Quantum Computing in Computer Vision

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***Abstract*—Quantum computing is revolutionizing computer vision by improving image classification, generation, and recognition tasks. This paper reviews recent advances in quantum-enhanced computer vision, including the use of Quanvolutional Neural Networks (QNNs) for image classification, quantum generative adversarial networks (qGANs) for image generation, and quantum activation functions to improve neural network performance. The paper also explores hybrid models that combine classical and quantum architectures, such as Dressed Quantum Circuits, to address real-world challenges in visual data processing. These innovations demonstrate the potential of quantum computing to transform computer vision.**

***Index Terms*—Quantum computing, computer vision, Quanvolutional Neural Networks (QNNs), quantum generative adversarial networks (qGANs), image classification, quantum activation functions, hybrid models, visual data processing, neural network performance, quantum-enhanced vision.**

I. Introduction

Quantum computing has the potential to revolutionize various fields, including computer vision, by harnessing quantum properties like superposition and entanglement. While classical methods in computer vision face challenges with processing complex visual data, Quantum computing offers a promising alternative. Recent developments in quantum-enhanced computer vision, such as Quanvolutional Neural Networks (QNNs) and quantum generative models, are demonstrating improvements in accuracy and efficiency. This paper explores the integration of classical and quantum models, focusing on hybrid architectures and transfer learning, and highlights how Quantum computing can advance computer vision tasks and address complex data processing problems.

II. Related Work

In the fast-evolving world of computer vision, quantum computing is emerging as a game-changer, offering new ways to tackle complex visual challenges. By harnessing the unique properties of quantum mechanics, researchers are developing hybrid frameworks, innovative algorithms, and creative activation functions to improve tasks like image classification, generation, and recognition. While this field holds immense promise, it also comes with challenges, particularly in integrating quantum technologies with existing systems. Nonetheless, these efforts are paving the way for breakthroughs that were previously unimaginable with classical methods.

Many studies have tried to modify the existing classical Convolutional Neural Network (CNN) Architectures, by integrating quantum algorithms to significantly improve image classification tasks. [1] investigates the impact of quantum image encoding techniques on hybrid quantum-classical quanvolutional neural networks, finding that trainable quantum circuits, paired with the Flexible Representation of Quantum Images (FRQI) encoding and smaller filter sizes, significantly improve classification accuracy. However, challenges related to increased algorithmic depth on current quantum hardware were also highlighted. Furthermore, the study [2], on quantum algorithms for deep convolutional neural networks (QCNNs), showed that quantum computation could efficiently handle convolutional layers, achieving exponential speedups under specific conditions. Simulations demonstrated the feasibility of this approach for image recognition tasks while providing insights into pooling strategies and activation functions. Moreover, [3] discusses the potential of Quantum Convolutional Neural Networks (QCNNs) in multi-channel supervised learning, offering efficient quantum-enhanced processing in convolutional architectures. Their hybrid design, combining classical and quantum layers, has demonstrated superior performance in high-dimensional data problems, particularly in quantum state recognition and classification tasks. [4] also discusses the utilization of Quanvolutional Neural Networks (QNNs) to leverage quantum circuits to extract features from images, employing quantum feature maps to enhance the representation of image data. Their hybrid integration with classical neural networks enables efficient computations for image recognition tasks, showing potential for significant improvements in high-dimensional datasets. Lastly, [5] introduces Quantum Convolutional Neural Networks with interaction layers to enhance classical data classification. By exploiting quantum entanglement and correlations, these interaction layers offer more expressive feature representations. This hybrid approach has improved classification accuracy and efficiency in handling complex data scenarios.

Apart from this some studies also explore the use of quantum computing in image generation tasks. [6] introduced a hybrid quantum-classical GAN framework for high-resolution image generation, using quantum circuits as generators and classical neural networks as discriminators. Results demonstrated that increasing the size of the generator improved image quality on datasets like MNIST and Fashion-MNIST, highlighting the potential of quantum-powered image generation. Furthermore, the study [7] presents the experimental realization of a quantum generative adversarial network (qGAN) for image generation. This work introduces a flexible qGAN framework capable of producing images with high-dimensional features by leveraging quantum superposition, enabling the simultaneous training of multiple examples. Notably, this study represents the first experimental achievement of image generation using a qGAN, marking a significant milestone in the integration of quantum computing with image processing. This advancement underscores the potential of quantum technologies in revolutionizing generative modeling and offers valuable insights for researchers exploring quantum methods in computer vision.

Apart from Image Classification and Generation Architectures, several studies explore the possibilities of quantum activation functions in different layers of neural networks. [8] addresses the "dying ReLU" problem by introducing two quantum activation functions, QReLU and m-QReLU. Testing on tasks such as COVID-19 diagnosis and Parkinson's detection revealed that these functions outperformed traditional activation methods, offering improved accuracy and generalization in critical medical applications. Moreover, [9] explored transfer learning in hybrid classical-quantum neural networks, showing that pre-training on classical datasets enhances the performance of quantum models, especially in data-limited scenarios. These findings underscore the potential of leveraging classical resources to boost the efficiency and effectiveness of quantum systems.

The integration of classical Deep Neural Networks (DNNs) with Quantum Neural Network (QNN) layers, as introduced in the QDNN framework, is another noteworthy development. This hybrid model leverages quantum properties like superposition and entanglement to outperform traditional DNNs in complex tasks. This approach is part of a growing trend in hybrid quantum-classical architectures, which promise enhanced efficiency and capabilities in machine learning [10].

The study [11] investigates the intersection of quantum computing and image classification, proposing a novel approach that integrates classical Principal Component Analysis (PCA) with quantum measurement for the classification of grayscale images. Despite the current challenges and uncertainties surrounding the practical implementation of quantum computers, the field continues to advance rapidly, particularly in areas such as quantum machine learning and image processing. By leveraging the strengths of both classical and quantum techniques, this work contributes to the growing body of quantum algorithm research, demonstrating the potential for innovative solutions in image classification through quantum technologies.

The paper [12] introduces a variational quantum classifier and proposes the "quantum neuron" as a fundamental unit for quantum machine learning. This model lays the groundwork for constructing complex architectures designed to address classification tasks on quantum computers. The authors examine the potential advantages of quantum-based approaches compared to classical machine learning methods, highlighting the transformative possibilities of quantum neurons. While the work remains theoretical and reliant on future advancements in quantum computing technology for practical realization, it offers a significant perspective on the foundational elements of quantum machine learning. For research on quantum image classification and computer vision, this paper provides valuable insights into how quantum neurons might be applied to image processing and classification tasks. It is recommended to include this paper in your library for reference and further exploration.

The article [13] investigates the application of classical and quantum neural networks for image classification and reconstruction in single-pixel imaging. Single-pixel cameras, which are particularly well-suited for non-visible light spectra, are combined with machine learning techniques to facilitate fast and efficient image analysis. The study simulates a single-pixel detection experiment using Hadamard basis patterns and images from the MNIST dataset, demonstrating how algorithms based on classical fully connected networks and parameterized quantum circuits can achieve classification and reconstruction with a limited number of measurements. This research highlights the potential of quantum computing to advance the capabilities of single-pixel imaging and offers a valuable perspective for studies on quantum image classification and computer vision.

Together, these advancements illustrate the transformative role of quantum computing in computer vision, offering innovative solutions to long-standing challenges while paving the way for deeper integration of quantum and classical technologies.

III. Transfer Learning

Transfer learning refers to the technique where a model trained on one task is adapted to a new but related task, utilizing pre-trained weights and learned features. In this study, we explore transfer learning between classical and quantum models, specifically focusing on two approaches:

A. Classical to Classical

The classical-to-classical approach involves fine-tuning a pre-trained classical model on a similar classical task. This is a traditional transfer learning method where the model's learned features are reused for new data, leading to improved convergence and generalization.

1) Classical Neural Networks: Classical feed-forward neural networks consist of multiple layers, each performing an affine transformation followed by a non-linear activation function. A single layer maps an input vector $x \in \mathbb{R}^{n_0}$ to an output vector $y \in \mathbb{R}^{n_1}$ as:

$$L_{n_0 \to n_1}(x) = \phi(Wx + b), \tag{1}$$

where $W \in \mathbb{R}^{n_1 \times n_0}$ is the weight matrix, $b \in \mathbb{R}^{n_1}$ is the bias vector, and ϕ is a non-linear activation function such as ReLU or the hyperbolic tangent.

A classical deep neural network concatenates d such layers, with the output of one layer serving as the input to the next:

$$C = L_{n_{d-1} \to n_d} \circ \cdots \circ L_{n_1 \to n_2} \circ L_{n_0 \to n_1}. \tag{2}$$

The network's hyperparameters include the depth d and the sequence of layer dimensions $\{n_0, n_1, \ldots, n_d\}$.

B. Classical to Quantum

In the classical-to-quantum transfer learning approach, we transfer a model trained on classical data to a quantum framework, leveraging the potential of quantum computing for faster computation and more compact representation. The goal is to enhance the model's performance on complex tasks by fine-tuning it within a quantum environment. For this experiment, the model was inspired by the official PyTorch tutorial on classical transfer learning, with specific configurations including the use of ImageNet, a public dataset containing 1000 classes, as the dataset (DA). The classical model used was ResNet18, a pre-trained residual neural network (A), designed for image classification with 1000 labels (TA). To adapt it for quantum processing, ResNet18 was used as a feature extractor (A), omitting the final linear layer to extract 512 features. The data set for fine-tuning consisted of a subset of ImageNet, focusing on a binary classification task involving ants and bees (DB), with 245 training images and 153 testing images. The quantum model (B) was based on a 4-qubit-dressed quantum circuit, taking 512 input features and producing two output labels for classification (TB).

1) Variational Quantum Circuits: A quantum layer acts as a unitary transformation $U(w)$ on the input quantum state $|x\rangle$ with variational parameters w [9]:

$$L : |x\rangle \to |y\rangle = U(w)|x\rangle. \tag{3}$$

A variational quantum circuit with depth q consists of a sequence of such quantum layers:

$$Q = L_q \circ \cdots \circ L_2 \circ L_1. \tag{4}$$

To process classical data, a variational embedding layer maps a real vector $x \in \mathbb{R}^n$ to a quantum state $|x\rangle$:

$$E : x \to |x\rangle = E(x)|0\rangle. \tag{5}$$

The output is extracted through a measurement layer, which computes the expectation values of observables:

$$M : |x\rangle \to y = \langle x|\hat{y}|x\rangle. \tag{6}$$

The full quantum network, including embedding and measurement, is expressed as:

$$Q = M \circ Q \circ E. \tag{7}$$

2) Dressed Quantum Circuits: To enhance flexibility, classical pre-processing and post-processing layers can be added to quantum circuits. A dressed quantum circuit maps classical input x to classical output y as:

$$\tilde{Q} = L_{n_q \to n_{\text{out}}} \circ Q \circ L_{n_{\text{in}} \to n_q}, \tag{8}$$

where L represents classical layers, and Q is the quantum circuit. This approach decouples the input and output dimensions from the number of quantum subsystems and allows efficient embedding and post-processing.

Both transfer learning approaches were tested and compared to evaluate the impact of quantum models on classical learning tasks, highlighting the trade-offs between performance and training stability.

IV. ReLU and the "Dying ReLU" Problem

The Rectified Linear Unit (ReLU) activation function has become widely used in deep learning due to its simplicity and efficiency. ReLU is defined as:

$$R(z) = \max(0, z)$$

where z is the input to the neuron. ReLU solves the vanishing gradient problem that occurs in sigmoid and tanh activation functions, allowing for faster convergence during training. However, a significant issue known as the "dying ReLU" problem arises when the input to the neuron is negative. In such cases, ReLU outputs zero, leading to neurons that do not update during backpropagation. This problem can negatively impact the generalization ability of Convolutional Neural Networks (CNNs), particularly in complex tasks like medical image classification.

V. QReLU: A Quantum-Based Solution

To address the "dying ReLU" problem, the quantum activation function *QReLU* was proposed. QReLU combines the principles of quantum computing with classical activation functions to overcome the limitations of ReLU [8]. The QReLU approach is based on quantum superposition and entanglement, which allow for both positive and negative solutions to be represented simultaneously.

A. Quantum Principles of QReLU

In QReLU, the positive solution for $z > 0$ remains the same as in ReLU:

$$R(z) = z, \quad \forall z > 0$$

For negative values ($z \leq 0$), instead of outputting zero as ReLU does, QReLU introduces a quantum-based modification to ensure a non-zero output. This modification is based on a combination of ReLU and Leaky ReLU, where:

$$R(z) = \alpha \times z - 2z, \quad \forall z \leq 0$$

Here, $\alpha = 0.01$ and ensures that negative values do not lead to zero outputs. The quantum principles of entanglement and superposition enable this dual approach, which allows the network to avoid the ”dying ReLU” issue while maintaining the efficiency of the original ReLU function for positive inputs.

B. Advantages of QReLU

QReLU benefits from the quantum properties of superposition and entanglement, which enable multiple possible states for each neuron. This results in better generalization during training and avoids the issue of neurons becoming inactive. Additionally, QReLU maintains the computational efficiency of ReLU while addressing its key drawback.

The QReLU function can be implemented on classical hardware (CPUs, GPUs, TPUs), making it practical for real-world applications. Its effectiveness has been demonstrated in medical image classification tasks, where improved generalization has been shown to lead to more accurate results in critical diagnostic applications such as COVID-19 and Parkinson’s disease (PD) detection.

VI. Experimental Results

Below are the accuracy graphs for the two transfer learning models: Classical-to-Classical and Classical-to-Quantum. These graphs show how each model’s accuracy evolves over the epochs during training.

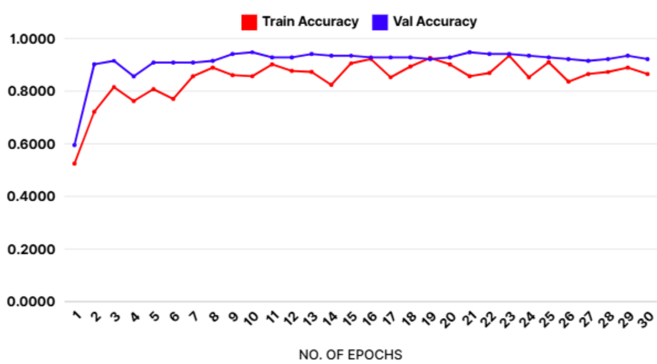

Figure 1: Classical-to-Classical Model Accuracy

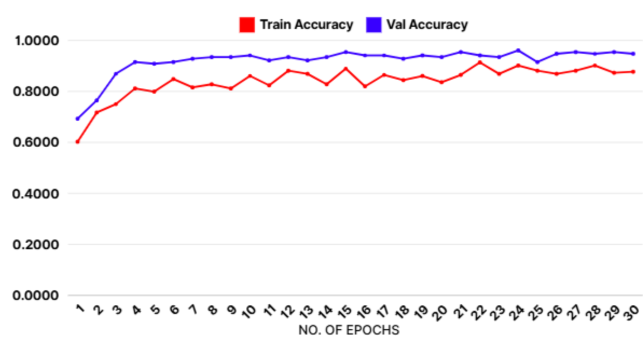

Figure 2: Classical-to-Quantum Model Accuracy

The loss graphs show the loss values over training epochs for the same models. Lower loss values indicate better model performance.

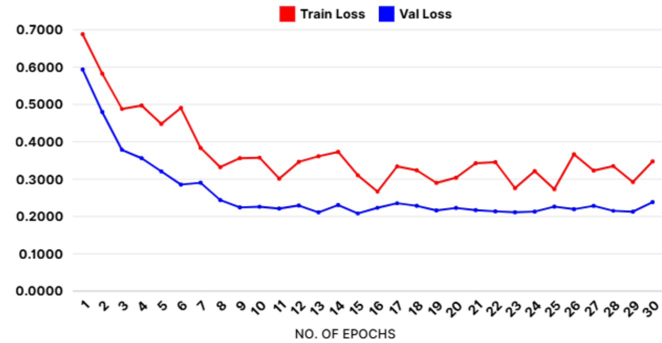

Figure 3: Classical-to-Classical Model Loss

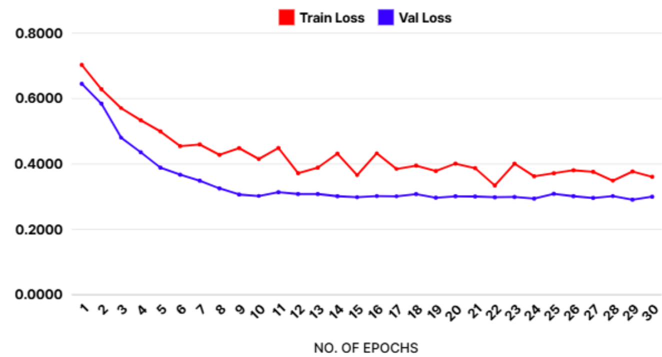

Figure 4: Classical-to-Quantum Model Loss

The confusion matrices below show the performance of the models on test data. They provide insights into how well the models are classifying different classes.

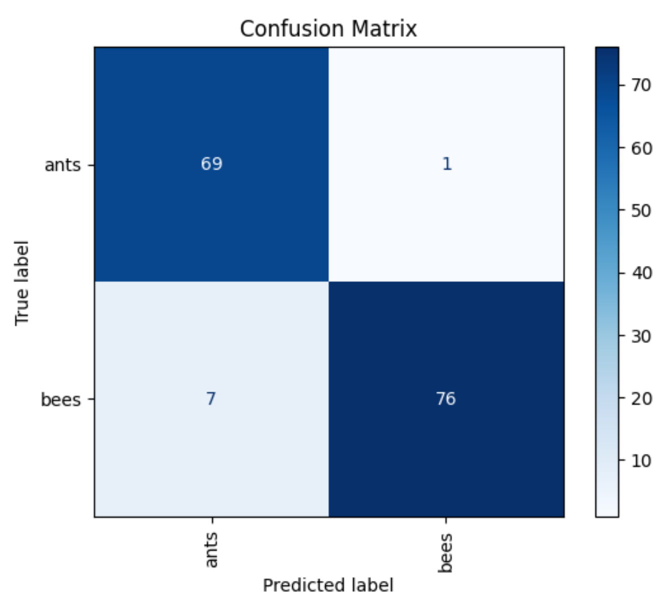

Figure 5: Classical-to-Classical Confusion Matrix

VII. Analysis

The performance of both models shows notable differences:

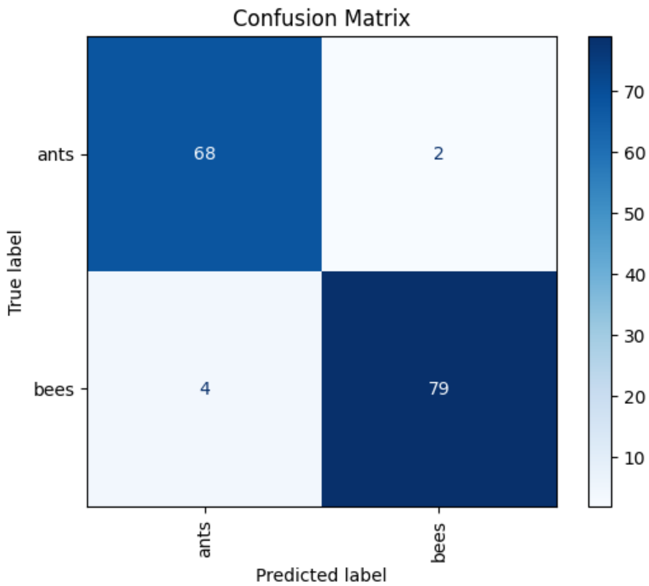

Figure 6: Classical-to-Quantum Confusion Matrix

Quantum-to-Classical (C_to_Q): Achieved a test accuracy of 96.08% with a test loss of 0.2941. The high accuracy suggests strong model performance, though the higher loss indicates some potential overfitting or training instability.

Classical-to-Classical (C_to_C): The test accuracy is 94.77%, with a lower test loss of 0.2080. This indicates more stable training and possibly better generalization, but slightly lower accuracy compared to the Quantum-to-Classical model.

In conclusion, the Quantum-to-Classical model excels in accuracy, while the Classical-to-Classical model demonstrates better stability in training.

The following graphs display the loss and accuracy of the CNN model using QReLU and ReLU activation functions over the training epochs, showing how the model's performance evolves during the learning process on the MNIST dataset.

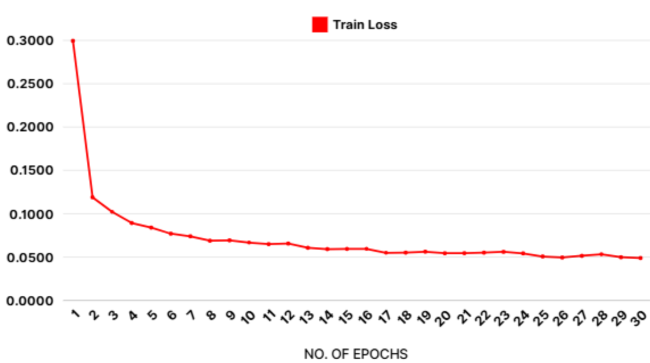

Figure 7: QReLU Loss

The performance of both activation functions shows similar trends, with only marginal differences in their impact on the model's loss and accuracy.

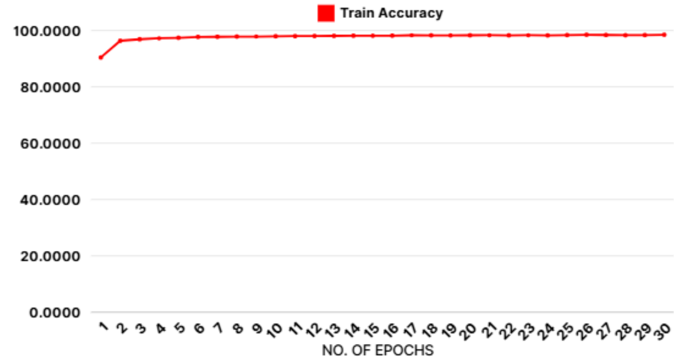

Figure 8: QReLU Accuracy

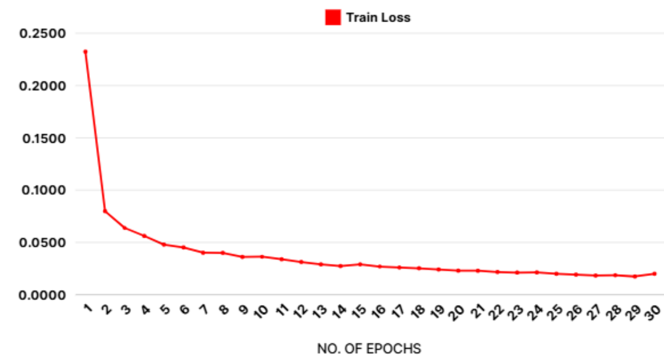

Figure 9: ReLU Loss

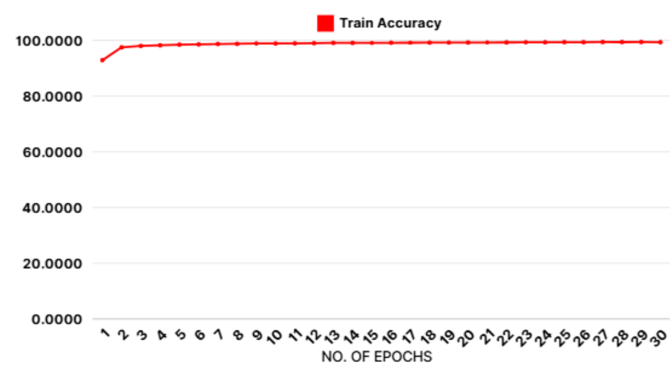

Figure 10: ReLU Accuracy

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