applications. Moving beyond benchmark datasets, our findings show that quantum encoding and variational entanglement can be effectively leveraged to achieve strong performance with just a handful of training samples per class. This highlights the potential success of hybrid quantum-classical systems for solving practical problems on small scale datasets.

A key strength of our model is its modularity and flexibility. The ensemble is designed to easily incorporate new QCNN variants or even different types of hybrid subnetworks in the future without requiring a complete architectural redesign. This adaptability is a significant advantage, as it opens up opportunities for the dynamic integration of emerging quantum circuit templates as the field advances.

Finally, while the current implementation relied on classical simulation, the architecture is intrinsically modular and portable. It is well positioned for execution on near term quantum devices as hardware noise is mitigated and qubit fidelity improves. This study provides a clear blueprint for deploying similar ensemble models on the nest generation of quantum hardware.

5 Conclusion

This paper presented a novel ensemble of QCNNs for multiclass facial recognition on the Yale Face Dataset. An application of the N-QCNN framework is utilized consisting of three unique QCNN architectures with their integration to three SVMs. The outputs of the SVMs required a majority voting mechanism to determine the best possible outcome and this particular designed model achieved 95.27% accuracy on a 7-class subset and a robust 80.00% accuracy on the full 15-class Yale Face Dataset.

Overall, our work successfully translates the theoretical N-QCNN framework into a concrete, functional pipeline demonstrating the feasibility of quantum-enhanced models for practical AI challenges such as face recognition systems that have limited research literature outcomes. This encouraging performance underscores the success of this hybrid approach, particularly in scenarios such that the training data is scarce and robust model generalization is critical. This study provides a strong foundation for future research, paving the way for more advanced hybrid systems that combine novel quantum feature extractors with powerful classical classifiers on near-term quantum hardware.

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