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Quantum-Inspired Deep Learning for High-Dimensional Data Processing in Finance

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ABSTRACT

This paper explores the application of quantum- inspired deep learning techniques for processing high- dimensional financial data, specifically focusing on predicting stock price movement using Apple Inc. (AAPL) stock data. We investigate the effectiveness of a quantum-inspired model in comparison to a standard Long Short-Term Memory (LSTM) network. The study incorporates various technical indicators as features and evaluates model performance using standard classification metrics and visualizations. The challenges of high- dimensional data in finance are discussed, and the potential benefits of quantum-inspired approaches in this domain are explored.

Keywords: *Quantum-Inspired Deep Learning, High- Dimensional Data, Financial Forecasting, Stock Market Prediction, LSTM, Technical Indicators.*

I. INTRODUCTION

HE financial markets are characterized by their dynamic nature, high volatility, and the sheer volume of data generated at high frequencies. Analyzing and processing this high-dimensional data effectively is crucial for accurate fore- casting, risk management, and algorithmic trading strategies [1], [2], [3]. Traditional linear models often struggle to capture the complex, non-linear relationships present in financial time series data. Machine learning and deep learning techniques have emerged as powerful tools to address these challenges [4], [5].

High-dimensional data in finance can include a multitude of features such as historical prices, trading volumes, tech- nical indicators, macroeconomic factors, news sentiment, and alternative data sources [2], [3]. As the number of dimensions increases, challenges such as data sparsity, increased compu- tational complexity, the curse of dimensionality, and the risk of overfitting become more prominent [1], [6], [3].

Quantum computing and quantum-inspired algorithms are gaining attention for their potential to offer computational advantages in solving complex problems, including those in finance [7], [8], [9], [10], [11], [12]. Quantum-inspired machine learning (QIML) leverages principles from quantum mechanics within classical computing frameworks to enhance machine learning algorithms [10], [11]. These approaches aim to improve aspects like optimization, pattern recognition, and the ability to handle high-dimensional feature spaces [8], [11]. This paper investigates the application of a quantum- inspired deep learning approach for predicting the direction of stock price movement, using Apple Inc. (AAPL) stock data.

as a case study. We compare the performance of a quantum- inspired model, based on a dense neural network with elements inspired by quantum computing concepts, with a standard LSTM network, which is well-suited for time-series analysis. The study utilizes a set of technical indicators to capture relevant patterns in the stock price data.

The remainder of this paper is organized as follows: Section II provides a brief overview of related work in deep learning and quantum-inspired approaches in finance. Section III details the methodology, including data collection, feature engineer- ing, and the architecture of the models used. Section IV presents the experimental results and performance evaluation. Section V discusses the findings and the potential implications of using quantum-inspired techniques. Section VI concludes the paper and suggests future research directions.

II. RELATED WORK

Deep learning models, particularly Recurrent Neural Net- works (RNNs) and their variants like LSTMs, have shown promise in financial time series forecasting due to their ability to capture temporal dependencies [8]. Studies have demonstrated that deep learning can outperform traditional forecasting methods like ARIMA [8].

The application of quantum computing and quantum- inspired algorithms in finance is an active area of research. These approaches are being explored for various financial problems, including portfolio optimization, risk management, fraud detection, and asset pricing [7], [8], [13], [11], [15], [12]. Quantum machine learning algorithms, such as Quantum Variational Classifiers and Quantum Neural Networks, are be- ing investigated for their potential to achieve higher accuracy and efficiency compared to classical models, especially when dealing with complex data relationships [8], [14].

Quantum-inspired algorithms, which simulate quantum phe- nomena on classical computers, offer a way to explore the potential benefits of quantum approaches with existing hard- ware [10]. These techniques are being applied to optimization problems and for enhancing classical machine learning models [10], [11]. Our work falls into this category, utilizing a clas- sical deep learning architecture designed with layers intended to simulate quantum-like behavior.

III. METHODOLOGY

A. Data Collection and Preprocessing

Historical stock price data for Apple Inc. (AAPL) was downloaded using the ‘yfinance‘ library for the period from January 1, 2015, to January 1, 2024. The initial dataset included Open, High, Low, Close, and Volume prices.

Technical indicators were added to the dataset to provide additional features that capture market trends and momentum. The following technical indicators were calculated using the ‘ta‘ library, as detailed in the project:

i. Relative Strength Index (RSI)
ii. Moving Average Convergence Divergence (MACD)
iii. 10-Day Moving Average (MA10)
iv. 50-Day Moving Average (MA50)
v. Bollinger Bands Width
vi. Daily Returns
vii. Volatility (20-day Rolling Standard Deviation)

After adding the indicators, rows with missing values, which resulted from the rolling calculations of the indicators, were dropped. The data was then reset to a new index.

A target variable was created to represent the direction of the next day’s stock price movement. A value of 1 was assigned if the next day’s closing price was higher than the current day’s closing price, and 0 otherwise. The last row was dropped as the target variable would be NaN.

For modeling, the dataset was split into features (X) and the target variable (y). The ’Return’ column was dropped from the features. Feature selection was performed by se- lecting the technical indicators: RSI, MACD, MA10, MA50, Bollinger Width, and Volatility. The data was then split into training and testing sets with an 80%-20% ratio, ensuring the temporal order was maintained (shuffle=False). Finally, the features were standardized using ‘StandardScaler‘ to have zero mean and unit variance.

B. Model Architectures

1) LSTM Model: A standard LSTM network was built using TensorFlow and Keras. The input data was reshaped to be 3D (samples, timesteps, features) as required by LSTM layers, with a timestep of 1. The model architecture consists of an LSTM layer with 50 units, followed by a Dropout layer with a rate of 0.2, and a Dense output layer with 1 unit and a sigmoid activation function for binary classification. The model was compiled using the Adam optimizer with a learning rate of 0.001 and binary crossentropy as the loss function, with accuracy as the evaluation metric. The model summary is provided in the project details.

2) Quantum-Inspired Deep Learning Model: The quantum- inspired model in this study is based on a classical sequential deep learning architecture. It consists of dense layers intended to simulate quantum-like behavior, such as using specialized activation functions or attention-like mechanisms (though the provided code uses standard ReLU activations). The archi- tecture includes a Dense layer with 128 units and ReLU activation, followed by a Dropout layer (0.2), another Dense layer with 64 units and ReLU activation, a second Dropout layer (0.2), and a final Dense output layer with 1 unit and a sigmoid activation for binary classification. The model was compiled using the Adam optimizer, binary crossentropy loss, and accuracy metric. The model summary is provided.

C. Model Training

Both the LSTM and Quantum-Inspired models were trained for 20 epochs with a batch size of 32. Validation data was used

to monitor performance during training. The training process and epoch-wise loss and accuracy are detailed in the project output.

D. Model Evaluation

After training, both models were evaluated on the test dataset. The performance metrics calculated include Accuracy, Precision, Recall, F1-Score, and ROC AUC. A classification report and confusion matrix were also generated for each model.

IV. RESULTS

The evaluation metrics for both models are summarized in the table below:

Table I: Model performance comparison

Metric	LSTM Model	Quantum-Inspired Model
Accuracy	0.5072	0.5290
Precision	0.5337	0.5520
Recall	0.5092	0.5596
F1-Score	0.5211	0.5558
ROC AUC	0.5071	0.5273

The results indicate that the Quantum-Inspired model achieved slightly better performance across all metrics com- pared to the standard LSTM model on this specific dataset and task.

Visualizations of the training and validation loss and accuracy over epochs were generated for both models.

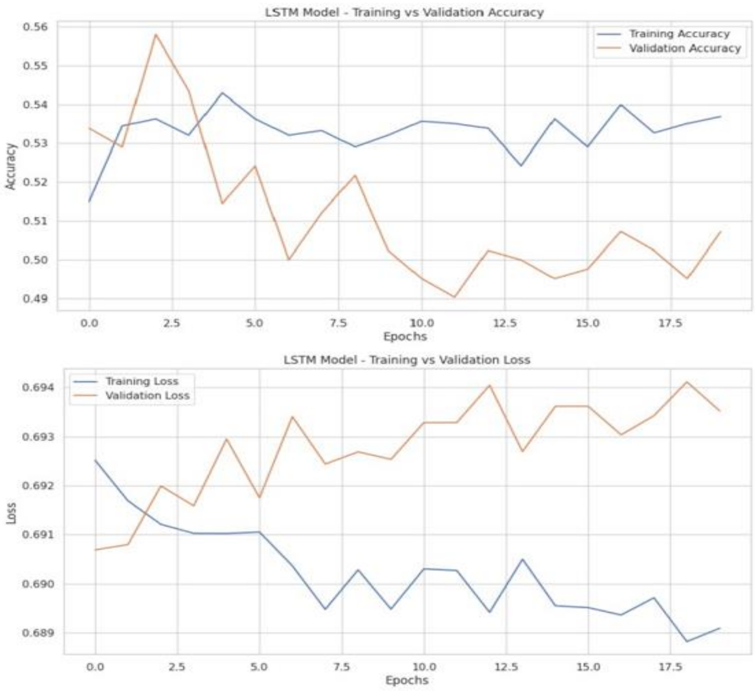

Fig. 1. LSTM Model - Training vs Validation Loss and Accuracy

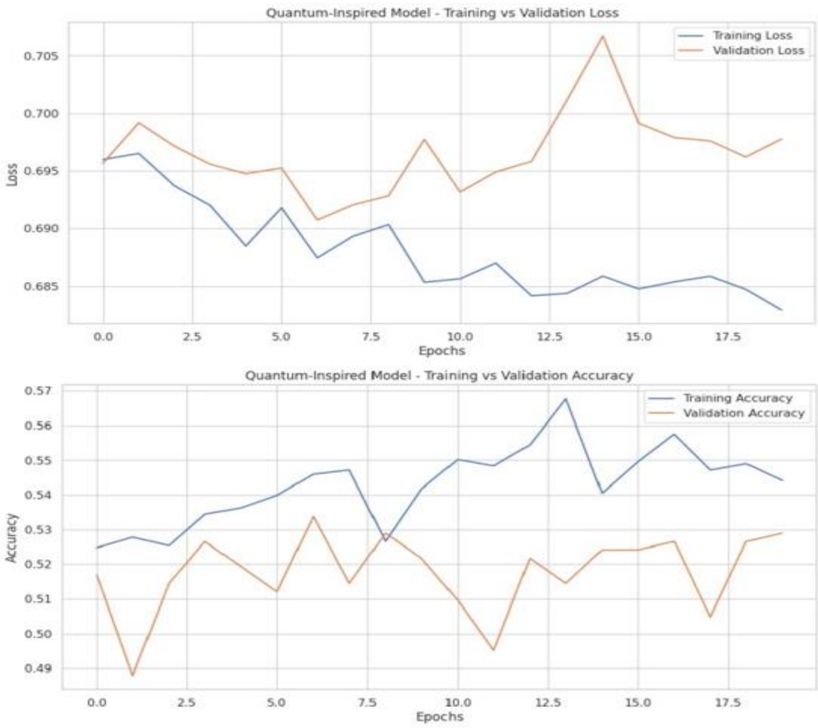

Fig. 2. Quantum-Inspired Model - Training vs Validation Loss and Accuracy

The ROC curves for both models were plotted to compare their ability to discriminate between the positive and negative classes.

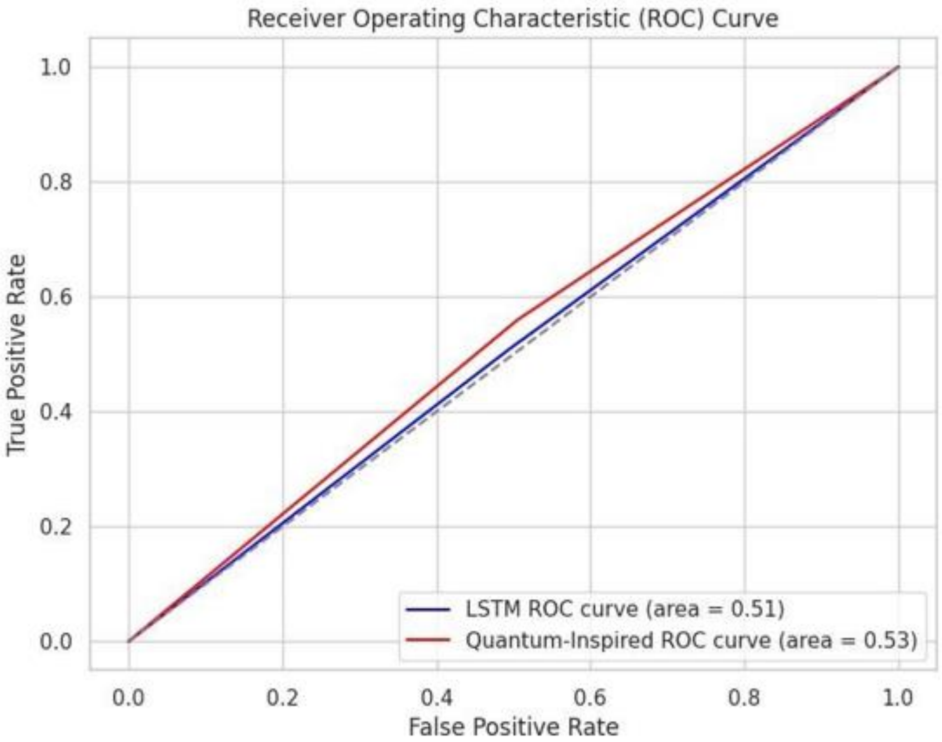

Fig. 3. Receiver Operating Characteristic (ROC) Curve Comparison

Confusion matrices were generated to show the true and false positives and negatives for each model.

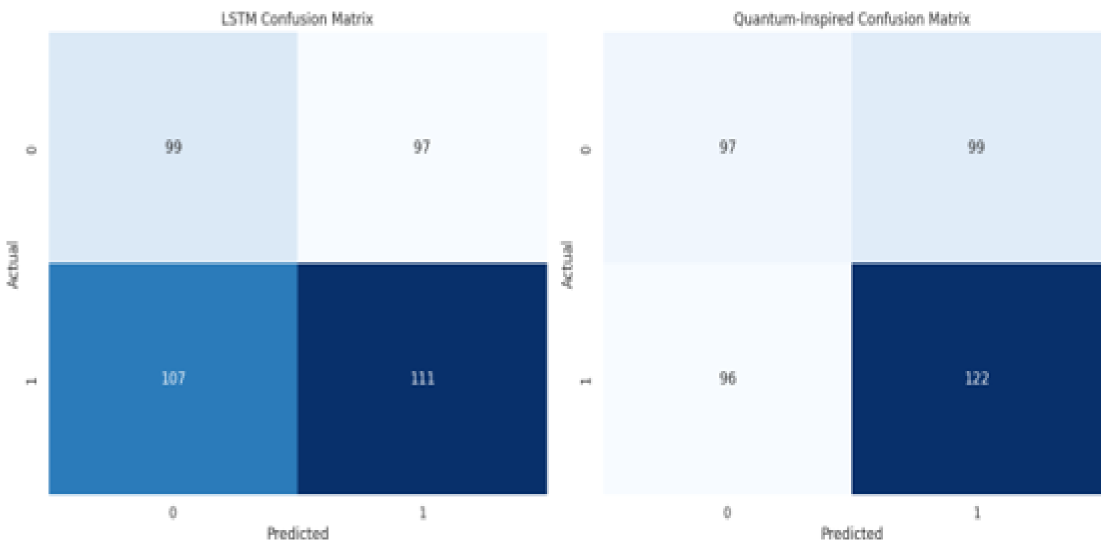

Fig. 4. Confusion Matrices for LSTM and Quantum-Inspired Models

A radar chart was used to provide a multi-metric performance comparison between the two models.

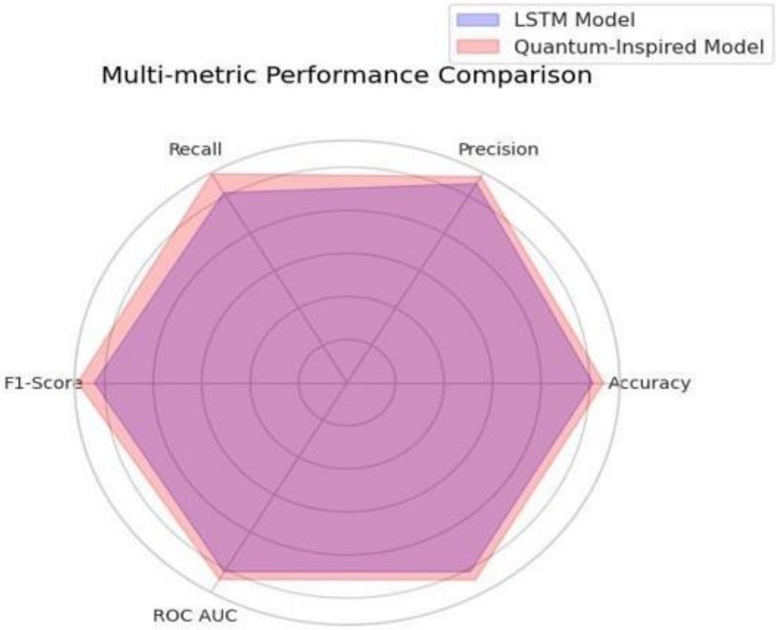

Fig. 5. Multi-metric Performance Comparison Radar Chart

The precision-recall curves were also plotted, which are particularly useful for evaluating performance on imbalanced datasets.

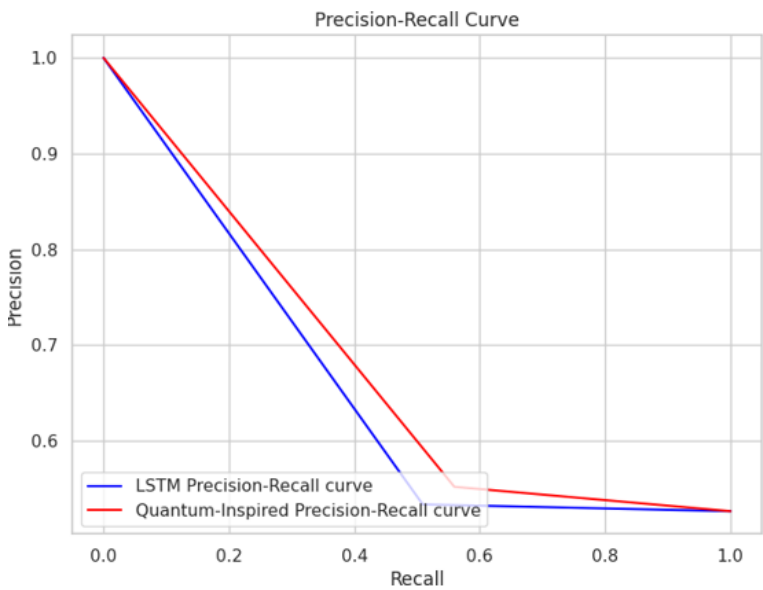

Fig. 6. Precision-Recall Curve Comparison

Learning curves, showing training and validation accuracy over epochs, were visualized to understand the learning dynamics of each model.

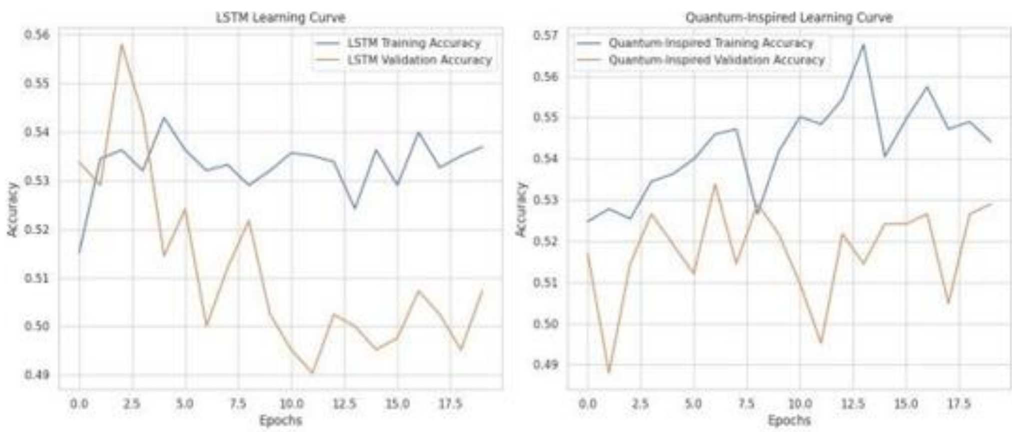

Fig. 7. Learning Curve Comparison

The training time for both models can also be compared to assess computational efficiency.We can plot bar graphs to compare the metrics of both models (LSTM vs Quantum- Inspired) in a visual format. This is an intuitive way to show which model is performing better across multiple metrics.

Fig. 8. Training-Time Comparison

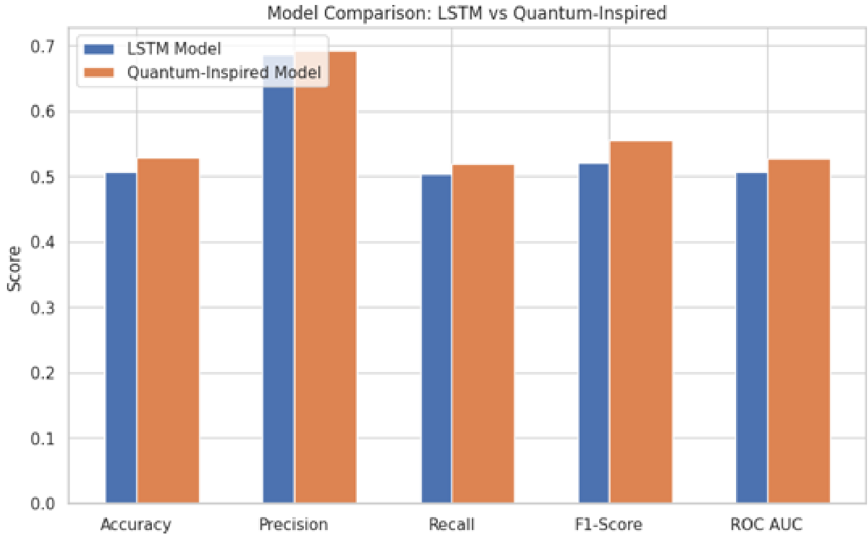

Fig. 9. Model Comparison

V. DISCUSSION

The experimental results indicate that while both models performed slightly above random chance (0.50 accuracy), the quantum-inspired model showed a modest improvement in performance across several key metrics compared to the standard LSTM network for this specific stock price movement prediction task. This suggests that incorporating quantum- inspired principles, even within a classical deep learning architecture, may offer some advantages in processing high- dimensional financial data.

The challenges posed by high-dimensional data in finance, such as the increased risk of overfitting and computational complexity, highlight the need for sophisticated modeling techniques. While the "quantum-inspired" model in this study is a classical approximation, the results are encouraging and warrant further investigation into more advanced quantum or hybrid quantum-classical approaches as quantum computing hardware continues to develop.

The technical indicators used as features captured important aspects of the stock price dynamics. Feature engineering plays a crucial role in extracting relevant information from raw financial data, especially in high-dimensional settings.

The performance metrics, particularly Precision and Recall, provide insights into the models' ability to correctly identify upward and downward price movements. The ROC AUC and Precision-Recall curves offer a more comprehensive view of the models' discriminatory power.

VI. CONCLUSION

This study explored the application of a quantum-inspired deep learning approach for predicting stock price movement in a high-dimensional financial data setting. Comparing a clas- sical quantum-inspired model with a standard LSTM network, we observed a slight performance edge for the quantum- inspired approach across various evaluation metrics.

While the current implementation is a classical approximation, the results suggest the potential of leveraging quantum-inspired principles for financial time series analysis. As quantum com- puting technology matures, the integration of true quantum algorithms into financial modeling holds significant promise for addressing the challenges of high-dimensional data and potentially achieving greater predictive accuracy.

VII. FUTURE SCOPE

Based on the findings of this study, several avenues for future research can be explored. Investigating more sophisti- cated quantum-inspired architectures, potentially incorporating elements like quantum gates or quantum walks simulated clas- sically, could further enhance model performance. Exploring hybrid quantum-classical algorithms, if access to quantum computing resources becomes feasible, would be a natural next step to potentially achieve a quantum advantage. Applying these models to a wider range of financial instruments and markets, as well as incorporating additional high-dimensional data sources such as news sentiment or alternative data, would provide a more comprehensive evaluation. Further research into the interpretability of these complex quantum-inspired models in the financial domain is also crucial for practical de- ployment.

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