CISC 520-90-O-2024

FINAL PROJECT REPORT

Harnessing Quantum AI

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Executive Summary

This report explores the groundbreaking fusion of quantum computing and machine learning (ML), with a focus on how this convergence can revolutionize the financial sector. Quantum computing, leveraging principles such as superposition and entanglement, offers the potential for significant advancements in computational efficiency. These capabilities enable new approaches to solving problems in fields such as cryptography, material science, and drug discovery—domains that have traditionally been constrained by classical computing (al. J. T., Oct. 2023).

Simultaneously, machine learning (ML), especially through neural networks and Large Language Models (LLMs), has revolutionized programming paradigms by shifting from traditional rule-based systems to data-driven methodologies. This transition enables models to learn from vast datasets, allowing for more adaptive and intelligent solutions without explicit hand-coded rules. These models excel at automating complex tasks across domains like natural language processing (NLP), image recognition, and predictive analytics. The fusion of quantum computing with ML introduces quantum-enhanced machine learning models that can process exponentially more variables and interactions than classical models. This synergy is revolutionizing programming methodologies by allowing algorithms to operate at unprecedented levels of complexity and efficiency (al. J. T., Oct. 2023).

This report demonstrates the creation of hybrid quantum-classical models using the PennyLane library for quantum machine learning (QML) and PyTorch Lightning for efficient deep learning training. PennyLane enables the seamless implementation and simulation of quantum algorithms, making it accessible for developers to experiment without the immediate need for specialized quantum hardware. PyTorch Lightning facilitates scalable, efficient model training and management. Together, these tools showcase how quantum computing and ML can revolutionize both individual fields and broader programming methodologies.

A particular focus is given to how QML can transform the financial sector. Financial models, which traditionally rely on large-scale data processing and complex pattern recognition, stand to benefit

immensely from quantum-enhanced computations. Quantum Neural Networks (QNNs) can analyze high-dimensional datasets involving real-world economic indicators such as stock prices, inflation rates, and interest rates, making it possible to perform more nuanced and detailed computations. This capability can lead to significant improvements in predictive accuracy, risk management, and portfolio optimization. Recent research published by IEEE demonstrates the potential of QML in financial modeling, showing that quantum models outperform classical algorithms in efficiency and accuracy, particularly in complex scenarios such as portfolio optimization and risk evaluation (N. K. Bhasin, 2024) (Y. J. Chang, April 2023).

Moreover, the integration of LLMs into these hybrid models enhances their ability to process unstructured textual data, such as financial reports, news articles, and sentiment analysis, enabling more holistic and informed decision-making. Research presented at the IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr) and similar conferences has investigated the application of quantum algorithms for optimizing complex financial systems. These studies highlight the potential for Quantum Machine Learning (QML) to revolutionize traditional financial paradigms by offering enhanced computational efficiency and problem-solving capabilities (Sharma, 2023).

The combination of quantum computing and ML in the financial sector offers a range of benefits, including improved forecasting, better asset allocation, and more efficient risk modeling. As quantum hardware continues to evolve, further IEEE research suggests that the application of quantum machine learning algorithms will become more viable, providing even greater opportunities for financial institutions to harness these advancements (al. J. T., Oct. 2023).

In conclusion, the integration of quantum computing and machine learning is poised to revolutionize the financial sector. The hybrid quantum-classical models explored in this report demonstrate the potential of quantum-enhanced computations to optimize decision-making and predictive analysis, offering faster, more accurate solutions to some of the most complex challenges in finance. As quantum hardware advances, these technologies will play an increasingly significant role in transforming financial operations, from risk assessment to portfolio management. The hybrid approach outlined in this report not only redefines the future of finance but also sets the stage for broader applications across various industries.

Literature Review

Large Language Models (LLMs) in Financial Text Processing

Large Language Models (LLMs) like GPT-4[1] have demonstrated exceptional capabilities in tasks such as text summarization, generation, and sentiment analysis. In the financial domain, Large Language Models (LLMs) are particularly effective for processing vast datasets of financial news, reports, and analyses. In their paper *FIN2SUM: Advancing AI-Driven Financial Text Summarization with LLMs*, (E. Wilson, 2024) introduce FIN2SUM, a specialized LLM designed specifically for financial text summarization. FIN2SUM is tailored to handle the unique linguistic structures and terminologies within financial documents, offering more precise and relevant summaries for stakeholders in the industry.

The model tackles the unique challenges posed by financial texts, such as ambiguity in forecasts, specialized terminologies, and the complexity of market reports. By employing a fine-tuning approach on a large corpus of financial documents, FIN2SUM improves comprehension of financial jargon and provides highly relevant, concise summaries. This capability is vital in financial applications like algorithmic trading and risk management, where quick and accurate information processing is crucial.

Wilson et al. demonstrate that FIN2SUM outperforms baseline models on various financial datasets, underscoring the potential of LLMs to enhance decision-making processes in finance. Their study highlights how these models can reduce information overload by converting vast amounts of financial data into actionable insights. As technologies like AI and quantum computing advance, LLMs are poised to play an even more critical role in financial text processing.

[1] https://openai.com/

Quantum Neural Networks (QNNs) for Finance Using PennyLane[2]

Quantum Neural Networks (QNNs) are a groundbreaking integration of quantum computing and machine learning (ML), offering immense potential in the financial sector for advanced tasks like predictive modeling, portfolio optimization, and risk management. By leveraging quantum circuits, QNNs can process and analyze complex, high-dimensional data more efficiently than classical models, thanks to quantum principles such as superposition and entanglement. This capability is particularly crucial in finance, where traditional ML models often falter due to the sheer scale and intricacy of financial data. Quantum algorithms within QNNs enable quicker, more precise financial predictions by optimizing multiple variables simultaneously. In portfolio management, QNNs can explore extensive solution spaces, developing more refined asset allocation strategies that effectively balance risk and return. Similarly, in risk management, QNNs enhance the analysis of economic indicators and market data, providing superior accuracy in forecasting market trends and assessing financial risk. Tools like PennyLane play a pivotal role, facilitating the integration of quantum circuits with classical ML frameworks, enabling the creation of hybrid quantum-classical models optimized for financial applications. While current quantum hardware limitations pose challenges, ongoing advancements in quantum computing are expected to make QNNs an indispensable part of future financial strategies, significantly improving decision-making in areas such as asset allocation and risk evaluation (N. K. Bhasin, 2024) (Bergholm, 2002) (Abbas, 2021).

PyTorch Lightning[3]

PyTorch Lightning is a powerful, high-level framework built on top of PyTorch, designed to streamline the development, training, and scaling of machine learning models. It abstracts much of the repetitive and boilerplate code involved in traditional PyTorch implementations, enabling researchers and developers to focus more on model architecture and experimentation. By

[2] https://pennylane.ai/
[3] https://lightning.ai/docs/pytorch/stable/

automating many aspects of the training process, such as distributed computing, gradient accumulation, and early stopping, PyTorch Lightning enhances efficiency and scalability. Its modular structure ensures clean, organized code, promoting best practices and enabling reproducibility. Additionally, PyTorch Lightning integrates seamlessly with libraries like PennyLane, making it an ideal framework for developing hybrid quantum-classical models. This integration is especially valuable in cutting-edge fields such as quantum machine learning, where combining the strengths of both classical and quantum computing can lead to enhanced performance and novel solutions to complex problems.

DATA SOURCES

This analysis utilizes a diverse range of data sources spanning the years 2005 to 2023, integrating both company-specific financial metrics and broader macroeconomic indicators. Key metrics from the *JPMorgan Chase 2023 Annual Report*[4] including Net Income, Diluted Earnings per Share (EPS), and Return on Tangible Common Equity (ROTCE), provide critical insights into the company's financial health and performance over time. These metrics are fundamental for evaluating profitability, shareholder returns, and overall financial stability.

For historical stock performance, data from Alpha Vantage[5] is used to track JPMorgan Chase's stock price and related indicators, such as the Simple Moving Average (SMA), which helps analyze stock trends and market behavior. Additionally, Alpha Vantage supplies key economic data, including the Consumer Price Index (CPI), Federal Funds Rate, and Inflation data, which are essential for understanding the economic environment and its influence on financial markets.

[4] https://www.jpmorganchase.com/content/dam/jpmc/jpmorgan-chase-and-co/investor-relations/documents/annualreport-2023.pdf

[5] https://www.alphavantage.co/documentation/

Complementing this, the analysis incorporates broader macroeconomic data sourced from the World Bank[6], specifically focusing on Unemployment rates and GDP growth, which provide valuable context for economic conditions impacting financial markets and corporate performance. Together, these datasets offer a comprehensive perspective on both JPMorgan Chase's financial trajectory and the macroeconomic forces that shape its market environment.

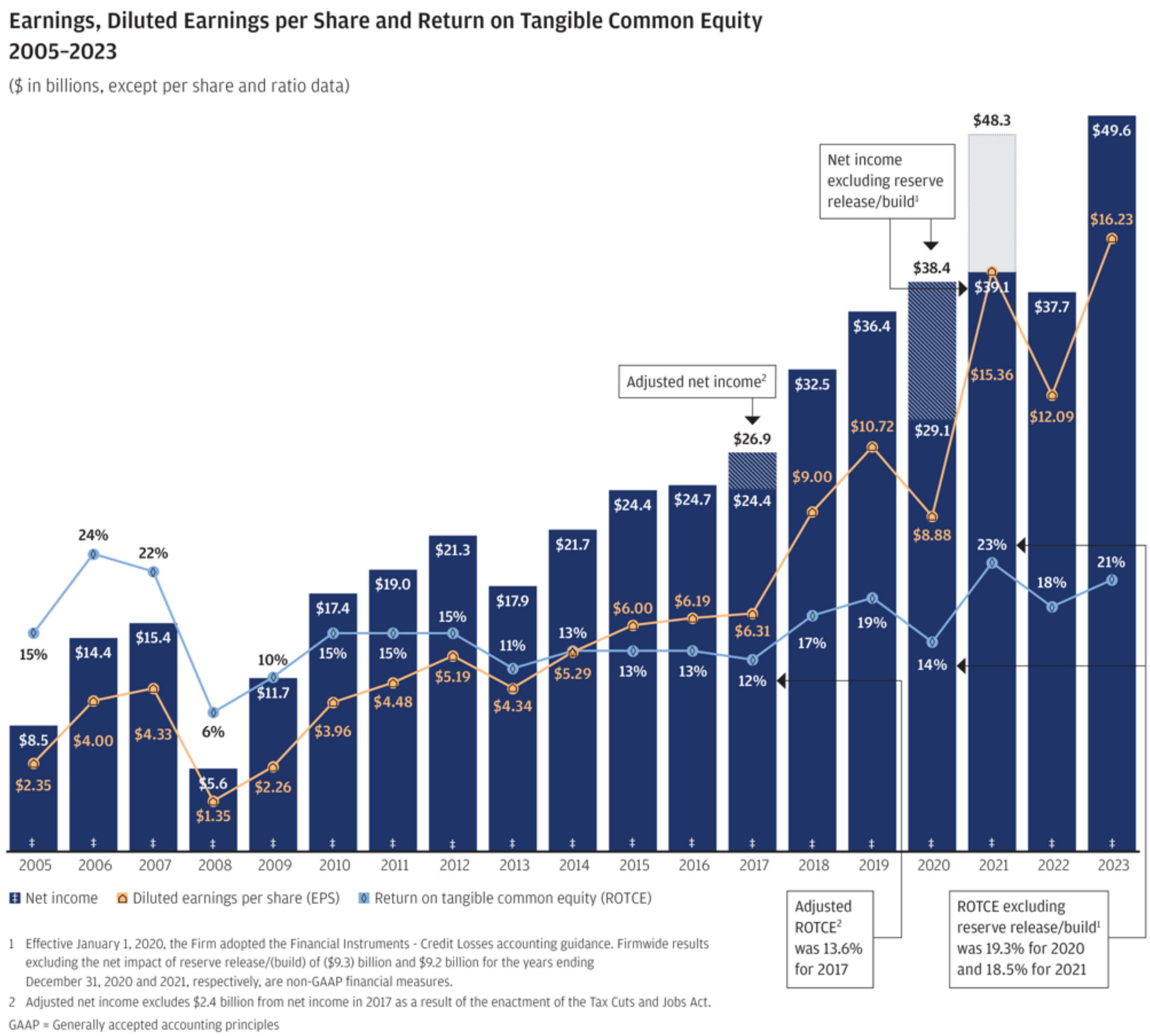

Figure 1. Earnings, Diluted Earnings per Share and Return on Tangible Common Equity

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6 https://data.worldbank.org

The chart you uploaded depicts key financial metrics from JPMorgan Chase from 2005 to 2023, including Net Income, Diluted Earnings per Share (EPS), and Return on Tangible Common Equity (ROTCE).

Here are some key insights from the chart:

1. **Net Income Growth**: JPMorgan's net income showed a general upward trend from 2005 to 2023, with notable increases after 2010. In 2023, net income reached $49.6 billion, a significant rise from $8.5 billion in 2005.
2. **Financial Crisis Impact**: 2008 (financial crisis year) shows a drop in net income to $5.6 billion from $15.4 billion in 2007, while 2009 reflects a recovery to $11.7 billion.
3. **Return on Tangible Common Equity (ROTCE)**: ROTCE fluctuated throughout the period, peaking at 24% in 2006 before dropping during the crisis (10% in 2008) and then recovering to higher levels like 19% in 2023. Adjusted ROTCE was 13.6% in 2017, and it was adjusted to exclude certain financial impacts for later years.
4. **Diluted EPS**: Diluted earnings per share also showed a growth trajectory, increasing from $2.35 in 2005 to $16.23 in 2023. There were dips during the crisis years (2008: $1.35, 2009: $2.26), followed by steady growth.
5. **Recent Trends (2021-2023)**: Net income remained strong in recent years, with $48.3 billion in 2021 and $49.6 billion in 2023. ROTCE remained stable at around 21% for 2023.

Figure 2. ChatGPT Response (GPT-4)

To extract specific values, I'll create a table based on the chart's key metrics (Net Income, EPS, and ROTCE):

Year	Net Income (Billion $)	Diluted EPS ($)	ROTCE (%)
2005	8.5	2.35	15
2006	14.4	4.00	24
2007	15.4	4.33	22
2008	5.6	1.35	10
2009	11.7	2.26	15
2010	17.4	3.96	15
2011	19.0	4.48	15
2012	21.3	5.19	15
2013	17.9	4.34	11
2014	21.7	5.29	13
2015	24.4	6.00	13
2016	24.7	6.19	13
2017	24.4	6.31	13 (Adjusted 13.6%)
2018	32.5	9.00	17
2019	36.4	10.72	19
2020	29.1	8.88	19 (Excluding reserve release/build)
2021	48.3	15.36	23
2022	37.7	12.09	18
2023	49.6	16.23	21

These are the values derived from the chart, giving an overview of JPMorgan Chase's financial performance over time.

Figure 3. Chat GPT - 4o response

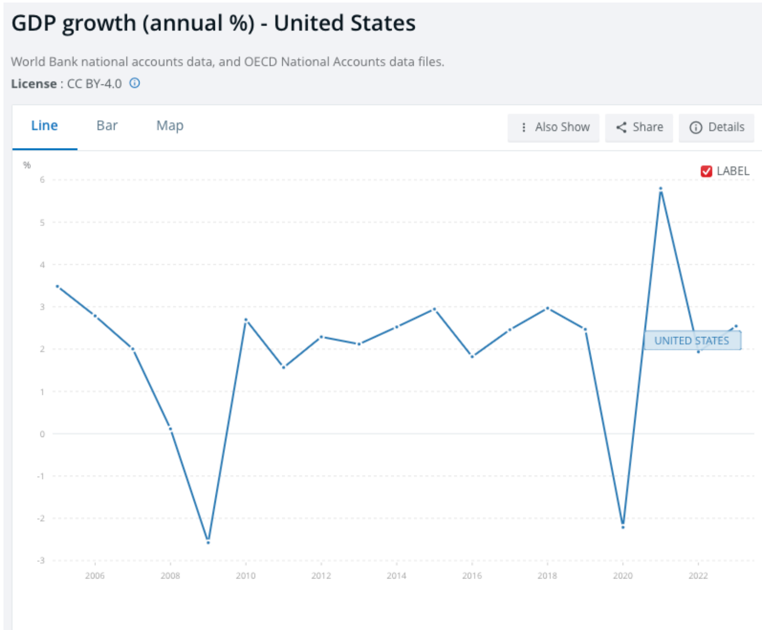

Figure 4. GDP - United States[7]

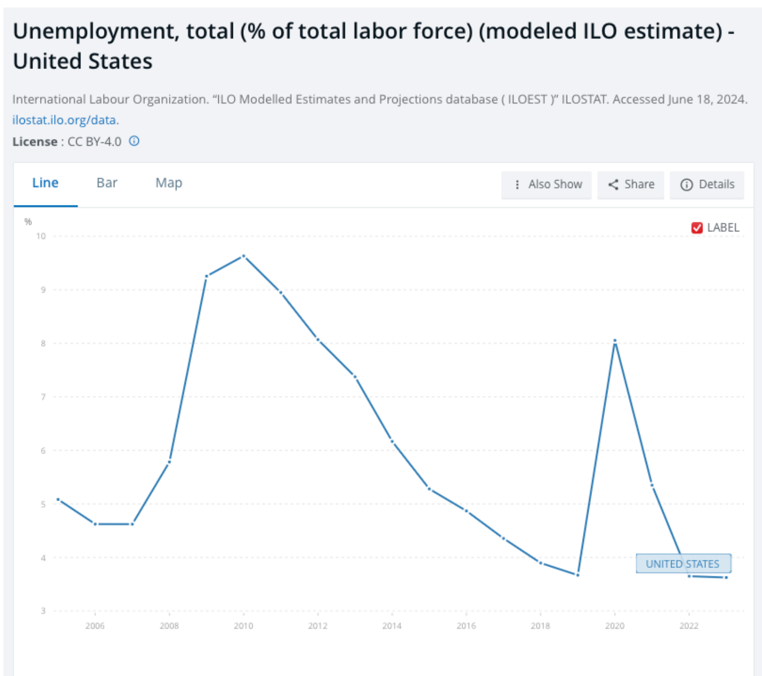

Figure 5. Unemployment, United States[8]

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7 https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?contextual=default&end=2023&locations=US&name_desc=true&start=2005&view=chart

8 https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?end=2023&locations=US&start=2005

Figure 6. JPMorgan Chase Stock - Historical Data

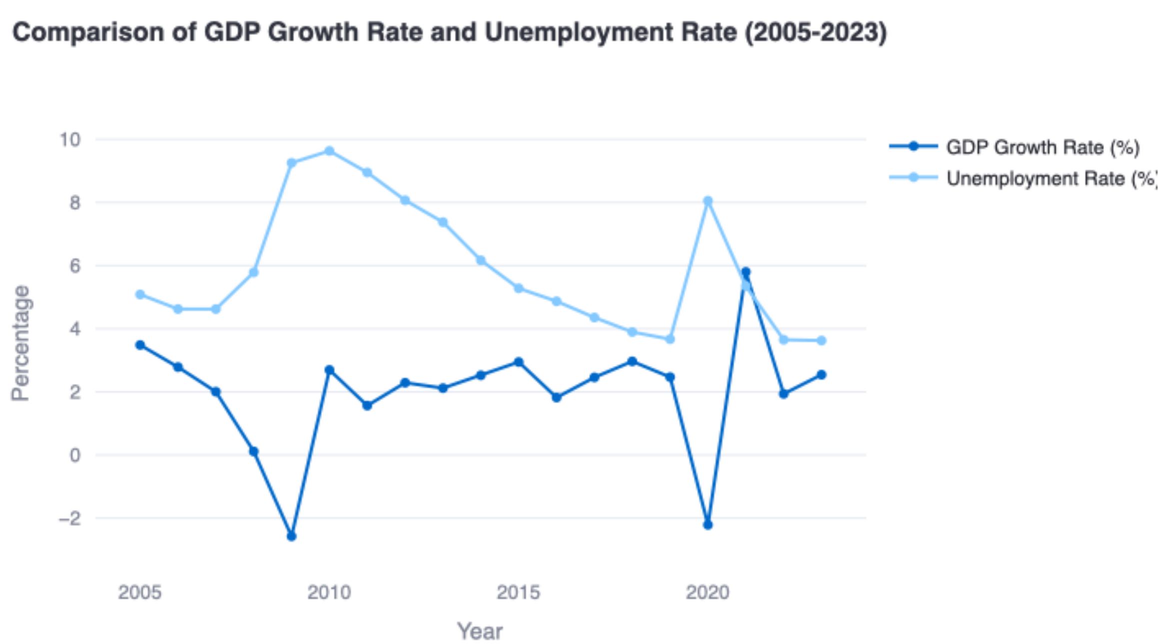

Figure 7. Comparison GDP Growth Rate Vs Unemployment

RESULTS

Quantum Machine Learning (QML) on CPU

Executing **Quantum Machine Learning (QML)** models on CPUs provides a practical and accessible environment for testing quantum-inspired algorithms, though it comes with significant computational challenges. Simulating quantum operations, such as entanglement and superposition, on classical hardware is resource-intensive, particularly as the number of qubits increases, leading to slower training and higher memory usage. Despite these limitations, CPU-based simulations play a crucial role in prototyping QML models, allowing researchers to experiment with quantum circuits and optimize algorithms before transitioning to quantum hardware. Moreover, integrating quantum simulations with classical machine learning frameworks enables the development of hybrid quantum-classical models, paving the way for future deployment on quantum processors. While CPUs are less efficient, they provide a flexible platform to refine QML models, ensuring they are well-prepared for quantum hardware implementation.

Running Quantum Machine Learning (QML) models on CPUs provides a practical environment for testing quantum algorithms, though it faces challenges like slower training and higher memory usage due to the resource-intensive nature of simulating quantum operations. Despite these limitations, CPU simulations are vital for prototyping and refining QML models, allowing researchers to experiment with quantum circuits and optimize algorithms. CPUs also enable the integration of quantum and classical machine learning frameworks, helping develop hybrid quantum-classical models. This approach is essential for fine-tuning models before deploying them on quantum hardware, bridging the gap between current simulations and future quantum computing applications.

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Year: 2005, Financial health prediction: 0.6958, Suggested outlook: Weak
Year: 2006, Financial health prediction: 0.9691, Suggested outlook: Strong
Year: 2007, Financial health prediction: 0.9794, Suggested outlook: Strong
Year: 2008, Financial health prediction: 0.9580, Suggested outlook: Weak
Year: 2009, Financial health prediction: 0.4922, Suggested outlook: Weak
Year: 2010, Financial health prediction: 0.6428, Suggested outlook: Weak
Year: 2011, Financial health prediction: 0.7764, Suggested outlook: Moderate
Year: 2012, Financial health prediction: 0.7794, Suggested outlook: Moderate
Year: 2013, Financial health prediction: 0.4595, Suggested outlook: Weak
Year: 2014, Financial health prediction: 0.7243, Suggested outlook: Weak
Year: 2015, Financial health prediction: 0.6465, Suggested outlook: Weak
Year: 2016, Financial health prediction: 0.6919, Suggested outlook: Weak
Year: 2017, Financial health prediction: 0.9882, Suggested outlook: Strong
Year: 2018, Financial health prediction: 0.4621, Suggested outlook: Weak
Year: 2019, Financial health prediction: 0.4749, Suggested outlook: Weak
Year: 2020, Financial health prediction: 0.8851, Suggested outlook: Strong
Year: 2021, Financial health prediction: 0.9617, Suggested outlook: Strong
Year: 2022, Financial health prediction: 0.5119, Suggested outlook: Weak
Year: 2023, Financial health prediction: 0.4819, Suggested outlook: Weak
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Figure 8. QML Prediction

Year	Net Income	EPS	ROTCE	GDP Growth	Unemployment	CPI	Interest Rate	Inflation	SMA
2005	8.5	2.35	15	3.48355	5.084	195.292	3.21333	3.39275	21.4691
2006	14.4	4	24	2.78454	4.623	201.592	4.96417	3.22594	26.5967
2007	15.4	4.33	22	2.00386	4.622	207.342	5.01917	2.85267	30.5635
2008	5.6	1.35	6	0.113587	5.784	215.303	1.9275	3.8391	27.1704
2009	11.7	2.26	10	-2.5765	9.254	214.537	0.16	-0.355546	23.2427
2010	17.4	3.96	15	2.69519	9.633	218.055	0.175	1.64004	27.6584
2011	19	4.48	15	1.56441	8.949	224.939	0.101667	3.15684	27.6276
2012	21.3	5.19	15	2.28911	8.069	229.594	0.14	2.06934	26.9963
2013	17.9	4.34	11	2.11783	7.375	232.957	0.1075	1.46483	36.7821
2014	21.7	5.29	13	2.52382	6.168	236.736	0.0891667	1.62222	43.1836
2015	24.4	6	13	2.94555	5.28	237.017	0.1325	0.118627	48.6238
2016	24.7	6.19	13	1.81945	4.869	240.007	0.395	1.26158	50.6913
2017	26.9	6.31	12	2.45762	4.355	245.12	1.00167	2.13011	72.9401
2018	32.5	9	17	2.96651	3.896	251.107	1.83167	2.44258	91.8439
2019	36.4	10.72	19	2.46704	3.669	255.657	2.15833	1.81221	94.3072
2020	38.4	8.88	14	-2.21347	8.055	258.811	0.375833	1.23358	95.2142
2021	48.3	15.36	23	5.80021	5.349	270.97	0.08	4.69786	138.329
2022	37.7	12.09	18	1.9355	3.65	292.655	1.68333	8.0028	121.724
2023	49.6	16.23	21	2.5427	3.625	304.702	5.02417	4.11634	136.454
2024	45.9596	13.4847	17.386	2.44534	4.58907	288.422	0.90807	3.44191	126.14
2025	48.0725	14.1578	17.5667	2.49135	4.45688	293.409	0.848456	3.52966	132.747

Figure 9. Tabulated Result - With Prediction for 2024, 2025

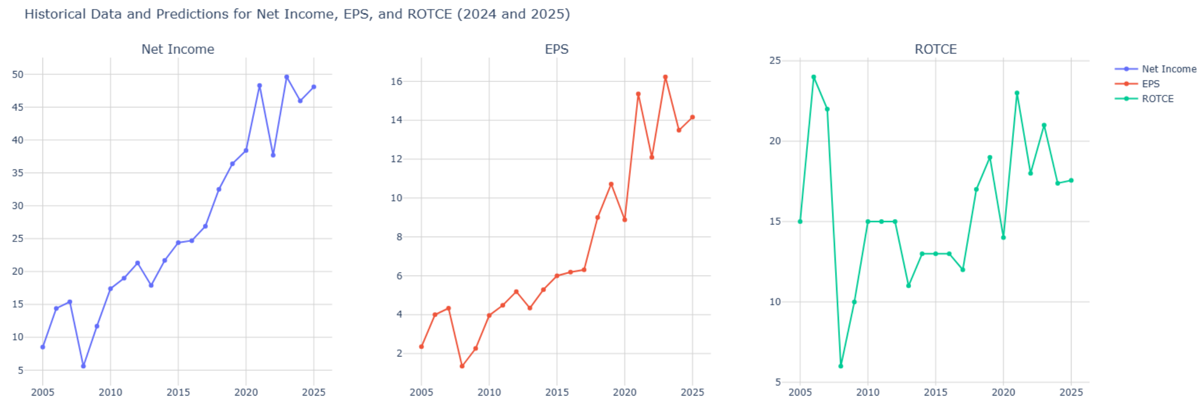

Figure 10. Historical Data and Predictions - Net Income, EPS and ROTCE

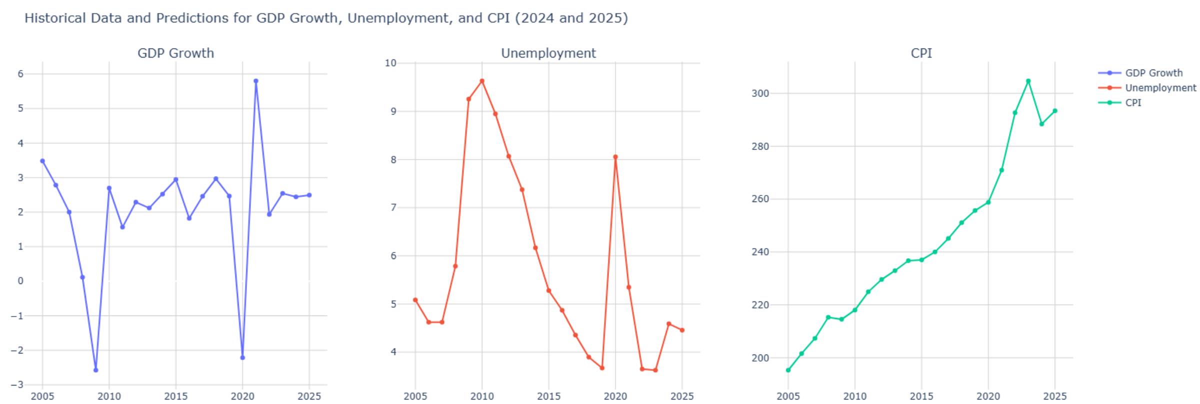

Figure 11.Historical Data and Predictions - GDP, Unemployment, CPI

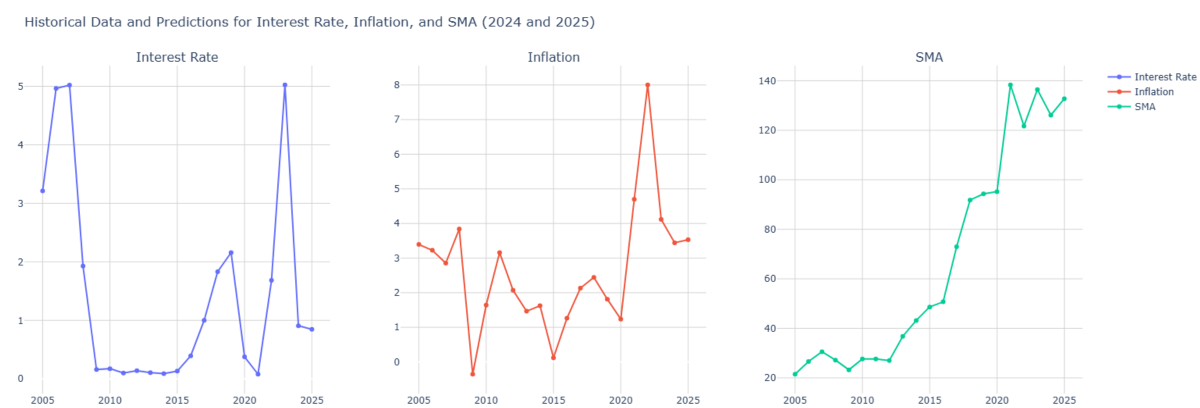

Figure 12. Historical Data and Predictions - Interest Rate, Inflation, SMA

Results: Quantum Machine Learning (QML) with PyTorch Lightning on GPU

Implementing Quantum Machine Learning (QML) models with PyTorch Lightning on GPUs offers substantial performance improvements compared to CPU-based simulations, particularly by accelerating training and optimizing computational efficiency. GPUs are ideally suited for parallelized computations, making them highly effective in handling the complex operations involved in simulating quantum circuits, especially in hybrid quantum-classical models that combine quantum layers with classical neural networks. By leveraging PyTorch Lightning's streamlined framework, researchers can fully exploit the computational power of GPUs, significantly reducing training time through automated processes like gradient updates, data parallelism, and resource management. This is especially valuable when working with complex quantum circuits, where the number of qubits and quantum gates scales exponentially, demanding immense computational resources. GPUs ensure these simulations run smoothly and efficiently, even as the complexity of the quantum models increases.

Furthermore, PyTorch Lightning integrates seamlessly with quantum libraries such as PennyLane, facilitating easy experimentation and optimization of hybrid models. This synergy allows for faster fine-tuning of both quantum and classical components, while also supporting scalability through multi-GPU and distributed training capabilities. The use of GPUs not only speeds up model development but also enhances the scalability of QML models, enabling researchers to handle more sophisticated simulations. Ultimately, PyTorch Lightning on GPUs significantly accelerates the advancement of quantum-classical hybrid models, bridging the gap between current classical simulations and the future deployment of QML on quantum hardware, positioning it as a vital tool for cutting-edge quantum computing research and applications.

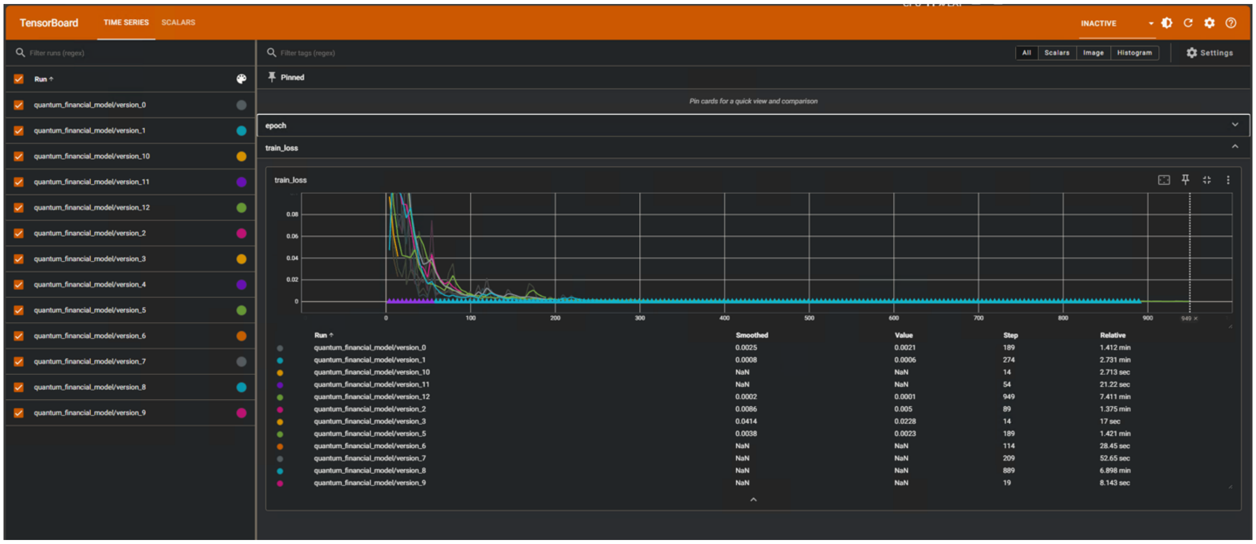

Figure 13. Tensor board Results - 1

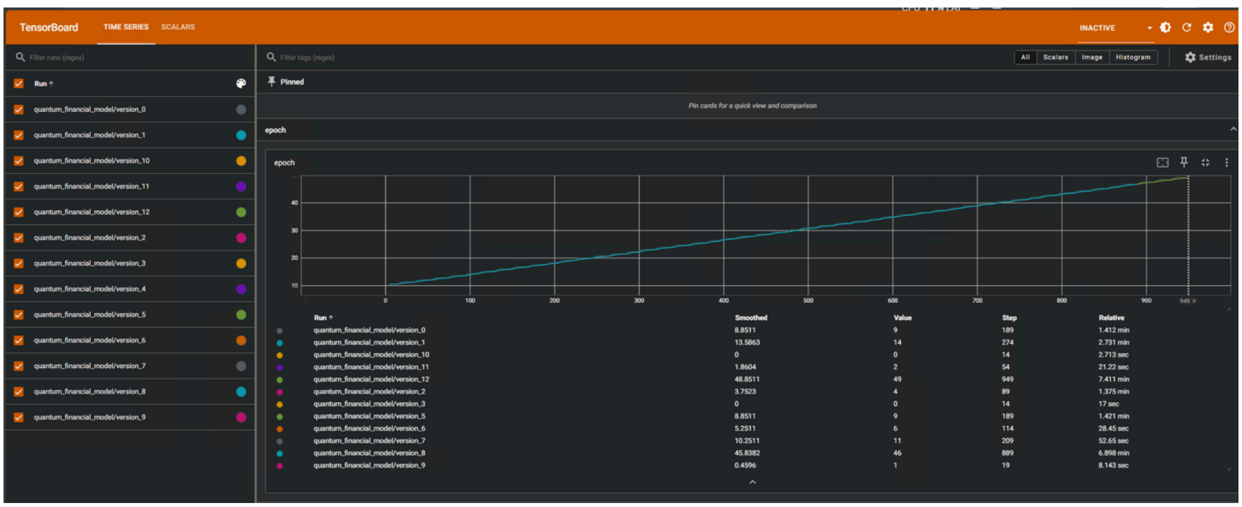

Figure 14. Tensor board Results - 2

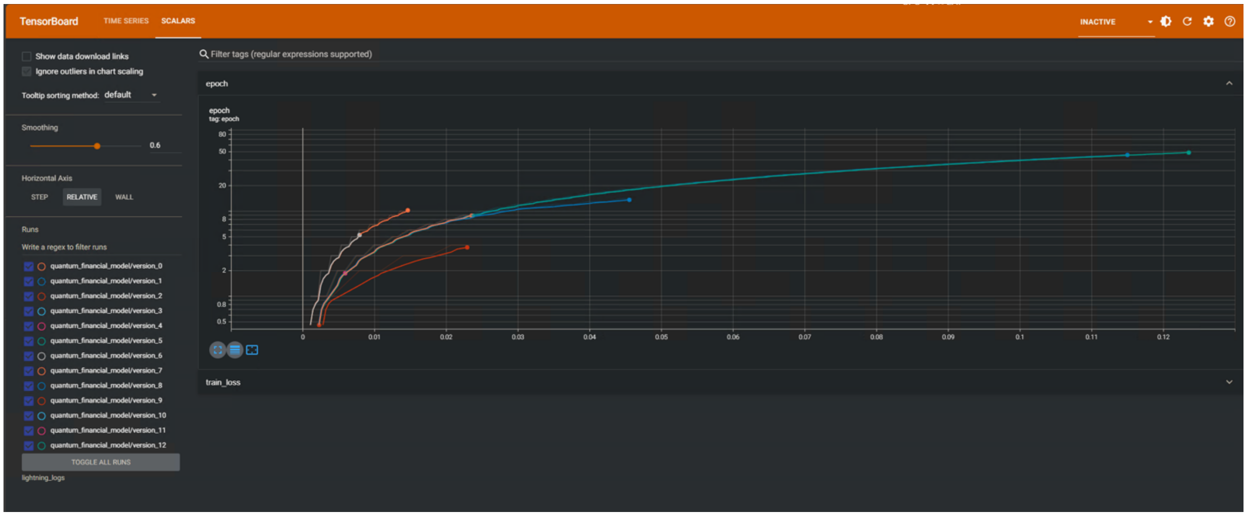

Figure 15. Tensor board Results - 3

Figure 16. Tensor board Results – 4

Future Scope

The future of Quantum Machine Learning (QML) is promising, particularly as advancements in quantum hardware allow models to process more complex data and perform faster, more accurate computations. As quantum processors evolve, QML will unlock new possibilities in fields such as finance, healthcare, and scientific research, enabling solutions to problems that classical systems have struggled to address.

A key development is the integration of Streamlit dashboards to visualize QML results, offering real-time interaction with model outputs. This will enable users to explore predictions and assess performance through intuitive interfaces, making complex quantum data easier to interpret and more practical for decision-makers across industries. In addition to enhanced visualization, leveraging larger and richer datasets will further improve the accuracy and generalizability of QML models. As quantum hardware becomes more capable, QML will efficiently process vast amounts of data, leading to better predictions and broader applications.

A major contributor to the future growth of QML is Qiskit[9], IBM's open-source quantum computing framework. Qiskit allows researchers to design, simulate, and execute quantum algorithms on IBM's quantum hardware, providing a vital platform for QML experimentation. Its integration with quantum hardware ensures that QML models are not only simulated but also run on real quantum processors, driving more realistic and scalable solutions. As Qiskit and quantum hardware advance, QML's potential for solving real-world problems will expand dramatically.

In conclusion, the future of Quantum Machine Learning will be shaped by improvements in quantum hardware, the integration of powerful visualization tools like Streamlit, richer datasets, and frameworks like Qiskit. These advancements will drive innovation and extend QML's impact across industries, offering transformative solutions to complex challenges.

[9] https://www.ibm.com/quantum/qiskit

CONCLUSION

This report explored the potential of Quantum Machine Learning (QML), with a focus on its application in the financial sector and the integration of classical and quantum models. While CPU-based simulations currently provide a useful platform for testing and prototyping QML models, the implementation of QML on GPUs is still in the development phase. In its current state, running QML on GPUs presents significant challenges due to the complexity of quantum simulations and the limitations of existing hardware. However, as GPU technology evolves, it is expected to play a critical role in speeding up model training and scaling QML models.

Tools such as PyTorch Lightning and PennyLane remain essential for accelerating the development of QML, making quantum computing more accessible and efficient. Additionally, the integration of Streamlit dashboards for real-time data visualization will enhance decision-making by providing users with intuitive and interactive insights. Expanding the use of richer and larger datasets will further improve model accuracy, generalizability, and predictive power.

In conclusion, although QML with GPU is still evolving, the ongoing advancements in quantum hardware, combined with enhanced modeling frameworks and richer datasets, will unlock new possibilities. This progress will pave the way for Quantum Machine Learning to drive transformative innovations across industries such as finance, healthcare, and beyond, as it overcomes current computational challenges.

CODE REVIEW

https://github.com/wanderabyss/cisc502_quantum

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