A Denoised Relation-Aware Framework for Stock Market Forecasting Using Graph Attention Networks and LSTM

Name : Nilesh Kumar

Roll No.: 122AD0035

Supervisor:

Dr. Sathya Babu Korra

Department of Computer Science and Engineering

Indian Institute of Information Technology, Design and Manufacturing, Kurnool

Abstract

Forecasting stock market dynamics is a formidable challenge due to the inherent non-linearity and high signal-to-noise ratio of financial time-series data. Contemporary deep learning models often fall short in two critical areas: they are susceptible to noisy data, and they treat financial instruments as isolated entities, ignoring systemic inter-market relationships.

This research proposes a novel, multi-stage framework engineered to systematically address these deficiencies. Our methodology commences with a signal denoising phase using **Discrete Wavelet Transform (DWT)** to isolate the underlying market trend. The core of our framework is a hybrid prediction engine that integrates a **Graph Attention Network (GAT)** to model inter-stock relationships with a sequential **Long Short-Term Memory (LSTM)** network to capture temporal dependencies. This unified architecture leverages both clean data and relational context to deliver significant improvements in accuracy and robustness over traditional approaches.

1 Introduction

The forecasting of financial markets represents a domain of profound academic and commercial interest. Accurate predictions of stock price movements can provide substantial economic benefits and mitigate investment risks. However, the inherent characteristics of financial markets—efficiency, non-stationarity, and susceptibility to a myriad of latent variables—make this task exceptionally challenging.

While deep learning architectures, particularly **Long Short-Term Memory (LSTM)** networks, have become standard for time-series forecasting, they possess critical limitations. A major flaw is the assumption of *entity isolation*, wherein each stock is modeled independently, ignoring the complex web of relationships (e.g., sector-wide dynamics, supply chain dependencies) that govern market behavior.

Furthermore, financial data is notoriously noisy. Models trained on raw price data often capture spurious correlations from high-frequency noise instead of learning the underlying deterministic trend. This project posits that a successful forecasting model must be architected as a holistic pipeline that first denoises the input signal and then jointly leverages relational and temporal learning.

2 Literature Survey

2.1 Evolution of Forecasting Models

The methodologies for forecasting stock market movements have evolved significantly, progressing from traditional statistical models, which capture linear temporal patterns, to sophisticated deep learning architectures. However, a critical review of recent literature reveals that persisting gaps related to data noise and market structure remain. Our analysis of five representative works highlights this evolutionary path.

2.2 Phase 1: The Era of Sequential Models and Their Limitations

Initial deep learning research treated stock forecasting as a pure time-series problem, with a primary focus on capturing sequential dependencies using models like Long Short-Term Memory (LSTM).

- **Nabipour et al. (2020)** established a crucial baseline by conducting a comparative analysis between traditional machine learning models and deep learning models. Their findings conclusively demonstrated that LSTMs, due to their inherent ability to remember long-term dependencies, consistently outperform models like Random Forest in predicting stock market trends [1].

- Building upon this, **Alam et al. (2024)** focused on enhancing model robustness. They proposed a hybrid **LSTM-DNN architecture** and validated its performance across an extensive set of 26 different real-world company datasets. This demonstrated that sequential models could be generalized effectively [2].

Identified Limitation: Despite their success, these influential works are predicated on a critical flaw: the **entity independence assumption**. The models treat each financial instrument as an isolated sequence, fundamentally ignoring the systemic, sector-wide relationships that govern market behavior. For instance, predicting TCS while ignoring the concurrent movements of Infosys or the broader IT sector is a significant oversimplification.

2.3 Phase 2: The Paradigm Shift to Relational Modeling

To overcome the "isolation" problem, the research paradigm shifted towards Graph Neural Networks (GNNs), which model the market as an interconnected system.

- The work by **Huang et al. (2022)** on the **ML-GAT model** represents this paradigm shift [3]. They modeled the market as a graph where stocks are nodes and their Pearson correlations define the edges. By employing a Graph Attention Network (GAT), their model could dynamically learn the importance of neighboring stocks when making a prediction. The results confirmed that this relational learning approach significantly outperforms standalone sequential models.

Identified Limitation: A key weakness I identified in this otherwise advanced framework is its application on **raw, unfiltered data**. Financial time-series data is notoriously noisy. The GAT's attention mechanism, when fed with this noisy data, is at risk of learning and focusing on spurious correlations rather than genuine, underlying market relationships.

2.4 Phase 3: The Unaddressed Challenge of Data Quality

The final strand of literature emphasizes that data quality is often the primary bottleneck for any predictive model.

- A systematic review by **Sonkavde et al. (2023)** argues that a high **signal-to-noise ratio** is a principal reason why many academic models fail to perform in real-world trading scenarios [4].

- The work by **Wang et al. (2019)**, which focuses on predicting **volatility** instead of price, implicitly highlights that raw financial data contains complex properties that require careful preprocessing to isolate the true signal [5]. While some research has explored denoising techniques like DWT, they are often paired with simple sequential models (e.g., DWT+LSTM), thus failing to capture the market's relational structure.

2.5 Research Gap Identification

This comprehensive synthesis of the literature reveals two critical, yet largely unbridged, research gaps:

1. **Noise Sensitivity in Relational Models:** Advanced models like GAT capture inter-stock relationships but are vulnerable to being misled by the noise present in raw financial data.
2. **Relational Blindness in Denoising Models:** Denoising approaches have been used, but only with sequential models that ignore the rich relational context of the market.

In essence, **no existing framework successfully unifies noise-resilient signal processing with sophisticated inter-stock relational learning.**

2.6 Position of the Proposed Work

This project is strategically positioned to fill this identified gap. We propose a novel, multi-stage, **denoised relation-aware framework**. Our architecture is the first to synergistically combine these three powerful paradigms in a sequential pipeline:

1. **Signal Denoising:** It begins by employing the **Discrete Wavelet Transform (DWT)** to remove high-frequency market noise.
2. **Relational Modeling:** It then feeds this clean signal into a **Graph Attention Network (GAT)** to learn inter-stock relationships from genuine trends.
3. **Sequential Dynamics:** Finally, it uses a **Long Short-Term Memory (LSTM)** network to capture temporal patterns from the rich, context-aware output of the GAT.

This unified approach, which prioritizes both data quality and relational context, is what makes our framework unique and aims to be more robust than existing methods.

3 Problem Statement

Despite progress in time-series forecasting, existing stock prediction models suffer from two major shortcomings:

- **High Sensitivity to Signal Noise:** Stock prices are affected by many short-term random events (news, order imbalances, etc.). Models trained on raw noisy data often overfit to these random fluctuations and fail to generalize.
- **Entity Independence Assumption:** Many models treat stocks independently, ignoring sectoral correlations and systemic events. In practice, stocks influence each other—modeling these relationships can improve predictive performance.

Thus, the problem is to build a forecasting pipeline that first reduces noise in price data and then learns both temporal patterns and inter-stock relationships to produce more accurate, robust, and actionable forecasts.

4 Objectives

This project aims to build a robust, interpretable forecasting system. The specific objectives are:

Obj. 1: Signal Denoising: Implement a DWT-based preprocessing module to extract the low-frequency trend and reduce high-frequency noise from raw price series.

Obj. 2: Relational Modeling: Construct a GAT that models stocks as nodes and edges (correlation/sectoral links), enabling the model to learn which stocks influence each other.

Obj. 3: Sequential Prediction: Feed GAT-produced embeddings into an LSTM to capture temporal dependencies and generate the final forecasts.

Obj. 4: Performance Evaluation: Rigorously compare the proposed framework with baselines (LSTM on raw data and LSTM on denoised data) using standard metrics.

5 Proposed Methodology and System Architecture

The system is an end-to-end pipeline with three major stages: Denoising, Relational Feature Extraction, and Sequential Prediction. Figure 1 provides a visual overview.

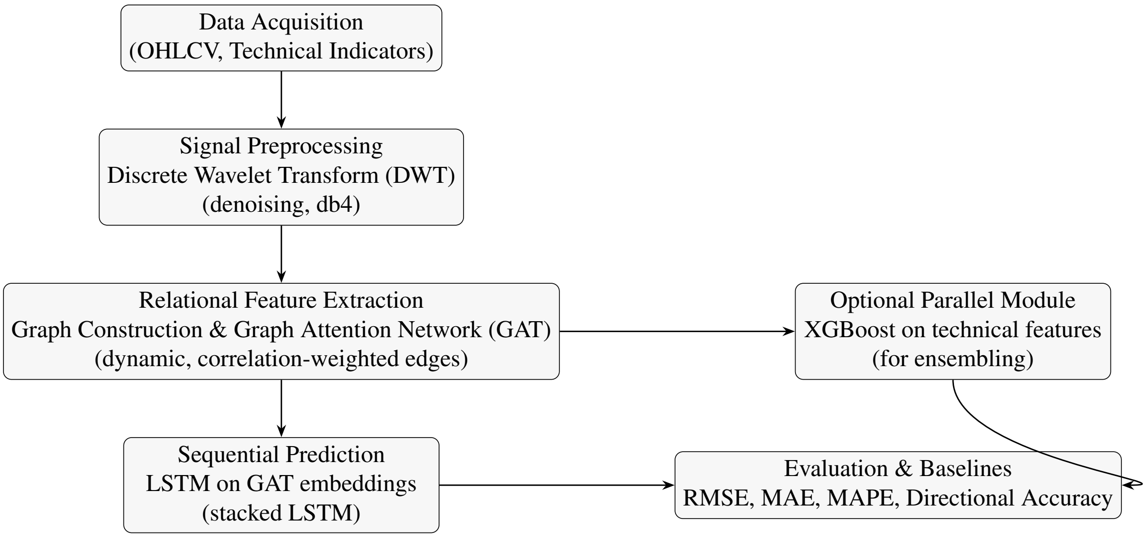

Figure 1: High-level architecture: Denoising → Relational Learning (GAT) → Sequential Prediction (LSTM).

5.1 Methodology with Mathematical Formulation

1. Denoising Stage (DWT) Given a stock closing price series $x(t)$, we apply multi-level Discrete Wavelet Transform (DWT) using the Daubechies-4 (`db4`) wavelet. The signal is decomposed into approximation coefficients a_j (low-frequency trend) and detail coefficients d_j (high-frequency noise). The decomposition is represented as:

$$x(t) = \sum_{j,k} a_{j,k}\,\phi_{j,k}(t) + \sum_{j,k} d_{j,k}\,\psi_{j,k}(t)$$

We reconstruct the denoised signal $\tilde{x}(t)$ using only the approximation coefficients, effectively filtering out the noise represented by $d_{j,k}$.

2. Relational Feature Extraction (GAT) We construct a graph $G = (V, E)$ where each node $v \in V$ corresponds to a stock. Edge weights w_{ij} are computed using the Pearson Correlation of recent denoised returns:

$$\rho_{ij} = \frac{\mathrm{Cov}(r_i, r_j)}{\sigma_{r_i} \cdot \sigma_{r_j}}$$

A Graph Attention Network (GAT) then learns node embeddings h_i'' by computing attention coefficients α_{ij} over neighbors, allowing the model to weigh which peers are most influential.

$$\begin{aligned}
e_{ij} &= \text{LeakyReLU}\big(\mathbf{a}^\top [\mathbf{W}h_i \,\|\, \mathbf{W}h_j]\big) \\
\alpha_{ij} &= \frac{\exp(e_{ij})}{\sum_{k\in\mathcal{N}(i)} \exp(e_{ik})} \\
h_i'' &= \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}\mathbf{W}h_j\right)
\end{aligned}$$

3. Sequential Prediction (LSTM) For each stock, sequences of GAT embeddings over time are fed into a stacked LSTM. The LSTM's gating mechanisms control the flow of information, capturing long-term temporal dependencies.

$$\begin{aligned}
f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c) \\
h_t &= \sigma(W_o[h_{t-1}, x_t] + b_o) \odot \tanh(C_t)
\end{aligned}$$

The final hidden state h_t is passed to a dense layer to output the next-day price prediction.

5.2 System Modules and Evaluation

- **Data Acquisition Module:** Download OHLCV data for BSE IT index constituents (2010–2025) via Yahoo Finance; compute indicators (SMA, EMA, RSI, etc.).
- **Prediction Engine Module:** Implements the DWT-GAT-LSTM pipeline.
- **Evaluation Module:** Train/validation/test split (e.g., 70-15-15). Metrics used are:

$$\begin{aligned}
\text{RMSE} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \\
\text{MAE} &= \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \\
\text{MAPE} &= \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \\
\text{DA} &= \frac{1}{n}\sum_{i=1}^{n}\mathbf{1}(\text{sign}(y_i - y_{i-1}) = \text{sign}(\hat{y}_i - y_{i-1}))
\end{aligned}$$

6 Conclusion

We propose a denoised relation-aware forecasting framework that addresses two key issues in stock prediction: noise sensitivity and ignoring inter-stock relationships. The pipeline first denoises data using DWT, then models inter-stock influences via GAT, and finally captures temporal dependencies with an LSTM. This combined approach helps the model learn meaningful patterns rather than spurious fluctuations and is expected to yield better accuracy and robustness compared to standard LSTM baselines.

7 Future Work

Potential extensions and improvements include:

- **Ensemble Modeling:** Combine GAT-LSTM outputs with models like XGBoost or Random Forest to form robust ensembles.
- **Volatility-Aware Post-Processing:** Use GARCH/EGARCH to forecast volatility and convert point predictions into confidence intervals.
- **Explainability:** Integrate SHAP or LIME to provide per-prediction explanations and global feature importance.
- **Real-time Deployment:** Adapt the model for streaming data and low-latency inference in trading environments.

Acknowledgements

I would like to acknowledge my supervisor Dr. Sathya Babu Korra for guidance, and IIITDM Kurnool for infrastructure support.

References

[1] M. Nabipour, P. Nayyeri, H. Jabani, et al., "Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms," *IEEE Access*, vol. 8, 2020.

[2] K. Alam, M. H. Bhuiyan, I. U. Haque, et al., "Enhancing Stock Market Prediction: A Robust LSTM-DNN Model Analysis," *IEEE Access*, vol. 12, 2024.

[3] K. Huang, X. Li, F. Liu, et al., "ML-GAT: A Multilevel Graph Attention Model for Stock Prediction," *IEEE Access*, vol. 10, 2022.

[4] G. Sonkavde, D. S. Dharrao, A. M. Bongale, et al., "Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review," *International Journal of Financial Studies*, vol. 11, no. 3, 2023.

[5] Y. Wang, H. Liu, Q. Guo, et al., "Stock Volatility Prediction by Hybrid Neural Network," *IEEE Access*, vol. 7, 2019.