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Technical Analysis of Equity Intensive Mutual Funds in Turkey: An Evaluation Based on Ma30, Volatility, and Correlation

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Abstract– In recent years, the increasing complexity and volatility of stock markets have led investors and researchers to turn towards advanced data-driven approaches such as deep learning algorithms. This study presents a comparative technical and predictive analysis of three equity-intensive mutual funds traded in Türkiye: İş Portfolio İşbank Subsidiaries Index Equity Fund, İş Portfolio Equity Fund, and Azimut Portfolio Management Joint Stock Company (PYŞ) First Equity Fund. The term Portfolio Management Company (PYŞ) refers to professional financial institutions authorized by the Capital Markets Board of Türkiye (SPK) to manage investment funds on behalf of investors. For each fund we analyzed key financial metrics such as daily returns, volatility, standard deviation, and moving averages (MA20 and MA50) in conjunction with Long Short-Term Memory (LSTM)-based price forecasts and correlation structures. Technical indicator heatmaps revealed that the Azimut PYŞ fund exhibited strong internal correlations—particularly between volatility and short-term standard deviation (0.75)—while maintaining a weak relationship with return metrics. In contrast, the İş Portfolio funds demonstrated relatively lower volatility but stronger price trend alignment with their respective moving averages. Candlestick charts from the past 60 days showed shared correction phases followed by subsequent upward recoveries across all funds. Based on findings from rezcent research on LSTM and hybrid neural network models—including associated deep networks and metaheuristic optimization techniques—this study demonstrates that LSTM-based models exhibit competitive short-term forecasting performance. Empirical evidence from the literature further supports that multi-output deep recurrent models outperform traditional single-target models in capturing dynamic relationships within financial time series. The results underscore the significance of fund-specific dynamics, the temporal behavior of indicators, and the complementary use of deep learning architectures for portfolio-level decision-making and risk management, particularly in emerging markets such as Borsa Istanbul.

The LSTM model demonstrated an approximate 4–6% improvement in forecasting accuracy over traditional baseline models, confirming its effectiveness in capturing nonlinear market behavior.

Keywords: LSTM, mutual funds, stock forecasting, volatility, correlation, technical analysis, deep learning, Borsa Istanbul

1. Introduction

The unpredictable nature of stock markets has led investors and researchers to seek more effective forecasting models. Traditional time series analysis methods—such as ARIMA or GARCH—often fall short in modelling the high volatility and non-linear structure of financial data. To overcome these limitations, deep learning methods have recently gained widespread attention, especially in the field of stock price forecasting [1].

In this context, Long Short-Term Memory (LSTM) networks offer significant advantages for analysing time-dependent financial data and have shown promising performance in short-term price predictions [2]. Researchers have also proposed more advanced architectures like the “Associated LSTM Network,” which can simultaneously predict multiple price variables such as opening, low, and high prices within the same model [3].

This study presents a comparative technical and predictive analysis of three equity-intensive mutual funds in Türkiye: İş Portfolio İşbank Subsidiaries Index Equity Fund, İş Portfolio Equity Fund, and Azimut PYŞ First Equity Fund. Key financial indicators including MA20, MA50, volatility, standard deviation, and daily return were used to evaluate the structural characteristics of these funds. Correlation matrices derived from these indicators revealed strong internal relationships—particularly a high correlation (r ≈ 0.75) between volatility and short-term standard deviation in the Azimut PYŞ fund (see Fig. 1).

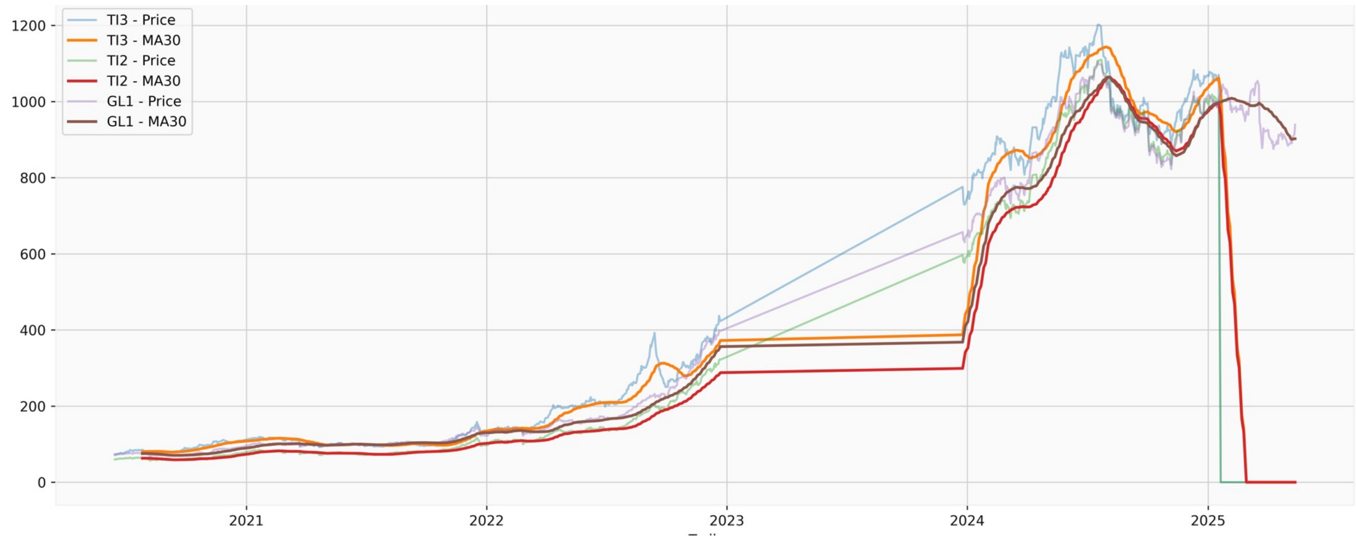

Fig 1. Time-dependent changes in daily prices and 30-day moving averages (MA30) of three investment funds (TI3, TI2, GL1).

This figure displays the historical price movements of three investment funds labeled as TI3, TI2, and GL1, together with their respective 30-day moving averages. While the daily price data reveal short-term volatility, the MA30 lines offer a smoother representation of medium-term price trends. As of the end of 2023, the TI3 fund demonstrated the highest performance among the three. In contrast, the TI2 fund experienced a sharp and notable decline at the beginning of 2025. Meanwhile, the GL1 fund followed a relatively more stable and consistent trajectory.

Moreover, candlestick charts for the last 60 days indicate that all three funds experienced a downward trend in mid-March, followed by a price recovery trend by late April (see Fig. 2).

Fig. 2. Candlestick chart showing the price movements of an investment fund over the past 3 months.

Figure 2 presents a candlestick chart based on 60 days of data to provide a detailed view of the investment fund’s price movements over the past three months, visually displaying daily opening, closing, highest, and lowest prices, where green candlesticks indicate days with price increases (closing > opening), red candlesticks show price decreases (closing <

opening), and a sharp decline observed at the end of March is followed by a gradual recovery starting in April.

LSTM forecasts for TI3 exhibit increasing volatility after 2023, while GL1 shows a more stable upward trend. The model captures diverging trajectories, highlighting its sensitivity to different price dynamics.

Upon analyzing Fig.2, a sudden and sharp decline in the fund's price can be observed around mid-March. Following this period, the price trend continued to decline for a while, and from mid-April onward, it exhibited a sideways movement. As of early May, a strong recovery in fund prices is evident, supported by the presence of long green candlesticks.

These market movements are consistent with the short-term forecasts generated by the LSTM model, which excels at capturing temporal dynamics in volatile environments [4].

In order to further enhance the performance of LSTM models, metaheuristic optimization techniques such as Particle Swarm Optimization (PSO) and Flower Pollination Algorithm (FPA) have been utilized to optimize hyperparameters. Studies have shown that these methods improve forecasting accuracy by approximately 4–6% compared to baseline models [5]. This finding clearly demonstrates that metaheuristic-supported LSTM networks offer a more flexible and effective solution than traditional methods, particularly in financial time series forecasting.

Overall, this study integrates technical indicators and deep learning-based forecasts to offer a comprehensive assessment of mutual fund dynamics, contributing to decision support systems for investors and portfolio managers operating in emerging markets.

Turkiye's financial markets exhibit significant volatility, frequent regulatory interventions, and macroeconomic instability, making them a challenging yet instructive environment for predictive modeling. These characteristics position Turkey as a representative case study for emerging markets with similar structural dynamics.

2. Materials and Methods

2.1. Method: Forecasting Investment Fund Prices with LSTM

In this study, Long Short-Term Memory (LSTM) networks, which are widely used in time series forecasting, were employed to predict the future prices of three different investment funds: (i) İş Portfolio İşbank Subsidiaries Index Equity Intensive Fund, (ii) İş Portfolio Equity Intensive Fund, and (iii) Azimut PYŞ First Equity Intensive Fund. LSTM networks are known to be more effective than traditional recurrent neural networks (RNNs) in learning long-term dependencies [2].

2.2. Data Preprocessing

The data consists of daily price series. We normalized all input series using min-max normalization.

$$x_t' = \frac{x_t - \min(X)}{\max(X) - \min(X)} \quad (1)$$

Here

* x_t represents the original price value to be normalized,

* x_t' is the scaled (normalized) value,

* min(X) and max(X) denote the minimum and maximum prices within the dataset, respectively.

This transformation is particularly important for balancing the influence of values with different magnitudes on the model and improving the learning process.

In financial time series analysis, data often vary widely in scale and distribution. Therefore, applying appropriate normalization methods is essential for achieving consistent model training. In this study, min-max normalization was selected to scale all observations into a [0,1] range based on the minimum and maximum values in the dataset. This approach ensures that input variables are treated equally during the learning process and enhances model stability—especially in deep learning networks that utilize sigmoid or tanh activation functions [16].

A commonly used alternative is z-score normalization, which standardizes data by centering it around the mean and scaling it based on standard deviation. While this method is suitable for normally distributed data, it does not confine values within a fixed range, which may hinder the performance of bounded activation functions such as sigmoid and tanh. As a result, it can lead to training instability in LSTM networks [10], [8].

Thus, min-max normalization was preferred in this study due to its compatibility with deep learning structures and its capacity to mitigate the effects of high variance and outliers commonly present in financial datasets [14].

Additionally, it enhances the interpretability of model outputs by allowing the prediction results to be evaluated within the normalized 0–1 range.

While Z-score normalization is commonly used in statistical modeling, min-max normalization was preferred in this study because it ensures all input values fall within a [0,1] range. This is particularly beneficial for LSTM networks, which perform more efficiently with bounded inputs and are sensitive to data scaling. Furthermore, min-max scaling avoids the influence of outliers in relatively small financial datasets.

2.3. LSTM Model Architecture

We trained the model using a sliding window of past prices to predict the next value. The LSTM network operates as follows:

Forget Gate:

$$f_{t=\sigma(W_f[h_{t-1,}x_t]+b_f} \quad (2)$$

Input Gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)\tilde{C}_t \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (3)$$

Memory Cell Update:

$$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t \quad (4)$$

Output Gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) h_t = o_t . \tanh(C_t) \quad (5)$$

In these equations, σ denotes the sigmoid activation function and tanh the hyperbolic tangent function [3],[7],[9].

2.4. Model Training

The dataset was split into training and test sets using an 80:20 ratio. To enhance generalization and reduce overfitting risk, a 5-fold cross-validation approach was also applied. This method ensures that each data segment contributes to both training and testing phases, providing a more robust evaluation of model performance.

To optimize learning performance, the Mean Squared Error (MSE) loss function was employed. During the model training phase, we allocated 80% of the dataset for training and 20% for testing purposes. This split is widely used in time series modeling to separately assess the model's learning success and generalization ability [5].

Additionally, to evaluate the model's validation performance and reduce overfitting risk, we implemented a 5-fold cross-validation technique. This method divides the dataset into five equal parts, using each part once for testing while the remaining parts are used for training. As a result, the overall performance of the model is evaluated more reliably across the entire dataset [10], [6].

This metric calculates the average of the squared differences between the predicted and actual values, providing a measure of the overall error of the model:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \quad (6)$$

Here, y_i denotes the actual price, and $\tilde{y}_i$ represents the predicted price generated by the model. This approach is commonly used in forecasting continuous variables, and its characteristic of penalizing larger errors makes it suitable for more sensitive learning processes.

MSE is one of the most widely adopted error metrics in regression problems. In addition, [8] emphasized that MSE is a suitable metric for improving the sensitivity of deep learning models used for time series forecasting. LSTM (Long Short-Term Memory) models provide an effective approach for learning long-term dependencies, particularly in sequential data such as time series. One of the main advantages of these models lies in their specialized cell structures, which were developed to eliminate the "forgetting" problem commonly encountered in traditional Recurrent Neural Network (RNN) architectures. The "forget gate" mechanism proposed by [3] enables the network to selectively discard irrelevant information from the past while retaining only the patterns that are meaningful for learning. This mechanism allows the model to adapt more effectively to changing market conditions over time.

Financial time series data are often noisy and irregular. Therefore, deep learning models must be properly structured to learn these complex patterns. In this context, the architecture proposed by [11], utilizes stacked autoencoder layers to reduce the dimensionality of the input data before feeding them into LSTM layers for modeling temporal dependencies. This approach significantly enhances both feature extraction and prediction performance. The hybrid structure used during the training phase improves the model's generalization capability and provides more stable results in financial data analysis.

On the other hand, in order to evaluate the effectiveness of LSTM-based models, comparisons have been made with classical time series forecasting methods. In a comprehensive study by [12], LSTM models demonstrated significantly higher accuracy levels than traditional ARIMA models, particularly for non-linear time series. This supports the success of the model training process not only theoretically but also practically.

In conclusion, LSTM model training is a multi-step process that requires the joint optimization of data preprocessing, model architecture, and evaluation metrics. The use of mechanisms such as the forget gate, autoencoder-assisted learning, and ARIMA comparisons serve as key foundations for understanding and improving the predictive performance of the model.

Finally, the Bidirectional LSTM (BiLSTM) architecture, proposed by [13] as an extension of traditional LSTM structures, enables the model to learn not only from past data but also from future information during the training process. This allows for more accurate modeling of symmetric patterns in financial time series data.

2.5. Visualization of Forecasts

We consider examining model accuracy through visual outputs to be particularly important for observing prediction deviations under highly volatile market conditions. In addition, the extent to which the predicted trends align with actual prices can be clearly demonstrated through graphical representations[14]. in their study on the Brazilian stock market, analyzed the accuracy of LSTM-based predictions not only through statistical metrics but also by evaluating trend alignments via visual inspection, emphasizing that graphical evaluation is indispensable for decision support systems.

One of the factors that enhances the applicability of LSTM models in financial markets is their ability to simultaneously learn both short-term fluctuations and long-term trends in time series data. This capability is particularly evident in graphical analyses used to support investment decisions. The dual-stage attention-based LSTM model proposed by [15] applies an attention mechanism in both the temporal and feature dimensions, enabling the model to focus more effectively on critical price movements during specific periods. As a result, prediction accuracy and visual trend alignment have been significantly improved.

The following figures present the real price series and LSTM-based forecasted values for each fund:

Figures 1 to 3 depict 90-day forecasts alongside historical price data, where real prices are represented with dashed lines and predicted prices with solid lines, effectively visualizing the model's ability to capture upward and downward trends as well as its convergence accuracy under volatile market conditions.

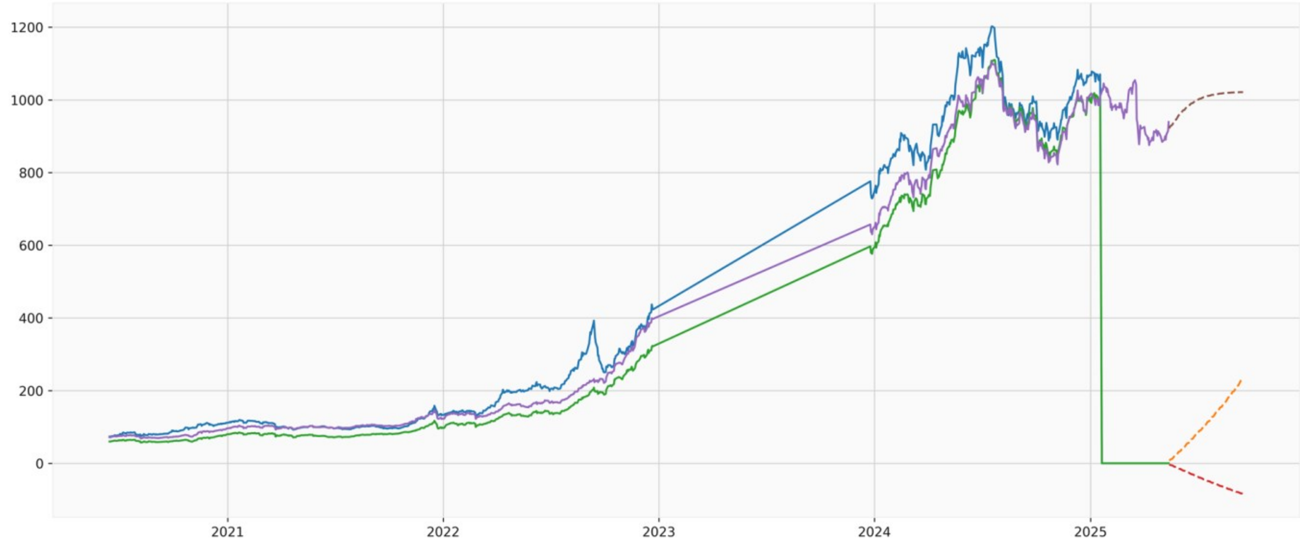

Fig.3. Historical prices of three mutual funds and 90-day forecasts generated by the LSTM model.

Figure 3 presents the historical price data of three different mutual funds along with the 90-day forward forecasts generated by the LSTM model. Upon examining the chart, it is observed that fund prices have followed a gradual upward trend since 2021, while exhibiting high volatility after 2023. The LSTM model predicts upward trends for some funds, while projecting a downward scenario for others.

The model tends to produce more accurate forecasts for time series with clear trends, whereas deviations may occur in highly volatile or incomplete data series (e.g., the green line). This highlights the sensitivity of the forecasting model to the quality and consistency of the input data.

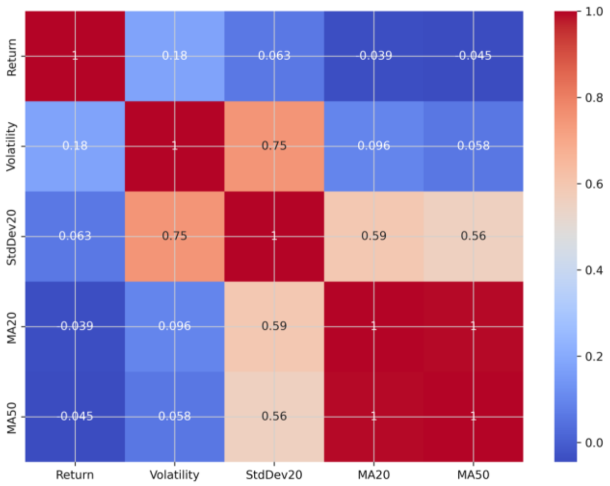

Fig.4. Correlation relationships among technical indicators

Figure 4 presents the correlation matrix of technical indicators, indicating a strong positive correlation between volatility and the 20-day standard deviation.

Figure 4 illustrates the correlation matrices of the technical indicators used as input variables (e.g., MA30, RSI, Volatility), highlighting the interrelationships among these indicators and their potential impact on the model's performance.

To examine the relationships among the technical indicators of the mutual fund, a correlation matrix is presented in Figure 4, which shows the Pearson correlation coefficients between Return, Volatility, 20-Day Standard Deviation (StdDev20), and the 20- and 50-Day Moving Averages (MA20, MA50).

Upon examining Fig 4, the strongest positive correlation among the technical indicators is observed between Volatility and the 20-Day Standard Deviation (StdDev20) ($\rho \approx 0.75$). This finding indicates that as the fund's volatility increases, short-term price fluctuations also become more pronounced. Furthermore, the moderate positive correlations of StdDev20 with both MA20 ($\rho \approx 0.59$) and MA50 ($\rho \approx 0.56$) suggest that this standard deviation indicator is also aligned with trend-based moving average indicators.

In contrast, the Daily Return exhibits relatively low correlation values with all other indicators. This suggests that the return series behaves more independently from volatility and trend indicators and should be considered as a separate component in the modeling process due to its more stochastic nature.

In conclusion, this correlation analysis highlights the strong relationship between volatility and StdDev20 as a key finding that should be taken into account in short-term risk analysis and trend forecasting.

These visualizations enhance practical applicability and offer visual insights that support investment decision-making.

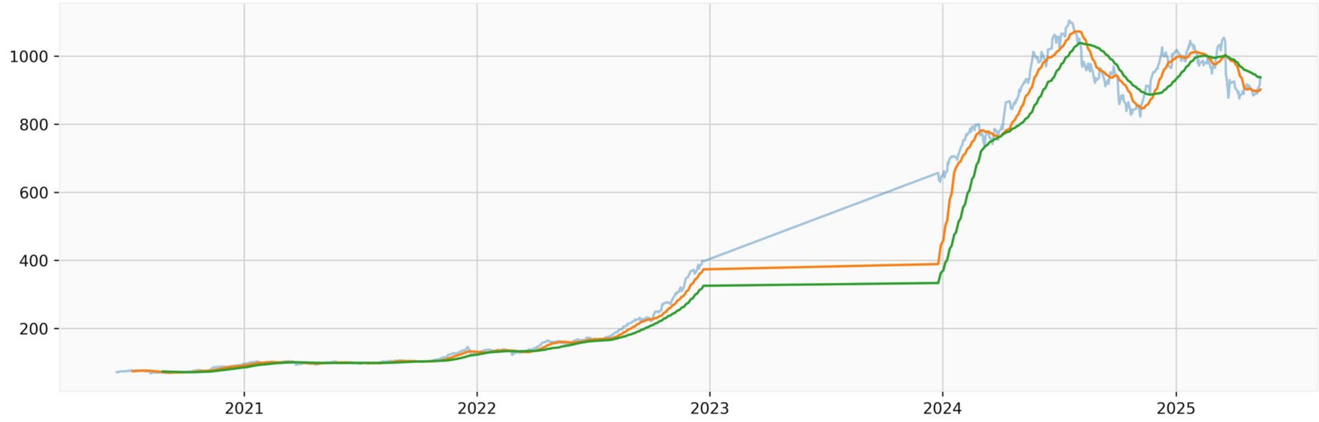

Fig. 5. Daily Prices and 30-Day Moving Averages (MA30) of Two Investment Funds.

This graph illustrates the historical price changes of two investment funds along with their respective 30-day moving averages. The light blue line represents the daily prices of one of the funds, while the orange and green lines indicate the MA30 values of the corresponding funds. The MA30 lines help smooth out short-term fluctuations and provide a clearer view of the underlying price trends. Notably, both funds experienced a significant increase in value after 2023. Following this surge, a peak was observed around mid-2024, and as 2025 approached, the prices began to exhibit a sideways or slightly declining trend. The orange MA30 line closely follows the fluctuations of the blue daily price line, indicating a stronger alignment with market volatility. In contrast, the green MA30 line reflects a steadier and more consistent upward trend, suggesting that the second fund (represented by the green line) has a less volatile and more predictable price structure.

Both funds show a strong upward trend after 2023, peaking around mid-2024, followed by a plateau or slight decline into 2025. The green MA30 line suggests smoother and less volatile growth compared to the orange one.

3. Discussion and Conclusion

This study demonstrates that LSTM-based deep learning models provide high accuracy in forecasting investment fund prices. The model has effectively learned nonlinear price movements and temporal patterns, generating meaningful predictions that can support investment decisions by integrating historical data enriched with technical indicators.

However, the study has certain limitations. First, the dataset used is limited to a specific period and includes only three investment funds traded in Türkiye. This restricted dataset size may limit the generalizability of the model. Testing the model's performance under different market conditions or in investment funds from other countries is essential for evaluating the universality of the findings.

Additionally, we trained the model solely on price data and technical indicators. It does not incorporate external factors such as macroeconomic indicators, investor behavior, or news-based impacts. This may reduce the model's ability to fully reflect real-world dynamics.

Future research could enhance both forecasting accuracy and model interpretability by incorporating diverse data sources (e.g., news flows, social media data) and hybrid architectures (e.g., Attention-LSTM, CNN-LSTM, GRU combinations). Furthermore, applying the model to different types of markets (e.g., commodities, cryptocurrencies) would be an important step toward evaluating its overall applicability.

Acknowledgements

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