

QUANTUM CONVOLUTIONAL NEURAL NETWORK FOR PANCREATIC CANCER IMAGE CLASSIFICATION

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ABSTRACT

Pancreatic cancer is among the most lethal malignancies, also late-stage diagnosis causes poor prognosis and significant fatality rates. Early identification of computed tomography (CT) images may improve survival rates nevertheless, current approaches suffer from noise, artefacts, and complex data structures. Quantum convolutional neural networks (QCNNs) are a possible substitute since their application of quantum principles like superposition and entanglement helps increase the accuracy of feature extraction and categorisation. This review investigates the integration of QCNN with deep learning models, including ALOCNN-GRU and FOA-based SVM optimization for pancreatic cancer detection. The hierarchical convolution and pooling layers of QCNN make it easier and more reliable to find cancerous tissue in medical images. Moreover, advances in segmentation and early diagnosis entail the Richer Convolutional Feature (RCF) approach and the Normalised Information for Modular Divergence Quality (NESTED) method. The findings provide a more accurate and dependable pancreatic cancer detection as well as highlight how well QCNN could change medical picture classification. Future developments in multi-scale learning and optimisation strategies might greatly improve diagnosis accuracy and treatment planning.



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1. INTRODUCTION

Medical imaging and its classification are rather important in the screening and early identification of cancer, preoperative evaluation and staging, differential diagnosis, follow-up, and therapeutic evaluation.

1.1 Overview of Techniques

Convolutional Neural Networks are perfect for image classification problems since they can extract pertinent data via convolutions (O'shea & Nash, 2015). When a trainable kernel is significantly smaller than the original image scans through, it generates a series of images with reduced dimensionality. Recent work has generated implementations of quantum convolutional neural

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networks (QCNNs) (Cong et al., 2019). This method starts with a state that codes classical information and then uses convolution and pooling layers in a digital quantum circuit. Applied to quantum error correction, QCNN has proved better than current methods in identifying quantum phases. Furthermore, several QCNN variants (Li et al., 2020b; Hur et al., 2022; Bokhan et al., 2022) are proposed for image categorization. Some of these models have an encoding layer that uses a quantum kernel that can't be trained to do convolution and a highly entangled circuit (Henderson et al., 2020). Using QCNNs for medical image identification has generated strong interest (Matic et al., 2022; Houssein et al., 2022). As the number of layers goes up, entanglement seems to reach a maximum, which makes these models more expressive (Sim et al., 2019; Jäger & Krems, 2023). Even so, it's hard to use these models with digital quantum circuits during the qubit coherence periods these days because of noisy intermediate-scale quantum (NISQ) processors. For getting the most out of both digital and analog quantum computing, the digital-analogue quantum computing (DAQC) paradigm has been put forward.

Combining the flexibility of digital quantum gates with the power of multipartite-entangled analogue blocks (Parra-Rodriguez et al., 2020; Yu et al., 2022; Martin et al., 2020; Lamata et al., 2018) results in this. Several diseases have made use of QCNN for its identification in the form of picture classifications, particularly for malignancies like pancreatic, brain, breast, etc. Pancreatic cancer (PC) affects health, so we must evaluate how it affects the pancreas; hence, we must comprehend it using picture categorisation since the disease is usually discovered at an advanced stage and lacks distinct symptoms. Usually, PC is defined by hypervascularity and extensive fibrous stroma, which explain the inadequate enhancement of the tumour relative to the pancreatic parenchyma surrounding it on computed tomography (CT). These result in low CT diagnostic accuracy and sensitivity to tumour identification. Also, there isn't a standard imaging screening procedure right now. This means that the accuracy of PC diagnosis and staging depends on the right protocol, post-processing technique, and the experience of the radiologist. Stated differently, especially in relation to early-stage small tumours, radiologists find it somewhat challenging to detect PC with merely a CT scan.

1.2 Pancreatic Cancer: An Overview

Pancreas solid tumours most often found are pancreatic ductal adenocarcinoma (PDAC). More generally referred to as "pancreatic cancer," it is aggressive and challenging for treatment (Wolfgang et al., 2013). Pancreatic cancer (Kamisawa et al., 2016) is highly fatal and has a rather poor prognosis. The 5-year survival rate is still a sad 8.7% (Howlader et al., 2016), notwithstanding recent developments in surgical methods, chemotherapy, and radiation treatments. Only 10–20% of individuals show up at the localised disease stage, at which comprehensive surgical resection and treatment offer the best chance for

life. Their 5-year survival rate is around 31.5%. The remaining 80–90% of patients miss the chance to gain from surgery depending on general or local metastases at the time of diagnosis (Khorana et al., 2017; Balaban et al., 2016).

Still, a terrible enemy, pancreatic cancer claims lives with a shockingly rapid speed. Its aggressive nature and deceptive presentation contribute to its poor prognosis, with a 5-year survival rate of approximately 10% (Takhar et al., 2004). The harsh reality is still that early detection is absolutely crucial for bettering the outcomes in this terrible illness. This urgency emphasises the critical part CT image analysis performs in revealing pancreatic tumours before they create their menacing shadow.

Many times, current pancreatic cancer diagnosis techniques depend on late-stage markers such as jaundice and stomach pain (Chari, 2007). By now, the tumour has probably crept into nearby tissues and travelled to far-off organs, greatly reducing therapy options and survival rates (Al-Hawary et al., 2014). On the other hand, early detection—ideally in the pre-symptomatic stage—offers some hope. Patients diagnosed with localised pancreatic cancer had a much higher 5-year survival rate—maybe reaching 60%, according to studies (Zhou et al., 2017). This clear disparity highlights the urgent need for strong and accurate techniques to detect the illness in its earliest phases.

Early pancreatic cancer detection has become mostly dependent on CT imaging because of its non-invasive character and precise view of internal organs. But for conventional interpretation, the sometimes delicate and complicated traits of pancreatic tumours provide a great deal of difficulty. Understanding these subtleties requires a keen eye and extensive experience, potentially leading to misdiagnoses and missed opportunities for prompt action (Chen et al., 2016). This emphasises the requirement of sophisticated CT image analysis methods that can not only detect a tumour but also precisely describe its stage and aggressiveness (Vargas et al., 2004). Within the field of medical image analysis, even experienced doctors often find it difficult to handle minute details or concealed elements in scans containing vital diagnostic signals.

Recent progress in AI, especially deep learning techniques like CNNs, has changed the way medical picture classification tasks are done. They can now accurately identify tumours, stage illnesses, and separate organs. But sometimes, when battling with complicated data structures present in medical images like noise, artefacts, and non-linear interactions between pixels, classical CNNs are essentially limited by the constraints of the silicon world. This bottleneck highlights the increasing potential of quantum computing, particularly quantum convolutional neural networks (QCNNs), which are poised to challenge medical image analysis and unlock previously unattainable diagnostic capabilities.

QCNNs, with their inherent quantum characteristics, have the potential to extract features that enhance the presentation of images in ways that conventional CNNs cannot. For classification, this could produce stronger and more discriminative properties. CT scans generate enormous volumes and QCNNs may more effectively extract patterns as well as features than conventional CNNs. CT scans, often including noise and artefacts, might complicate correct classification. Quantum computing's ability to look into non-linear correlations should help find faint patterns in CT scans that traditional methods would miss, which would make the diagnosis more accurate.

Operating on quantum states, QCNNs use quantum mechanical ideas including superposition and entanglement to provide three main advantages over their classical counterparts. First of all, especially for large medical datasets, the intrinsic parallelism of quantum systems enables quick exploration of enormous parameter spaces, facilitating faster and more efficient training of complicated models (Chen et al., 2016). Second, quantum states may hold more data than classical bits. This means that QCNNs can find small patterns and hidden connections in medical images that classical CNNs might miss. This could lead to more accurate diagnoses and the discovery of new disease signs. At last, the inherent noise resistance of quantum states shows promise for overcoming obstacles presented by noisy medical pictures; hence, perhaps improving the dependability and generalisability of QCNN models in clinical environments (Yang et al., 2018).

2. QCNN AND FUNDAMENTAL OF QUANTUM COMPUTING

Quantum computers were able to do amazing things that classical computers couldn't. They coded using the parallelism of quantum bits and contemporary quantum physics ideas like superposition and entanglement, which guided their behaviour. Researchers see quantum computing in the field of machine learning (ML) as a powerful tool to apply in other domains, even if development in real-time is still in its developing stage and is theoretical. Researchers are currently conducting a study on this topic. Quantum Convolutional Neural Networks (QCNN) can be used in computer vision applications like CNN to get the most out of a powerful multi-class classification model. Reviewed and established to have efficient performance using ML hyperparameters, the gradient descent approach is used for optimising quantum computers (Chen et al., 2021; Oh et al., 2020). Retaining the CNN layers complete, QCNN creates its neural network using quantum bits (qubits/quons), the same as binary bits in conventional computing. The totally linked layer did not preserve the observed association between the adjacent picture pixels, while it performed really well in ML. CNN can, however, restrict the correlation, so enhancing performance. At the very end of a CNN is a fully connected layer and a stack

of convolutional and pooling layers with activation functions. By passing the input data—pictures—through the pooling, convolutional, and fully connected layers, one can obtain feature maps. These feature maps lead to classification findings thereafter. Using ML in quantum physics expressed in Hilbert space should transfer the quantum data into conventional computer data. Many studies and investigations were conducted to answer current problems, advance the present technologies, and build new frameworks using QCNN (Chen et al., 2017; Killoran et al., 2019).

The data size in quantum physics rises with system size. In a quantum environment, data stored in qubits is sent to a quantum computer to eagerly turn on CNN architectures. CNN models for quantum systems employ pooling and convolution layers. Applying several qubit gates between consecutive qubits reveals hidden states in a convolution layer. Applying 2-qubit gates helps a pooling layer to shrink quantum system size. In a small system, completely connected layers predict categorical outcomes. QCNN, which are based on quantum physics and architecture used in CNN, are useful for making systems that can recognise objects and put pictures into groups. The architecture of QCNN is like that of CNN, but qubits are used to build a neural network between the CNN architecture's stacked layers (Kumar et al., 2020a; 2020b; Franklin, 2020).

Linked by the qubit neural network, a set of convolutional layers and pooling layers make up the architecture. Two states comprise the qubit neural network: 1 (firing or active) and 0 (resting). Quantum circuits in the convolutional layer find hidden data by pairing pixels in the input image that are next to each other in a straight line. The convolutional layer passes the picture through and applies activation functions to derive the corresponding feature maps. It passes via the pooling layer to shrink feature maps' size. Additionally, by filtering away the extraneous resources required for learning, quantum circuits at this layer help prevent overfitting. We repeat the aforementioned procedure until we sufficiently reduce the data size. The feature maps then transit via the fully connected layer to produce the categorical findings. We reviewed the training of the model using the performance variance between the produced label and the originally defined label (Prasad & Shivashankar, 2019). Figure 1 shows the CNN's comparable quantum circuit layout. Three methods by which quantum computing paradigms are implemented using classical data: QC with classical data, a classical computer with quantum data, and QC with quantum data.

CNNs are a type of deep learning model that uses sound to help with things like identifying objects and sorting pictures (Aradhya, 2020; Biswas et al., 2018; Jain et al., 2020). CNN architecture produces the feature maps by first including fully connected layers, then convolutional layers, and pooling layers. For some of the more complex, high-degree Poisson events, CNN still cannot

react in real time. Quantum computing for information processing is defined by the postulates and features of quantum mechanics, specifically quantum bits, interference, superposition, and entanglement. Faster and better resolution of difficult issues is provided by quantum computers than by traditional ones. The basic unit in a quantum computer is a qubit to manage data, just like in conventional computing. In QCNN architecture, quantum bits (qubits) are added to the rest of the structure that is similar to CNN for the neurons. By adding quantum mechanics to regular neural networks, the system has become more stable and can handle a wider range of problems, as well as performing much better (Meghana et al., 2019). Building QCNN models and algorithms mostly depends on CNN as the framework. The intended use determines the architecture and frameworks of QCNNs, which in turn rely on the domain from which the application has to start. Nevertheless, the construction of QCNN models extensively incorporates new physics ideas and signal processing, complementing CNN architecture. In essence, two approaches define the construction of QCNN designs: first, ordinary CNN equivalent structures (Aradhya et al., 2019).

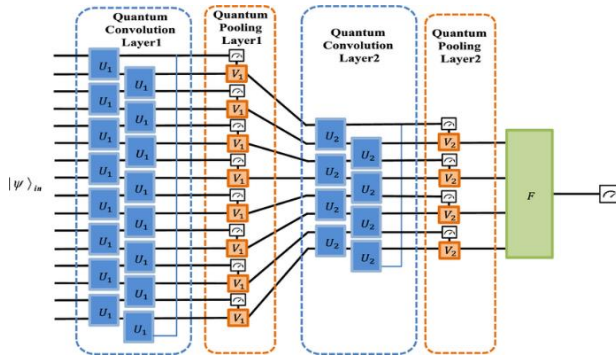


Figure 1. Application based architecture of QCNN

Designed for quantum-based image categorisation, especially for operations like pancreatic cancer diagnosis, Figure 1 shows the QCNN architecture. Beginning with an input quantum state ($|\psi\rangle_{in}$), which stands for the quantum-encoded image data, the process proceeds. Like classical convolutional layers extracting spatial information, the first stage—Quantum Convolutional Layer 1—applies unitary operations (U_1) to the input qubits in Quantum Pooling Layer 1 (V_1) and then lowers the qubit count while maintaining the necessary information, hence guaranteeing computing efficiency. Quantum Convolutional Layer 2 then handles the lowered quantum representation using another set of unitary transformations (U_2), thereby improving the obtained features. Quantum Pooling Layer 2 comes next, further lowering qubit dimensionality by pooling activities (V_2). Finally, the quantum data that has been processed is sent to a fully connected quantum layer (FFF). This layer takes all the features that have been collected and uses them together to make a final classification. At the end of the pipeline, the last output of a quantum measurement operation can be thought of as a binary classification result: tissue that is cancerous

or not cancerous. By means of hierarchical quantum convolution and pooling operations, this architecture optimises qubit usage and uses quantum computation to improve feature extraction and classification performance.

3. QCNN MODEL FOR PANCREATIC CANCER IMAGE CLASSIFICATION

Stacking several convolution layers and pooling layers helps QCNN extract information from images. Whereas the convolution layer gathers local information from the input (Xuan & You, 2020), the pooling layer is used to reduce the size of the feature map. Multiple convolution layers and pooling layers let QCNN progressively extract image abstract features (see Figure 2). Although the feature extraction techniques of various kinds of model structures are rather varied, the particular feature extraction is somewhat correlated with the CNN structure chosen by the fusion method.

Usually following feature extraction, QCNNs consist of one or more fully connected layers mapping features to the final category score. Every neuron in the fully connected layer is coupled to every other neuron in the layer below; the activation function weights each neuron's output using all of the inputs from the previous layer (Muhammad et al., 2019).

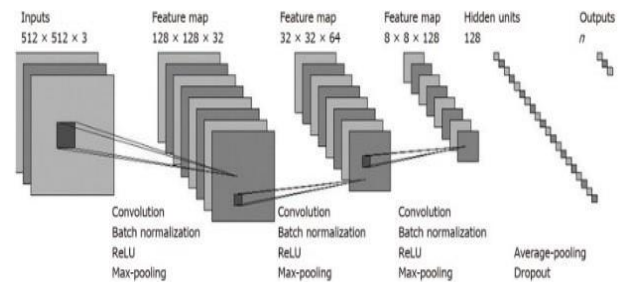


Figure 2. Model of CNN (Ma et al., 2020)

Combining a computer-aided diagnosis model with computerised pancreatic cancer segmentation and classification helps one to keep track of, classify, and arrange cancer cases. Deep learning-based methods can offer therapeutic needs accurate visual interpretation. The image pre-processing allows one to remove noise from the obtained dataset by means of several image alterations. The pre-processing can be achieved using a hybrid Gaussian and median filter. Quantum encoding and operation provide a fresh detector capacity and improve the fitness optimization algorithm (FOA).

Finally, we applied the enhanced FOA to optimise the activity variable device's (SVM) parametric amount, thereby establishing a better SVM classification. The Richer Convolutional Characteristic system (RCF) (Hussein et al., 2019, Li et al., 2020a) was suggested for the exocrine gland cleavage of learnt professional CT images of malignant neoplastic disease. This network

idea looks at how the picture's overall linguistic context information (exocrine gland) can be used to do gland cleavage if an up-sampling framework is applied instead of a simple up-sampling technique. The suggested technique makes good use of CT scans. Adding the exocrine gland to the more complex convolutional mathematical function makes the RCF Network's multi-layer test system better and raises insulin production by the pancreas by about 1%. Multiscale input and information-based experiments, moreover, improved learning could result in better network performance. We utilized the Normalised Information for Modular Divergence (NESTED) method (Dhruv et al., 2021) for early identification of pancreatic tumour therapy responses.

4. DISCUSSION

In the classification pipeline for pancreatic cancer using Quantum Convolutional Neural Networks (QCNN), the process begins with raw CT scan images as input. These images require a series of preprocessing steps to standardize their format and ensure compatibility with quantum encoding methods. Typical preprocessing operations include resizing the images to a fixed resolution, normalizing pixel intensities, and adjusting image contrast to enhance visibility of anatomical features. This step ensures consistency across the dataset and facilitates effective encoding into quantum representations. Following preprocessing, the classical image data is transformed into quantum states through encoding mechanisms such as amplitude encoding or qubit-based encoding. Amplitude encoding compresses classical information into the amplitude of quantum states, allowing efficient representation of high-dimensional data, while qubit encoding maps pixel values onto individual qubits, offering simpler implementation at the cost of higher qubit usage.

After encoding, the quantum data undergoes feature extraction, performed by parameterized quantum circuits (PQCs) that simulate convolutional operations. These circuits utilize quantum gates such as Hadamard, Controlled-Z, and SWAP gates to detect spatial patterns and encode complex features within the image data. The Hadamard gate introduces superposition, enabling parallel processing of features, while the SWAP and Controlled-Z gates manage entanglement and spatial dependencies, mimicking the behavior of classical convolutional filters. The extracted quantum feature maps are then subjected to pooling operations, which reduce dimensionality and highlight the most significant features. Quantum pooling is implemented using strategies such as Probabilistic Amplitude Measurement (PAM) or Maximum Amplitude Selection (MAS). PAM selects outputs based on measurement probabilities, while MAS identifies the highest-amplitude quantum states for feature retention. These pooling strategies are crucial for downsampling and maintaining computational efficiency within the quantum architecture.

To facilitate the transition from quantum to classical domains, measurement techniques are applied to collapse the quantum states into interpretable classical values. This step often involves additional normalization and dimensionality reduction to prepare the feature vectors for the subsequent classification stages. Following measurement, the extracted features are passed through quantum dense layers, also implemented as PQCs. These layers are responsible for learning decision boundaries that distinguish between cancerous and benign regions of the pancreas. At this stage, the model produces a final quantum state, from which a probability distribution is derived—indicating the likelihood of the image belonging to each diagnostic class (e.g., cancerous head, body, tail, or healthy tissue). To optimize the model's performance, variational quantum circuits (VQCs) are introduced. These circuits leverage optimization algorithms such as Adam or gradient descent to iteratively update the circuit parameters and minimize classification error. Optimization is driven by a defined loss function, which may integrate both quantum and classical components to guide the training process effectively.

The integration of QCNNs into medical image classification offers several significant advantages. One of the most notable is the potential for superior feature extraction, enabled by quantum phenomena such as superposition and entanglement. These properties allow QCNNs to capture more complex, non-linear, and high-dimensional features than traditional CNNs, potentially leading to enhanced classification accuracy. Moreover, quantum models demonstrate reduced sensitivity to noise, which is advantageous in the clinical context where image quality may vary due to acquisition conditions. Additionally, the generalization ability of QCNNs is believed to be higher, as quantum models may learn more abstract and transferable features from relatively limited training data, which is particularly relevant for medical datasets that are often small and imbalanced.

Despite these promising benefits, several challenges must be addressed before QCNNs can be deployed at scale. The most critical limitation is the scarcity of qubit resources on current quantum hardware. Present-day quantum computers support only a limited number of qubits, constraining the size and depth of QCNN architectures and preventing the modeling of high-resolution medical images. Moreover, quantum noise and system decoherence introduce errors in computations, which can significantly affect model performance. These issues underscore the need for robust quantum error mitigation techniques tailored to image classification tasks. Another challenge relates to the availability of high-quality annotated datasets. Although numerous CT scan images of the pancreas exist, not all are labeled with the clinical precision required for supervised learning. The performance of QCNNs is highly dependent on the quality of training data, making the curation of reliable

datasets a key area of concern. Furthermore, the preprocessing and encoding of large-scale medical image datasets into quantum states remain computationally intensive and technically demanding, especially given the hardware limitations.

Several promising future research directions can be pursued to overcome these limitations and harness the full potential of QCNNs. Firstly, the development of novel encoding schemes that are both memory-efficient and capable of preserving spatial and semantic information is critical. Innovations in encoding could enable better compression of image data into quantum circuits while maintaining high classification performance. Secondly, more effective quantum feature extraction techniques must be explored. This includes designing new PQC architectures tailored for medical imaging, capable of isolating subtle patterns associated with disease phenotypes. These circuits could integrate domain-specific priors from radiology to improve interpretability and clinical relevance. Thirdly, researchers should focus on building noise-resilient quantum models that can function reliably even on noisy intermediate-scale quantum (NISQ) devices. This may involve leveraging classical denoising techniques in conjunction with quantum gates or developing entirely new quantum error correction protocols for medical data. Another fruitful area of research is the design of hybrid quantum-classical models. These architectures combine classical convolutional layers with quantum classification layers, thus reducing quantum resource requirements while benefiting from quantum advantages in the final decision-making stages. Hybrid models offer a practical compromise that can be implemented on current hardware and still deliver performance gains. Additionally, integrating domain knowledge and expert-driven guidance into quantum models—through supervised attention mechanisms or radiologist feedback—can help prioritize diagnostically relevant features and improve the model's trustworthiness.

In conclusion, QCNNs represent a groundbreaking frontier in medical image analysis, especially for complex tasks like pancreatic cancer classification. By exploiting the principles of quantum mechanics, QCNNs

offer the potential for enhanced feature extraction, improved classification accuracy, and better generalization across diverse datasets. However, practical implementation remains challenged by current hardware limitations, noise, and data availability. Overcoming these hurdles will require a multidisciplinary effort involving quantum computing, machine learning, medical imaging, and clinical expertise. If successfully developed, QCNN-based systems could revolutionize diagnostic workflows and enable earlier and more accurate detection of pancreatic cancer, ultimately improving patient outcomes.

5. CONCLUSION

This review paper suggests that the most important medical research is being done to foresee cancer, which could impact many different parts of the body and show itself in numerous forms. Among the most regularly occurring malignancies deemed to be incurable is pancreatic cancer. Medical research has progressed to enable automated systems to identify cancer stages and, if found, provide enhanced diagnosis and treatment recommendations. Moreover, it can be concluded that the diagnosis of pancreatic cancer depends critically on CNN's quantum computation. Combining deep learning models, such as QCNN, and FOA-based SVM optimizations, enhances photo segmentation and classification accuracy. NESTED supports early diagnosis and treatment evaluation, but the RCF method further enhances segmentation. By combining many convolutions and pooling layers, QCNN effectively recovers visual features. This makes it possible to gradually separate data into smaller pieces. Convolution layers collect local features, whereas pooling layers trim feature map size for efficient processing. The selected CNN structure and fusion approach influence the feature extraction procedure. An activation function gives each neuron weighted inputs from the layer below it. After extraction, fully linked layers then convert these features into final classification scores. Future advancements in multiscale learning and optimisation techniques could enable even greater detection of pancreatic cancer and direct therapy options.

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