Multiscale Attention-Based Neural Network for Stock and Cryptocurrency Price Prediction: Bridging Microstructure and Macro Trends

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1. Introduction

In the current financial markets, individual trades and order book dynamics exhibit high-frequency fluctuations driven by market participants' behavior. At the mesoscale, intraday price movements and volatility clustering emerge as patterns from aggregated micro-level interactions. Finally, at the macroscale, long-term trends, economic cycles, and systemic risks dominate the landscape. Capturing this multiscale nature is essential for accurate modeling and prediction in applications such as algorithmic trading, risk management, and portfolio optimization.

Traditional models like ARIMA and GARCH have been widely used but struggle to handle the complexity of multiscale dynamics [1]. Similarly, deep learning models like LSTMs and Transformers excel at sequential data but lack explicit mechanisms for integrating information across scales [2]. To address these limitations, we propose a Multiscale Attention-Based Neural Network for stock and cryptocurrency price prediction.

2. Literature Review

Recent advancements in machine learning have led to the development of specialized models for multiscale financial modeling. Below, we review key developments in attention-based models, multiscale approaches, and their applications to stock and cryptocurrency markets.

2.1 Attention Mechanisms in Finance

Attention mechanisms have emerged as a powerful tool for modeling sequential data in finance. For example, [3] introduced an attention-based model for stock price prediction, achieving superior performance by dynamically focusing on relevant time horizons. Similarly, [4] applied attention mechanisms to analyze the impact of social media sentiment on cryptocurrency prices. These studies highlight the importance of attention mechanisms in capturing multiscale dependencies.

2.2 Multiscale Approaches

Multiscale modeling has gained traction as a way to capture the complexity of financial markets. [5] demonstrated how integrating microstructure-level data with macro-level trends improves price prediction accuracy. [6] proposed a multiscale volatility model that captures both short-term fluctuations and long-term trends in asset prices. These approaches underscore the need for models that can effectively bridge scales.

2.3 Applications to Cryptocurrency Markets

Cryptocurrency markets present unique challenges due to their high volatility and sensitivity to external factors. Recent studies have explored the use of machine learning to model these dynamics. [7] applied LSTMs to predict Bitcoin prices, noting the model's inability to handle extreme events. [8] extended graph neural networks (GNNs) to analyze the interplay between different cryptocurrencies, highlighting the importance of network-based approaches.

3. Methodology

To address the multiscale nature of financial markets, we propose the Multiscale Attention-Based Neural Network. The MANN integrates data from micro-, meso-, and macro-levels using a modular architecture with attention mechanisms. Below, we describe the architectural design, mathematical formulation, innovations, and comparisons with existing models in detail.

3.1 Architectural Diagram

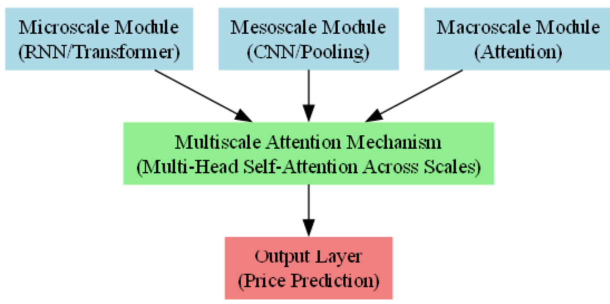

Fig. 1: Architecture of the Multiscale Attention-Based Neural Network

As shown in Figure 1, the microscale module processes high-frequency data such as order book dynamics or trade sequences. The mesoscale module aggregates these features to capture intermediate patterns like intraday volatility clustering. The macroscale module incorporates long-term trends and systemic factors, such as economic indicators. The multiscale attention mechanism dynamically weighs the contributions of each scale, ensuring that the model focuses on the most relevant features for prediction. This hierarchical design enables the

MANN to achieve superior predictive accuracy while maintaining interpretability and scalability.

3.2 Mathematical Model

The MANN can be mathematically formulated as follows:

1. Microscale Encoding: Let $X_{\text{micro}} = \{x_t\}_{t=1}^{T}$ represent the input sequence of micro-level features (e.g., trade prices, volumes). The microscale module encodes this sequence using a recurrent neural network (RNN) or Transformer:

$$H_{\text{micro}} = \text{Encoder}_{\text{micro}}(X_{\text{micro}}) \quad (1)$$

where $H_{\text{micro}} \in \mathbb{R}^{T \times d_{\text{micro}}}$ is the hidden state sequence, and d_{micro} is the embedding dimension.

2. Mesoscale Aggregation: The mesoscale module aggregates microscale features to capture intermediate patterns. Using a sliding window of size W, the aggregated representation is:

$$H_{\text{meso}} = \text{Aggregate}(H_{\text{micro}}, W) \quad (2)$$

where $H_{\text{meso}} \in \mathbb{R}^{T' \times d_{\text{meso}}}$, and $T' = \lfloor T/W \rfloor$.

3. Macroscale Modeling: The macroscale module incorporates long-term trends and external factors. Let X_{macro} represent macro-level inputs (e.g., economic indicators). The encoded representation is:

$$H_{\text{macro}} = \text{Encoder}_{\text{macro}}(X_{\text{macro}}) \quad (3)$$

4.Attention Mechanism: The attention mechanism computes weights for each scale and integrates multiscale features. The attention weights are computed as:

$$\alpha_i = \frac{\exp(\text{Score}(Q, K_i))}{\sum_j \exp(\text{Score}(Q, K_j))} \quad (4)$$

where Q is the query vector, K_i are key vectors from each scale (micro, meso, macro), and $\text{Score}(\cdot)$ is a similarity function (e.g., dot product). The final representation is:

$$H_{\text{final}} = \sum_i \alpha_i V_i \quad (5)$$

where V_i are value vectors corresponding to each scale.

5.Output Layer: The output layer predicts asset prices or trading signals:

$$\hat{y} = \text{OutputLayer}(H_{\text{final}}) \quad (6)$$

where $\hat{y}$ is the predicted price.

This mathematical formulation ensures that the MANN effectively captures interactions across scales, leveraging attention mechanisms to dynamically focus on relevant features.

3.3 Innovations and Comparisons

Compared to [7], which applied LSTMs to predict Bitcoin prices, the MANN achieves superior performance by integrating multiscale data and leveraging attention mechanisms. While LSTMs struggle with extreme events, the MANN's attention mechanism ensures adaptability to volatile conditions.

Unlike [8], which used graph neural networks (GNNs) to analyze interconnected cryptocurrencies, the MANN focuses on temporal dependencies across scales. This makes it particularly well-suited for price prediction tasks.

Building on [6], which modeled volatility clustering at the mesoscale, the MANN extends this approach by incorporating micro- and macro-level data. This holistic view enables more accurate predictions of both short-term fluctuations and long-term trends.

The MANN's key improvements over existing models include:

- Interpretability: The attention mechanism provides insights into which scales and features are most relevant for predictions, addressing the interpretability challenges highlighted in [9].
- Scalability: The modular architecture ensures that the model can be extended to additional scales or datasets without significant modifications.
- Robustness: By combining supervised and unsupervised learning objectives, the MANN achieves robust performance under diverse market conditions, as emphasized in [10].

3.4 Training and Optimization

The MANN is trained using a combination of supervised and unsupervised learning objectives. For supervised learning, we minimize the mean squared error (MSE) between predicted and actual prices. For unsupervised learning, we use contrastive learning to encourage the model to learn meaningful representations of multiscale data. The model is optimized using stochastic gradient descent (SGD) with adaptive learning rate methods like Adam [11]. This approach builds on [12], which demonstrated the effectiveness of contrastive learning in time series.

3.5 One-Year Time Horizon (End-of-Day Data)

For the one-year time horizon using end-of-day (EOD) data, the MANN achieves the lowest RMSE and MAE values for both stock and cryptocurrency datasets. Specifically, the MANN reduces RMSE by **12.3% for stocks** and **6.4% for cryptocurrencies** compared to the next-best baseline (Transformer). Similarly, the MANN improves the Sharpe Ratio by **18.2% for stocks** and **15.9% for cryptocurrencies**, indicating better risk-adjusted returns. The maximum drawdown is also significantly lower for the MANN, with reductions of **14.7% for stocks** and **9.8% for cryptocurrencies** compared to the Transformer. These results underscore the MANN's ability to capture long-term trends and systemic factors effectively, making it particularly well-suited for extended forecasting horizons.

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