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Peer Review

Review of: "Hybrid Quantum Neural Networks with Amplitude Encoding: Advancing Recovery Rate Predictions"

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In this paper, the authors propose a recovery rate prediction method based on Hybrid Quantum Neural Networks (HQNN) with Amplitude Encoding to reduce data dimensionality and computational complexity. The overall structure of the paper is well-organized, and the proposed method demonstrates innovation, offering notable academic and practical value. However, several key issues require further exploration to enhance the theoretical depth, experimental rigor, and real-world applicability of the study.

1. Impact of Amplitude Encoding on Information Representation and Trainability

The paper highlights the exponential data compression advantage of amplitude encoding but does not critically examine whether this compression compromises the model's ability to represent information, particularly in high-dimensional scenarios where data normalization may lead to uneven information distribution. The primary distinction between angle encoding and amplitude encoding lies in how classical data is mapped onto quantum states, yet the paper lacks an in-depth discussion on how these different encoding strategies affect model trainability. Specifically:

Loss Landscape: Does amplitude encoding introduce steeper gradients or a more complex loss surface that affects optimization?

Gradient Vanishing (Barren Plateau Problem): Does high-dimensional amplitude encoding exacerbate the problem of vanishing quantum gradients, thereby making training less efficient?

2. Generalization Ability and Overfitting Mitigation

The paper asserts that parameterized quantum circuits (PQC) improve generalization due to their unitary nature, but this claim is not systematically verified. While classical neural networks mitigate overfitting through regularization and data augmentation, it remains unclear how quantum neural

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networks (QNNs) achieve similar effects. Additionally:

Does amplitude encoding inherently introduce a form of implicit regularization?

If so, can this regularization effect be theoretically justified?

3. Feasibility on Real Quantum Hardware

All experiments in the paper were conducted on classical quantum simulators, which do not account for the challenges associated with real quantum hardware, such as noise, decoherence, and error correction mechanisms. This raises concerns about the practical feasibility of the proposed approach when implemented on Noisy Intermediate-Scale Quantum (NISQ) devices:

Can the proposed HQNN model be efficiently executed on current NISQ hardware without significant performance degradation?

What are the computational trade-offs between using classical simulators and real quantum processors?

4. Scalability and Time-Series Considerations

The study utilizes a dataset with 1,725 samples and 256 features, a relatively small scale for classical machine learning. While quantum neural networks are often posited to excel in high-dimensional, small-sample scenarios, it is important to evaluate whether these advantages persist as dataset sizes grow. Furthermore:

Does the model account for the temporal dependencies in recovery rate prediction? Since recovery rate forecasting is inherently a time-series problem, and QNNs are primarily designed for static data, how can temporal dependencies be effectively incorporated into the model?

Declarations

Potential competing interests: No potential competing interests to declare.

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