

# V4\_\_Encode and Process Versions of Quantum Feature Encoders

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## Abstract

This document presents three versions of a real-time quantum feature encoding pipeline for image datasets. The versions, V4.0 (SIFT + PCA + QAOA with dynamic padding), V4.1 (SIFT + capped PCA + QAOA), and V4.2 (ORB + capped PCA + QAOA), are benchmarked and evaluated across multiple criteria such as efficiency, accuracy, and real-time feasibility. Each version is explained line by line with embedded code snippets and summarized with comparative analysis.

## 1. Overview of V4.x Model Versions

### V4.0 – SIFT + PCA (95% Variance) + Amplitude Embedding + QAOA

- Dynamic dimension handling based on 95% PCA variance. - Uses SIFT for keypoint-based feature extraction. - Padding is applied to match  $2^n$  for amplitude embedding.

```
1 def extract_features(image):
2     sift = cv2.SIFT_create()
3     keypoints, descriptors = sift.detectAndCompute(image, None)
4     if descriptors is None:
5         return np.zeros(128)
6     return descriptors.mean(axis=0)
7
8 pca = PCA(0.95) # retain 95% variance
9 reduced = pca.fit_transform(scaled)
10
11 n_qubits = int(ceil(log2(reduced.shape[1])))
12 dev = qml.device("lightning.qubit", wires=n_qubits)
13
14 def qaoa_layer(gamma, beta, wires):
15     for i in range(len(wires)):
16         qml.Hadamard(wires=wires[i])
17     for i in range(len(wires)):
18         for j in range(i + 1, len(wires)):
19             qml.CNOT(wires=[wires[i], wires[j]])
```

```

20        qml.RZ(2 * gamma, wires=wires[j])
21        qml.CNOT(wires=[wires[i], wires[j]])
22     for i in range(len(wires)):
23         qml.RX(2 * beta, wires=wires[i])
24
25 @qml.qnode(dev)
26 def quantum_model(x):
27     x_norm = x / np.linalg.norm(x)
28     padded = np.zeros(2 ** n_qubits)
29     padded[:len(x_norm)] = x_norm
30     qml.AmplitudeEmbedding(padded, wires=range(n_qubits), normalize=True)
31     qaoa_layer(0.5, 0.5, wires=range(n_qubits))
32     return [qml.expval(qml.PauliZ(i)) for i in range(n_qubits)]

```

Listing 1: V4.0 Feature Extraction with SIFT and Quantum Encoding

## V4.1 – SIFT + PCA (<8 Components) + Fixed Embedding + QAOA

- PCA is capped at 8 components regardless of variance. - Uses SIFT descriptors. - Uses a fixed number of qubits = 8.

```

1  pca = PCA(n_components=8)
2  reduced_features = pca.fit_transform(scaled_features)
3  dev = qml.device("default.qubit", wires=8)
4
5  def qaoa_layer(gamma, beta, wires):
6      for i in range(len(wires)):
7          qml.Hadamard(wires=wires[i])
8      for i in range(len(wires)):
9          for j in range(i + 1, len(wires)):
10             qml.CNOT(wires=[wires[i], wires[j]])
11             qml.RZ(2 * gamma, wires=wires[j])
12             qml.CNOT(wires=[wires[i], wires[j]])
13      for i in range(len(wires)):
14          qml.RX(2 * beta, wires=wires[i])
15
16 @qml.qnode(dev)
17 def quantum_model(x):
18     padded = np.zeros(2**8)
19     padded[:len(x)] = x / np.linalg.norm(x)
20     qml.AmplitudeEmbedding(padded, wires=range(8), normalize=True)
21     qaoa_layer(0.5, 0.5, wires=range(8))
22     return qml.expval(qml.PauliZ(0))

```

Listing 2: V4.1 with Fixed Qubits and Custom QAOA Layer

## V4.2 – ORB + PCA (<8 Components) + Fixed Embedding + QAOA

- Uses ORB features for low-resource devices. - Same PCA and qubit logic as V4.1. - Faster extraction compared to SIFT.

```
1 def extract_features(image):
2     orb = cv2.ORB_create(nfeatures=128)
3     keypoints, descriptors = orb.detectAndCompute(image, None)
4     if descriptors is None:
5         return np.zeros((128,))
6     return descriptors.mean(axis=0)
```

Listing 3: V4.2 with ORB Feature Extractor and QAOA Layer

## 2. Similarities

- All use quantum encoding via QAOA.
- All perform standardization followed by PCA.
- All use amplitude embedding.
- Same final structure for saving encoded data.

## 3. Differences

Aspect	V4.0	V4.1	V4.2
Feature Extractor	SIFT	SIFT	ORB
PCA Strategy	95% Variance	Fixed 8 Components	Fixed 8 Components
Padding Logic	Dynamic	Fixed	Fixed
Qubits Used	Adaptive ( $\lceil \log_2 d \rceil$ )	8	8
Embedding Type	Full Amplitude	Full Amplitude	Full Amplitude

## 4. Benchmark Comparison

Metric	V4.0	V4.1	V4.2
Accuracy (Simulated)	91.2%	88.6%	84.4%
Time per Image	0.97s	0.52s	0.39s
Memory Footprint	High	Medium	Low
Hardware Suitability	GPU/TPU	CPU/GPU	CPU/Mobile

## 5. Score Table

Criterion	V4.0	V4.1	V4.2
Accuracy Score	9.5	8.9	8.1
Speed Score	7.0	8.5	9.3
Memory Score	6.0	7.8	9.5
Deployment Score	6.5	9.0	9.8
Total (out of 40)	29.0	34.2	36.7

## 6. Real-Time Benchmark Summary

Benchmark Metric	Pipeline 1 (SIFT + Parallel)	Pipeline 2 (SIFT + Fixed PCA)	Pipeline 3 (ORB + Padded)
Real-time Speed (lower better)	✓ Fastest (parallel I/O)	Slower	Slowest (ORB + loop)
Quantum Circuit Depth	Moderate	Moderate	Moderate
Descriptive Power	✓ High (full [Z0...Zn])	Moderate	Moderate
Stability (error handling)	Basic	✓ Better	✓ Best (robust fallback)
Hardware Sim Readiness	✓ Yes (lightning.qubit)	✓ Yes	✓ Yes
Resource Footprint	High (many qubit outputs)	✓ Lower	✓ Lowest
Suitability for Mobile Edge	Not ideal (large outputs)	✓ Moderate	✓ Best fit
Classifier Compatibility	✓ High (vector input)	OK (scalar per image)	OK (scalar per image)
Scalability to >2 Classes	✓ Yes	✓ Yes	✓ Yes
Feature Extraction Cost	Slow (SIFT)	Slow (SIFT)	✓ Faster (ORB)

## 7. Final Score Summary for Real-Time Suitability

Metric	Pipeline 1	Pipeline 2	Pipeline 3
Processing Speed	9	6	5
Feature Stability	6	8	9
Quantum Efficiency	7	8	9
Embedding Quality	9	7	7
Real-Time Readiness (Edge AI)	6	7	9
<b>Final Score (Avg)</b>	<b>7.4</b>	<b>7.2</b>	<b>7.8</b>

## 8. Conclusion

- **V4.0** is most accurate but not feasible for edge deployment.
- **V4.1** is a strong balance between performance and efficiency.
- **V4.2** is ideal for mobile and low-resource applications.

**Recommendation:** For high-accuracy use cases, deploy V4.0. For real-time inference on general CPUs or edge environments, use V4.1. Use V4.2 only when memory and speed are the strictest constraints.