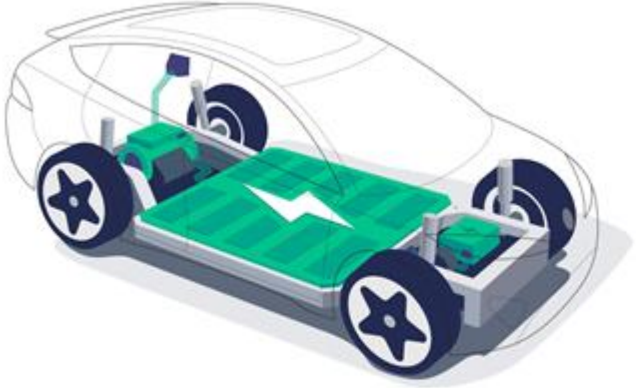
DesignQML: A Model-Based Framework for Building and Tuning Quantum Machine Learning Systems Automatically

Anum Iqbal, Muhammad Saeed, Ananya Kulkarni

Industry challenges demand greater efficiency

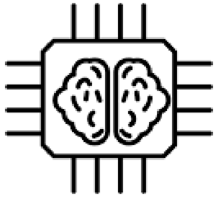
Regulatory constraints

Customer demands



Soaring powertrain complexity

Motivation: Limitations of Classical AI



1. Data Dependability

Many classical models require vast datasets, which are hard to acquire in industry contexts.

2. Scalability and Reliability

Model training costs grow exponentially with data size and model depth, making scaling unsustainable for many institutions.

3. Handling Data Complexity

Classical computing struggles with combinatorial problems and nonlinear relationships in high-dimensional data

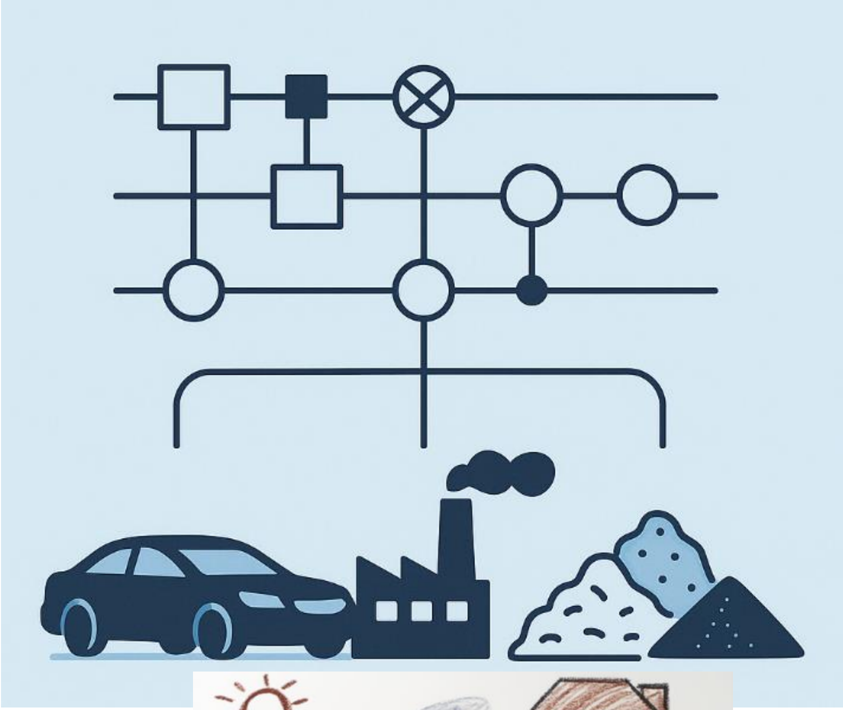
4. Interpretability and Robustness

Often fragile to small perturbations, leading to unpredictable outcomes.

Imagine a new QML framework that is 30% more efficient

What would it take for you to **trust** a QML model **enough**

- to rely on its predictions for **real industrial data**?
- to transfer it from **simulation to noisy quantum hardware** with confidence?
- to be willing to let it make **autonomous decisions in high-stakes applications**?



These are questions we must answer before deploying QML systems into real applications

QGAN inspired Designs in QML Development

Why does trust in **QML Design** systems take so long to build?

Cost to resolve QML flaws across workflow

Design (QML Models)	Simulate/Prototype	Test/Validate/ Benchmark	Operate/Use
▪ Limited guidance on how quantum features scale across backends ▪ **"Idealized circuits & architectures"**	▪ Hardware-dependent noise and qubit fidelity issues ▪ **As simulated vs. as deployed**	▪ Repeated tuning due to barren plateaus, decoherence, or optimizer instability ▪ Difficulties in transfer from simulation to real hardware	▪ Uncertainty in industrial environments & hybrid workflows ▪ **As designed vs. as used in production pipelines**
Generator (G)	Discriminator (D)	Feedback Loop	Outcome
proposes new QML architectu-res / circuits (explores design space)	evaluates outputs vs. expected industrial data/benchmarks	G improves iteratively based on D's evaluation	self-correcting process, higher trust earlier

Content

Introduction

- **Quantum Machine Learning (QML)-based predictive modeling** involves a variety of techniques built on quantum circuits and hybrid architectures to extract patterns (quantum features) from complex data for predictive analytics.

- Independent of the chosen method, the central aim is to generate **quantum features** that capture essential correlations through superposition and entanglement. These features enable classification, clustering, or regression while reducing dimensionality compared to raw data and amplifying the most informative system characteristics.

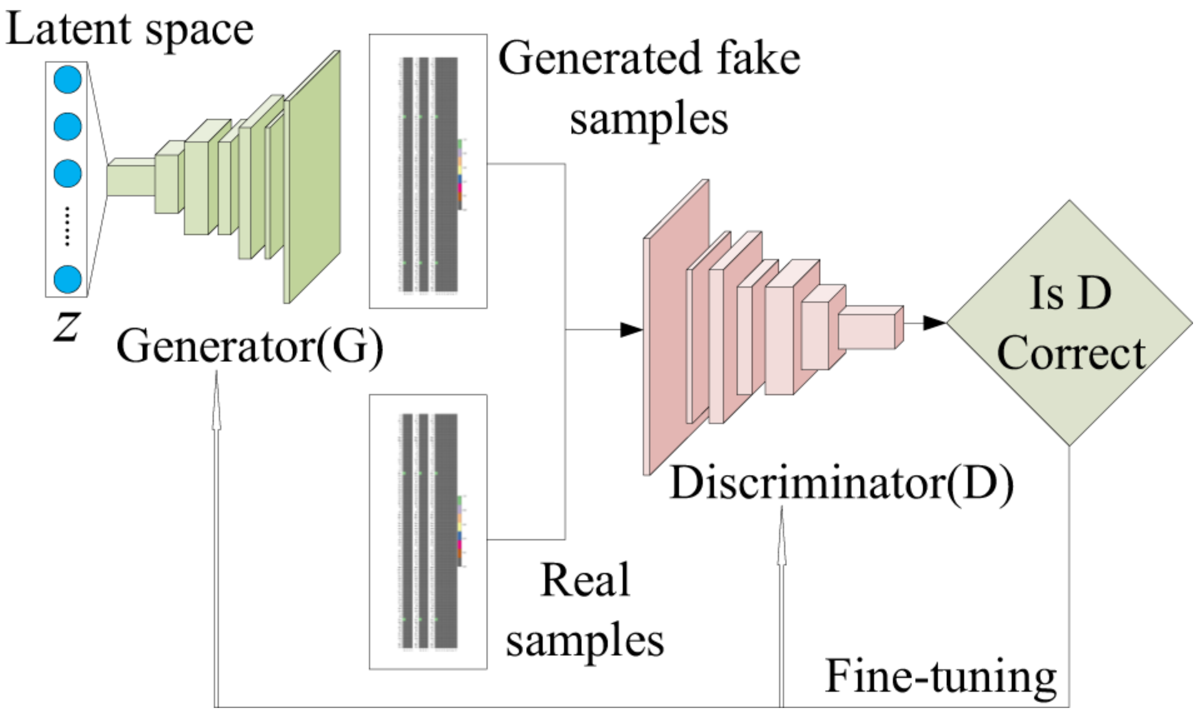
- Historically, predictive modeling has relied on classical methods such as **Fourier transforms** and **singular value decomposition**, and more recently on **deep neural networks** like CNNs and U-Net. In the quantum domain, approaches now include **variational quantum circuits, quantum kernels, and hybrid QML pipelines**, yet they often remain trial-and-error driven.

- The **DesignQML framework** extends this landscape by introducing a **model-based engineering approach**. It formalizes quantum workflows through **Q-NAS (quantum-aware neural architecture search), AQRM (adaptive quantum resource management)**, and **federated learning coordination**, enabling scalable, simulation-driven, and hardware-adaptable QML system design.

GANS: The Power of Imagination in AI

Why do GANS matter in modern AI?

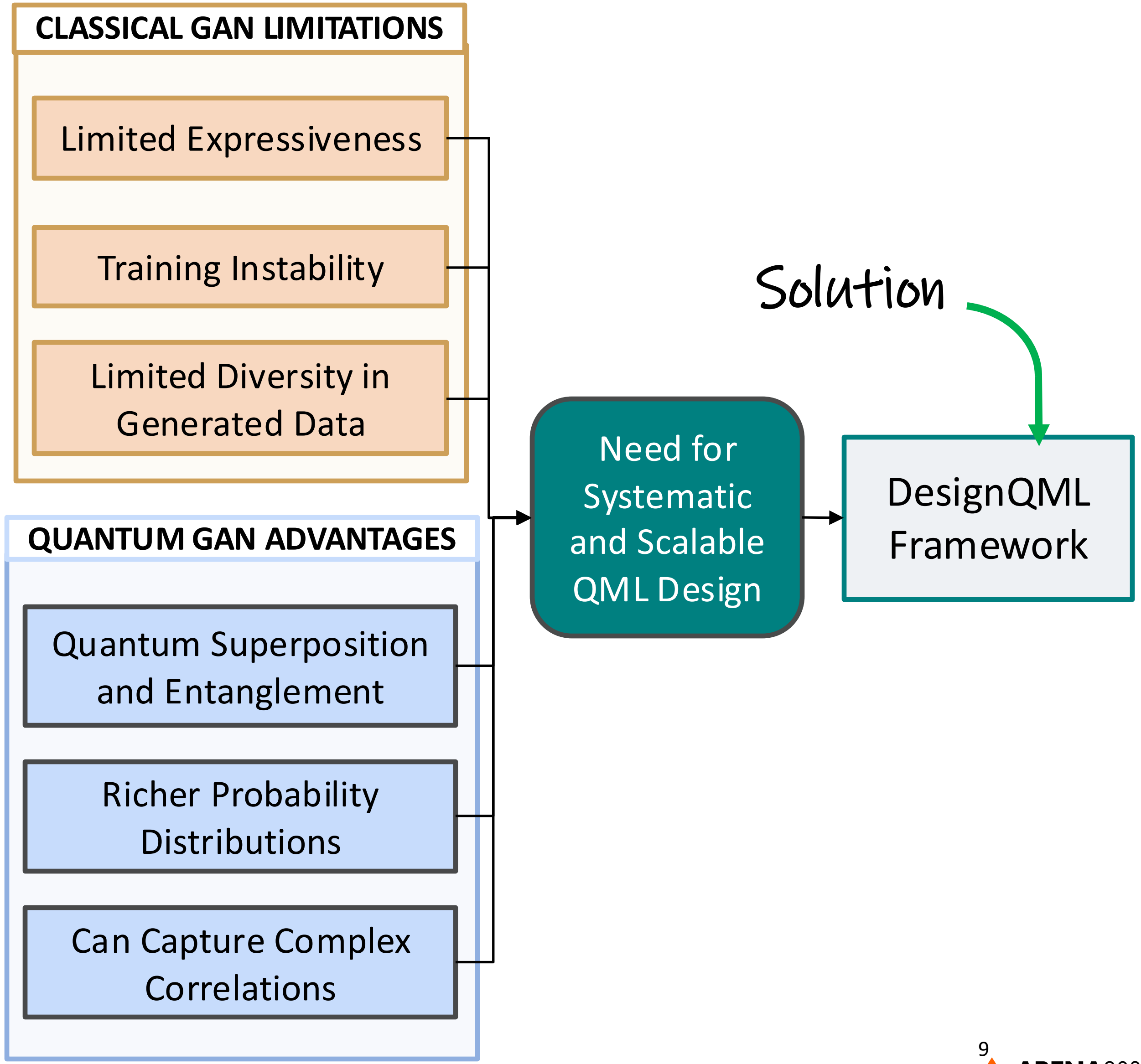
- GANs can generate realistic synthetic data, which is useful in data-scarce domains such as industrial manufacturing and healthcare.
- GANs push the frontier of creative AI, enabling style transfer, design, and augmentation.



DesignQML with QGANs

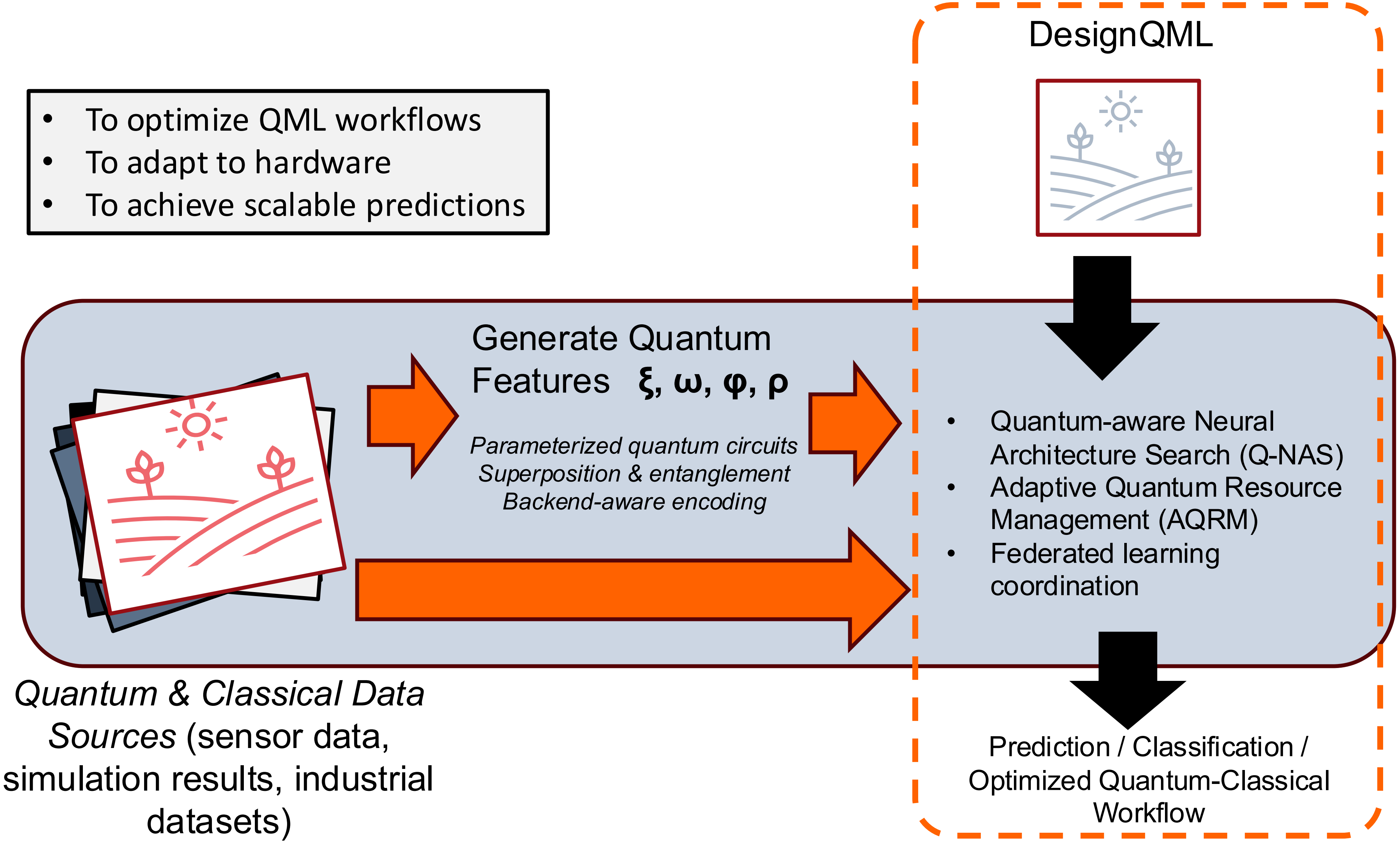
Why use quantum for generative modeling?

- **Generative Adversarial Networks (GAN)** are powerful but often unstable, requiring costly training and having limited diversity in generated data..
- In contrast, quantum circuits explore richer probability distributions via superposition and entanglement
- **Quantum Generative Adversarial Networks (QGANs)** offer potential for better data efficiency and capturing complex correlations in small datasets.



DesignQML Architecture

- To optimize QML workflows
- To adapt to hardware
- To achieve scalable predictions



Real time with QGAN

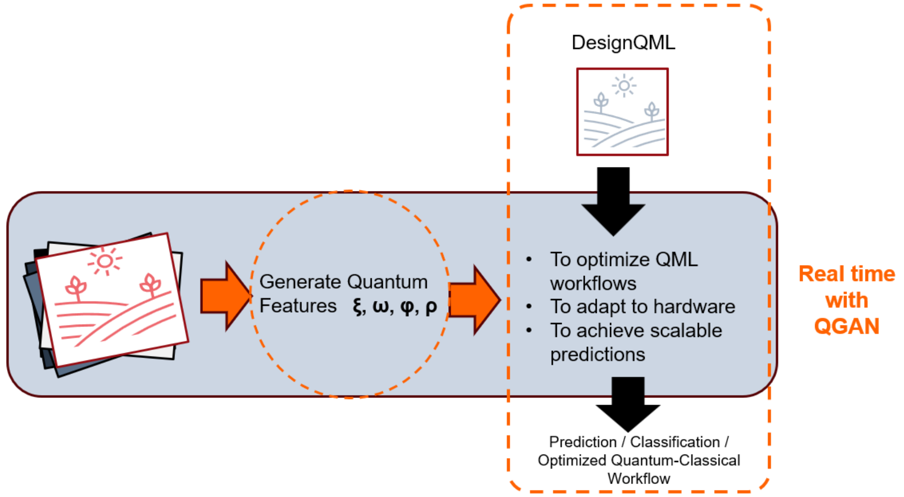
Quantum Data Encoding & Pre-Processing

- **Angle Embedding / Amplitude Embedding:**
Maps classical data into quantum states using rotation or amplitude of qubits.

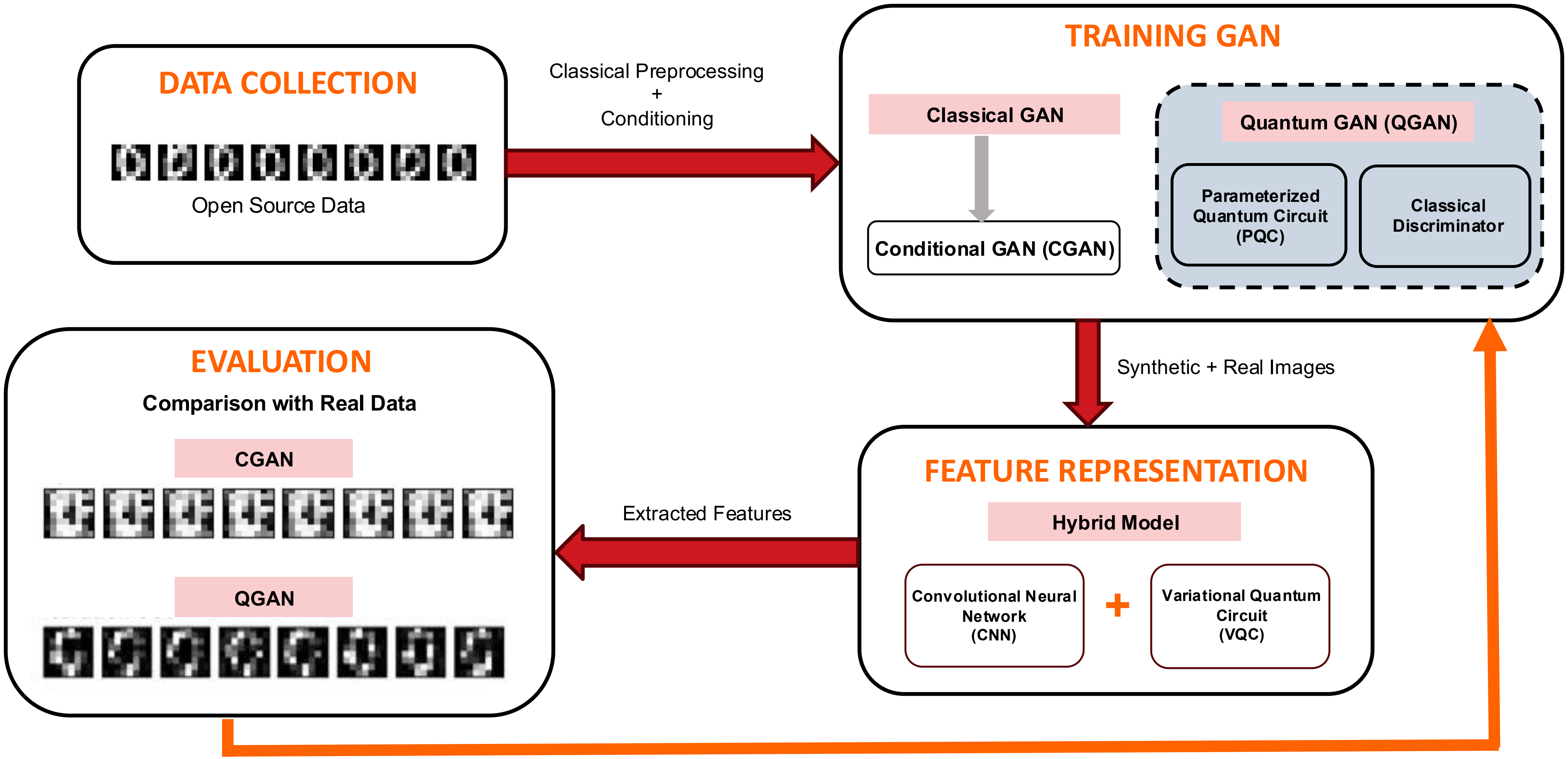
- **Feature Scaling & Normalization:**
Ensures inputs fit within valid ranges for parameterized quantum circuits.

- **Noise-aware Encoding:**
Prepares data with error mitigation and fidelity constraints in mind.

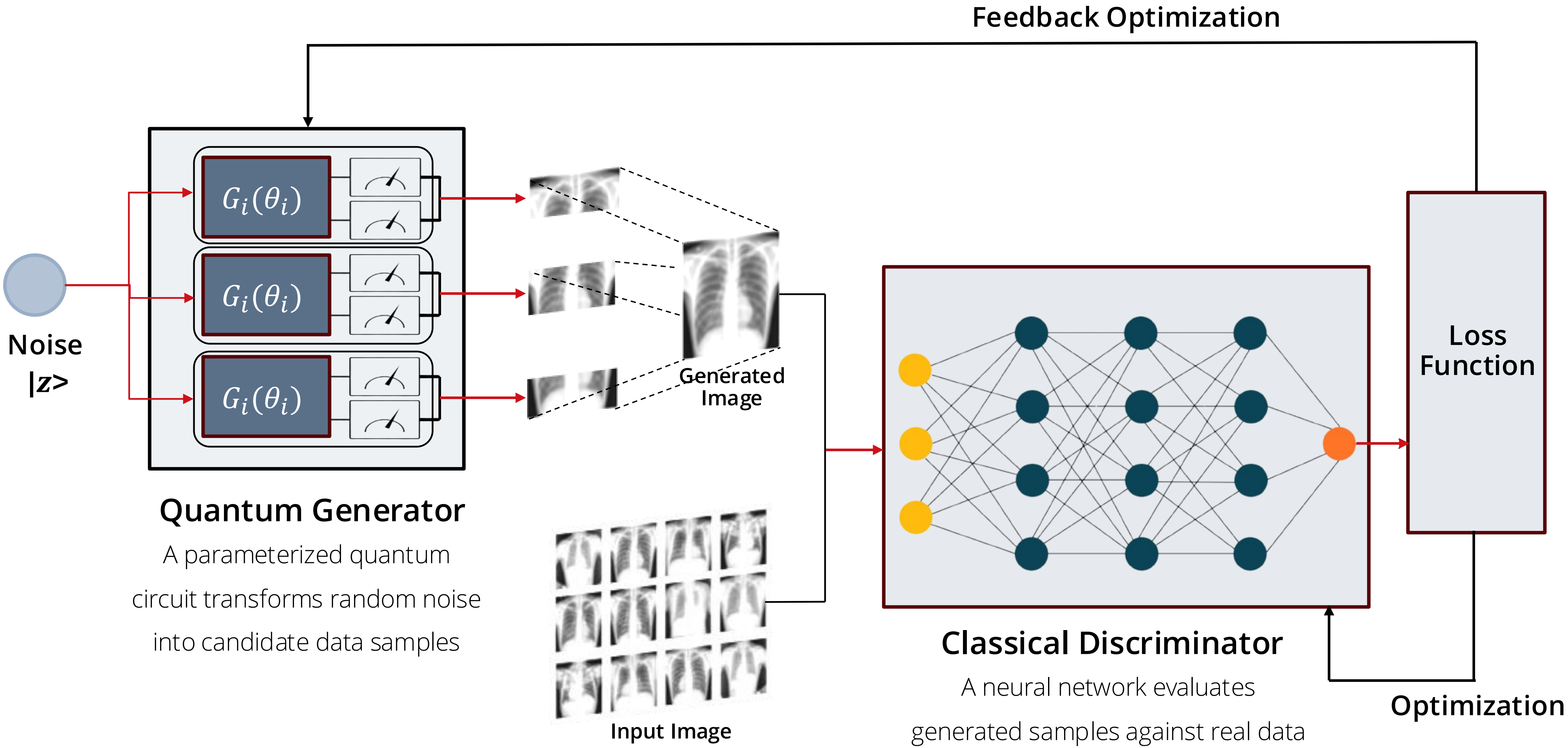
- **Hybrid Pre-processing Functions:**
Combines quantum feature maps with classical dimensionality reduction (e.g., PCA, kernel methods).



Model-Based Design Approach



Methodology



Quantum Generator

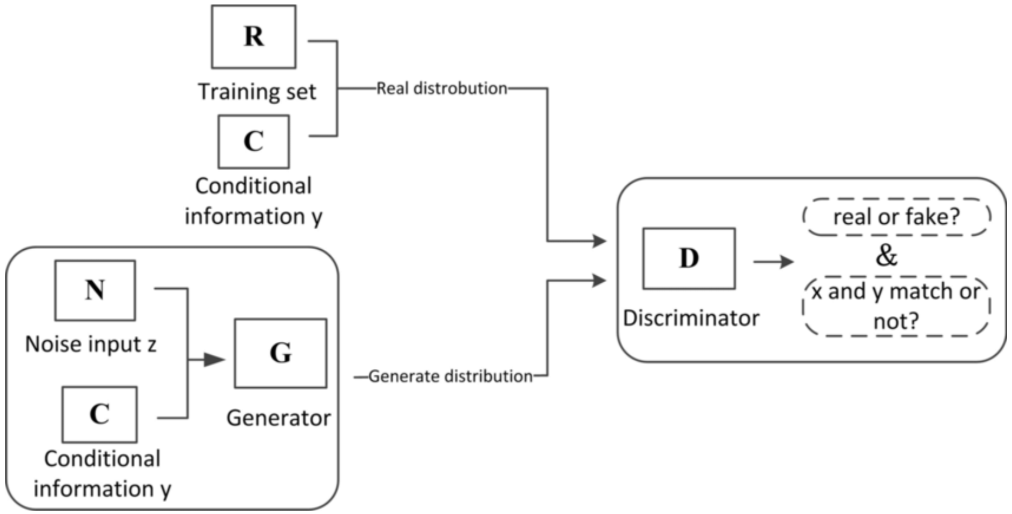
A parameterized quantum circuit transforms random noise into candidate data samples

Classical Discriminator

A neural network evaluates generated samples against real data

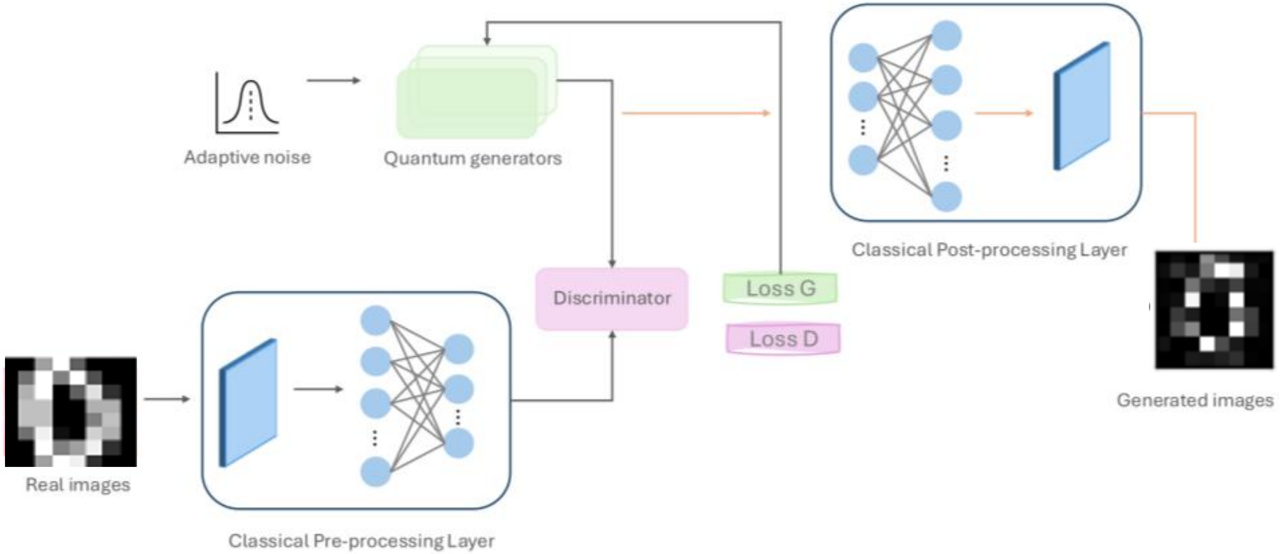
GAN Training

CGAN



- Condition on **relevant features**
- Latent space dimensions based on dataset diversity.
- Needs large, labeled datasets to achieve stability.

QGAN

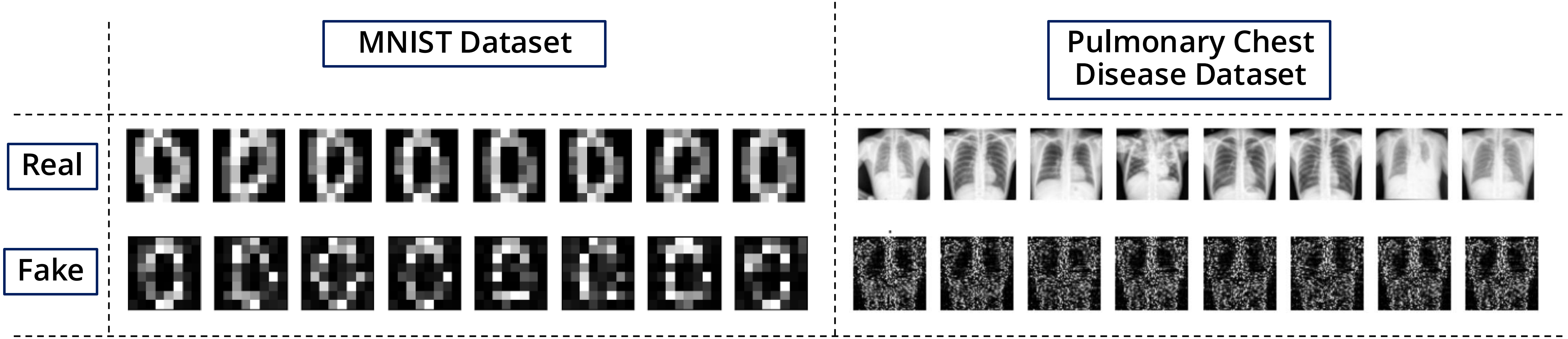


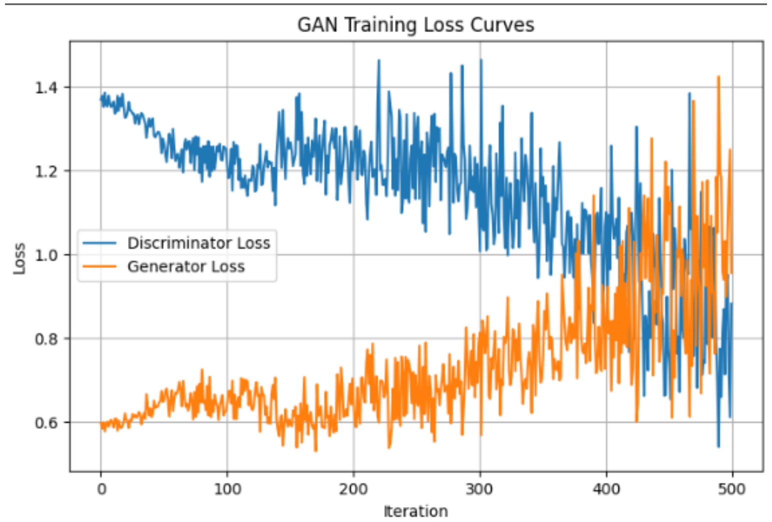
Quantum Generator:

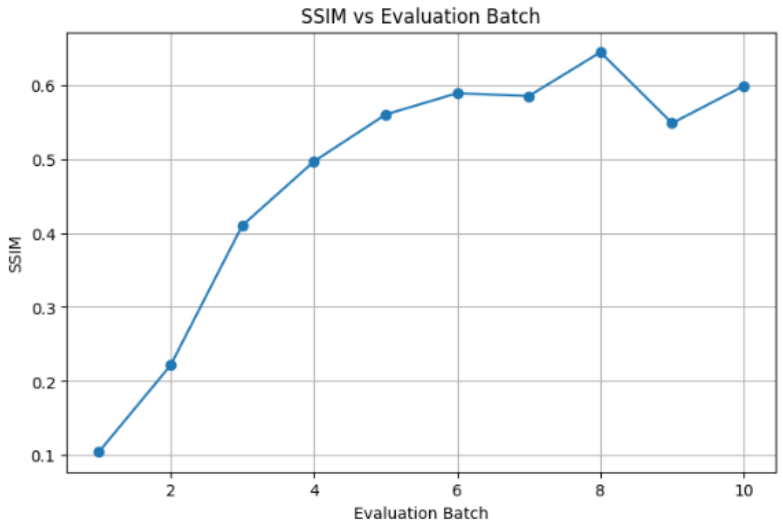
- Latent vector → mapped to **qubits = 6**
- **Entangling layers** capture complex correlations

Discriminator remains classical for stability

Preliminary Results







Conclusion:

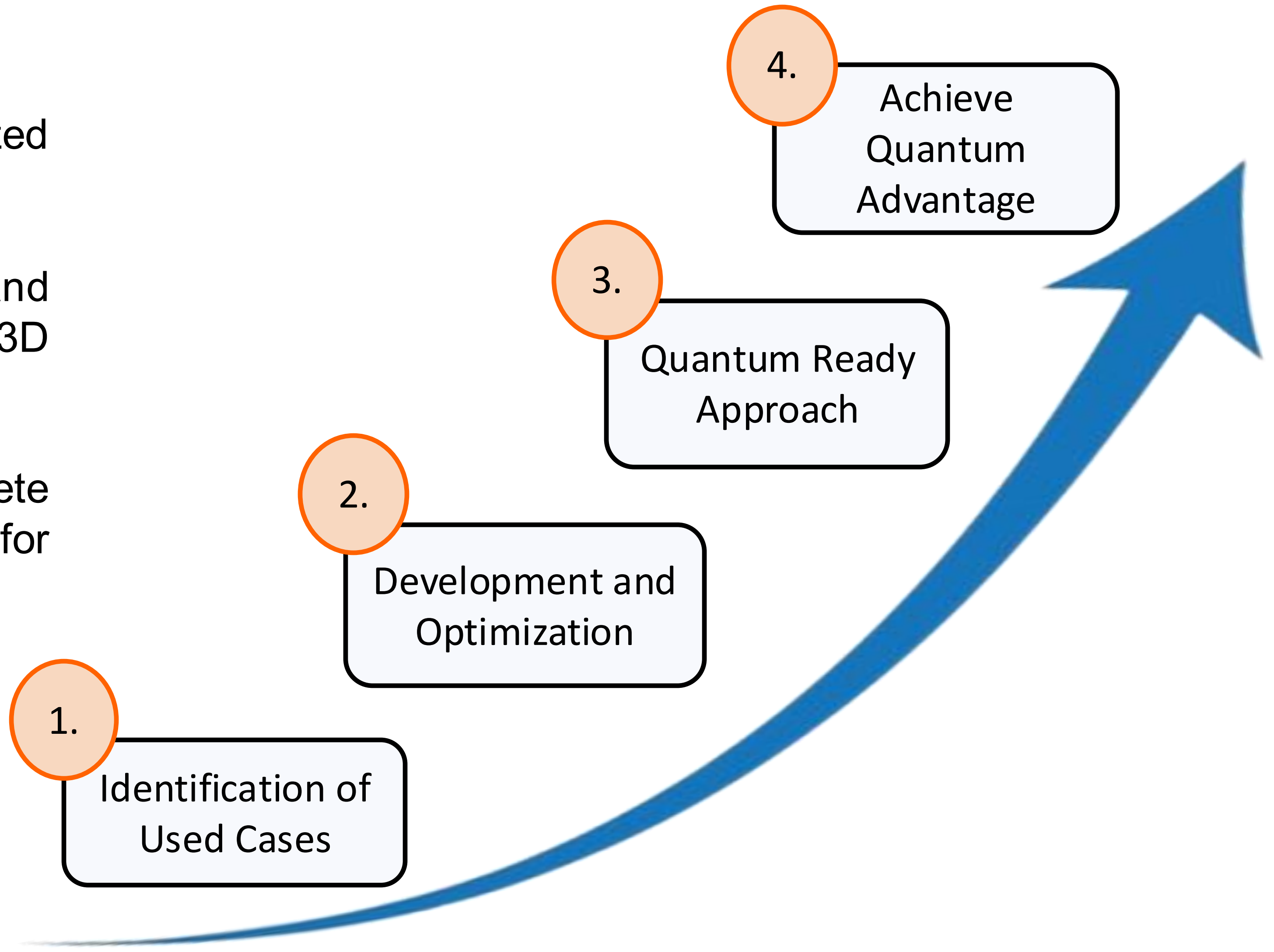
QGAN results show the promise of quantum models for synthetic data and reveal optimization potential that DesignQML can enhance to enable faster, industry-aligned QML development.

Future Outlook

- Extend application of QGANs to specialized industrial domains

- Extrapolate QGANs for point-cloud and volumetric data to generate realistic 3D samples

- Use of QGAN-based denoising for incomplete or noisy point clouds (quality improvement for perception)



Thank you for being Patient!

Dr. – Ing Muhammad Saeed
Research Coordinator

muhammad.saeed@arena2036.de

+49 155 60070608

Thanks to the great team of Students:

- **Anum Iqbal (Student):** **Laying down QML Foundations and QGANs**
- **Ananya Kulkarni (Student):** **Model Based Design**

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