Project Report: Advanced Deep Learning Models for Time Series Analysis in Stock Price Forecasting

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1 Introduction

Time series forecasting is a pivotal challenge within the realm of data science and machine learning, finding utility in areas as diverse as finance, meteorology, energy management, and healthcare [1]. Unlike spatial data, where patterns are primarily extracted from static snapshots, time series data is inherently dynamic, capturing evolving trends, cyclical behaviors, and seasonal variations over time. Accurately predicting future values based on historical data is therefore crucial for informed decision-making. In the financial sector, stock price prediction stands out as a particularly demanding and high-stakes application. Markets are volatile, influenced by myriad economic and geopolitical factors, and sensitive to abrupt fluctuations. Consequently, robust, data-driven approaches to forecasting can have substantial practical and economic implications, aiding investors, traders, and analysts alike.

While deep learning architectures have achieved remarkable success in modeling spatial data—often surpassing human capabilities in fields such as image recognition—harnessing their potential for time series forecasting remains a developing frontier. Temporal data pose unique challenges: non-stationarity, long-range dependencies, and abrupt regime shifts complicate traditional modeling approaches. In response, recent advancements in deep learning for time-dependent data have introduced sophisticated architectures designed specifically to handle these intricacies. Among these, state-of-the-art (SOTA) models like *TimesNet* [2] and *iTransformer* [3] represent cutting-edge approaches that leverage advanced mechanisms for capturing temporal patterns, trends, and relationships.

In this project, we focus on applying and comparing TimesNet and iTransformer models to the task of stock price prediction, using a historical dataset of Apple Inc. shares as our testbed. By implementing both architectures and evaluating their relative performance, we aim to expand our understanding of deep learning strategies for complex financial time series forecasting. The insights gained here may also inform other time-sensitive domains, facilitating improvements in model design and application for diverse temporal prediction tasks.

2 Dataset

Our empirical evaluation is based on the Apple Stock Price Dataset sourced from a public Kaggle repository. This dataset offers a comprehensive historical record, spanning from December 12, 1980, through May 24, 2024, and encompassing approximately 10,954 daily entries. Each record provides essential features for financial analysis, including the date, opening price, highest price, lowest price, closing price, adjusted closing price, and trading volume. The extended temporal coverage, combined with rich price and volume information, makes this dataset ideal for exploring advanced deep learning models tailored to time series forecasting.

Prior to model training, we undertake a rigorous data preprocessing phase to ensure both data quality and temporal consistency. First, we inspect the dataset for anomalies such as missing values or outliers. Depending on their nature, these irregularities are either corrected, imputed, or excluded to maintain the integrity of subsequent analyses. We designate the closing price as our primary target variable, and where appropriate, consider transformations (e.g., log scaling) to improve stationarity. Additionally, we engineer temporal features, such as lagged values or rolling-window statistics, to help the models capture local trends and seasonality.

To reflect real-world predictive scenarios, our data splitting strategy respects the temporal order of observations. Early portions of the time series serve as the training set, enabling TimesNet and iTransformer models to learn historical patterns. Later segments form the validation and testing sets, ensuring that model performance is assessed on genuinely unseen future data. This chronological approach mitigates data leakage and provides a more realistic evaluation of forecasting capabilities.

By the conclusion of this data processing stage, we obtain a clean, structured dataset well-suited for training and evaluating deep learning-based forecasting models.

3 Exploratory Data Analysis (EDA)

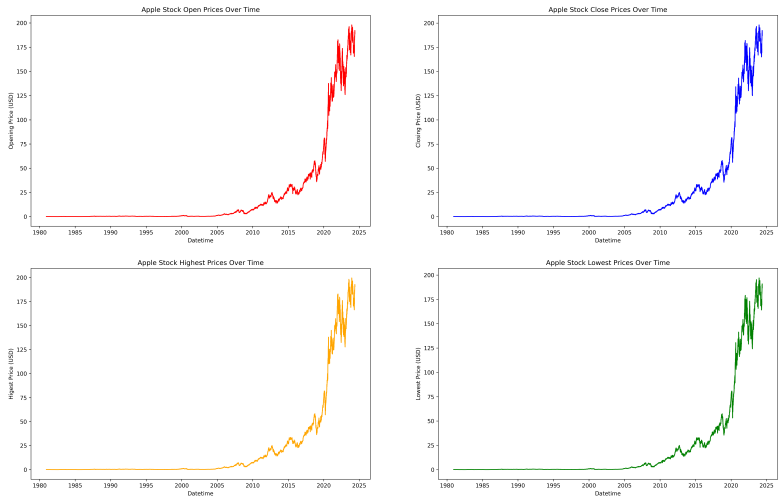

Figure 1: Apple Stock Prices Overtime

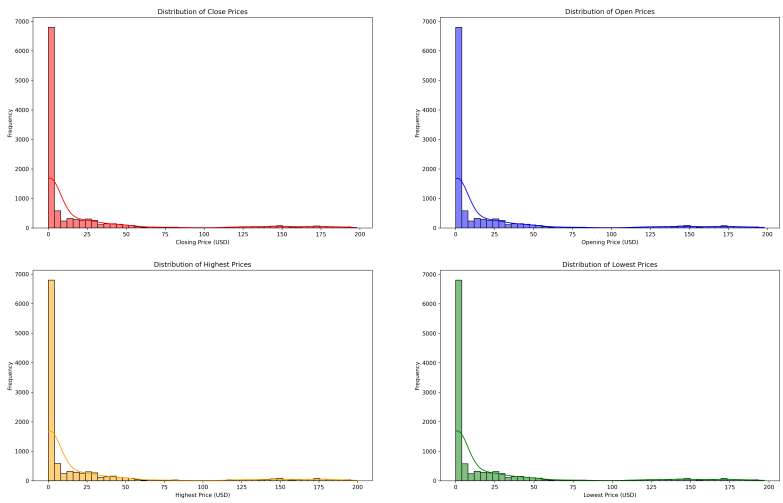

Figure 2: Apple Stock Prices Distribution

The exploratory data analysis of Apple's historical stock price dataset provides an overview of its trends, distributions, and relationships between key financial variables. First, a time-series analysis of the stock prices (open, close, high, and low) revealed significant growth over the dataset's nearly 44-year span, with periods of rapid increase aligning with major milestones in Apple's business history (Figure 1). The visualized trends illustrate not only the long-term appreciation of Apple's stock but also highlight volatility, particularly during market corrections and economic downturns. Furthermore, a distribution analysis of these prices displayed a right-skewed pattern, reflecting Apple's substantial growth trajectory

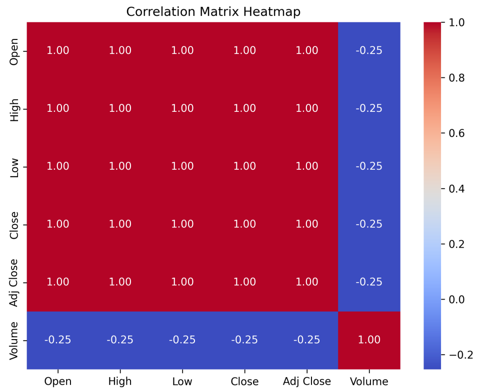

Figure 3: Variables Correlation Matrix

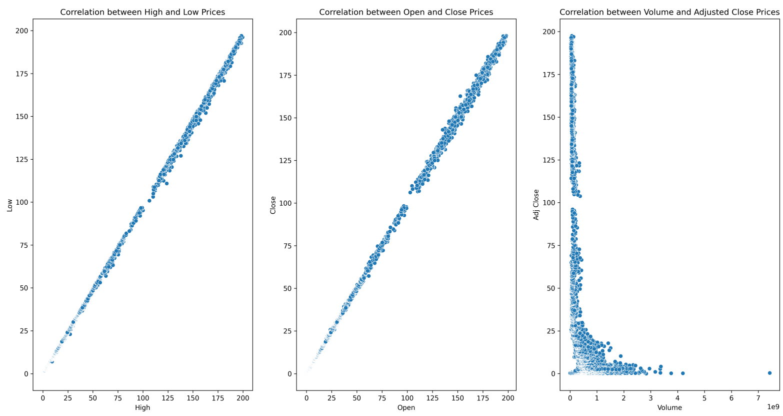

Figure 4: Correlation Scatter Plots (High vs. Low and Open vs. Close and Adjusted Close vs. Volume)

and the increasing valuation of its stock over time (Figure 2).

In addition to individual trends, the correlation matrix and scatter plots shed light on interdependency among key features. Strong positive correlations were observed between high, low, open, close, and adjusted close prices, indicating consistent intraday movements in stock pricing (Figure 3). The the prices exhibited weaker correlations with trading volume, suggesting that stock prices may not directly depend on the volume traded. Scatter plots, such as those comparing high vs. low prices, open vs. close prices, and adjusted close vs. volume, further validated these relationships while offering insights into the data's spread and variability (Figure 4). Together, these analyses provide a comprehensive understanding of the dataset's characteristics and set the stage for predictive modeling efforts.

4 Data Mining Algorithms

In this project, we implemented two state-of-the-art deep learning models for time series forecasting: *TimesNet* and *iTransformer*. These models were selected for their innovative approaches to capturing temporal dependencies and their demonstrated performance on various real-world time series forecasting tasks.

4.1 TimesNet

TimesNet introduces a novel approach to time series analysis by transforming 1D temporal data into 2D tensors, enhancing its representation capability. This transformation allows the separation of temporal patterns into intraperiod variations, representing short-term changes within a period (captured as columns), and interperiod variations, reflecting long-term trends across periods (captured as rows). Leveraging multi-periodicity in time series data, TimesNet employs Fast Fourier Transform (FFT) to identify significant frequencies, enabling a modular representation of overlapping periodic patterns. At the core of TimesNet is the TimesBlock, which utilizes parameter-efficient inception blocks with multi-scale 2D convolution kernels to process the transformed tensors, effectively capturing both intraperiod and interperiod variations. This modular design ensures computational efficiency by sharing parameters across periods while maintaining scalability. Furthermore, TimesNet bridges time series analysis and computer vision by enabling the use of vision backbones like ResNet and ConvNext, leveraging advancements in 2D processing to enhance representation learning. Designed as a task-general foundation model, TimesNet achieves state-of-the-art performance across diverse time series tasks, including forecasting, classification, anomaly detection, and imputation. Its consistent success across benchmarks highlights its ability to disentangle complex temporal patterns, making it a versatile and high-performing tool for time series analysis.

4.2 iTransformer: Key Ideas and Innovations

iTransformer reimagines the application of Transformers for time series forecasting by introducing an inverted perspective on data tokenization and processing. Traditional Transformer-based forecasters treat multivariate observations at the same timestamp as a single token, which often fails to capture meaningful correlations and introduces noise from temporally misaligned features. In contrast, iTransformer embeds entire time series for each variate as independent tokens, enabling the attention mechanism to focus on multivariate correlations and the feed-forward network (FFN) to independently process nonlinear representations for each variate. This architecture enhances interpretability and performance, particularly in handling long lookback windows.

The self-attention mechanism in iTransformer operates on variate tokens, explicitly learning inter-variate relationships, while the FFN extracts series-specific representations for each token. Layer normalization is applied at the variate level to mitigate discrepancies caused by inconsistent physical measurements, improving robustness to non-stationarity. By avoiding architectural modifications to the core Transformer components, iTransformer ensures compatibility with efficient attention mechanisms, allowing scalability to datasets with numerous variates.

Experimentally, iTransformer achieves state-of-the-art performance across diverse real-world benchmarks, demonstrating superior generalization to unseen variates and effective utilization of extended lookback series. Its ability to disentangle multivariate correlations and capture temporal dependencies makes it a powerful backbone for time series forecasting, addressing longstanding challenges in Transformer-based approaches for multivariate temporal data.

4.3 Rationale for Algorithm Selection

The primary objective of this project is to apply and compare state-of-the-art deep learning models for time series forecasting to gain insights into their effectiveness and limitations, particularly in the financial domain. The task of stock price prediction presents unique challenges, including non-stationarity, abrupt fluctuations, long-range dependencies, and multivariate correlations among features such as price and trading volume. To address these complexities, we selected *TimesNet* and *iTransformer*, two cutting-edge models known for their innovative approaches to handling diverse temporal patterns.

TimesNet was chosen for its ability to capture multi-periodicity and disentangle overlapping temporal patterns through its novel transformation of 1D time series into 2D tensors. This design enables it to effectively analyze both short-term (intraperiod) and long-term (interperiod) variations, which are crucial for understanding cyclical and trend-based behaviors in stock prices. Moreover, TimesNet's modular architecture, based on multi-scale 2D convolution kernels, ensures scalability and computational efficiency, making it well-suited for large, feature-rich datasets like the Apple Stock Price Dataset.

iTransformer, on the other hand, was selected for its focus on multivariate correlations and its reimagined tokenization process, which treats each time series as an independent variate token. This approach allows the model to leverage inter-variable relationships through its self-attention mechanism, while its feed-forward networks handle nonlinear, variate-specific representations. These capabilities align well with the financial dataset's multivariate structure, where interactions between features like trading volume and price dynamics are critical for accurate predictions.

TimesNet excels in capturing temporal dependencies and periodic trends, while iTransformer focuses on modeling the dynamic interplay of multivariate features. By comparing their performance on the

Apple Stock Price Dataset, we aim to not only evaluate their respective strengths but also derive broader insights into the application of deep learning for time-sensitive financial data. This analysis contributes to advancing understanding in both model selection and financial forecasting strategies, with potential implications for other domains involving complex temporal prediction tasks.

5 Visualizations

To thoroughly analyze and compare the performance of TimesNet and iTransformer, we utilized several visualization techniques. These visualizations highlight different aspects of the models' forecasting abilities, from individual predictions to aggregate trends, offering both quantitative and qualitative insights into their strengths and limitations. Each visualization includes separate figures for TimesNet and iTransformer to facilitate direct comparison.

5.1 True vs Predicted Prices for a Single Sample

Figures 5 and 6 illustrate the true and predicted prices for a single sample. This plot provides a detailed view of how well each model captures temporal patterns over the prediction horizon. True prices are shown as solid lines with circular markers, while predicted prices are displayed as dashed lines with cross markers. The purpose of this visualization is to evaluate the ability of each model to track price fluctuations accurately and to detect instances where predictions deviate from actual values. For example, it can help identify if the model systematically overestimates or underestimates prices at specific time steps.

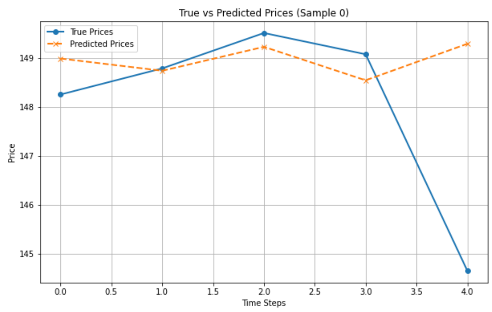

Figure 5: True vs Predicted Prices for a Single Sample (TimesNet)

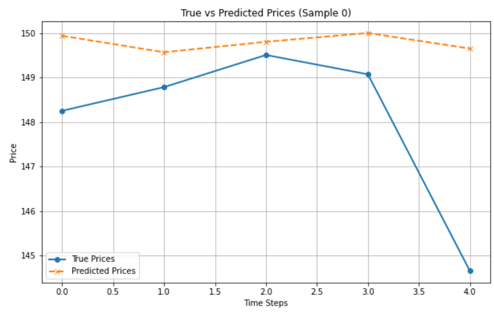

Figure 6: True vs Predicted Prices for a Single Sample (iTransformer)

5.2 Scatter Plot of Predicted vs True Prices

Figures 7 and 8 present scatter plots of predicted prices versus true prices across all samples. Each point represents a single prediction, and its proximity to the diagonal line indicates its accuracy. This visualization provides a global view of model performance by showing the overall correlation between predictions and true values. It highlights trends such as whether predictions are consistently biased (e.g., overestimations for high prices or underestimations for low prices). For well-performing models, the points should cluster tightly around the diagonal.

5.3 Prediction Errors Over Time

Figures 9 and 10 depict the prediction errors (i.e., the difference between predicted and true prices) for a single sample over the prediction horizon. These plots are crucial for understanding temporal variations in errors. A consistent pattern of errors might indicate systematic biases, such as the model being overly optimistic or pessimistic during specific time intervals. The zero-error reference line serves as a baseline to help visualize deviations. By comparing these plots, we can identify whether one model is more stable and accurate than the other over time.

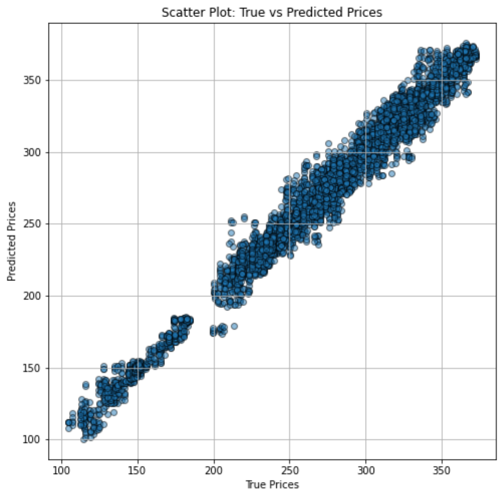

Figure 7: Scatter Plot: True vs Predicted Prices (TimesNet)

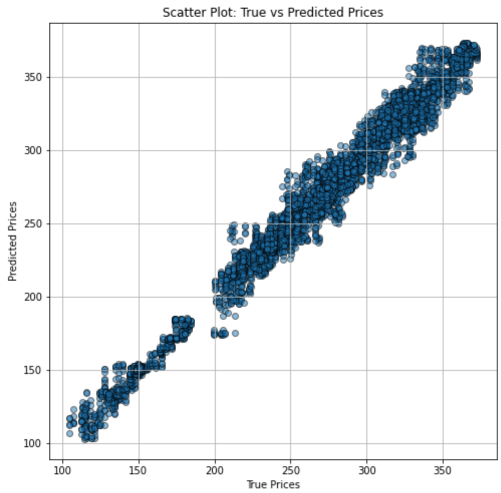

Figure 8: Scatter Plot: True vs Predicted Prices (iTransformer)

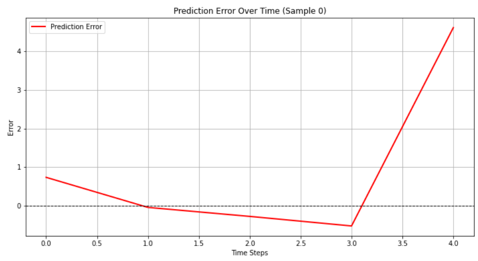

Figure 9: Prediction Error Over Time (TimesNet)

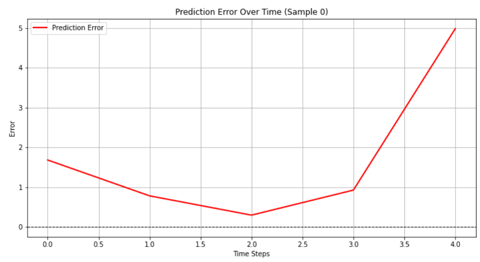

Figure 10: Prediction Error Over Time (iTransformer)

5.4 Distribution of Prediction Errors

Figures 11 and 12 show histograms of prediction errors across all samples. These visualizations provide a statistical perspective on the error distributions, highlighting their spread, symmetry, and central tendency. A narrow, symmetric distribution centered around zero indicates low bias and high reliability. Comparing these distributions allows us to determine which model has more concentrated and less extreme errors.

5.5 Mean True vs Predicted Prices Across All Samples

Figures 13 and 14 compare the mean true prices and mean predicted prices across all samples. These plots aggregate predictions and actual values over the entire dataset, offering a high-level view of each model's ability to capture overall trends. They help assess whether the model is accurately reflecting the dataset's global structure or if it struggles with specific trends or biases. This visualization is particularly useful for understanding the generalizability of the models beyond individual samples.

These visualizations collectively provide a comprehensive analysis of the models' performance, enabling detailed comparisons of their strengths and weaknesses. They reveal patterns, identify errors, and highlight trends that inform conclusions about the predictive capabilities of TimesNet and iTransformer.

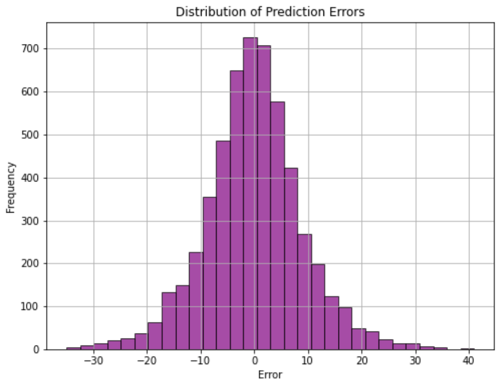

Figure 11: Distribution of Prediction Errors (TimesNet)

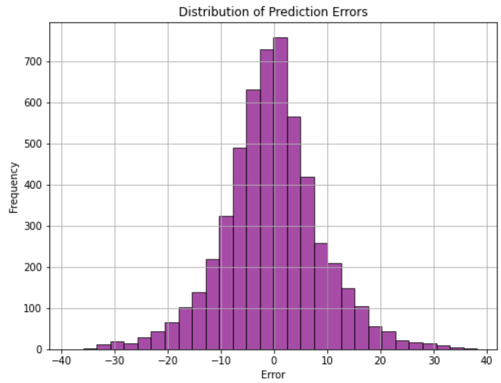

Figure 12: Distribution of Prediction Errors (iTransformer)

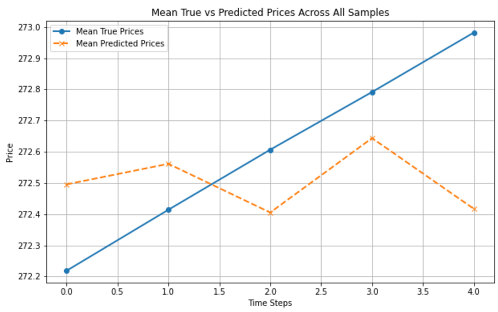

Figure 13: Mean True vs Predicted Prices Across All Samples (TimesNet)

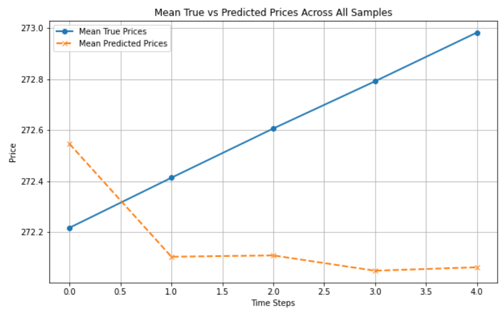

Figure 14: Mean True vs Predicted Prices Across All Samples (iTransformer)

6 Analysis and Findings

This section analyzes the results obtained from TimesNet and iTransformer, focusing on the visualizations and their implications. Both models were applied to the task of stock price forecasting, and their performance was evaluated based on various metrics and visual comparisons.

6.1 Analysis of TimesNet Plots

TimesNet demonstrated strong performance in capturing patterns within the stock price data, as reflected in the following key observations:

1. **True vs Predicted Prices (Sample 0):** The plot of true and predicted prices for a single sample shows that TimesNet accurately tracks overall trends, with predicted prices closely aligning with true values across most time steps. However, minor deviations are observed toward the end of the prediction horizon, where the predicted prices diverge slightly from the true prices. This indicates that TimesNet excels at capturing short-term patterns but exhibits reduced accuracy for longer prediction windows (Figure 5).

2. **Scatter Plot of True vs Predicted Prices:** The scatter plot reveals a strong positive correlation between true and predicted prices, with points clustering tightly around the diagonal. This demonstrates TimesNet's high predictive accuracy across the dataset. However, some spread is observed, particularly at extreme values, indicating occasional underestimation or overestimation (Figure 7).

3. **Mean True vs Predicted Prices Across All Samples:** The comparison of mean true and mean predicted prices across all samples shows that TimesNet effectively captures overall trends.

However, oscillations in the predicted mean values suggest that the model may face challenges in producing smooth predictions for aggregated data (Figure 13).

4. **Prediction Error Over Time (Sample 0):** The prediction error plot highlights that errors remain low and stable for most time steps but increase sharply at the end of the prediction horizon. This underscores TimesNet's strength in short-term prediction and suggests potential limitations in handling abrupt price changes or extended forecasting horizons (Figure 9).

5. **Distribution of Prediction Errors:** The distribution of errors is approximately symmetric and centered around zero, with the majority of errors falling within a narrow range. This indicates that TimesNet does not exhibit significant bias toward overprediction or underprediction. The presence of some larger errors suggests that outlier cases may occasionally impact its performance (Figure 11).

6.2 Analysis of iTransformer Plots

iTransformer demonstrated weaker performance compared to TimesNet in capturing patterns within the stock price data, as reflected in the following key observations:

1. **True vs Predicted Prices (Sample 0):** The plot of true and predicted prices for a single sample shows significant deviations between predicted values and true prices, particularly at the end of the prediction horizon (Figure 6). While iTransformer captured the overall trend to some extent, the predicted prices consistently overestimated or underestimated true values, indicating poor alignment and reduced accuracy even for short-term predictions.

2. **Scatter Plot of True vs Predicted Prices:** The scatter plot reveals a weaker correlation between true and predicted prices, with points exhibiting greater scatter around the diagonal compared to TimesNet (Figure 8). This suggests higher variability in predictions, with iTransformer failing to consistently align predicted values with true ones, especially for extreme price ranges.

3. **Mean True vs Predicted Prices Across All Samples:** The comparison of mean true and mean predicted prices across all samples highlights a significant divergence (Figure 14). iTransformer produced nearly flat predictions, failing to capture the upward trend observed in the true mean values. This behavior indicates that the model struggled to generalize patterns across aggregated data.

4. **Prediction Error Over Time (Sample 0):** The prediction error plot shows substantial fluctuations in errors, with sharp spikes toward the end of the horizon (Figure 10). These fluctuations indicate instability in predictions over time, reflecting iTransformer's inability to handle temporal dependencies effectively.

5. **Distribution of Prediction Errors:** The error distribution is symmetric but significantly broader compared to TimesNet, as shown in Figure 12. This wider spread indicates higher variability in iTransformer's predictions, with frequent large errors reducing the model's reliability.

6.3 Effectiveness of the Models

The comparative analysis of TimesNet and iTransformer led to the following findings:

- **Short-Term Trends:** Both models captured short-term patterns to a certain extent, but TimesNet demonstrated better alignment with true values in the initial prediction steps.

- **Long-Term Trends:** Both models struggled to maintain accuracy over extended horizons. However, iTransformer exhibited larger deviations and less consistency in capturing long-term patterns.

- **Variability and Errors:** TimesNet exhibited a narrower error distribution and better clustering in scatter plots, indicating higher precision and lower variability compared to iTransformer.

- **Aggregated Trends:** TimesNet performed better in capturing aggregated mean trends across samples, while iTransformer produced flat and inconsistent predictions.

The analysis highlights that both models have limitations in handling abrupt changes and maintaining accuracy over longer prediction horizons. However, TimesNet consistently outperformed iTransformer in key areas, including short-term trend prediction, variability handling, and aggregated trend generalization. iTransformer's relatively weaker performance suggests that further tuning or architectural improvements may be required for effective application to this dataset.

7 Conclusion

This study explored the application of TimesNet and iTransformer models for stock price forecasting, evaluating their effectiveness through comprehensive analysis and visualizations. Both models faced challenges, particularly in handling abrupt changes and maintaining accuracy over extended prediction horizons. However, TimesNet consistently demonstrated superior overall performance compared to iTransformer, excelling in precision, stability, and general trend prediction.

Performance of TimesNet: TimesNet's ability to capture multi-periodicity and dynamic patterns made it particularly effective for datasets with cyclical behavior. Its narrower error distribution and closer alignment with true values underscore its reliability for short-term forecasting tasks. Nonetheless, limitations were observed in its handling of abrupt price changes and long-term trends, where prediction errors tended to accumulate toward the end of the forecast horizon. These findings suggest that while TimesNet is well-suited for many financial time series forecasting tasks, further improvements in its ability to manage volatile conditions could enhance its applicability.

Performance of iTransformer: Despite its advanced architectural features, such as tokenization and attention mechanisms, iTransformer underperformed in both short- and long-term forecasting. Its broader error distribution, inconsistent trend alignment, and limited ability to generalize across multivariate data highlighted significant shortcomings. These results indicate that iTransformer requires further tuning and architectural refinements to effectively address the complexities of financial datasets.

Comparative Insights: The analysis clearly established TimesNet as the more reliable and effective model for this study. Its balanced trade-off between precision, robustness, and generalization makes it better suited for the challenges posed by stock price forecasting. iTransformer, while theoretically promising, needs substantial improvements to compete effectively in this domain.

Limitations and Future Work: This study identified several limitations that warrant further exploration. Both models exhibited reduced performance in scenarios involving abrupt changes and extended prediction horizons. Future work could focus on integrating additional features, such as external economic indicators or sentiment analysis, to enhance predictive capabilities. Moreover, investigating advanced hybrid models or ensemble approaches that combine the strengths of TimesNet and iTransformer could yield better overall performance. Fine-tuning hyperparameters and exploring alternative architectures for iTransformer may also address its current limitations.

In conclusion, TimesNet emerged as a robust and reliable model for financial time series forecasting, demonstrating its potential for practical applications. However, the limitations observed in both models underscore the need for continued research and innovation to tackle the inherent complexities of financial data, paving the way for more accurate and reliable forecasting tools in the future.

References

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