**Intro Slide *(Title Slide — You speak while showing title)***

Hello everyone — my name is Andrew Nerud.  
Today, I’ll be presenting my State of the Field research on Hybrid Quantum Neural Networks — or HQNNs — focusing on their efficiency, real-world viability, and where this technology is heading.

**So, Why am I looking at HQNNs?**

Well, AI models are becoming increasingly large and power-hungry.  
and HQNNs aim to address this by combining classical deep learning with quantum computation.  
They promise efficiency, generalization, and new ways to process information.

They also they represent a new approach to overcoming the limitations of today’s AI — particularly for applications where power, data, or hardware are limited.

So the key question is: Are HQNNs ready for real-world AI adoption?

**Before I get into the core of my research, I wanted to give some quantum background.**  
Quantum computing is centered around qubits, looking at the diagram to the left, like bits are to a classical computer, but qubits can be in a state of superposition — think of it like a probability vector between 0 and 1.  
They have an important trait of entanglement, which links qubits together, so measuring or performing operations on one affects the others.  
Then, we have quantum gates like Rotational gates or CNOT which perform transformations on the qubit’s vector, kind of like logic gates in classical computing.  
These quantum properties allow us to build Variational Quantum Circuits — or VQCs — which act as the quantum layer in HQNNs.

The VQC uses n qubits to encode data, often through angle or amplitude encoding. Amplitude encoding compresses data logarithmically — n qubits for 2ⁿ inputs — but is harder to implement.

**Now, let’s visit the HQNN structure.**  
Looking at the first diagram, we feed input data — often images — through a classical convolutional layer to reduce dimensionality and help extract features  
Then, the feature vector is passed into the VQC, where quantum embeddings and transformations are applied.  
The output is sent back to classical layers to make the final prediction.  
[Pause — 20 seconds here to describe your VQC diagram]

This is a VQC that I used for a project I will showcase shortly, it has 4 qubits and three strongly entangled trainable layers. The input x0-3 is embedded with a rotational gates, then they go through those three layers, with the trainable parameters theta0-11 and CNOT gates to entangle each qubit and at then end it is measured, transforming back into classical outputs.

One key thing here is that quantum circuits operate in Hilbert space — a high-dimensional mathematical space — due to entanglement which lets HQNNs encode more complex patterns than classical networks with fewer parameters.

And because qubits interact via entanglement, the model can naturally learn correlations that classical models would need more layers to capture.

**Next, I will walk you through the core of my research**

Let’s talk performance.

I looked at various model comparisons in reseach, and these were the most documented that I could take from. I compared training time, parameters, floating point operations (or FLOPs), and accuracy.

Resultingly, HQNNs consistently reduce trainable parameters — often by 40 to 50 percent.  
and FLOPs can be cut by about 30 percent, leading to smaller, more efficient models.  
And they still maintain competitive accuracy — even outperforming CNNs in medical imaging and chemistry datasets.

However, the classical models performed better training time-wise.

**On that note, there are some Challenges in HQNN Adoption**

First, training time — HQNNs trained on simulators are much slower to due the high computation cost of simulators.

Next, we are currently in the Noisy Intermediate Scale quantum Era, where we have qubits that are effected by noise and decoherance – where qubits are guaranteed to change state between 10 to 50 microseconds, which effects the size of VQCs since they need to complete before that time.

The other part with the NISQ Era is that hardware is still relatively small. The current most qubits on a QPU is roughly 1000, where we’d need roughly 1000000 to break current encryption schemes.

And finally, there’s a lack of standardized benchmarks, making comparisons inconsistent, one trouble I was having with gathering data for my research.

**Experimental Results: HQNN on Digit Classification**

Now I want to describe my own explorations project. For my project, I implemented a HQNN on the MNIST dataset.  
As can be seen in the comparison with the classical models, it performed with 1.5% less accuracy but with 88% fewer parameters and 63% fewer FLOPs.  
And — as expected — training was significantly slower due to simulation.  
[Refer to table — and nod to accuracy convergence graphs on right-hand side.]  
These results once again suggest HQNNs are efficient but still impractical for time-sensitive tasks.

**Future Research**

Building on this, I’m applying HQNNs to reinforcement learning.  
In this setup, a drone uses a camera to guide a car through a track — and HQNNs will replace the classical model in the future.  
The goal is to test generalization and efficiency in dynamic, real-time settings.

The HQNN policy model would aim to learn visual-guided decision-making with fewer parameters than classical networks — potentially allowing this system to run on lighter hardware.  
If successful, it could demonstrate how HQNNs can scale beyond static tasks like classification into real-time, embodied AI environments like robotics or autonomous control.

**What’s Next for HQNNs?**

Several exciting trends are pushing HQNNs forward.  
First — circuit cutting and new optimization techniques are enabling deeper circuits even on today’s limited hardware.  
As seen with the first diagram, the current NISQ devices we have now will need hardware optimization, then alongside error correction we can optimize HQNNs to obtain the most reliable use of these models.  
Second — interpretability tools like Q-LIME are emerging to explain predictions — especially important for trust in quantum AI.  
Third — applications are expanding rapidly.  
This graph is the number of publications in arXiv that have “quantum machine learning” in their title or abstract. This shows growth in quantum machine learning research — and HQNNs are a central part of that.  
Finally, hardware progress: Amazon’s Ocelot and Microsoft’s Majorana chips are expected to dramatically improve coherence times and scalability.

**Responsible Quantum AI**

As these models progress, we also need to think about ethical issues when they enter domains like healthcare and finance.

For example, if I were getting diagnosed by one of these models, I would want to know two things: that the model is making the decision correctly, and that the medical professionals know WHY it’s making that decision: right, we want explainablity and accuracy.  
Research should focus on building ethical, interpretable HQNN systems — and that will be critical for real-world adoption.

We're also entering a phase where quantum systems could introduce new kinds of opacity.  
Just as classical deep learning struggles with explainability, quantum models add an extra layer of abstraction — and that makes transparency even more essential.

**Final Thoughts**

Before ending, I wanted to leave you some key points to remember.  
My research has found that HQNNs offer meaningful advantages in efficiency and generalization — especially for small-data, domain-specific applications.  
But key challenges remain: noise, speed, and hardware constraints still limit their deployment.  
With better hardware, smarter hybrid training, and responsible design, HQNNs could become a steppingstone towards understanding and creating fully quantum neural networks.  
Until then, they are best viewed as powerful tools for specific, high-impact use cases where efficiency truly matters.

**Thank You**

Thank you for listening — I’m happy to answer any questions.