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Article

Quantum-inspired neural networks enhance stock prediction accuracy

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SUMMARY

The inherent complexities and turbulence of the stock market often challenge the predictive capabilities of traditional neural networks like long short-term memory (LSTM) models. However, recent explorations into quantum-inspired computing to deal with the inherent volatility of the stock market offer novel paradigms for handling uncertainty. In this study, we investigated whether incorporating quantum-inspired elements into LSTM neural networks could improve stock price prediction accuracy, especially during periods of high market volatility. We developed a quantum-inspired LSTM (QiLSTM) model featuring a layer designed to mimic quantum concepts like wave-like behavior using sine functions and compared its performance against a traditional LSTM model. We hypothesized that the QiLSTM would outperform the standard LSTM, especially in volatile markets, due to its potential to better capture uncertainty and errata. Using stock data from 2010 to 2024, we tested both models during a recent low volatility period (late 2023-early 2024) and a high volatility period corresponding to the COVID-19 market crash (early 2020). Supporting our hypothesis, the QiLSTM model demonstrated statistically significant superior performance during the high volatility period, achieving lower mean squared error (MSE) and mean absolute percentage error (MAPE) with large effect sizes. During the low volatility period, performance differences were large, with the traditional LSTM significantly outperforming QiLSTM on both MSE and MAPE, indicating that the quantum-inspired layer may be detrimental in low volatility cases.

INTRODUCTION

Financial market prediction has remained an insurmountable challenge due to the inherent complexity, non-linearity, and volatility of market behavior (1). Reliant on fundamental and technical analysis, forecasting has increasingly incorporated machine learning (ML) models to discern patterns in large datasets. Among these, long short-term memory (LSTM) networks, a type of recurrent neural network, have shown empirically backed positive performance in modeling sequential data like stock prices due to their ability to capture long-range dependencies (1-3). This is due to their inherent ability to store ‘memory’ over long periods of time.

However, and importantly, LSTMs often struggle most acutely during high market volatility (e.g., market crashes or sudden economic shocks) when price movements become rapid and the movement deviates highly from past training (1). This limitation arises partly because LSTMs primarily learn from past sequences, and an unprecedented event not included in model training leads to errors in the traditional model (1).

Recent advancements in quantum computing have inspired novel paradigms (2). While large-scale quantum computers are still developing, researchers are exploring “quantum-inspired” algorithms, which are classical algorithms that emulate principles of quantum mechanics like superposition and interference without the strenuous costs of a pure quantum computer (2, 6). For example, quantum superposition, in theory, allows representation of multiple states at the same time, while interference enables the structural combination of computational paths (5, 7). These concepts offer new insights for computation. For instance, quantum-inspired models might represent a wider range of potential market states simultaneously (analogous to superposition), improving adaptability during volatile periods where anything can happen (4). Furthermore, interference-like effects could theoretically help model interactions between market factors that are amplified during turbulent times (5, 6, 8). Some quantum-inspired approaches also incorporate controlled randomness or utilize unique nonlinear functions derived from quantum theory (7, 8).

Based on these theoretical advantages, we hypothesized that incorporating quantum-inspired elements into an LSTM network would enhance stock prediction accuracy, particularly during periods of high market volatility, by better capturing the inherent uncertainty and complex dynamics of turbulent markets.

To test this, we developed a quantum-inspired LSTM (QiLSTM) network, integrating a custom quantum-inspired computational layer with a standard LSTM architecture **(Algorithm 1, Figure 1**). We compared the QiLSTM against a traditional LSTM model, using the Chicago Board of Exchanges (CBOE) Volatility Index (VIX) to identify distinct periods of high and low market volatility for evaluation (9).

The main goal of this research was to bridge quantum-inspired contexts with a realm of risk and volatility. In this case, our results demonstrated that the QiLSTM did, in fact, perform significantly better in high volatility settings. However, the QiLSTM underperformed significantly during low volatility periods. These results suggest that quantum-inspired models like the QiLSTM could be used to create more resilient financial forecasting tools, which would be particularly valuable for managing risk during periods of extreme market turbulence.

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RESULTS

To evaluate our hypothesis, we compared the predictive performance of our QiLSTM model, developed by adding a custom quantum-inspired layer to a standard LSTM architecture, against a traditional LSTM model under different stock market volatility conditions.

We defined two distinct test periods: a low volatility period from November 1, 2023 to March 28, 2024 and a high volatility period from February 19, 2020 to April 17, 2020, coinciding with the initial COVID-19 market crash **(Figure 2A)**. Both models were trained on historical stock data from January 2010 up to the start of the low volatility period **(Figure 2B)**.

Performance was evaluated using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) on daily predictions for eight major stocks (Apple [AAPL], Microsoft [MSFT], Amazon [AMZN], NVIDIA [NVDA], Alphabet [GOOGL], Meta [META], Tesla [TSLA]) and the S&P 500 index (SPY) **(Table 1)**. These stocks were chosen because they represent major, highly-capitalized market leaders known to experience significant volatility, while the S&P 500 index provides a benchmark for the broader market (3). Visual comparisons for the SPY index illustrate these key findings. During the low volatility period **(Figure 3)**, the traditional LSTM performed more accurately, as shown by its closer tracking of actual prices **(Figure 3A)** and its consistently lower daily Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) **(Figure 3B, 3C)**. Conversely, during the high volatility period **(Figure 4)**, the QiLSTM's predictions better tracked actual prices **(Figure 4A)** and achieved lower daily MSE and MAPE **(Figure 4B, 4C)**.

During the low volatility period (November 1, 2023 - March 28, 2024), the QiLSTM demonstrated weaker performance compared to the LSTM **(Table 1)**. The traditional LSTM achieved a significantly lower average MSE (22584.68) compared to the QiLSTM (27011.65) (p < 0.001). Similarly, the traditional LSTM had a significantly lower average MAPE (56.24%) compared to the QiLSTM (61.25%) (p < 0.001). Based on two-sample t-tests, both differences were statistically significant and showed large effect sizes, indicating a robust advantage for the standard LSTM in stable market conditions. Daily MSE and MAPE comparisons for the SPY index during this period are illustrated **(Figure 3B, 3C)**.

In contrast, during the high volatility period (February 19, 2020 - April 17, 2020), the QiLSTM model significantly outperformed the traditional LSTM **(Table 1)**. The QiLSTM achieved a significantly lower average MSE (310.85) compared to the traditional LSTM (386.77) (p < 0.05). Similarly, the QiLSTM's average MAPE (15.33%) was significantly lower than the traditional LSTM's MAPE (17.29%) (p < 0.05). Based on the two-sample t-tests, these differences were statistically significant with medium effect sizes, suggesting that the QiLSTM model was more accurate and robust during this period of extreme market turbulence **(Figure 4B, 4C)**.

The aggregated metrics, which combine performance across all eight major stocks and the SPY index, reflect the overall trends of the QiLSTM outperforming during high volatility but underperforming during low volatility **(Table 1)**. While individual stock performance varied to some degree, the general pattern of QiLSTM outperforming during high volatility and underperforming during low volatility was largely consistent across the majority of the individual stocks when their daily MSE and MAPE values were examined, supporting the aggregated findings. The detailed daily performance for the SPY index serves as a representative illustration of these broader trends **(Figure 3, Figure 4)**.

These results indicate that under the conditions tested, the QiLSTM model incorporating our specific quantum-inspired layer provided enhanced prediction accuracy during the extreme volatility of the early COVID-19 pandemic. However, the traditional LSTM model was more effective during periods of low market volatility.

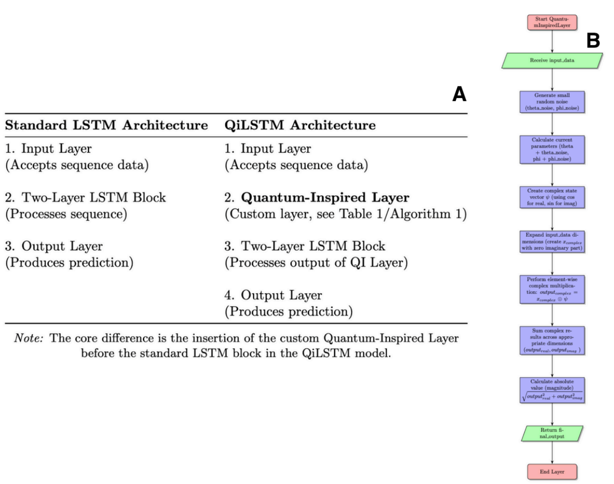

Figure 1: Model Architectures and Quantum-Inspired Layer Flowchart. (A) Comparative block diagram of the standard LSTM and QiLSTM model architectures. The standard LSTM consists of an Input Layer, a Two-Layer LSTM Block for sequence processing, and an Output Layer for prediction. (B) Flowchart illustrating the computational steps within the Quantum-Inspired Layer. The process begins by receiving input data, then generating small random noise added to learnable parameters (theta, phi). A complex state vector (ψ) is created using cosine for the real part and sine for the imaginary part of these current parameters. Finally, the absolute value of this complex sum is calculated and returned as the final real-valued output of the layer.

DISCUSSION

Our study aimed to determine if quantum-inspired elements could enhance LSTM-based stock prediction. The hypothesis was that such enhancements would be evident during high market volatility. The results provided partial support for this hypothesis. The QiLSTM model significantly outperformed the traditional LSTM during the high volatility period of the COVID-19 crash. However, contrary to expectations of a general improvement or at least non-inferiority, the QiLSTM performed significantly worse than the traditional LSTM during the low volatility period.

The improved performance of the QiLSTM during high volatility market conditions requires careful consideration. The quantum-inspired layer utilized sine functions as non-linear activations, inspired by the wave-like nature of quantum states, added small random noise to mimic uncertainty, and involved operations designed to simulate complex-valued states and interference (5, 7). It is plausible that these features, particularly the ability to represent a broader range of states or to introduce a form of structured non-linearity and randomness, helped the QiLSTM adapt better to the sharp, chaotic movements of the market crash, but limited

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Figure 2: Market Volatility and Model Training Performance. (A) The Chicago Board Options Exchange (CBOE) Volatility Index (^VIX) from 2010 to 2024, highlighting the designated low volatility (November 1, 2023 - March 28, 2024; green shaded area) and high volatility (February 19, 2020 - April 17, 2020; red shaded area) test periods. (B) Model training and validation loss, measured by Mean Squared Error (MSE) on a logarithmic scale, over 200 epochs. For the QiLSTM model, the solid blue line represents training loss and the dashed light-blue line represents validation loss. Similarly, for the standard LSTM, the solid red line is training loss and the dashed salmon line is validation loss. Lower values indicate a better model fit during the training process.

model robustness during the conventional, calm movement of the low volatility period. The standard LSTM's gating mechanisms, while robust, might have been too constrained by historical patterns during such unprecedented market behavior to adequately predict trends in the high-volatility market. The quantum-inspired elements of the QiLSTM most likely provided the flexibility required to more accurately model such a high volatility time period. The non-linearities from the sine functions or the added randomness in the QiLSTM were intended to mimic quantum uncertainty, which could have made the model overly sensitive or led to less precise predictions compared to the more deterministic gating of the standard LSTM in stable conditions. The concepts intended to help (superposition-like state representation, interference-like patterns) might not have translated into an advantage and perhaps introduced detrimental complexity when market dynamics were less extreme.

It is crucial to acknowledge the limitations of this study. The findings pertain to a single and specific implementation of a quantum-inspired layer on top of a traditional LSTM. Other architectural designs or different ways of incorporating quantum principles (e.g., inspired by entanglement, different activation functions, or quantum optimization techniques) might yield different results (2, 8). The hyperparameter tuning was standard but not exhaustive; further optimization might alter performance, although the divergent results across volatility regimes suggest a more fundamental interaction between the model design and market conditions.

Furthermore, the model's predictive power is inherently limited by the data it uses, as financial markets are influenced by numerous external factors not captured in the price data alone. Incorporating alternative data sources (e.g., news sentiment, economic indicators) could be beneficial.

Investigating alternative quantum-inspired architectures and algorithms is essential as the robustness of the QiLSTM was clearly demonstrated during high volatility market conditions. Comparing different methods for simulating quantum phenomena classically within neural networks is needed. Testing models across a wider range of market conditions, including different types of volatility and longer time horizons, would provide a more comprehensive understanding. Expanding the evaluation to include other performance metrics beyond MSE and MAPE (e.g., metrics related to risk-adjusted returns if used for trading) and testing on diverse financial instruments like bonds, commodities, or cryptocurrencies would assess the versatility of such approaches. Moreover, exploring the potential applicability of refined quantum-inspired models to other domains characterized by high volatility and uncertainty, such as healthcare outcome prediction or extreme weather forecasting, remains an intriguing possibility for broader impact.

While quantum-inspired approaches have shown promise

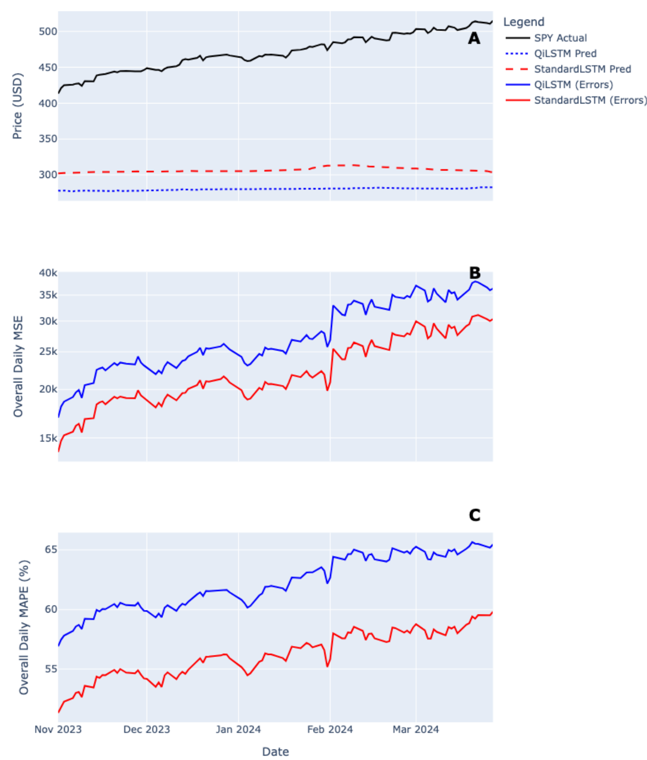

Figure 3: Performance analysis during Low Volatiltiy Period. (A) A comparison of the actual daily closing prices for the SPY index (solid black line) with the one-day-ahead predictions from the QiLSTM model (dotted blue line) and the standard LSTM model (dashed red line). (B) The overall daily Mean Squared Error (MSE), plotted on a logarithmic scale, for the QiLSTM (blue line) and standard LSTM (red line) predictions. (C) The overall daily Mean Absolute Percentage Error (MAPE) for the QiLSTM (blue line) and standard LSTM (red line). For panels B and C, lower values indicate superior predictive accuracy.

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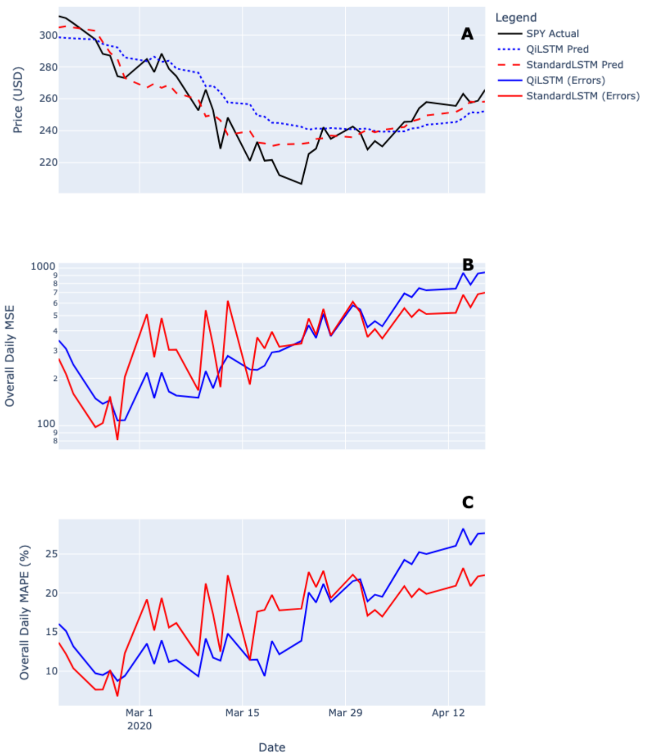

Figure 4: Performance Analysis during High Volatility Period (A) A comparison of the actual daily closing prices for the SPY index (solid black line) with the one-day-ahead predictions from the QiLSTM model (dotted blue line) and the standard LSTM model (dashed red line). (B) The overall daily Mean Squared Error (MSE), plotted on a logarithmic scale, for the QiLSTM (blue line) and standard LSTM (red line) predictions. (C) The overall daily Mean Absolute Percentage Error (MAPE) for the QiLSTM (blue line) and standard LSTM (red line). For panels B and C, lower values indicate superior predictive accuracy.

in other complex domains like combinatorial optimization (2), our study found that this specific integration resulted in a performance trade-off. The specific QiLSTM developed here showed enhanced performance during high market volatility but underperformed the traditional LSTM in low market volatility conditions. This underscores the complex challenges and potential benefits of translating quantum concepts effectively into classical ML frameworks and highlights the need for continued research and innovation in developing robust and reliable quantum-inspired models for financial forecasting across diverse market states.

MATERIALS AND METHODS

Data acquisition

Historical daily stock data were obtained for eight major stocks (Apple [AAPL], Microsoft [MSFT], Amazon [AMZN], NVIDIA [NVDA], Alphabet [GOOGL], Meta [META], Tesla [TSLA]) and the S&P 500 ETF [SPY] from January 1, 2010 to March 28, 2024 using the Yahoo Finance API (yfinance library, version 0.1.63). Daily adjusted closing prices were used. To measure market volatility, daily CBOE VIX closing price data were obtained for the same period from the CBOE website (9). Stock and VIX data were joined based on date. Rows with any missing values after the join were dropped (599 rows removed as indicated in the log). Input features (stock prices) were scaled using MinMaxScaler fitted only on the training data portion to prevent data leakage. No other specific strategies for handling outliers were applied beyond scaling. Python (version 3.8.5) was utilized for data processing with pandas (version 1.1.3), matplotlib (version 3.3.2), and numpy (version 1.19.2) (12-14). We implemented two models for comparison using PyTorch (version 1.7.0) (15).

Model development

The QiLSTM model consisted of an input layer, the custom quantum-inspired layer **(Algorithm 1, Figure 1)**, followed by a standard two-layer LSTM, and finally an output layer producing the price predictions.

The Traditional LSTM had the same fundamental architecture but without the quantum-inspired layer. It consists of an input layer, a two-layer LSTM, and an output layer.

Sequences of the past 60 days of stock prices were accepted as input in both models to predict the next day's prices for all stocks/index. The core difference was solely in the presence of the quantum-inspired layer preceding the standard LSTM layers in the QiLSTM model.

The quantum-inspired layer was implemented as a custom PyTorch module **(Algorithm 1)**. It aimed to mimic quantum phenomena using classical computations. Key elements included: learnable parameters (theta, phi) initialized for the layer; addition of small random noise to these parameters during the forward pass to simulate inherent quantum uncertainty; creation of a complex-valued "state" inspired by quantum state vectors, using cos(theta + noise) for the real part and sin(phi + noise) for the imaginary part, where the use of trigonometric functions is inspired by the wave-like nature of quantum states and representations like Euler's formula (5, 7);

Period	Volatility	Model	Avg Overall MSE	Avg Overall MAPE (%)	MSE (p-value)	MSE (Cohen's d)	MAPE (p-value)	MAPE (Cohen's d)
Nov 1, 2023 - Mar 28, 2024	Low	QiLSTM	2701	1.65	1.27×10^{-9} *	0.898	1.92×10^{-40} *	2.389
Nov 1, 2023 - Mar 28, 2024	Low	Standard LSTM	22584.68	56.24	(ref)	(ref)	(ref)	(ref)
Feb 19, 2020 - Apr 17, 2020	High (COVID-19)	QiLSTM	310.85	15.33	0.0412 *	-0.453	0.0452 *	-0.444
Feb 19, 2020 - Apr 17, 2020	High (COVID-19)	Standard LSTM	386.77	17.29	(ref)	(ref)	(ref)	(ref)

Table 1: Model Performance Comparison During Low and High Volatility Test Periods. MSE (Mean Squared Error) and MAPE (Mean Absolute Percentage Error) are shown based on overall daily price errors for eight major stocks and the SPY index. Lower values indicate better performance. Statistical significance (*p*-value) and effect size (Cohen's d) are based on two-sample t-tests comparing QiLSTM vs Standard LSTM daily errors within each period.

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element-wise complex multiplication between the input data (expanded to match dimensions) and this quantum-inspired state vector; summation of the resulting complex values; and taking the absolute value of the complex summation output to yield a real-valued output passed to the subsequent LSTM layer. This step draws inspiration from quantum measurement, which yields real-valued outcomes. The sine function also acts as a non-linear activation function (8). The data was split chronologically. A training period was defined from January 1, 2010 up to October 31, 2023; a low volatility testing period was defined from November 1, 2023 to March 28, 2024; and a high volatility testing period was defined from February 19, 2020 to April 17, 2020. A portion of the training data (last ~15%, corresponding to 278 sequences) was used as a validation set during training for hyperparameter tuning (like learning rate adjustments) and selecting the best model checkpoint based on validation loss. Both models were trained using the Adam optimizer with an initial learning rate of 0.001 and Mean Squared Error (MSE) as the loss function (10). A learning rate scheduler reduced the learning rate if validation loss plateaued. Training was performed for 100 epochs with a batch size of 32. The input sequence length was set to 60 days.

For generating predictions during the test periods, the previous 60 days of actual historical data were used by the models in a rolling window approach. For each day in the test period, the model predicted the next day's price based on the preceding 60 days. Model performance was evaluated using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), calculated by comparing the predicted prices to the actual closing prices for each day in the respective volatility periods. Average MSE and MAPE across all predicted stocks/index and all days in the period were reported (**Table 1**).

Statistical analysis

To rigorously compare the models, two-sample *t*-tests were conducted to compare the daily MSE and daily MAPE values between the QiLSTM and traditional LSTM models within each volatility period. Effect sizes were calculated using Cohen's d to understand the magnitude of the differences. All statistical analyses were performed using statsmodels (version 0.12.0) and SciPy (1.5.2) (16, 17). Statistical significance was set at $p < 0.05$. Visualizations were created using matplotlib (version 3.3.2) and seaborn (0.11.0) (13, 18). To ensure reproducibility, a fixed random seed of 42 was used for all random number generations. The full implementation is available in our GitHub repository: https://github.com/WesternDundrey/advanced-stock-predictor.

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Appendix

function QuantumInspiredLayer(*input_data*) ▷ Layer's learnable parameters (initialized once)

$\theta \leftarrow$ learnable_parameter ▷ Learnable parameter vector θ

$\phi \leftarrow$ learnable_parameter ▷ Learnable parameter vector ϕ

▷ — Forward pass — ▷ 1. Add small random noise to mimic quantum uncertainty

$\theta_{\text{noise}} \leftarrow$ small_random_value_like(θ)

$\phi_{\text{noise}} \leftarrow$ small_random_value_like(ϕ)

$\theta_{\text{current}} \leftarrow \theta + \theta_{\text{noise}}$

$\phi_{\text{current}} \leftarrow \phi + \phi_{\text{noise}}$

▷ 2. Create a complex-valued quantum-inspired state vector ▷ (Using cos for real, sin for imaginary, inspired by Euler's formula)

$\psi_{\text{real}} \leftarrow \cos(\theta_{\text{current}})$

$\psi_{\text{imag}} \leftarrow \sin(\phi_{\text{current}})$ ▷ $\psi = \psi_{\text{real}} + i \cdot \psi_{\text{imag}}$ (conceptually complex)

▷ 3. Expand input data dimensions if needed (assume real-valued input)

$x_{\text{real}} \leftarrow$ expand_dimensions(*input_data*)

$x_{\text{imag}} \leftarrow \mathbf{0}_{\text{like}}(x_{\text{real}})$ ▷ Create zero imaginary part for input ▷ $x_{\text{complex}} = x_{\text{real}} + i \cdot x_{\text{imag}}$

▷ 4. Perform element-wise complex multiplication and sum ▷ Complex product: $x_{\text{complex}} \odot \psi = (x_{\text{real}}\psi_{\text{real}} - x_{\text{imag}}\psi_{\text{imag}}) + i(x_{\text{real}}\psi_{\text{imag}} + x_{\text{imag}}\psi_{\text{real}})$ ▷ Since $x_{\text{imag}} = 0$: Real part is $x_{\text{real}}\psi_{\text{real}}$, Imaginary part is $x_{\text{real}}\psi_{\text{imag}}$

$\text{output}_{\text{real}} \leftarrow \sum(x_{\text{real}} \odot \psi_{\text{real}})$ ▷ Sum over appropriate dimensions

$\text{output}_{\text{imag}} \leftarrow \sum(x_{\text{real}} \odot \psi_{\text{imag}})$ ▷ Sum over appropriate dimensions

▷ 5. Take absolute value (magnitude) for real-valued output ▷ (Inspired by quantum measurement yielding real values)

$\text{final\_output} \leftarrow \sqrt{\text{output}_{\text{real}}^2 + \text{output}_{\text{imag}}^2}$

return final_output

end function

Algorithm 1. Pseudocode of the Custom Quantum-Inspired Layer Used in the QiLSTM. This outlines the main computational steps within the layer designed to mimic quantum principles using classical operations. Learnable parameters and added noise aim to capture state uncertainty, while complex value simulation and trigonometric functions draw inspiration from quantum state vectors and wave functions.