Sprint Retrospective

Liked	Learned	Lacked	Longed For
The successful implementation of multiple models (KNN, CNN, H-QNN) allowed us to compare results effectively and draw valuable conclusions about their performance in DDoS detection.	We learned that quantum-enhanced models, while still in development, can outperform classical models in terms of both accuracy and processing speed, especially with high-dimensional data.	We lacked comprehensive access to real-time network data for testing, limiting our ability to validate model performance in dynamic, live environments. Additionally, documentation on quantum tools like PennyLane could have been more detailed for smoother implementation.	I longed for a better integration between the classical and quantum components to reduce computational overhead and make the hybrid model more scalable for real-time applications. More diverse datasets and greater clarity on quantum resource constraints would have further improved our results.
The collaboration between team members, especially in troubleshooting the integration of classical and quantum layers, was efficient and fostered knowledge sharing.	The importance of data preprocessing (cleaning, scaling, and encoding) was reinforced, especially for high-dimensional datasets like CIC-DDoS2019, which impacted model performance greatly.	We lacked sufficient hardware resources to fully utilize GPU and quantum cloud services simultaneously, causing bottlenecks in the training phase. There was also a need for clearer documentation on integrating quantum and classical models seamlessly.	I longed for more automation in the testing process to handle large datasets efficiently and for more opportunities to experiment with deep quantum models such as Quantum CNNs or Quantum RNNs for broader exploration.
The flexibility of using Python libraries (e.g., TensorFlow, Scikit-learn) alongside quantum libraries (e.g., PennyLane) provided a versatile development environment, making model experimentation smoother.	We learned that balancing technical debt (such as complex feature extraction) with model experimentation is essential to achieving stable, scalable results, especially in an advanced field like quantum computing.	We lacked deeper insights into handling noisy quantum circuits, which affected the accuracy of some H-QNN tests. This was a limiting factor in optimizing our quantum layer's performance.	I longed for additional training or tutorials specific to quantum machine learning models to fast-track implementation and avoid trial-and-error in critical areas. Greater access to optimized, noise-resistant quantum hardware would also have accelerated testing and reduced errors.