QNN Optimization via Circuit Compression, QEM, and Hybrid Optimizers

A. Objective

The objective is to optimize a quantum neural network (QNN) training workflow by applying circuit optimization, Depth reduction, noise modelling, optimizer tuning (QNGD) and Quantum error mitigation.

B. Circuit optimization

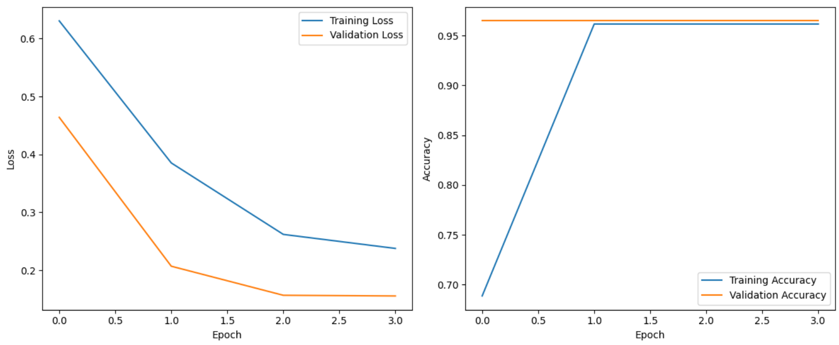
Original circuit

- Gate count:

  ('ry', 32), ('cx', 21), ('h', 8)

- Loss/Accuracy:

```
Epoch  1/20 | Train Loss: 0.6306 | Train Acc: 0.6885 | Val Loss: 0.4641 | Val Acc: 0.9649 | Time: 749.64s
Epoch  2/20 | Train Loss: 0.3853 | Train Acc: 0.9617 | Val Loss: 0.2070 | Val Acc: 0.9649 | Time: 578.56s
Epoch  3/20 | Train Loss: 0.2619 | Train Acc: 0.9617 | Val Loss: 0.1568 | Val Acc: 0.9649 | Time: 583.23s
Epoch  4/20 | Train Loss: 0.2377 | Train Acc: 0.9617 | Val Loss: 0.1556 | Val Acc: 0.9649 | Time: 567.52s
```

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0: ──H──RY(0.74)─╭●──RY(0.06)─────────╭●──RY(0.85)─────────╭●──RY(0.45)───────────┤  <Z>
1: ──H──RY(0.37)─╰X─╭●───────RY(0.67)─╰X─╭●───────RY(0.27)─╰X─╭●────────RY(0.86)─┤  <Z>
2: ──H──RY(0.76)─╭●─╰X───────RY(0.41)─╭●─╰X───────RY(0.88)─╭●─╰X────────RY(0.71)─┤  <Z>
3: ──H──RY(0.01)─╰X─╭●───────RY(1.00)─╰X─╭●───────RY(0.67)─╰X─╭●────────RY(0.12)─┤  <Z>
4: ──H──RY(0.35)─╭●─╰X───────RY(0.32)─╭●─╰X───────RY(0.63)─╭●─╰X────────RY(0.40)─┤  <Z>
5: ──H──RY(0.04)─╰X─╭●───────RY(0.62)─╰X─╭●───────RY(0.12)─╰X─╭●────────RY(0.71)─┤  <Z>
6: ──H──RY(0.88)─╭●─╰X───────RY(0.36)─╭●─╰X───────RY(0.01)─╭●─╰X────────RY(0.58)─┤  <Z>
7: ──H──RY(0.28)─╰X──RY(0.23)─────────╰X──RY(0.56)─────────╰X──RY(0.26)───────────┤  <Z>
```

```
Actual circuit depth: 11
```

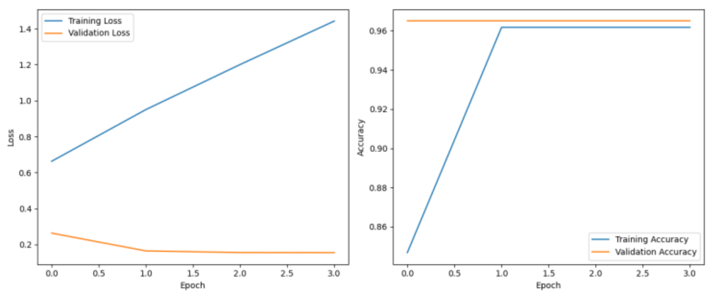
Optimised circuit

- Gate count:

  ('ry', 24,('cx', 7), ('h', 8)

- Loss/Accuracy:

```
Epoch  1/20 | Train Loss: 0.6631 | Train Acc: 0.8468 | Val Loss: 0.2641 | Val Acc: 0.9649 | Time: 416.39s
Epoch  2/20 | Train Loss: 0.9502 | Train Acc: 0.9617 | Val Loss: 0.1651 | Val Acc: 0.9649 | Time: 426.08s
Epoch  3/20 | Train Loss: 1.2004 | Train Acc: 0.9617 | Val Loss: 0.1561 | Val Acc: 0.9649 | Time: 407.24s
Epoch  4/20 | Train Loss: 1.4420 | Train Acc: 0.9617 | Val Loss: 0.1557 | Val Acc: 0.9649 | Time: 407.84s
```



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0: ──H──RY(0.22)──RY(0.49)──────────╭●──RY(0.49)─┤  <Z>
1: ──H──RY(1.58)─╭●──────────RY(0.62)─╰X──RY(0.02)─┤  <Z>
2: ──H──RY(0.75)─╰X──────────RY(0.45)─╭●──RY(0.69)─┤  <Z>
3: ──H──RY(0.86)─╭●──────────RY(0.15)─╰X──RY(0.84)─┤  <Z>
4: ──H──RY(1.00)─╰X──────────RY(0.93)─╭●──RY(0.55)─┤  <Z>
5: ──H──RY(0.38)─╭●──────────RY(0.44)─╰X──RY(0.33)─┤  <Z>
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7: ──H──RY(1.00)──RY(0.71)──────────╰X──RY(0.32)─┤  <Z>

circuit depth: 6
```
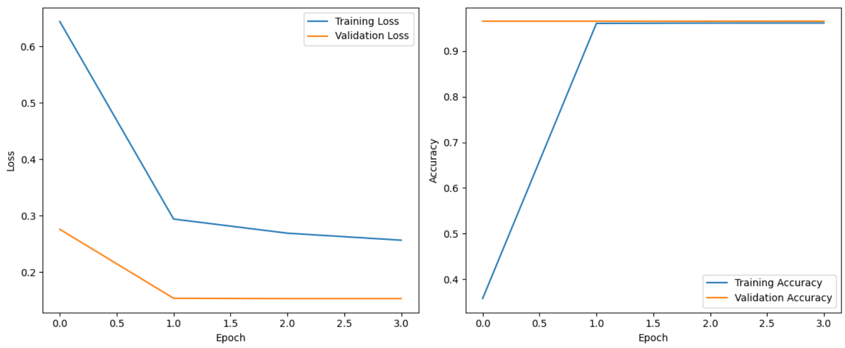

Circuit with noise (default.mixed)

- Loss/Accuracy:

```
Epoch 1/20 | Train Loss: 0.6443 | Train Acc: 0.3572 | Val Loss: 0.2760 | Val Acc: 0.9650 | Time: 1395.23s
Epoch 2/20 | Train Loss: 0.2941 | Train Acc: 0.9609 | Val Loss: 0.1537 | Val Acc: 0.9650 | Time: 1369.89s
Epoch 3/20 | Train Loss: 0.2691 | Train Acc: 0.9616 | Val Loss: 0.1531 | Val Acc: 0.9650 | Time: 1497.00s
Epoch 4/20 | Train Loss: 0.2566 | Train Acc: 0.9617 | Val Loss: 0.1531 | Val Acc: 0.9650 | Time: 1303.47s
```

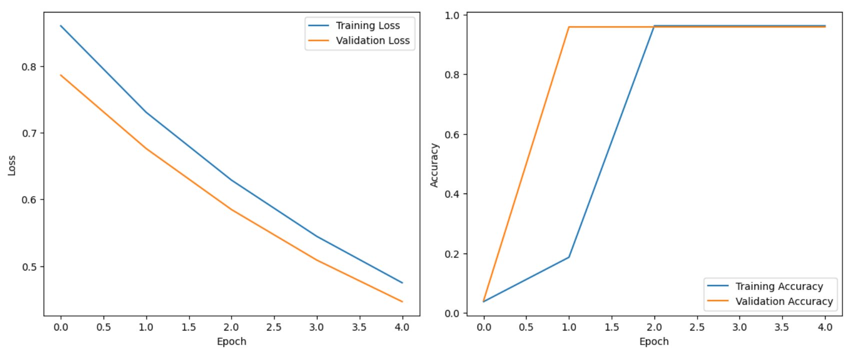



```
Quantum Circuit Diagram:
0: ──H──RY(0.07)─╭●──RY(0.83)─╭●──RY(0.39)─╭●──RY(0.51)─┤  <Z>
1: ──H──RY(0.27)─╰X──RY(0.74)─╰X──RY(0.46)─╰X──RY(0.59)─┤  <Z>
2: ──H──RY(0.06)─╭●──RY(0.10)─╭●──RY(0.46)─╭●──RY(0.98)─┤  <Z>
3: ──H──RY(0.83)─╰X──RY(0.68)─╰X──RY(0.20)─╰X──RY(0.65)─┤  <Z>
4: ──H──RY(0.10)─╭●──RY(0.87)─╭●──RY(0.09)─╭●──RY(0.06)─┤  <Z>
5: ──H──RY(0.79)─╰X──RY(0.24)─╰X──RY(0.33)─╰X──RY(0.16)─┤  <Z>
6: ──H──RY(0.77)─╭●──RY(0.16)─╭●──RY(0.91)─╭●──RY(0.19)─┤  <Z>
7: ──H──RY(0.78)─╰X──RY(0.57)─╰X──RY(0.73)─╰X──RY(0.80)─┤  <Z>

Ciruit Depth: 8
```

PEC applied circuit

- Loss/Accuracy:

```
Epoch 1/20 | Train Loss: 0.8601 | Train Acc: 0.0376 | Val Loss: 0.7861 | Val Acc: 0.0412 | Time: 59.38s
Epoch 2/20 | Train Loss: 0.7305 | Train Acc: 0.1864 | Val Loss: 0.6762 | Val Acc: 0.9588 | Time: 67.54s
Epoch 3/20 | Train Loss: 0.6288 | Train Acc: 0.9624 | Val Loss: 0.5847 | Val Acc: 0.9588 | Time: 71.12s
Epoch 4/20 | Train Loss: 0.5445 | Train Acc: 0.9624 | Val Loss: 0.5089 | Val Acc: 0.9588 | Time: 60.13s
Epoch 5/20 | Train Loss: 0.4749 | Train Acc: 0.9624 | Val Loss: 0.4467 | Val Acc: 0.9588 | Time: 55.53s
```



```
Quantum Circuit Diagram:
0: ──H──RY(0.29)─╭●──────────RY(0.01)───Y─────────RY(0.54)──╭●──────────Z──────────RY(0.52)────────────┤
1: ──H──RY(0.30)─╰X──────────RY(0.65)──╭●─────────RY(0.79)──╰X──────────RY(1.00)───────────────────────┤
2: ──H──RY(0.39)─╭●──────────RY(0.47)──╰X─────────RY(1.00)──╭●──────────RY(0.65)───────────────────────┤
3: ──H──RY(0.94)─╰X──────────RY(0.79)──╭●─────────RY(0.05)──╰X──────────Y──────────RY(0.18)────────────┤
4: ──H──RY(0.75)─╭●──────────RY(0.75)──╰X─────────RY(0.90)─────────────╭●──────────RY(0.68)────────────┤
5: ──H──RY(0.55)─╰X──────────RY(0.85)───Y────────╭●──────────RY(0.78)──╰X──────────X──────────RY(0.98)─┤
6: ──H──RY(0.12)───────────╭●───────────RY(0.84)─╰X──────────RY(0.93)──╭●──────────RY(0.25)────────────┤
7: ──H──Y─────────RY(0.20)─╰X───────────RY(0.69)──RY(0.04)─────────────╰X──────────RY(0.58)────────────┤
```

```
Circuit depth: 10
```

C. Result Analysis:

- Circuit optimisation significantly reduced the gate count (CX gates), which improved the performance under noise, while maintaining accuracy. So, the circuit optimisation-expressibility trade-of has been handled well.
- QNGD is applied to the quantum parameters for improved convergence in quantum circuits. QNGD updates the step size more suitable for VQCs.
- ADAM is applied to classical parameters, as it known for its fast convergence in classical deep learning.
- Hybrid of these two- QNGD for noisy circuits and ADAM for classical parameters without computational overhead, The division ensures that quantum and classical parts of the model are optimized using the most appropriate strategies, which leads to a faster and more stable training in noisy environments.
- Realistic noise (decoherence) using default.mixed has reduced the accuracy as the noise overwhelms the model if no QEM is applied. PEC restored the accuracy even under noise, resulting in increased circuit evaluation time.

D. Conclusion

The model with optimised circuits, dynamic depth reduction, adaptive PEC and a hybrid optimiser (QNGD and ADAM) achieved good efficiency while maintaining accuracy with reduced gates and circuit depth. The hybrid optimiser ensured both stable training and fast convergence. For next steps, training over more epochs and testing on real quantum hardware will further validate the results.