

Towards Fully Quantum Implicit Neural Representations

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1 Introduction

Quantum computing^{1,2,3} offers theoretical computational advantages,^{4,5,6} although these remain constrained in practice by the limited qubit counts and shallow circuit depths characteristic of the current Noisy Intermediate Scale Quantum (NISQ) era.^{7,8,9} This has motivated hybrid Quantum Machine Learning (QML) approaches¹⁰ that exploit the natural expressivity of quantum spaces, despite challenges including barren plateaus^{11,12,13,14,15} and local minima.¹⁶

An application of QML is Quantum Enhanced Computer Vision (QECV).¹⁷ Explicit quantum image representations such as the Flexible Representation of Quantum Images (FRQI)¹⁸ and the Novel Enhanced Quantum Representation of images (NEQR)¹⁹ offer lossless encoding, but require gate depths that scale poorly with image size, making them unsuitable for NISQ hardware. Parametrising these representations reduces gate complexity at the cost of accuracy.²⁰ Alternative approximate approaches, including Quantum Circuit Born Machines (QCBMs)^{21,22} and Quantum Generative Adversarial Networks (QGANs),^{23,24} encode image data into measurement outcome probabilities, but require normalised inputs, risk information loss, and become error-prone as probabilities reduce with the increasing size of input data. Quantum Implicit Neural Representations (QINRs) address these limitations by encoding coordinate data into the quantum system and using a variational ansatz to produce distinct outputs for each query coordinate.

QINRs extend classical Implicit Neural Representations (INRs), which are continuous differentiable functions mapping query coordinates to signal values, with data encoded in network weights and supporting arbitrary-resolution querying, making INRs well-suited to compression, super-resolution, and differential equation solving. Early MLP-based INRs^{25,26,27,28} struggled to capture high-frequency detail due to the frequency principle.^{29,30} This was addressed through periodic activations such as those used in Sinusoidal Representation Networks (SIRENs)³¹ and Fourier feature encodings,³² which can mathematically be shown to be equivalent to truncated Fourier series with network weights as coefficients.³³ However, as task complexity increases, classical INRs require an increasing number of trainable parameters motivating the search for alternative approaches capable of efficiently distributing parameters to preserve both non-linearity and representational power.³⁴

Quantum computing offers a natural alternative in the form of Parametrised Quantum Circuits (PQCs) as their outputs are mathematically expressible as Fourier series in their parameters³⁵ and are inherently differentiable. Models such as the Quantum Implicit Representation Network (QIREN)³⁶ exploit this with shallow data-reuploading³⁷ PQCs interleaved with classical layers, supporting tasks including compression, denoising,³⁸ super-resolution, and integration into QGAN frameworks.^{24,39} The Quantum Visual Field (QVF) model⁴⁰ takes a simpler approach, using classical pre-processing followed by a single PQC without classical post-processing. Together, these differing models raise the question of whether future QINRs should maximise fully quantum computation or treat PQCs primarily as expressive components within classical architectures.

Model	Encoding	H	R	A	MSE ($\times 10^{-5}$)	PSNR	P_q	P_c	P_t
VQA	R_x	–	20	2	34.9	34.6	1008	3	1011
VQA	R_y	–	20	2	56.3	32.5	1008	3	1011
VQA	R_z	–	20	2	15.8	38.0	1008	3	1011
VQA	Chebyshev	–	20	2	5.09	42.9	1008	3	1011
QIREN	R_z	2	5	3	1.81	47.4	864	137	1001
QIREN	Cheby (Arctan)	2	5	3	1.66	47.8	864	137	1001
QIREN	Cheby (Sigmoid)	2	5	3	1.50	48.2	864	137	1001
QIREN	Cheby (Softsign)	2	5	3	2.06	46.9	864	137	1001
QIREN	Cheby (Tanh)	2	2	6	2.60	45.8	864	137	1001

Table 1: Performance results and configurations of different quantum implicit representation models. H, R, A represent the number of hybrid, reuploading, and ansatz layers present in the model respectively. For the VQA models H is left empty as the architecture is different to the QIREN models. P_q and P_c represent the number of parameters used in quantum layers and classical layers respectively, and $P_t = P_q + P_c$ is the total number of parameters in the model. The best performing model is highlighted in bold.

All models were optimised using Mean Squared Error (MSE) loss and ADAM⁴⁵ with a learning rate of 1×10^{-2} and a linear decay schedule applied over 3000 epochs, simulated in PennyLane.⁴⁶ The target image for all experiments was the iconic *Camerman* image, down-scaled to 32×32 pixels and shifted so that the intensities ranged from -0.5 to 0.5 .

3 Results

Table 1 summarises the best-performing configuration for each model, with results restricted to models whose total parameter count satisfies $P_t \leq 1024$, resulting in minor compression and a fair basis for comparison between architectures.

The novel Chebyshev model illustrated in Figure 1 outperformed the equivalent architecture using standard angle encoding through Pauli rotation gates R_x, R_y , or R_z , although it did not surpass the baseline QIREN. Nevertheless, it achieved a competitive PSNR of 42.9 dB, demonstrating that Chebyshev encoding provides meaningful gains in expressivity. Notably, this result approaches the baseline QIREN performance, indicating that substituting the majority of classical parameters with quantum counterparts does not significantly compromise reconstruction quality.

Additionally, incorporating Chebyshev encoding into the QIREN framework, a novel contribution of this work, produced models surpassing the baseline under two compactification functions, Sigmoid and Softsign, further indicating the expressive benefits of Chebyshev-based coordinate encoding.

4 Discussion

These preliminary results demonstrate that expressive feature map encodings can improve QINR performance, with Chebyshev maps representing one promising instance. Future work will explore a wider range of encoding strategies, including other functional bases and learnable monotonically increasing encodings that retain the character of Chebyshev maps. The strong performance of the quantum-centric model further suggests that fully quantum QINR architectures are achievable, and future work will also examine near-fully quantum design configurations best suited to natural image representation, including analysis of target image pre-processing, eliminating classical post-processing entirely.

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