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Hybrid Quantum–Classical Convolutional Neural Network for Medical Image Classification

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Abstract

Significant advances have been made in quantum computing, enabling researchers to create hybrid quantum-classical learning models for various tasks, including medical image classification. The classical approach to deep learning often faces challenges with limited data availability, high computational costs, and poor generalization. The hybrid Quantum- Classical Convolutional Neural Networks (HQCNNs) provide a new direction for overcoming the challenges faced by classical approaches. The hybrid approach enables the use of quantum circuits for feature encoding in higher-dimensional space, improving discrimination between patterns and reducing overfitting. In this paper, a hybrid quantum-classical convolutional neural network is developed for medical image classification. The hybrid approach is expected to capture non-linear relationships within medical image data while maintaining a lightweight network structure. The hybrid approach is found to have significant potential for efficient operation with limited data availability and noisy data. The classical approach is often outperformed by the hybrid approach. The focus of this paper is on architectural design and analysis of the developed hybrid quantum-classical convolutional neural network. The advantages of the developed hybrid quantum-classical convolutional neural network are de- lineated, including current challenges with quantum hardware.

Keywords: *Index Terms—Hybrid Quantum–Classical CNN, Medical Image Classification, Variational Quantum Circuits, Quantum Ma- chine Learning, Deep Learning, Biomedical AI.*

1. Introduction

The impact of deep learning on the classification of images in the medical domain is significant, as it can be used for tumor detection, disease screening, and decision-making. With the increase in the digitization of the healthcare system, the complexity and amount of image data available have increased significantly, thereby making the requirement for efficient diagnostic tools strong. In this regard, the use of Convolutional Neural Networks (CNNs) has been significant, as it allows the network to learn features from the images. However, it has also been observed that these networks often require a lot of resources. In the real world, the availability of medical images might be limited, restricted, or scarce, making it difficult to effectively use these resource-intensive networks [1], [2]. In order to overcome these problems, the field of hybrid quantum–classical machine learning has been identified as a potential solution. This is a relatively new direction in the field and offers the advantages of classical machine learning combined with the representational power of quantum comput- ing. Quantum computing can map classical inputs into higher- dimensional spaces using the principles of superposition and entanglement, which may enable the identification of complex patterns that are difficult to detect using classical systems [3], [4]. One such technique is Hybrid Quantum–Classical Con- volutional Neural

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Networks (HQCNNs), which have gained significant attention due to their ability to incorporate quantum feature processing into conventional CNN frameworks. Research has shown that HQCNNs have the potential to perform better than traditional CNNs, especially in situations where limited, noisy, or unbalanced data is used. For example, Dong et al. presented a hybrid model that performed better than a traditional CNN in the classification of brain tumors [5]. Such trends have also been observed in other scenarios, where quantum layers improve feature discriminability, thus increasing the robustness of the models against noise and adversarial attacks [2], [6]. Moreover, other studies have shown that quantum models can be simulated, thus being useful in current research environments [7]–[9]. Despite these promising developments, several challenges remain. Current quantum devices are limited by noise, decoherence, and a restricted number of qubits, which constrain the scalability of quantum models. As a result, many existing approaches rely on simulations rather than real quantum hardware. Nevertheless, recent studies have demonstrated that hybrid models can achieve strong performance with reduced model complexity [10]–[12]. In our research, a new architectural framework for image classification, called a Hybrid Quantum-Classical Convolutional Neural Network (HQCNN), is proposed. The main idea is to leverage recent advances in hybrid learning paradigms to improve performance in low-data and noisy environments. The paper focuses on the architectural design and theoretical analysis of the HQCNN, with a special emphasis on its potential benefits and possible directions for future experimental evaluation.

2. Literature Review

2.1.Hybrid Quantum–Classical Models in Biomedical Imaging

As quantum machine learning is advancing at a fast pace, hybrid quantum machine learning architectures have been developed to address the main challenges of classical deep learning, including the number of parameters, overfitting, and data efficiency. For instance, Dong et al. have shown that an improved hybrid quantum-classical convolutional neural network can be used to enhance brain tumor image classification with multiple classes, compared to classical CNNs [5]. In another study, Huang et al. have used hybrid quantum machine learning to work with noisy and adversarial environments, showing significant improvements in the stability of the image classification process [2]. A number of researchers have also attempted to integrate quantum layers within regular convolutional neural networks to test their robustness. For instance, Li et al. have designed a hybrid convolutional network where quantum circuits are used to improve feature transformation. The results showed improved accuracy compared to classical convolutional neural networks of similar complexity for regular image tasks [1]. Majumder et al. have also used hybrid classical–quantum neural networks within the image domain of vehicle traffic classification. The results showed a significant improvement in robustness against adversarial attacks with well-defined boundaries between classes [6]. This trend is also followed for other computer vision tasks. For instance, Rajesh et al. and Trochun et al. have successfully used hybrid and quantum convolutional neural networks for image tasks, thereby paving the way for integrating QCNNs within the biomedical domain [7], [13]. Recent research has also extended these results to the realm of multi-modal and multi-class problems. To illustrate this point, Gordienko et al. created a quantum-classical convolutional neural network, which combines the standard convolutional neural network with ”quanvolutional” layers. They showed the efficacy of this model on a variety of image datasets, which are diverse in terms of class [10]. In a similar manner, Fan et al. and Ranga et al. carried out extensive evaluation of their hybrid models on imaging data, which confirms the fact that these models are not only scalable but also efficient. In other words, these models can decrease the parameters while maintaining the accuracy. This, in turn, would be highly beneficial for medical imaging, as the resources are often scarce.

2.2.Quantum Data Encoding and Variational Circuits

A major challenge that has often hindered the hybrid modeling process is the efficient conversion of classical medical images into quantum states. Several

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approaches have been identified, including amplitude encoding and angle encoding. However, the latter has gained popularity in modern NISQ- era devices based on its practical implementability. The significance of this was also noted in the research conducted by Hur et al. to examine quantum convolutional neural networks (QCNNs); the encoding maps used in the design of the models determine the expressiveness of the models [3]. At the heart of most HQCNN frameworks is the concept of Variational Quantum Circuits (VQCs), which essentially act as the main learning blocks. Through the studies of Chen et al. and Yousif et al., it has been made evident that these VQCs can significantly improve the learning of features in X-ray image classification. This is because the quantum variational layer is able to learn complex nonlinear features that might not be learned with classical convolutional layers [8], [9]. This has further been validated through the frameworks proposed in the studies of Fan et al. and Hafeez et al., where the learning efficiency is enhanced while at the same time removing unwanted architectural complexity from the VQCs.

2.3.Comparisons With Purely Classical and Quantum Approaches

Current literature on the topic indicates that hybrid quantum-classical models are able to perform much better in adverse conditions, including low-data and noisy conditions, compared to conventional convolutional neural network models. Researchers such as Dong et al. and Huang et al. indicate that hybrid quantum-classical models have shown significant robustness and generalization compared to conventional classical models. Although conventional quantum models have shown significant potential, there are a number of challenges associated with them, including hardware challenges. The hybrid quantum-classical approach has shown significant promise in addressing this issue by using classical convolutional neural network models for feature extraction and quantum circuits for higher-level feature transformations. This is also supported by Yousif et al. and Hafeez et al. through their findings, which indicate that hybrid quantum-classical models can be used for achieving high accuracy with a reduced number of parameters, an important factor in clinical applications where efficiency is of utmost importance Shown in Figure 1.

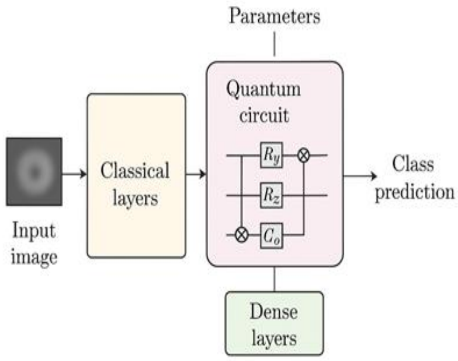

Figure 1 General Architecture of a Hybrid Quantum–Classical CNN Integrating Classical Convolutional Layers with Variational Quantum Circuits

2.4.Challenges, Hardware Limitations, and Future Outlook

Despite the rapid pace of current advancements, the practical application of hybrid models from the laboratory to a real- world clinic remains a difficult challenge to overcome. The major problem with current quantum processor technology is that they are subject to a lot of ”noise,” have ”shallow” circuit depths, and a critical lack of ”qubits.” All of this makes it extremely difficult to directly” encode” a “high-resolution” Shown in Table 1.

Table 1 Selected Literature on Hybrid Quantum–Classical CNNS

Study	Use-Case	Quantum Component	Dataset	Key Result
Dong et al. [5]	Brain tumor MRI	Hybrid QC–CNN	Multi-class MRI	Improved accuracy via enhanced hybrid layers

Majumder et al. [6]	Traffic image classification	Hybrid deep QCNN	Adversarial dataset	Higher robustness under attack
Li et al. [1]	General image classification	Hybrid QCNN with VQC	Benchmark datasets	Improved performance with fewer parameters
Huang et al. [2]	Adversarial image analysis	Hybrid QC–CNN	Medical and synthetic data	Reduced sensitivity to perturbations
Gordienko et al. [10]	Multi-class image classification	Quanvolution+ CNN	Multimodal datasets	Higher accuracy with multimodal hybrid layers
Chen et al. [8]	General image classification	QCNN with VQC	Digital He alth dataset	Effective nonlinear feature extraction
Yousif et al. [9]	X-ray classification	QCNN with new circuits	Chest X-ray	Enhanced classification efficiency

medical image onto a quantum circuit without running into a"brick wall" [3]. However, there is a silver lining to this dark cloud, as recent research indicates that even "very 'shallow' VQCs, used as part of conventional classical CNNs, can pro- vide a performance 'boost'" [4], [12]. As quantum processor technology improves, reaching the point where" quantum error correction" becomes a reality, this hybrid technology will likely become much easier to implement. It may very well become the" go-to" technology for the next generation of medical imaging tools.

3. Methodology

This section discusses the proposed architecture of the Hybrid Quantum-Classical Convolutional Neural Network (HQCNN) in the context of medical image classification. The proposed architecture is motivated by the idea of using classical feature extraction and quantum processing in the context of image representation learning. Our proposed HQCNN is designed to fill the existing gap between feature extraction in the conventional sense and quantum processing. In particular, we propose a novel approach to combine a conventional front-end CNN with a quantum variational block, in line with recent trends in medical image processing research [1], [4], [5]. Our proposed model is divided into three stages.

3.1.Classical Convolutional Backbone:

The first stage is concerned with extracting spatial features from the input image. For this purpose, two consecutive layers of Conv2D with max pooling are applied to extract features such as edges, gradients, and textures. A lightweight backbone is used for feature representation to reduce complexity, as suggested by various studies [2], [7].

3.2.Quantum Embedding:

In the second stage, the extracted features are repre- sented as a quantum state, and this is achieved by a technique called angle encoding, in which the values of the features are represented as a combination of rotation gates. This technique is commonly employed in NISQ-based architectures due to its efficiency and scalability. Generally, 8–16 dimensional feature vectors are represented as a combination of 3–5 qubits [3].

3.3.Variational Quantum Circuit (VQC):

Quantum processing is composed of a parameterized VQC with rotation gates denoted as Ry and Rz, fol- lowed by entangled CNOT operations in a ring structure. This has been demonstrated as a successful approach in hybrid learning-based functions [8], [9], [12]. The mea- sured outputs are used as classically processed values in fully connected layers.

3.3.1. Data and Preprocessing

The proposed model can be tested on existing medical image datasets such as MedMNIST, Chest X-ray datasets, or Brain MRI datasets. Some of the standard preprocessing operations performed on the image are resizing the image to a specific size, such as 128 × 128, normalization, etc. Converting the

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image to grayscale is optional.

3.3.2. Training Setup

A general training configuration for the suggested model might involve an optimization process with algorithms like Adam, with specific learning rates and batch sizes. The hybrid quantum parts of the model might be simulated with tools like PennyLane or Qiskit, which are popular in current research.

3.3.3. Evaluation Metrics

The performance of the model may be evaluated using various metrics for classification problems, including accuracy, precision, recall, and ROC-AUC. Furthermore, the complexity of the model and its efficiency from a computational point of view may also be taken into consideration.

4. Results

4.1.Expected Outcomes and Analysis

Expected Classification Performance: Based on recent hybrid quantum-classical learning results, it is expected that the HQCNN architecture will show improved performance compared to classical CNN models. This is particularly true for low-data and noisy environments [2], [5]. Previous research on hybrid quantum-classical learning has shown promising results in effectively learning complex nonlinear relationships. This is likely to result in improved accuracy, sensitivity, and reliability of the learning outcomes for medical imaging datasets such as MedMNIST and Brain MRI, it is expected that the integration of variational quantum circuits with CNN will improve feature representation. This is likely to result in improved detection of subtle patterns and better generalization for different classes, particularly where classical learning is likely to perform poorly due to low data availability.

Model Complexity and Efficiency: Another significant aspect of hybrid architectures is their parameter efficiency. The literature indicates that HQCNN-based models have the ability to deliver performance while requiring less trainable parameters compared to classical CNNs [4], [12]. This is a significant aspect since it is possible for the suggested approach to deliver efficiency in terms of memory and computational efficiency, making it possible for it to be used in resource-constrained environments. Practically, it is worth pointing out that the ability to reduce the size of a model without affecting performance is significant in healthcare applications where there is a possibility of limited resources. The suggested HQCNN-based approach is significant since it can deliver performance.

Impact of Quantum Component: The addition of the Variational Quantum Circuit is expected to significantly impact the feature transformation. Past studies have shown that a quantum circuit is capable of mapping classical data to a higher dimension, thus enhancing feature separability and the ability of the model to capture small changes in the data [8], [9]. In comparison to the classical model, the hybrid model is expected to have a better representation. The lack of this feature in the classical model shows the need for the addition of the quantum components.

Robustness to Noise and Data Variability: It should be noted that hybrid quantum-classic models are generally regarded as being more robust to noise and data perturbations. The quantum embedding process may be regarded as a type of implicit regularization, which enables the model to maintain its performance even if the data fed to the model is noisy or unbalanced. As implied in previous research, hybrid models may be regarded as being more stable than classical models, which makes them applicable in real-world scenarios in the health domain where the quality of the data cannot be guaranteed.

Interpretability Considerations: Additionally, the pro- posed HQCNN architecture may have advantages in terms of interpretability. For instance, the variational quantum circuits are expected to learn unique feature subspaces, and this may help in the interpretability of the features in relation to the classification outcome. This is especially important in the medical field, where interpretability is a critical aspect. Compared to the conventional deep learning architectures, which have been found to be black boxes, the hybrid architecture may have a more structured outcome, which can be further explored in relation to interpretability.

Limitations and Future Work: However, the approach also has some limitations. First, the research focuses only on the architectural design and theoretical analysis. There is no experimental validation. In addition, there are some limitations in

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quantum hardware, which include noise, decoherence, and the number of qubits available. The future work will involve the implementation of the HQCNN model and validation of the performance using real- life datasets and quantum simulation tools. There is also a need for further research to improve the design of the quantum circuit Shown in Table 2.

Table 2 Comparison of Classical CNN and Proposed HQCNN (Expected Characteristics)

Criteria	Classical CNN	Proposed HQCNN
Feature Representation	Moderate	High (Quantum-enhanced)
Performance in Low Data	Limited	Improved (Expected)
Robustness to Noise	Moderate	High (Expected)
Parameter Efficiency	High Parameters	Reduced Parameters (Expected)
Generalization Ability	Moderate	Improved (Expected)
Computational Complexity	High	Optimized Hybrid
Interpretability	Limited	Potentially Improved

5. Discussion

The newly proposed architecture of the Hybrid Quantum- Classical Convolutional Neural Network (HQCNN) follows a new paradigm in the domain of medical image analysis, where classical deep learning models are being supplemented with quantum computing to enhance the expressiveness of feature learning. Instead of depending only on conventional convolutional neural networks, the inclusion of quantum computing through variational quantum circuits adds an extra degree of expressiveness to the network, which enables the network to learn non-linear relationships that might be difficult to identify through classical models. The domain of medical images often requires subtle pattern changes to be critical for a particular diagnosis. Existing literature on hybrid quantum-classical models of learning indicates that such models can lead to improved performance, particularly in environments that are limited, noisy, or imbalanced in terms of data [2], [5], [9]. This is particularly evident in terms of the ability of quantum circuits to map data in higher-dimensional feature space, thus improving the ability to separate classes of data. Based on this, the proposed model, HQCNN, is likely to benefit from such improved capabilities in classification, particularly in medical imaging environments. Another notable feature of the suggested model is its parameter efficiency. It is a known fact that deep learning models require a large number of parameters, which can lead to increased complexity. However, hybrid models have shown promising results in terms of achieving optimal results using a smaller number of trainable parameters [4], [12]. It is possible that this feature of the model can make it even more suitable for deployment in real-world scenarios, especially when the environment is computationally challenged, such as mobile devices. From a practical point of view, the trade-off between performance and efficiency is a fundamental requirement in medical scenarios. This is because, in most cases, the volume of data in the medical field is quite large, and the ability to efficiently process the data without compromising the accuracy is a fundamental requirement. This challenge, in the proposed HQCNN framework, is addressed by the potential integration of the advantages of the classical and quantum approaches. Robustness to noise and data variability is another important factor in medical image classification. In a real-world set- ting, medical images are prone to noise, changes in imaging conditions, and differences in imaging equipment. Previous research indicated that quantum embedding can function as an implicit regularization method, enabling robust performance in noisy and changing environments [2], [6]. The integration of quantum feature transformation is expected to provide robust performance compared to classical approaches. Besides the robustness, the novel HQCNN architecture also promises certain benefits in terms of interpretability. Deep learning models, in general, are often criticized for their "black box" nature. However, the hybrid approach might allow for the investigation of new possibilities in feature representation. The variational quantum circuits are likely to learn feature subspaces that are different and, possibly, more organized, which might be beneficial in terms of the interpretability of the classification process. In the context of medicine, it is especially critical. Despite these possible benefits, there are a number of challenges. One of the main challenges is the current state of quantum hardware, which is still limited in terms of noise, number of qubits, and coherence time. This limits the practical application of the hybrid model and forces the use of simulation-based environments in the majority of the research studies. It is expected that with the development of quantum hardware, these limits will gradually decrease, allowing more realistic applications of the hybrid model. Another challenge comes from the design of efficient quantum circuits and encoding strategies. The most efficient method of representing classical information in quantum sys- tems still needs to be found. Moreover, the training of the hy- brid quantum model also poses a challenge, which might add complexity to the optimization process. All these challenges need to be addressed to enhance the HQCNN models. Furthermore, the connection between quantum-enhanced feature representations and clinically relevant interpretations is another important research area. Although the hybrid model is able to recognize complex patterns, the interpretation of these patterns in a manner that is meaningful and interpretable for medical professionals is not trivial. Visualization tools and interpretability frameworks specific to quantum-enhanced models will be necessary in the future. Overall, the proposed HQCNN architecture is a promising advancement in the integration of quantum computing and medical image analysis. It is a hybrid architecture designed to enhance the learning potential and generalization ability of the proposed architecture, along with the efficient computation capability. It is worthwhile to note that, with the advancement in the field of quantum machine learning, the proposed architecture is bound to contribute significantly to the design and development of the next generation in intelligent health care systems.

Conclusion

This work proposes a Hybrid Quantum-Classical Convolutional Neural Network (HQCNN) architecture for medical image classification, emphasizing its prospect as a novel and advanced technique in the field of medical image classification, which combines classical deep learning and quantum computing techniques. As derived from the insights of the existing literature, hybrid models show great potential in enhancing the performance of classification tasks, especially in situations where the dataset is noisy or scarce. Although the practical application of the proposed model is currently hindered by the limitation of existing quantum hardware, it is believed that the rapid advancements in the field of quantum computing in the coming years will make the practical application of hybrid models like the proposed one feasible. This work proposes a theoretical architecture for the pro- posed model, and in the future, it is planned to be implemented and validated on actual datasets and frameworks. As the field of quantum computing and hybrid learning techniques continues to evolve, it is believed that the proposed model, which is based on the architecture of the proposed HQCNN, has great potential in significantly contributing to the development of intelligent and efficient medical diagnosis techniques in the future.

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