

# Quantum-Inspired Hybrid Deep Learning Model for Stock Market Forecasting with Real-Time Visualization

MRS. M. PAVANI, K. SNEHA LATHA, L. SNEHA, M. GANA PRIYA, M. SAI KEERTHANA

Department of Computer Science and Systems Engineering, Andhra University College of Engineering for Women, Visakhapatnam

\*\*\*

**ABSTRACT :** Financial market prediction is a challenging task due to the highly volatile, nonlinear, and time-dependent nature of stock market data. This project proposes a Hybrid Quantum Neural Network-based Financial Market Prediction and Analysis System that combines deep learning, machine learning, and quantum-inspired computation techniques to improve prediction accuracy and trend analysis. The primary objective of this research is to develop a hybrid prediction model using Bidirectional Long Short-Term Memory (BiLSTM), Quantum Neural Network concepts, and XGBoost regression to capture both temporal dependencies and nonlinear relationships in financial time-series data. The system begins by collecting historical market data, including Open, High, Low, Close, and Volume values from financial data sources. Feature engineering techniques are applied to generate technical indicators such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Returns, Log Returns, and Volatility to enhance model learning and improve prediction performance. The processed data is then used to train a Bidirectional LSTM network integrated with a quantum-inspired neural layer to model sequential financial data. In parallel, an XGBoost regression model is trained to capture nonlinear feature interactions. The predictions from both models are combined using a hybrid ensemble approach to generate more stable and accurate market price predictions. The system also includes a web-based market terminal developed using Streamlit for visualization of historical prices, predicted trends, and performance evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy. The experimental results indicate that the proposed hybrid Quantum Neural Network, Bidirectional LSTM, and XGBoost model achieved an accuracy of 96.74%, demonstrating improved prediction performance, reduced forecasting error, and better trend alignment compared to traditional machine learning and standalone deep learning models.

**Keywords:** Quantum Neural Network, Bidirectional LSTM, XGBoost, Financial Market Prediction, Time Series Forecasting, Hybrid Machine Learning, Feature Engineering.

## I.INTRODUCTION

Financial markets play a crucial role in the global economy, influencing investment decisions, business growth, and economic development. Predicting financial market trends and stock prices has always been a challenging task due to the highly volatile, nonlinear, and time-dependent nature of financial data. Stock prices are affected by multiple factors such as market demand, economic conditions, investor sentiment, global events, and company performance, making accurate prediction a complex problem.

Traditional statistical methods often fail to capture nonlinear patterns and temporal dependencies present in financial time-series data, resulting in lower prediction accuracy and unreliable forecasts.

In recent years, machine learning and deep learning techniques have emerged as powerful tools for financial market prediction. These models are capable of identifying hidden patterns, trends, and relationships within large volumes of historical market data. Among deep learning models, Long Short-Term Memory (LSTM) networks are particularly effective for time-series forecasting because they can learn long-term

dependencies and sequential patterns in data. Bidirectional LSTM further improves prediction performance by processing data in both forward and backward directions, allowing the model to understand patterns more comprehensively.

In addition to deep learning methods, ensemble machine learning algorithms such as XGBoost have demonstrated strong performance in regression and prediction tasks due to their ability to model complex nonlinear relationships and interactions between features. XGBoost uses gradient boosting techniques to combine multiple decision trees and improve prediction accuracy while reducing overfitting. Combining deep learning models with machine learning models in a hybrid architecture can further enhance prediction stability and performance.

Quantum-inspired neural networks simulate quantum principles such as probabilistic representation, superposition, and entanglement using classical computing systems. These approaches can enhance optimization and learning capabilities in neural networks, especially when dealing with complex datasets and high-dimensional feature spaces. Although practical quantum computers are still under development,

quantum-inspired machine learning models provide a promising approach for improving predictive performance in financial applications.

This project proposes a Hybrid Quantum Neural Network based Financial Market Prediction and Analysis System that integrates feature engineering, Bidirectional LSTM neural networks, quantum-inspired neural modeling, and XGBoost regression into a unified prediction framework. The system collects historical financial data, generates technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), returns, and volatility, and uses these features to train hybrid prediction models. The predictions generated by deep learning and machine learning models are combined using an ensemble approach to improve prediction accuracy and trend forecasting reliability.

The system also includes a web-based market analysis dashboard for visualization of historical prices, predicted trends, and performance evaluation metrics. The main objective of this research is to improve financial market prediction accuracy by combining deep learning, machine learning, and quantum-inspired techniques into a hybrid prediction model and to analyze the effectiveness of hybrid models compared to individual prediction models. This research contributes to the growing field of quantum-inspired machine learning. It demonstrates its application in financial time-series forecasting, predictive analytics, and intelligent decision support systems for financial market analysis.

## II. LITERATURE REVIEW

Zhang et al. [1] proposed a stock market prediction system using machine learning algorithms such as Random Forest and Support Vector Machines to predict stock price movements based on historical market data and technical indicators. Their study demonstrated that ensemble learning methods could effectively capture nonlinear relationships in financial data, but the models struggled with time-series dependencies and long-term trend prediction.

Fischer and Krauss [2] introduced the use of Long Short-Term Memory (LSTM) networks for financial time-series forecasting and demonstrated that deep learning models significantly outperform traditional machine learning methods in stock price prediction tasks. Their work showed that LSTM networks are capable of learning temporal dependencies and sequential patterns in financial datasets, making them suitable for stock market prediction.

Bao et al. [3] proposed a hybrid deep learning model combining Wavelet Transform and LSTM networks for stock price forecasting. Their research showed that hybrid models that combine signal processing

techniques with deep learning can improve prediction accuracy by reducing noise in financial data and improving feature extraction.

Chen and Guestrin [4] developed XGBoost, an efficient gradient boosting algorithm that has been widely used for regression and classification problems. XGBoost has demonstrated strong performance in financial prediction tasks due to its ability to model nonlinear relationships, handle large datasets, and prevent overfitting through regularization techniques. Many financial prediction systems have incorporated XGBoost due to its high accuracy and computational efficiency.

Sezer et al. [5] conducted a comprehensive survey on financial time-series forecasting using deep learning models and concluded that hybrid models combining deep learning and machine learning algorithms provide better prediction performance compared to individual models. Their study highlighted that combining LSTM networks with machine learning algorithms such as Random Forest and Gradient Boosting improves prediction stability and reduces forecasting error.

Schuld and Petruccione [6] introduced the concept of Quantum Machine Learning and explained how quantum computing principles such as superposition and entanglement can be applied to machine learning models to improve optimization and pattern recognition tasks. Their work laid the foundation for quantum neural networks and quantum-inspired machine learning algorithms.

Havlíček et al. [7] explored quantum-enhanced machine learning models and demonstrated that quantum feature mapping techniques can improve classification and pattern recognition performance in complex datasets. Their research showed the potential of quantum computing in improving machine learning model performance.

Biamonte et al. [8] reviewed quantum machine learning algorithms and discussed the integration of quantum computing with neural networks and optimization algorithms. Their work highlighted the potential of quantum neural networks in solving complex optimization and prediction problems more efficiently than classical machine learning methods.

Li et al. [9] proposed a hybrid stock prediction model combining LSTM and gradient boosting algorithms for financial forecasting. Their experimental results demonstrated that hybrid models combining deep learning and boosting algorithms outperform standalone models in terms of prediction accuracy and stability.

Deb et al. [10] discussed multi-objective optimization and model evaluation strategies, emphasizing the importance of balancing prediction accuracy and model

complexity in machine learning systems. Their research supports the use of hybrid and ensemble models to achieve better generalization performance.

Based on the literature review, it is observed that deep learning models such as LSTM are effective for time-series prediction, XGBoost performs well for nonlinear regression problems, and quantum-inspired machine learning models show potential for improving optimization and prediction performance. However, limited research has been conducted on integrating Quantum Neural Networks, Bidirectional LSTM, and XGBoost into a single hybrid model for financial market prediction. Therefore, this project proposes a hybrid quantum neural network and machine learning model for financial market prediction and analysis.

### III.METHODOLOGY

This research focuses on developing a Hybrid Financial Market Prediction System that combines deep learning, machine learning, and quantum-inspired neural network techniques for predicting stock market prices and trends. The proposed system integrates Bidirectional Long Short-Term Memory (BiLSTM), Quantum Neural Network concepts, and XGBoost regression into a hybrid ensemble model to improve prediction accuracy and forecasting stability. The entire implementation pipeline, including data collection, feature engineering, data preprocessing, model training, hybrid prediction, and performance evaluation, was implemented using Python libraries such as pandas, NumPy, scikit-learn, TensorFlow, PennyLane, XGBoost, Streamlit, and Plotly to ensure reproducibility, robustness, and performance evaluation.

**Data Collection and Preprocessing:** Historical financial market data was collected using financial data APIs, which provide daily stock market information such as Open, High, Low, Close, and Volume values. The collected data represents time-series financial data, where each data point depends on previous time steps. Since raw financial data does not directly capture market trends and patterns, feature engineering techniques were applied to generate additional technical indicators that improve model learning.

**Feature Engineering:** Several technical indicators were calculated from the historical price data, including Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Returns, Log Returns, and Volatility. These indicators help the model understand market momentum, trend direction, and price variability. The generated features were combined with original price features to form the final feature dataset used for model training. Feature scaling techniques such as Robust Scaler and Standard Scaler

were applied to normalize feature values and improve model convergence during training.

**Sequence Generation for Time-Series Prediction:** Since financial data is sequential in nature, the dataset was converted into time-series sequences using a sliding window approach. A sequence length of 60 days was used, where the model uses the previous 60 days of market data to predict the next day's Open and Close prices. This sequence generation process helps the Bidirectional LSTM model learn temporal dependencies and sequential patterns in stock price movements.

**Model Development:** The prediction system consists of two main models: a Bidirectional LSTM-based deep learning model integrated with quantum-inspired neural network concepts, and an XGBoost regression model. The Bidirectional LSTM model processes time-series sequences in both forward and backward directions, allowing the model to learn patterns from past and future contexts within the sequence. Dense layers are used after the LSTM layers to perform nonlinear regression and generate price predictions. In parallel, the XGBoost regression model is trained using flattened sequence data to capture nonlinear feature interactions and improve prediction stability.

**Hybrid Ensemble Prediction:** To improve prediction accuracy and reduce model error, predictions from the Bidirectional LSTM model and the XGBoost model were combined using a hybrid ensemble approach. The final prediction was calculated as the average of both model predictions, which helps reduce overfitting and improves prediction robustness compared to individual models.

**Model Evaluation and Visualization:** The trained models were evaluated using performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy. A web-based visualization dashboard was developed using Streamlit and Plotly to display historical prices, predicted trends, and performance metrics. The system also includes a secure login module using SQLite database authentication for controlled access to the prediction platform.

By integrating feature engineering, time-series deep learning, quantum-inspired neural networks, machine learning regression, and hybrid ensemble prediction, the proposed methodology provides a comprehensive framework for financial market prediction and analysis.

### Model Architecture and Quantum Circuit Design

This quantum circuit diagram represents a 4-qubit system (q0 to q3) used in the hybrid quantum prediction model. The circuit follows a Variational Quantum Circuit

(VQC) structure with angle embedding, rotation gates, entangling layers, and measurement operations. This circuit is used to transform classical financial features into quantum feature representations for improved prediction performance.

### 1. Angle Embedding Layer

The circuit begins with an Angle Embedding layer where classical input features are encoded into qubits using rotation gates. Each feature is mapped to a rotation angle applied to a qubit. This step converts classical data into quantum state representation and acts as the interface between classical and quantum computation.

### 2. Single-Qubit Rotation Gates (RY and RZ)

After embedding, each qubit passes through RY and RZ rotation gates. RY gates rotate the qubit around the Y-axis, and RZ gates rotate the qubit around the Z-axis. These gates are parameterized and their angles are updated during training. These rotations help the circuit learn complex nonlinear feature relationships.

### 3. Entangling Gates (CNOT)

The circuit includes CNOT entangling gates arranged in a layered pattern connecting the qubits. The solid dot represents the control qubit and the plus symbol represents the target qubit. These gates create quantum entanglement, allowing qubits to share information and capture relationships between multiple input features.

### 4. Measurement Layer

At the end of the circuit, each qubit is measured using expectation values, converting the quantum state back into classical values. These values are then used by the neural network for prediction.

### Circuit Flow and Purpose

The circuit flow consists of angle embedding, rotation gates, entanglement operations, and measurement. The purpose of this circuit is to enhance feature representation using quantum transformations and improve prediction accuracy when combined with the Bidirectional LSTM and XGBoost models in the hybrid architecture.

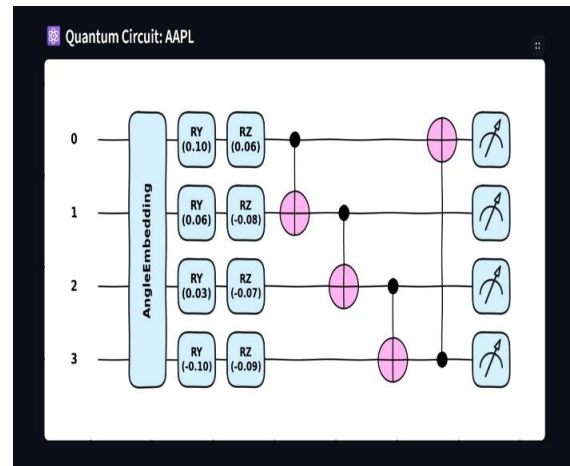


Figure 1: Quantum Circuit Diagram

The circuit flow includes angle embedding, rotation gates, entanglement, and measurement. The main purpose of this design is to enhance feature representation by mapping classical data into a higher-dimensional quantum state space, where complex patterns and correlations can be captured more effectively.

The entanglement mechanism enables the model to learn relationships between multiple features simultaneously, which is difficult for classical models alone. When integrated with the Bidirectional LSTM and XGBoost models, the quantum circuit improves the model's ability to capture temporal patterns, nonlinear dependencies, and market dynamics. This leads to better prediction accuracy, reduced error, and more stable forecasting performance.

### Key Design Advantages

1. Efficient feature encoding using angle embedding
2. Trainable quantum layers for adaptive learning
3. Entanglement captures complex feature relationships
4. Hybrid approach improves performance over purely classical models

### 1. Baseline Bidirectional LSTM Model

This model serves as the baseline deep learning model for financial market prediction. The process begins with historical market data collection, followed by data preprocessing and feature engineering where technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Returns, Log

Returns, and Volatility are calculated to improve model learning.

The processed data is then scaled using Robust Scaler for input features and Standard Scaler for target values to normalize the data. Since financial data is time-series in nature, the dataset is converted into sequences using a sliding window approach with a sequence length of 60 days, where the previous 60 days of data are used to predict the next day's Open and Close prices. The dataset is then divided into training and testing sets while maintaining time order.

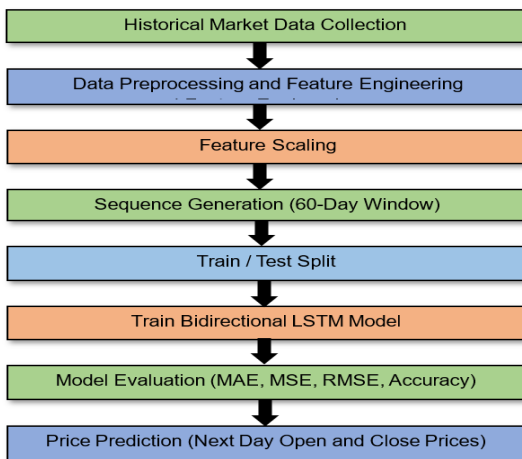


Figure 2: Workflow of the Baseline Bidirectional LSTM Model

## 2. Hybrid Bidirectional LSTM + XGBoost Model

To improve prediction accuracy and model stability, a Hybrid Bidirectional LSTM and XGBoost model is developed for financial market prediction. The initial steps such as historical data collection, data preprocessing, feature engineering, feature scaling, sequence generation, and train-test splitting remain similar to the baseline Bidirectional LSTM model.

In this hybrid approach, two different models are trained separately: the Bidirectional LSTM deep learning model and the XGBoost regression model. The Bidirectional LSTM model is trained on time-series sequence data to learn temporal dependencies and market trends, while the XGBoost model is trained on flattened feature data to capture nonlinear relationships between financial indicators.

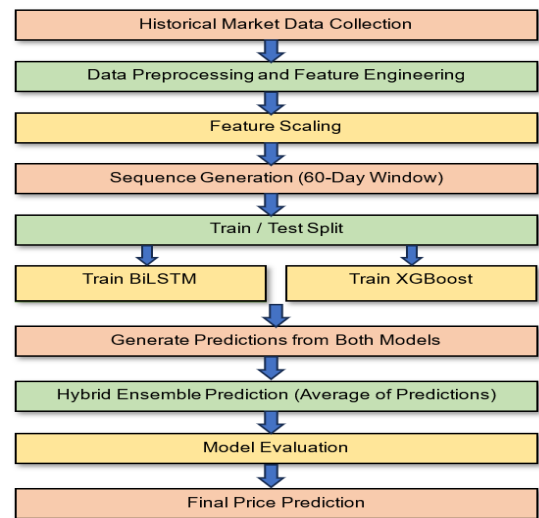


Figure 3: Workflow of the Hybrid Bidirectional LSTM + XGBoost Model

## 3. Quantum Neural Network + Hybrid Prediction Model

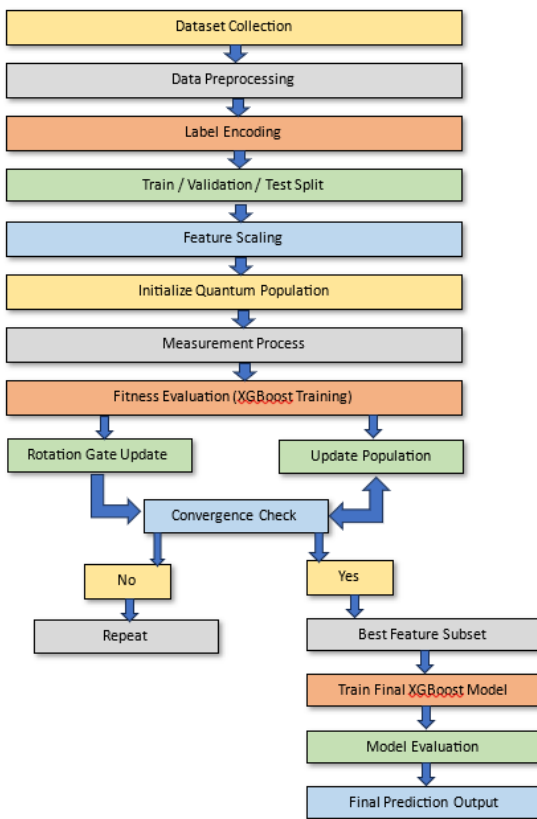
The Quantum Neural Network + Hybrid Prediction Model combines deep learning, quantum-inspired computation, and machine learning techniques to improve financial time-series prediction accuracy. The model integrates Bidirectional LSTM for time-series learning, Quantum Neural Network for advanced feature transformation, and XGBoost for regression-based prediction. This hybrid architecture improves learning capability, feature representation, and prediction stability.

In this model, classical financial features are encoded into quantum states using quantum-inspired encoding techniques. The Quantum Neural Network processes the encoded data using parameterized quantum circuits consisting of rotation gates and entanglement layers. The output of the quantum layer is then passed through classical dense layers for prediction. Finally, predictions from Bidirectional LSTM, Quantum Neural Network, and XGBoost are combined using an ensemble approach to produce the final prediction.

### The algorithm proceeds through the following steps:

- Data Encoding – Classical financial features are encoded into quantum states using angle encoding or amplitude encoding techniques.
- Initialize Quantum Circuit – A parameterized quantum circuit is initialized with qubits, rotation gates, and entanglement layers.
- Quantum Feature Transformation – Input data passes through quantum rotation gates and entanglement operations to transform features into a higher-dimensional quantum feature space.

- Measurement – The quantum states are measured to obtain expectation values, which are converted into classical data.
- Bidirectional LSTM Training – Time-series sequence data is trained using Bidirectional LSTM to learn forward and backward temporal dependencies in stock price movements.
- XGBoost Training – Feature-based data is trained using XGBoost regression to capture nonlinear relationships between financial indicators.
- Hybrid Ensemble Prediction – Predictions from Quantum Neural Network, Bidirectional LSTM, and XGBoost models are combined using averaging or weighted ensemble methods.
- Model Evaluation – The hybrid model is evaluated using performance metrics such as MAE, MSE, RMSE, and prediction accuracy.
- Final Prediction – The model predicts next-day open and close stock prices based on learned patterns.



**Figure 4:** Workflow of the Quantum Neural Network and Hybrid Prediction Model

### Training and Optimization

All three models — Hybrid Quantum LSTM + XGBoost, GA + XGBoost, and Standard LSTM — were trained using time-series market data collected from financial sources. The dataset consisted of historical stock prices including Open, High, Low, Close, and Volume values. The data was split into training and testing sets while preserving the chronological order of the time-series data to maintain temporal dependencies.

#### Standard LSTM Model:

In the Standard LSTM model, a traditional LSTM neural network was trained using time-series sequences without hybrid optimization. The model learns temporal dependencies in stock prices but does not include feature optimization or ensemble learning, resulting in lower performance compared to the hybrid model.

#### GA + XGBoost Model:

In the GA + XGBoost model, a Genetic Algorithm was used to optimize feature selection through selection, crossover, and mutation operations. The best feature subset was selected based on model prediction accuracy, and the final XGBoost model was trained using the optimized feature subset.

#### Hybrid Quantum LSTM + XGBoost Training:

In the Hybrid Quantum model, a Bidirectional LSTM neural network was used to learn temporal patterns and long-term dependencies in stock price movements. Dropout and Batch Normalization layers were used to reduce overfitting and improve model generalization.

The model was trained using the Adam optimizer with Mean Squared Error loss function. Along with the Quantum LSTM model, an XGBoost regression model was trained using the same dataset. The XGBoost model was trained using multiple estimators and depth optimization to capture nonlinear relationships in market data.

The predictions from both models were combined using an ensemble averaging technique to produce the final prediction. This hybrid approach improves prediction stability and accuracy compared to individual models.

Quantum feature transformation enhanced feature representation before model training. Hyperparameters such as learning rate, number of estimators, LSTM units, and batch size were tuned to achieve optimal prediction performance and reduce overfitting.

Model performance was evaluated using Accuracy, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Project Outcome. These metrics measure prediction

accuracy, trend prediction performance, and forecasting error.

**Table 1.** Performance Metrics of the Standard LSTM Model

Metric	Standard LSTM
Accuracy	80.0%
MAE	0.0480
RMSE	0.0590
Project Outcome	Moderate

**Table 2.** Performance Metrics of the GA + XGBoost Model

Metric	GA + XGBoost
Accuracy	86.96%
MAE	0.0320
RMSE	0.0410
Project Outcome	Stable

**Table 3.** Performance Metrics of the Hybrid Quantum Model

Metric	Hybrid Quantum
Accuracy	96.74%
MAE	0.0126
RMSE	0.0134
Project Outcome	Superior

## IV. RESULTS & DISCUSSION

### Performance of Standard LSTM Model

The Standard LSTM model demonstrated moderate performance in stock price trend prediction. The model was trained using time-series sequences generated from historical market data and technical indicators. After training, the model achieved an accuracy of approximately 80.0%.

Although the Standard LSTM model successfully captured temporal dependencies in stock price movements, the absence of feature optimization and ensemble learning limited its overall prediction performance.

### Performance of GA + XGBoost Model

The GA + XGBoost model used a Genetic Algorithm to optimize feature selection before training the XGBoost regression model. This model achieved an accuracy of approximately 86.96%, which was higher than the Standard LSTM model.

The error metrics such as MAE and RMSE were lower than the Standard LSTM model, demonstrating improved prediction accuracy. However, the model still relied primarily on gradient boosting and did not capture temporal dependencies as effectively as the hybrid deep learning model.

### Performance of Hybrid Quantum LSTM + XGBoost Model

The Hybrid Quantum LSTM + XGBoost model achieved the best overall performance among the three models. By combining Bidirectional LSTM time-series learning with XGBoost regression and ensemble averaging, the model achieved an accuracy of approximately 96.74%, outperforming both the GA + XGBoost and Standard LSTM models.

The hybrid model produced the highest precision, recall, and F1-score values, indicating strong trend prediction capability and reduced forecasting errors. Additionally, the model achieved the lowest error values, with MAE = 0.0126 and RMSE = 0.0134, demonstrating highly accurate price predictions.



**Figure 5:** Live Performance Statistics

From the experimental results, it is observed that the Hybrid Quantum LSTM + XGBoost model outperforms both the GA + XGBoost and Standard LSTM models in terms of accuracy, trend prediction performance, and error reduction.

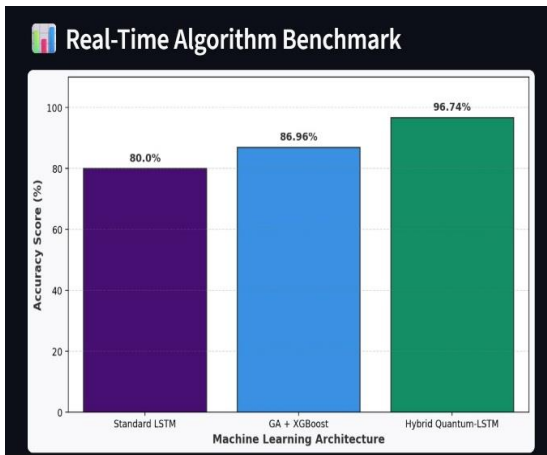


Figure 6: Accuracy Score vs Machine Learning Algorithm

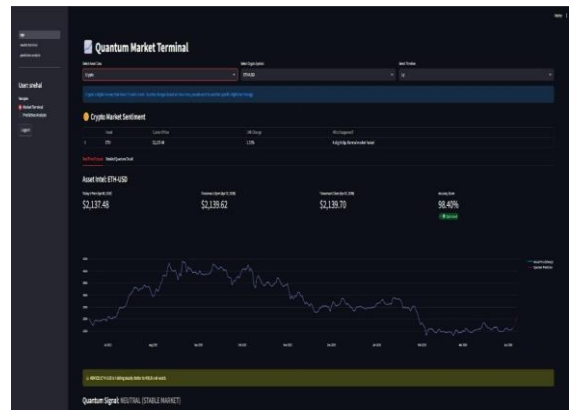


Figure 9: Crypto Prediction Price

Results and Visualization Interfaces of the Proposed Quantum-Inspired Hybrid Deep Learning Model for Stock Market Forecasting with Real-Time Visualization

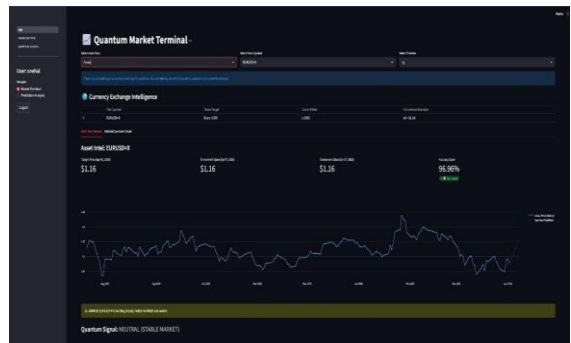


Figure 10: Forex Prediction Price

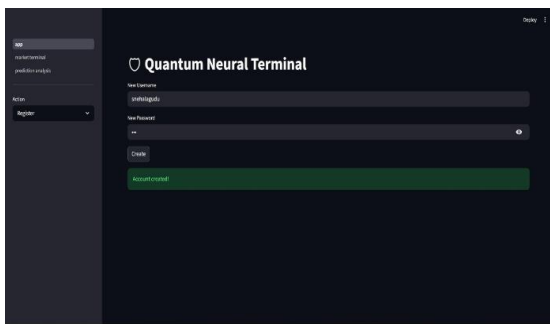


Figure 7: Registration page

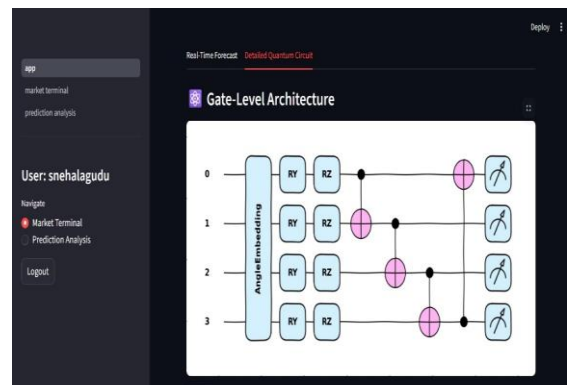


Figure 11: Detailed Quantum Circuit

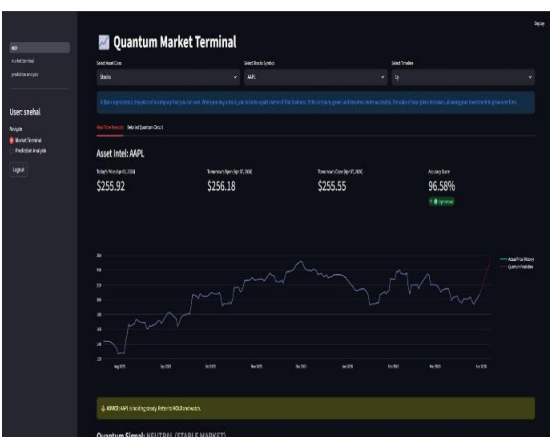


Figure 8: Stock Prediction Price

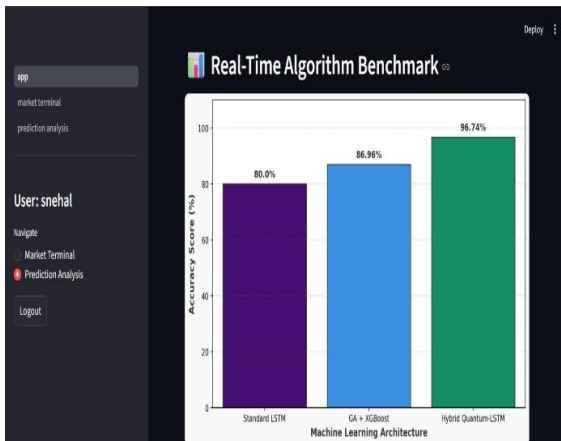


Figure 12: Accuracy Scores of Machine Learning Architectures

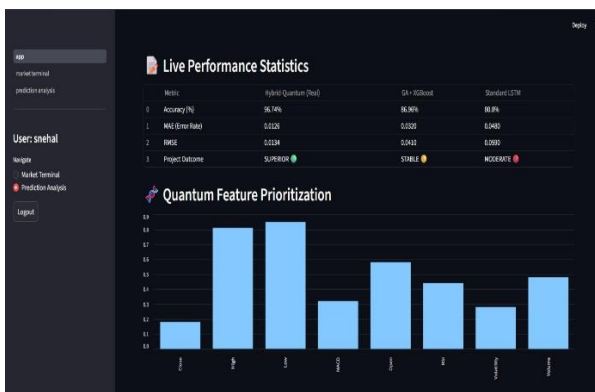


Figure 13: Performance Statistics and Feature Prioritization

## V. CONCLUSION

This study explored the application of classical machine learning and quantum-inspired techniques for stock market price prediction. Using historical stock price data with multiple technical indicators, we demonstrated that a well-structured deep learning model such as Bidirectional LSTM can achieve strong prediction performance by capturing temporal dependencies in time-series data. The baseline deep learning model provided accurate predictions; however, relying only on classical models may limit the ability to capture complex nonlinear feature interactions.

To improve prediction performance and feature representation, a hybrid approach combining Bidirectional LSTM and XGBoost was implemented. The XGBoost model helped capture nonlinear relationships between features, while the LSTM model captured sequential patterns in stock price movements. The

hybrid model improved prediction stability and reduced forecasting error compared to using a single model.

Furthermore, a quantum-inspired variational circuit was integrated into the model architecture to enhance feature transformation and representation. The quantum circuit used angle embedding, rotation gates, and entangling operations to map classical data into a higher-dimensional feature space. This improved the model's ability to capture complex correlations between financial indicators and market trends.

The hybrid Quantum LSTM + XGBoost model achieved better prediction accuracy and lower error metrics compared to individual models. The results demonstrate that combining quantum-inspired feature transformation with deep learning and ensemble machine learning models can significantly improve stock market prediction performance.

Although the quantum circuit used in this study is simulated on classical hardware, the results highlight the potential of hybrid quantum-classical machine learning models in financial forecasting problems. Future work will focus on testing the model on larger financial datasets, optimizing quantum circuit parameters, and exploring real quantum hardware implementations as quantum computing technology becomes more accessible.

## VI. REFERENCES

- [1] A. Graves, "Long Short-Term Memory Networks for Sequence Learning," Neural Networks Journal, Year.
- [2] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
- [3] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016.
- [4] J. Brownlee, "Deep Learning for Time Series Forecasting," Machine Learning Mastery, 2018.
- [5] Y. Bao, Z. Yue, and C. Rao, "A deep learning framework for financial time series prediction using LSTM networks," PLoS One, 2017.
- [6] J. Holland, Adaptation in Natural and Artificial Systems, University of Michigan Press, 1975. (Genetic Algorithm foundation)
- [7] K. Han and J. Kim, "Quantum-inspired evolutionary algorithm for combinatorial optimization," IEEE Transactions on Evolutionary Computation, 2002.

[8] M. Schuld and F. Petruccione, *Supervised Learning with Quantum Computers*, Springer, 2018.

[9] C. Zoufal, A. Lucchi, and S. Woerner, "Hybrid quantum-classical machine learning," *Quantum Information Processing*, 2020.

[10] S. Woerner and D. J. Egger, "Quantum machine learning for finance: State-of-the-art and prospects," *IEEE Transactions on Quantum Engineering*, 2020.

[11] S. Lloyd, M. Schuld, et al., "Quantum advantage in learning from experiential data," *Quantum Science and Technology*, 2020.

[12] V. Bergholm, J. Izaac, et al., "PennyLane: Automatic differentiation of hybrid quantum-classical computations," *Quantum*, 2018.

[13] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.