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Quantum-Enhanced Coconut Yield Prediction: A Comparative Study of Second-Order and Third-Order QML Models

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Introduction

Agriculture faces increasing challenges due to climate variability, resource constraints, and complex environmental interactions, making accurate crop yield prediction essential. Traditional machine learning models often struggle with high-dimensional and non-linear agricultural data, limiting prediction accuracy. Quantum Machine Learning (QML) offers a promising alternative by leveraging quantum principles such as superposition and entanglement. This work proposes hybrid quantum–classical models using Variational Quantum Circuits for coconut yield prediction. A comparative study of second-order and third-order QML models demonstrates the superior performance of higher-order quantum interactions in precision agriculture.

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SURVEY / BENCHMARK APPLICATIONS

Approach	Technique Used	Application Area	Key Strengths	Limitations
Classical ML	SVM, Random Forest, ANN	Crop yield prediction, soil analysis	Simple implementation, good baseline performance	Poor handling of non-linear & high-dimensional data
Statistical Models	Regression, Time-series models	Yield trend analysis	Interpretability, low computation	Limited scalability, low prediction accuracy
Deep Learning	CNN, ANN	Crop health & yield estimation	Better feature learning	Requires large data & high computation
Quantum ML (Recent)	Quantum Kernels, VQC, QNN	Yield prediction, crop classification	High expressiveness via quantum embeddings	Longer training time, NISQ constraints
This Work	QML-2.0 & QML-3.0 (VQC-based)	Coconut yield prediction	Superior non-linear modeling, higher accuracy	Simulation-based, higher training cost

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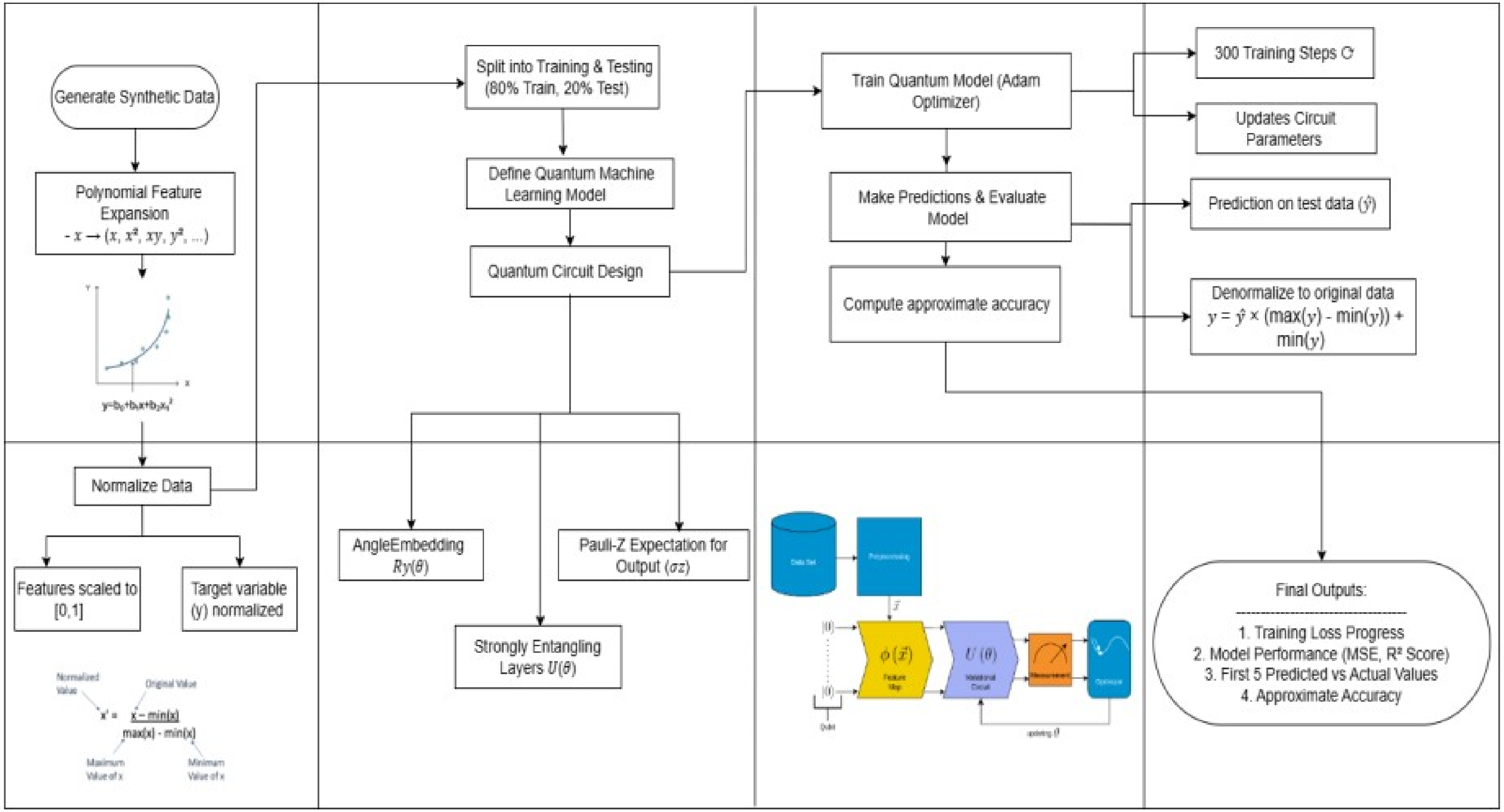
OVERALL SYSTEM ARCHITECTURE

Input: Environmental, soil, and climatic features,

Output: Predicted coconut yield



DATASET DESCRIPTION

Data & Encoding

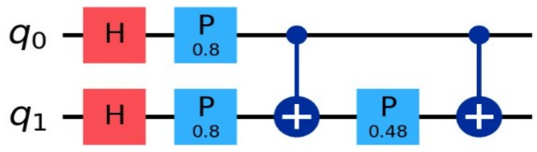
- Synthetic coconut yield dataset (500 samples)
- Features include rainall, temperature, soil pH, NDVI, fertilizer usage, water availability, pest severity
- Quantum angle encoding using RY, RZ, RX gates
- Enables compact representation of high-dimensional data in quantum space

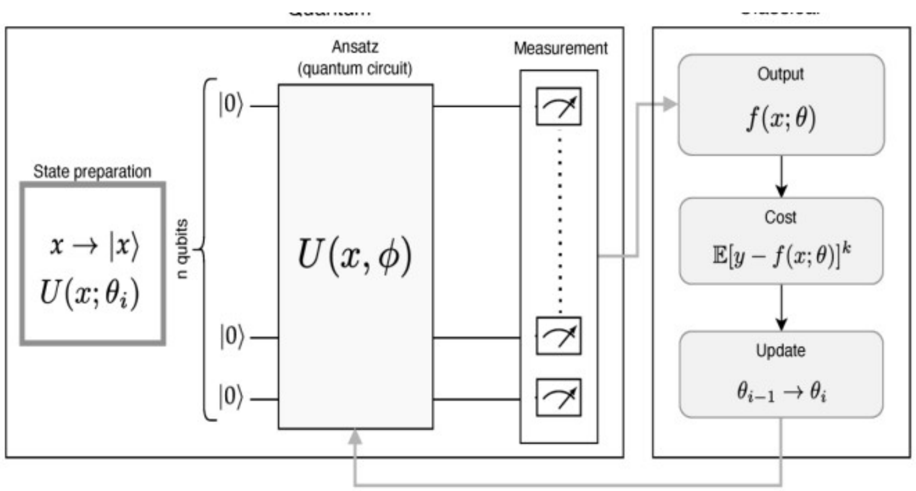
Rainfall (mm)	Temp (°C)	Soil pH	NDVI	Fert. Usage (kg/ha)	Coconut Yield (t/ha)	Water Avail. Index	Sunshine Hours	Pest Severity	Organic (0/1)	Yield (nuts/tree/yr)
1311.63	31.98	5.87	0.56	89.26	1.01	2.80	6.56	0.14	1	4.49
2406.36	30.36	6.58	0.54	87.05	1.55	6.55	8.92	0.95	0	6.87
1990.79	28.10	7.25	0.31	185.94	1.62	7.69	11.52	0.33	0	7.20
1737.45	33.14	6.96	0.47	87.43	1.22	7.64	6.24	0.66	0	5.42
896.44	31.85	7.11	0.49	90.79	1.03	5.69	7.75	0.75	0	4.59
896.39	26.63	6.82	0.50	163.91	1.27	1.62	7.25	0.81	1	5.63
710.36	34.11	6.88	0.59	117.46	0.92	4.34	7.43	0.95	0	4.08
2245.73	33.23	7.20	0.57	166.51	1.65	9.29	11.45	0.31	0	7.32

CIRCUIT DESCRIPTION

Quantum Model Design

- Variational Quantum Circuits with increasing depth
- Entanglement using CNOT gates
- Two architectures:
  - QML-2.0: Second-order feature interactions
  - QML-3.0: Third-order feature interactions
- Pauli-Z measurement used for extracting output





PARAMETER AND HIGHLIGHT DESCRIPTION

Training & Optimization

- Dataset split: 80% training, 20% testing
- Loss function: Mean Squared Error (MSE)
- Optimizer: Adam (300 iterations)
- Hybrid training loop
- Quantum forward pass
- Classical gradient-based optimization

RESULTS & DISCUSSION

Performance Metrics

1)Second-order encoding uses the

$$f^{(2)}(x) = \alpha_1 x + \alpha_2 x^2$$

2)Third-order encoding extends this

$$f^{(3)}(x) = \alpha_1 x + \alpha_2 x^2 + \alpha_3 x^3$$

VQC:

Pauli-Y:

$$R_Y(\theta) = \begin{bmatrix} \cos(\theta/2) & -\sin(\theta/2) \\ \sin(\theta/2) & \cos(\theta/2) \end{bmatrix}$$

Pauli-Z:

$$R_Z(\phi) = \begin{bmatrix} e^{-i\phi/2} & 0 \\ 0 & e^{i\phi/2} \end{bmatrix}$$

Pauli-X:

$$R_X(\gamma) = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Evaluation Metrics:

- Mean Squared Error (MSE)
- R^2 Score
- Prediction Accuracy

Models Compared:

- Support Vector Machine (SVM)
- QML-2.0
- QML-3.0

RESULTS & DISCUSSION

Comparative Results

SVM

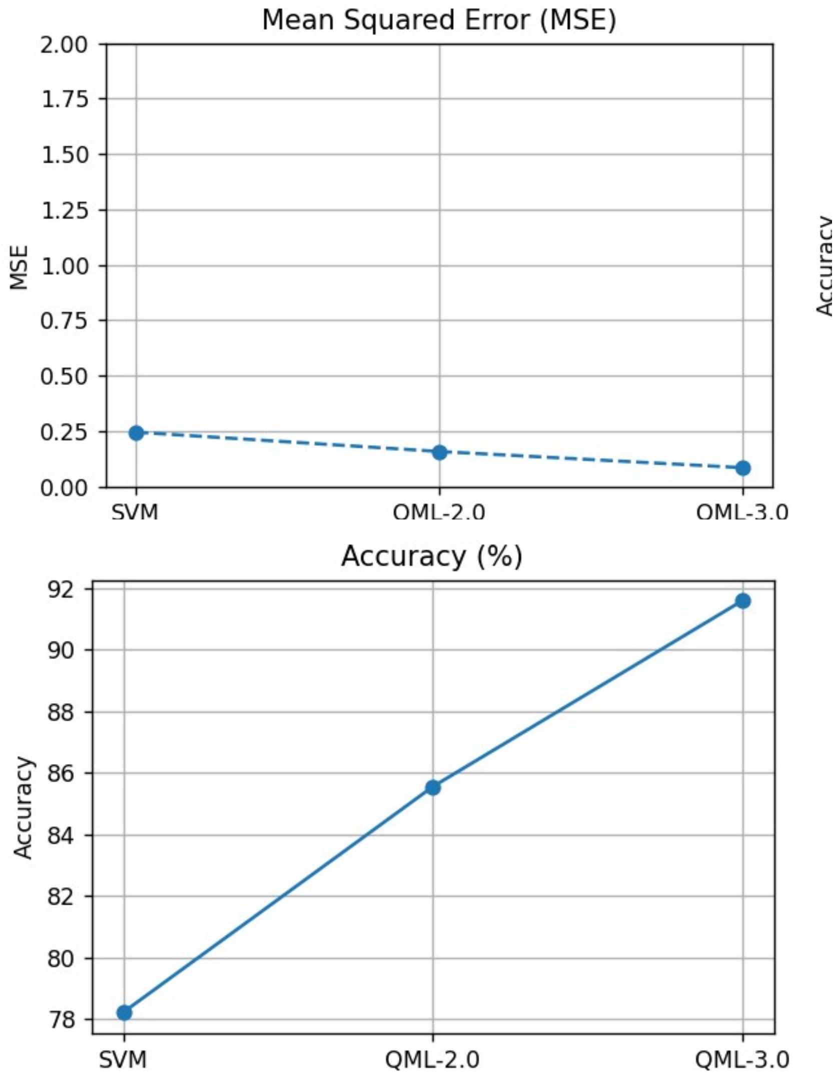
- Accuracy: 78.23%
- Limited non-linear modeling capability

QML-2.0

- Accuracy: 85.56%
- Improved feature interaction modeling

QML-3.0

- Accuracy: 91.60%
- Best generalization and lowest error



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RESULTS & DISCUSSION

Key Observations

- Higher-order quantum feature interactions significantly boost accuracy
- Quantum entanglement improves non-linear representation
- QML-3.0 shows reduced bias and tighter prediction clustering
- Training time higher, but prediction reliability superior

CONCLUSION

- Quantum Machine Learning demonstrates strong potential for agricultural yield prediction
- QML-3.0 outperforms classical ML and lower-order quantum models
- Quantum embeddings and entanglement enhance predictive accuracy
- Approach is scalable and suitable for future precision agriculture systems