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Example of an outstanding review

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The topic of the article is the formalization of a quantum method to implement an artificial neuron, that is a $(\boldsymbol{\phi}, \phi_0)$-parametrized non-linear function that maps an input vector $(\boldsymbol{\theta}, \theta_0)$ to a single number. Classically this is often done with the ReLu function $\max\{0, \boldsymbol{\theta}^T \boldsymbol{\phi} + \theta_0 + \phi_0\}$. The key insight of the article is that one can construct a quantum analog as $|\langle\theta|\phi\rangle|^2$ where the encoding is performed as $|\phi\rangle = N^{-1/2} \sum e^{i\phi_j} |j\rangle$, and similarly with $|\theta\rangle$. Then the article explores noise resilience and experimental implementations of this scheme. The main merits of the article are:

- It leverages the phase encoding to construct non-linearities.
- It seems to be relatively noise resilient, even experimentally.
- It can encode continuous data, which is nice.

On the other hand, the main disadvantage I see is concerning the state preparation of $|\phi\rangle$ and $|\theta\rangle$. My understanding is that without an efficient preparation method, the method is efficiently simulable, and thus probably not that interesting in practice. As such, I think something that could improve the quality of the article is to set a third appendix where you briefly review some efficient preparation methods that could be used to avoid the $O(N)$ cost. Perhaps an even better idea would be to explore how to convert quantum data into in the form of $|\theta\rangle$, although this may not always be possible (eg, if the data is in the amplitudes) although efficient preparation of $|\phi\rangle$ would probably still be desirable. This is because, to the best of my knowledge, the area where quantum neural networks may surpass classical ones in accuracy is when dealing with quantum data directly from quantum sensors. Or perhaps handling the data faster, with similar accuracy.

Some smaller comments:

1. I think it would be convenient to release the code you used for your simulations.
2. In line 39-41 of page 1, you mention ”could be used for enhanced pattern recognition tasks, i.e. going beyond the capabilities of classical computing

machines [19]." but I believe that reference does not particularly relate to neural networks. Also I believe one should point that such reference is talking about a speedup, not an accuracy improvement. I would suggest adding reference `https://arxiv.org/pdf/1911.01117.pdf` which mentions: "In this work we propose a quantum algorithm to perform a complete convolutional neural network (QCNN) that offers potential speedups over classical CNNs". Although being fare in the numerical results in MNIST it did get worse accuracy than CNNs. So again, QNN are probably better suited for quantum data.

3. As a continuation of the previous point, notice that they use qRAMs, so that could be one of the preparation method of states that you could point to.

4. In page 3 you mention that the error is extracted from a uniform distribution in $(-a/2, a/2)$. ¿Am I right in that a more realistic model of error would be to assume gaussian instead of uniform? Nevertheless I do not think this would affect the result, so I would just say this is more convenient for analysis purposes.

5. In page 4 you mention "However, with the idea of implementing the quantum computing version of a feedforward neural network, it is essential to have a model for which information is easily transferred from each neuron to the following layer. This can be accomplished by using an ancilla qubit per artificial neuron, where the quantity of interest can be loaded [32]."

   I think this interesting, so I would suggest expanding a bit more so that the reader gets an idea of how it works.

6. On the SPSA, I'm fine with this choice, but I would like to know if there is some reason to not use a variation of gradient descent, which is probably more common.

7. In page 8 you mention "Even if classical machine learning techniques can yield a classification accuracy above 99%, the present results show a remarkable degree of precision, also considering that in this particular example no learning and optimization procedure has been used, and just a single quantum neuron has been used for the classification."

   I'm uncertain whether saying that the procedure requires no learning is "fare" since what you are making is more similar to clustering, where no parameters are involved... In fact you are performing swap tests between a given image and the rest. Nevertheless I am surprised that it gets to 98% accuracy since it does not involve translation invariance of the image, as one would achieve using Classical convolutional NN.

8. Also, why are you using $t = 0.85$ in Eq. (17), in that example (or $t = 0.95$ in fig 7 and 8)? Is that an optimized hyperparameter?

9. In page 9 you say "When compared to other works using only quantum resources, our model seems to yield better results [28, 37]."

   Could you give more detail on this claim?

10. I'm somewhat confused by the naming of figure 10, because I would say that a (classical) confusion matrix would be something that compares the number of actual X vs classified Y. Instead you seem to be comparing the inner product between some samples of $|\phi = 1\rangle$ and $|\phi = 0\rangle$. From such point it is expected that the diagonal scores high. Are the activation values related to the threshold t indicated previously? Also, why the top left quarter of the matrix seems more activated than the rest? I would expect that the bottom right also gets quite activated as it is a similar case as comparison between 1s.

So, overall I think that if the above comments are addressed the article is probably suitable for publication.