**Slide 2: Quantum Definitions — A Crash Course**

“To understand HQNNs, we first need a few core quantum computing terms.”

“A **qubit** is the quantum version of a bit. Instead of being just 0 or 1, it can exist in a superposition — a probability mix of both. Visually, you can think of this as a vector on a 3D Bloch sphere.”

“Next, **entanglement** is a quantum effect where two qubits are linked. Changing or measuring one instantly affects the other, even over distance.”

“**Quantum gates** manipulate qubits, changing their vector direction on the Bloch sphere. Think of it like rotating probability amplitudes.”

“And finally, **measurement** collapses a qubit to a classical value — usually 0 or 1 — based on its probability distribution. Measurement typically happens along a specific axis, like the z-axis.”

**Slide 3: What Is an HQNN?**

“HQNNs combine both classical and quantum components in their architecture.”

“Here’s a typical layout: We begin with classical input, often passed through convolutional layers to reduce dimensionality. Then, data is encoded into a quantum layer — typically a **Variational Quantum Circuit**, or VQC.”

“The VQC is made up of qubits — the number depending on the model — and uses rotation gates with trainable parameters (like $R\_y(\theta)$) to transform the data in quantum space. Crucially, this transformation happens in a high-dimensional Hilbert space.”

“Amplitude encoding is often used to map classical inputs efficiently into qubit states, sometimes reducing input size from n to log(n) qubits.”

**Slide 4: Image Processing HQNN Example**

“Here’s a concrete example from medical imaging: a CNN first extracts features from a chest X-ray. Those features are then encoded into qubits using amplitude encoding and passed through a VQC.”

“After entangling the qubits and applying the trainable rotation gates, we measure the final quantum state and map it to a prediction.”

“This approach reduces parameter count and FLOPs, and still achieves competitive accuracy.”

**Slide 5: HQNNs vs Classical Neural Networks**

“My research compared HQNNs to classical neural networks across four main metrics: **training time**, **FLOPs**, **parameter count**, and **accuracy**.”

“Across studies, HQNNs generally outperformed classical models in training efficiency and size, while maintaining — and sometimes improving — accuracy. In one case, training time dropped by 29% and parameter count was cut nearly in half.”

“It’s worth noting that most of these experiments used simulators — and the datasets were smaller, due to current hardware limitations.”

**Slide 6: Additional Performance Visual**

“Here’s another comparison visual showing how HQNNs can have slightly lower accuracy than a classical model — but still be more efficient overall in computation and resource usage.”

“It’s a trade-off: lower FLOPs and fewer parameters can be worth it, depending on the application.”

**Slide 7: The Quantum Bottleneck — Where We Are Today**

“We are currently in what’s called the **NISQ Era** — Noisy Intermediate-Scale Quantum. This refers to hardware that’s powerful, but still noisy and limited.”

“The top QPUs today support around 1,000 qubits. But to break modern encryption or train fully quantum models, we’d need **millions**.”

“There’s also a constraint called **coherence time** — the window during which a qubit retains its quantum state. Typically, this is just 10 to 50 microseconds. If your circuit doesn’t finish in that time, you lose the quantum information.”

“Add to that the delays from cloud-based quantum-classical integration — where QPUs are remote — and you can see why HQNNs are still research-stage systems.”

**Slide 8: The Future of HQNNs**

“So what’s next?”

“The future of HQNNs depends heavily on **hardware improvements** — more stable qubits, longer coherence times, and tighter classical-quantum integration.”

“As these barriers are overcome, we could move toward **fully quantum neural networks**, with no classical components at all. That could unlock massive speedups and novel learning behaviors.”

**Slide 9: Ethics and Industry Readiness**

“One key topic that can’t be ignored is **ethics and interpretability**.”

“Imagine a quantum-enhanced AI used to diagnose cancer. If it gives a result, can we explain why it reached that conclusion?”

“As HQNNs enter high stake fields, they’ll need to be **transparent and reliable** — not just fast or efficient. That’s going to be essential for industry trust and public acceptance.”

**Slide 10: Final Thoughts**

“To wrap up: HQNNs are showing real promise. My research found that they consistently reduce parameters, training time, and computation — even on today’s limited simulators.”

“But they’re also constrained by hardware noise, short coherence times, and classical integration delays.”

“That’s why I think it’s best to see HQNNs not as the final product — but as a **transitional architecture** — paving the way for fully quantum learning systems.”

“If we can maintain transparency, interpretability, and performance, HQNNs could offer a real quantum advantage in the near future.”

**Slide 11: Thank You**

“Thank you for listening. I’d be happy to answer any questions!”