



Variational Quantum Circuits for Classification: A Hybrid Approach

Presented By:

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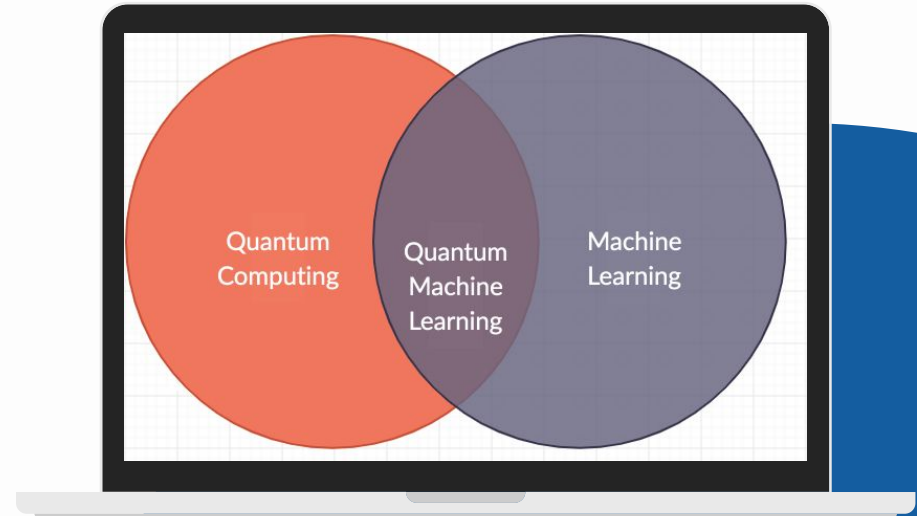
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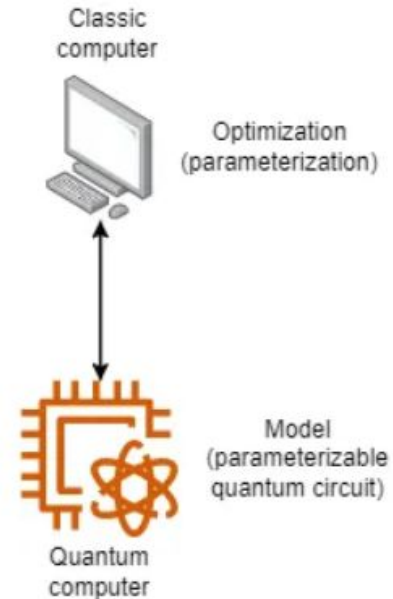
Problem Statement

- **Challenge:** Classical machine learning models struggle with **complex pattern recognition** and **high-dimensional data**.
- **Quantum Advantage:** Variational Quantum Circuits (VQCs) leverage quantum properties like **superposition** and **entanglement** for better classification performance.
- **Key Question:** Can a VQC-based classifier outperform classical models in real-world datasets?

Research Gap

Current Limitations:

- **Lack of comparative studies** between classical feature engineering and quantum feature mapping.
- **Limited understanding** of which quantum embeddings are most effective for specific data types.
- **Few real-world applications** demonstrating the practical advantage of quantum models in reducing feature engineering.



Our Contribution

✓ Implemented a Variational Quantum Classifier (VQC) using **PennyLane** & **Qiskit**.

🧬 Used the **Titanic dataset**, encoding passenger attributes as quantum states

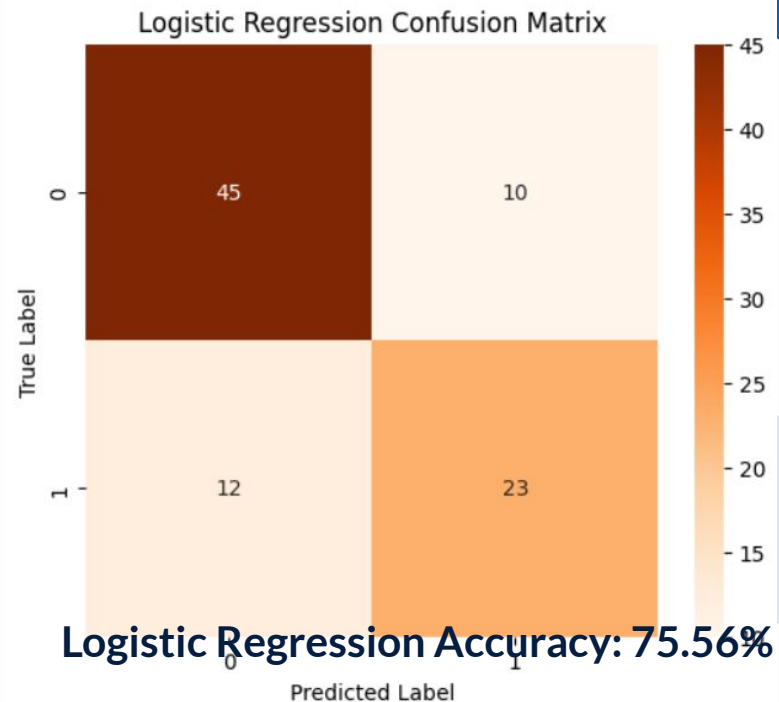
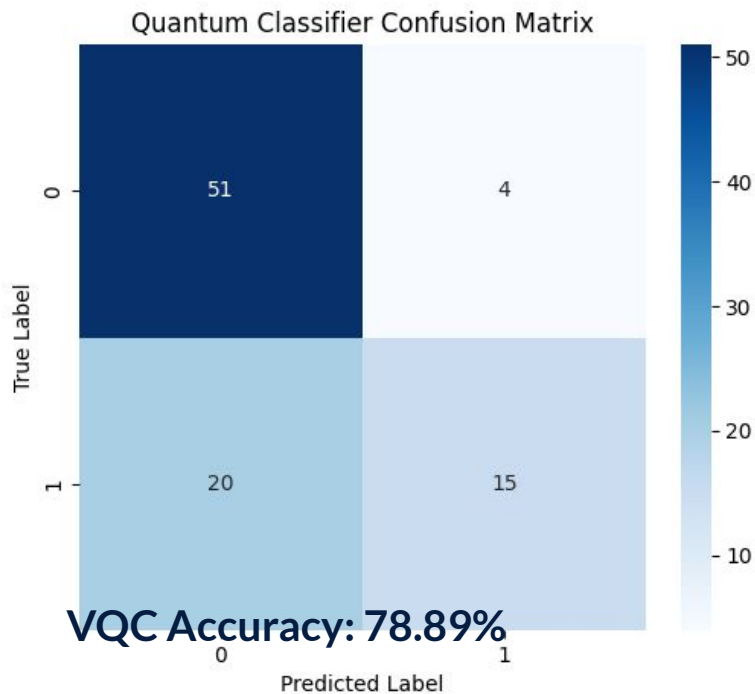
⚖️ Compared VQC against a **Logistic Regression** model for performance benchmarking.

📈 Analyzed the impact of different circuit depths on classification accuracy.

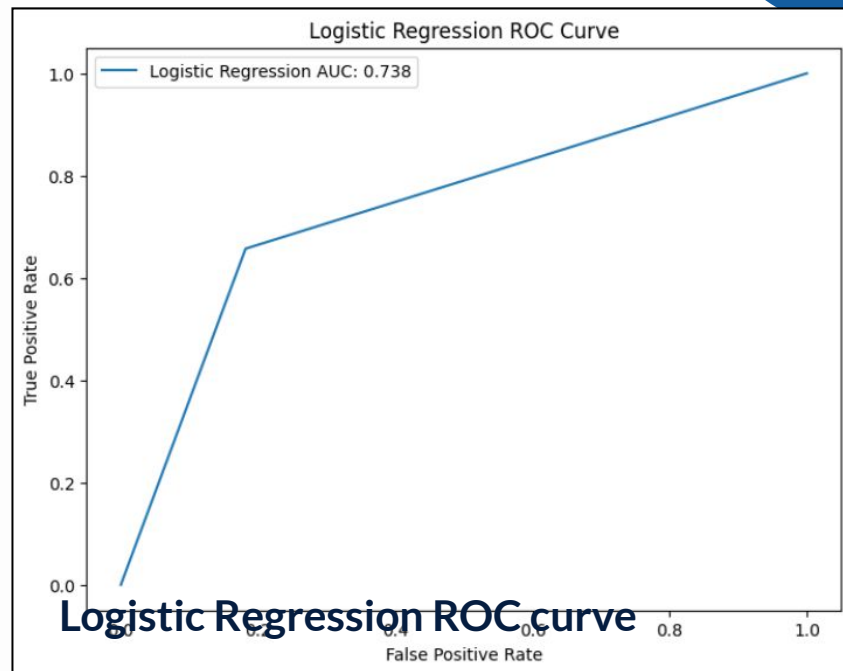
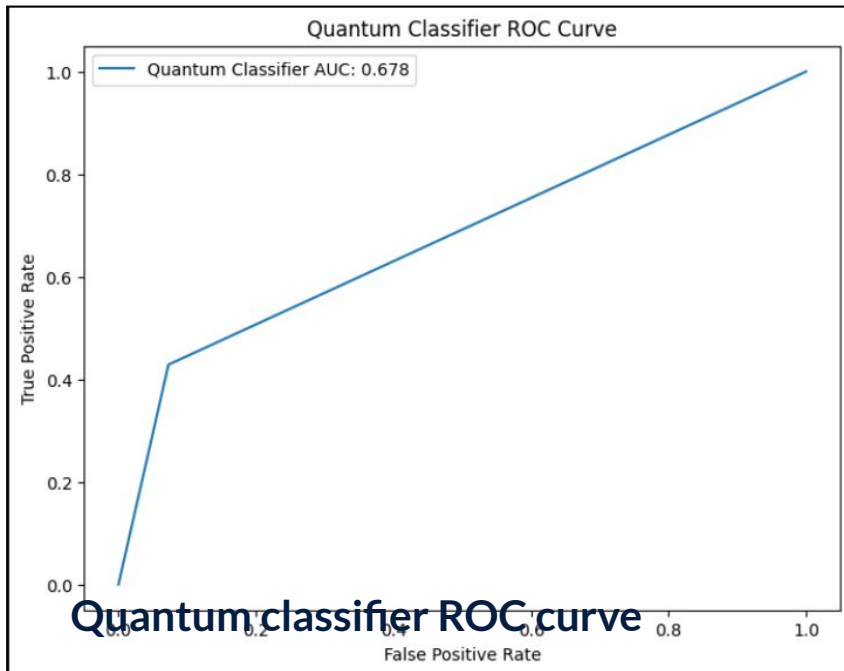
Methodology

- **Feature Embedding:** Basis encoding of classical features into quantum states.
- Quantum Circuit Design:
 - Rotation gates for superposition.
 - Controlled-NOT (CNOT) gates for entanglement.
 - Two-layer ansatz to balance complexity and performance.
- **Training:** Optimized using Adam optimizer with a qubit simulator.
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-score.

Results & Findings



Results & Findings



Observations

- VQC showed better performance, but results depend on feature selection and circuit depth.
- Overfitting observed with excessive layers, highlighting the need for optimal architecture selection.

Conclusion & Future Work

- **Key Takeaways:**

- VQCs show potential but require fine-tuning to outperform classical methods consistently.
- Feature embedding choices significantly impact results.

- **Future Directions:**

- Test on larger datasets to validate scalability.
- Explore different embedding methods (Amplitude Encoding, Angle Encoding).
- Implement on actual quantum hardware for real-world feasibility analysis.

**THANK
YOU!**

