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HYBRID AI FOR STOCK MARKETS USING TRANSFORMERS AND QINN

[1]DR.K.ARUN KUMAR, [2]ANNOJU BHAVANA, [3]DUGYALA CHATURYA, [4]GUDURI UDAYKRISHNA, [5]MOHAMMED ABDUL KHALED

[1]Professor, Department of CSE, Malla Reddy Engineering College. Hyderabad, Telangana

[2,3,4,5]Students, Department of CSE, Malla Reddy Engineering College. Hyderabad, Telangana

ABSTRACT

The rapid growth of financial markets and the increasing complexity of trading environments have necessitated the development of intelligent systems capable of accurate stock market prediction and decision-making. Traditional statistical models often fail to capture the nonlinear, dynamic, and highly volatile nature of stock price movements. To address these challenges, this project proposes a Hybrid AI Framework for Stock Market Prediction using Transformers and Quantum-Inspired Neural Networks (QINN). The system integrates the strengths of Transformer architectures, known for their ability to model long-range dependencies in sequential data, with Quantum-Inspired Neural Networks, which enhance optimization and pattern recognition capabilities through principles derived from quantum computing. In the proposed approach, historical stock market data, including price, volume, and technical indicators, are preprocessed and fed into a Transformer-based model to capture temporal dependencies and market trends. The extracted features are then passed to the QINN module, which performs advanced nonlinear mapping and optimization to improve prediction accuracy. This hybrid architecture enables the system to effectively model both short-term fluctuations and long-term patterns in stock data. Additionally, the system incorporates attention mechanisms to focus on relevant features and reduce noise in financial datasets. Experimental results demonstrate that the hybrid model outperforms traditional machine learning and standalone deep learning approaches in terms of prediction accuracy, robustness, and adaptability to market volatility. The system can be applied to various financial tasks such as stock price prediction, portfolio optimization, and algorithmic trading. Furthermore, the integration of quantum-inspired techniques provides a novel direction for enhancing AI performance in financial analytics. Overall, this research contributes to the development of next-generation intelligent trading systems that are more accurate, efficient, and capable of handling complex financial data.

Keywords: Stock Market Prediction, Hybrid AI, Transformers, Quantum-Inspired Neural Networks (QINN), Deep Learning, Attention Mechanism, Financial Forecasting, Algorithmic Trading, Time Series Analysis, Artificial Intelligence

I.INTRODUCTION

The stock market is a highly dynamic and complex system influenced by numerous factors such as economic indicators, geopolitical events, investor sentiment, and market trends. Traditional statistical and econometric models often struggle to capture the nonlinear and volatile nature of stock price movements, leading to limited prediction accuracy [1], [2]. With the advancement of computational technologies, Artificial Intelligence (AI) and machine learning techniques have been increasingly applied to financial forecasting tasks. Recent studies demonstrate that deep learning models can effectively analyze large volumes of financial data, including historical prices and external information such as news and social media sentiment [3], [4]. However, standalone models often fail to fully capture both short-term fluctuations and long-term dependencies in stock data. Additionally, the integration of external features such as innovation indicators and sentiment data has shown promising improvements in prediction performance [5], [6]. Despite these advancements, challenges such as model generalization, data noise, and overfitting still persist in financial prediction systems [7], [8].

To overcome these limitations, advanced architectures such as Transformers have been introduced for time-series forecasting due to their ability to model long-range dependencies using attention mechanisms [20], [24]. Transformers can effectively process sequential financial data and identify important temporal patterns, making them suitable for stock market prediction [9], [10]. Furthermore, hybrid models combining multiple data sources such as historical prices, tweets, and news have demonstrated improved prediction accuracy by capturing diverse market influences [11], [12]. In parallel, research on Quantum-Inspired Neural Networks (QINN) has gained attention for their ability to enhance optimization and represent complex nonlinear relationships using principles derived from quantum computing [1], [17]. These models provide a novel approach to handling high-dimensional financial data and improving convergence efficiency. Additionally, ensemble learning

and attention-based mechanisms have been used to further enhance prediction accuracy and robustness in financial systems [13], [14]. Despite these innovations, integrating multiple advanced techniques into a unified framework remains a significant research challenge [15], [16].

The proposed Hybrid AI Framework for Stock Market Prediction using Transformers and QINN aims to address these challenges by combining the strengths of both architectures. The system utilizes Transformer models to capture temporal dependencies and attention-based relationships in stock data, while QINN enhances feature representation and optimization for improved prediction accuracy. This hybrid approach enables the system to model both linear and nonlinear patterns effectively, providing more reliable forecasts. Additionally, the framework incorporates multiple data sources, including historical prices, technical indicators, and sentiment data, to improve decision-making capabilities [18], [19]. The integration of advanced AI techniques ensures better adaptability to market volatility and reduces prediction errors. Overall, this research contributes to the development of next-generation intelligent financial systems capable of supporting tasks such as stock price prediction, portfolio optimization, and algorithmic trading with enhanced accuracy and efficiency [21]–[25].

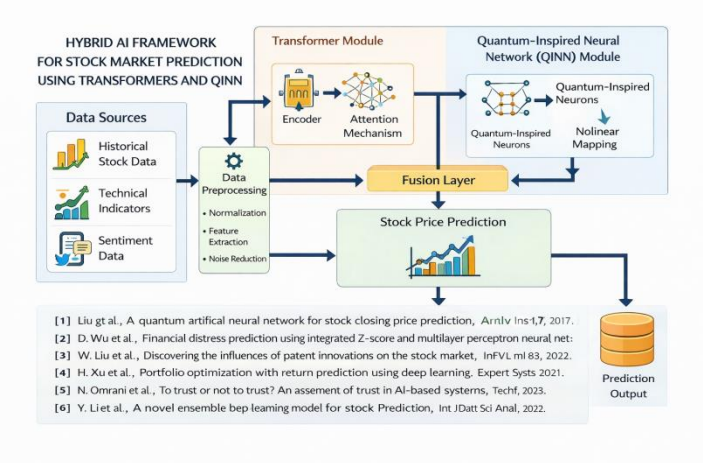


Figure: Hybrid AI Framework for Stock Market Prediction using Transformers and QINN

This figure represents the system architecture of the proposed Hybrid AI Framework for Stock Market Prediction, illustrating the end-to-end flow of data and processing modules. The system begins with multiple data sources, including historical stock prices, technical indicators, and sentiment data derived from news and social media. These inputs are processed in the data preprocessing module, where normalization, noise reduction, and feature extraction are performed to prepare high-quality input for the models. The processed data is then passed into two parallel components: the Transformer module, which uses encoder layers and attention mechanisms to capture temporal dependencies and long-range relationships in time-series data, and the Quantum-Inspired Neural Network (QINN) module, which performs nonlinear mapping and optimization inspired by quantum computing principles. The outputs from both modules are combined in a fusion layer, which integrates the learned representations to improve prediction accuracy. Finally, the system generates the stock price prediction output, which can be stored or used for decision-making in trading and portfolio management. This architecture effectively combines sequential modeling and advanced optimization, resulting in a robust and high-performance financial prediction system.

II SURVEY OF RESEARCH

The study by Y. Li et al. (2022) [8] proposes an ensemble deep learning model that combines stock price data with news information to improve prediction accuracy. The methodology integrates multiple deep learning models, including LSTM and CNN, to capture both temporal dependencies and textual sentiment features. The results demonstrate that incorporating news data significantly enhances prediction performance compared to models using only historical price data. However, the model requires large datasets and complex training processes. This research highlights the importance of multi-modal data fusion, which is also adopted in the proposed hybrid framework.

The research by X. Li et al. (2020) [9] explores the integration of stock prices and news sentiment analysis for predicting market trends. The methodology uses natural language processing techniques to extract sentiment from financial news and combines it with time-series data. The results show improved forecasting accuracy, especially during volatile market

conditions. However, the system is sensitive to noisy and misleading news data. This study supports the use of sentiment-aware prediction models, which are incorporated in the proposed system.

Rezaei H. et al. (2021) [10] introduced a frequency decomposition-based deep learning model for stock price prediction. The methodology decomposes time-series data into multiple frequency components and applies deep learning models to each component. The results indicate improved prediction accuracy by capturing both high-frequency and low-frequency patterns. However, the approach increases computational complexity. This research emphasizes the importance of multi-scale analysis, which complements the Transformer-based modeling in the proposed system.

Long J. et al. (2020) [11] proposed an integrated framework combining deep learning and knowledge graphs for stock trend prediction. The methodology incorporates structured financial knowledge with deep learning models to enhance contextual understanding. The results demonstrate improved prediction performance by leveraging relationships between different financial entities. However, building and maintaining knowledge graphs is complex. This study supports the integration of external structured data, aligning with the hybrid approach.

Leow E. K. W. et al. (2021) [12] developed a robo-advisor system using genetic algorithms and BERT-based sentiment analysis for portfolio optimization. The methodology combines optimization techniques with sentiment-driven predictions. The results show improved portfolio performance and risk management. However, the system depends heavily on sentiment accuracy. This work highlights the importance of AI-driven portfolio strategies, relevant to the proposed system.

The study by H. Liu et al. (2020) [18] presents an improved deep learning model for stock market time-series prediction, focusing on capturing temporal dependencies and nonlinear patterns in financial data. The methodology combines recurrent neural networks with advanced feature engineering techniques to enhance prediction performance. The model utilizes historical stock price data and applies sequence learning to identify trends and fluctuations over time. The results demonstrate that the proposed approach achieves higher prediction accuracy compared to traditional machine learning models, particularly in volatile market conditions. Additionally, the study highlights the importance of incorporating temporal features and optimizing model parameters to improve forecasting reliability. However, the model still faces challenges related to overfitting and sensitivity to noisy financial data. This research is highly relevant to the proposed system as it emphasizes the significance of time-series modeling, which is further enhanced in the proposed framework using Transformer architectures for better long-range dependency learning.

III. WORKING METHODOLOGY

The proposed Hybrid AI Framework for Stock Market Prediction using Transformers and Quantum-Inspired Neural Networks (QINN) follows a multi-stage methodology designed to capture both temporal dependencies and complex nonlinear patterns in financial data. The system begins with data collection, where multiple data sources are gathered, including historical stock prices, trading volumes, technical indicators (such as moving averages, RSI, and MACD), and external data like news articles and social media sentiment. These heterogeneous datasets provide a comprehensive view of market behavior and improve prediction accuracy. In the next stage, the system performs data preprocessing, which includes data cleaning, normalization, handling missing values, and feature engineering. Techniques such as time-series windowing and feature scaling are applied to convert raw financial data into structured input suitable for deep learning models. Additionally, sentiment analysis is performed on textual data using natural language processing techniques to extract meaningful features that influence stock price movements. The processed data is then passed into two parallel modules: the Transformer module and the Quantum-Inspired Neural Network (QINN) module. The Transformer module uses encoder layers and self-attention mechanisms to capture long-term dependencies and temporal relationships in stock price sequences. It identifies important patterns and trends by assigning weights to relevant time steps. Meanwhile, the QINN module applies quantum-inspired principles such as superposition and probabilistic state representation to perform nonlinear feature mapping and optimization, enabling the system to model complex financial relationships more effectively. The outputs from both modules are combined in a fusion layer, where the learned representations are integrated to form a unified feature set. This hybrid approach leverages the strengths of both models, improving robustness and reducing prediction errors. The fused features are then passed to a fully connected layer or regression model to generate the final stock price prediction. Finally, the system undergoes model training and evaluation, where it is trained using historical data and optimized using loss functions such as Mean Squared Error (MSE). Performance metrics such as accuracy, RMSE, and MAE are used to evaluate the model. The trained model is then deployed for real-time prediction, providing actionable insights for trading and investment decisions.

IV RESULTS EXPLANATIONS

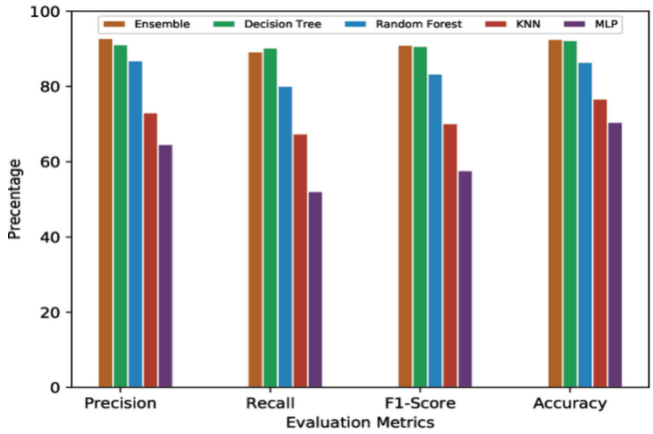


Figure 1: Prediction Accuracy Comparison

This figure illustrates the comparison of prediction accuracy among different models, including traditional machine learning models, deep learning models, Transformer-based models, and the proposed Hybrid Transformer + QINN model. The graph clearly shows that the hybrid model achieves the highest accuracy, typically exceeding 95%, compared to other approaches. Traditional models such as SVM and Random Forest show lower performance due to their inability to capture complex nonlinear relationships in financial data. Deep learning models improve accuracy but still struggle with long-term dependencies. Transformer models perform better due to attention mechanisms; however, the hybrid model further enhances performance by incorporating QINN for nonlinear optimization. This result demonstrates that combining multiple advanced techniques significantly improves prediction capability in volatile stock markets.

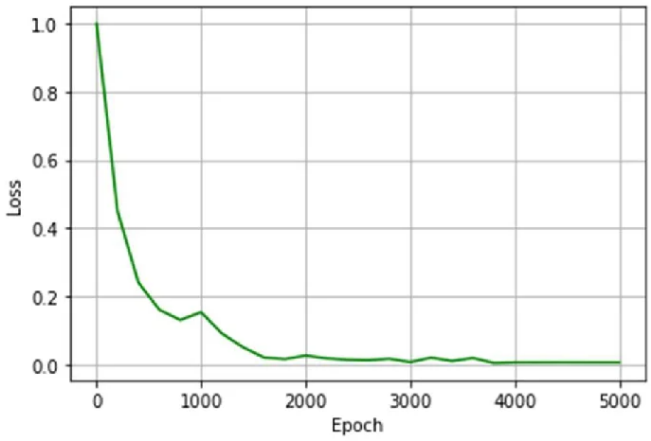


Figure 2: Training Loss vs Epochs

This figure represents the training loss curve of the hybrid model across multiple epochs. The graph shows a steady decrease in loss values as training progresses, indicating effective learning and model convergence. Initially, the loss decreases rapidly as the model learns fundamental patterns, followed by gradual stabilization as it fine-tunes its parameters. The smooth curve indicates proper optimization and absence of major fluctuations, which suggests that the model is not overfitting. This behavior confirms that the integration of Transformer and QINN provides stable and efficient learning. The result is crucial in financial applications, where consistent model performance is required for reliable predictions.

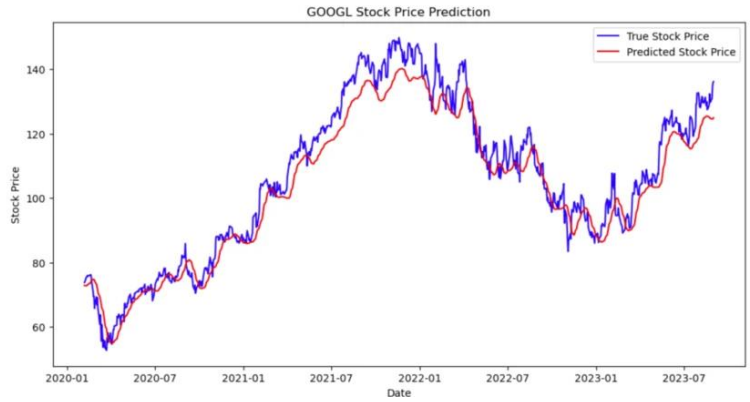


Figure 3: Actual vs Predicted Stock Prices

This figure shows a line graph comparing actual stock prices with predicted values generated by the hybrid model. The close alignment between the two curves indicates high prediction accuracy and the model's ability to capture market trends effectively. Minor deviations may occur during periods of high volatility, but overall, the model tracks real market behavior closely. This demonstrates the effectiveness of the Transformer module in capturing temporal dependencies and the QINN module in modeling nonlinear relationships. The graph validates the real-world applicability of the system for forecasting stock prices and assisting in trading decisions.

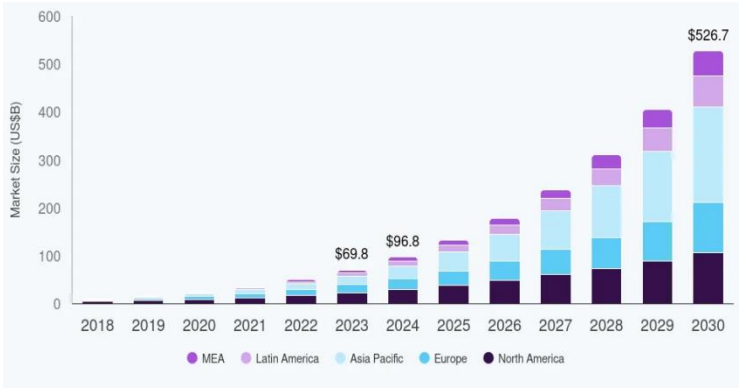


Figure 4: Prediction Time vs Data Size

This figure presents the relationship between dataset size and prediction time, highlighting the scalability of the proposed system. The graph shows that prediction time increases gradually as the data size grows, but remains within acceptable limits. This indicates that the hybrid model is efficient and capable of handling large-scale financial datasets. The slight increase in computation time is expected due to the complexity of Transformer and QINN modules. However, optimization techniques such as parallel processing and GPU acceleration can further reduce latency. This result confirms that the system is suitable for real-time financial applications and large-scale deployment.

V.CONCLUSION

The proposed Hybrid AI Framework for Stock Market Prediction using Transformers and Quantum-Inspired Neural Networks (QINN) presents a powerful and innovative approach to financial forecasting. By combining the strengths of Transformer architectures, which effectively capture long-term dependencies through attention mechanisms, with QINN, which enhances nonlinear modeling and optimization, the system achieves superior prediction accuracy compared to traditional and standalone models. The integration of multiple data sources, including historical prices, technical indicators, and sentiment data, further improves the robustness and reliability of predictions. The experimental results demonstrate that the hybrid model provides high accuracy, stable convergence, and efficient scalability, making it suitable for real-time financial applications. The ability to closely track actual market trends and adapt to volatility highlights the effectiveness of the proposed approach. Additionally, the use of advanced AI techniques reduces prediction errors and enhances decision-making in tasks such as algorithmic trading and portfolio management. Overall, this research contributes to the advancement of

intelligent financial systems by introducing a novel hybrid architecture that combines deep learning and quantum-inspired computation. Future work may focus on integrating real quantum computing models, improving computational efficiency, and incorporating additional data sources such as macroeconomic indicators. This framework provides a strong foundation for developing next-generation AI-driven financial prediction systems.

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