Predicting Capital Market and Cryptocurrency Performance in Higher Sequences Using Deep Learning Techniques

Maryam Baradaran[1], Hamidreza Gholamnia Roshan[2*], Mahdis Nikzad Ghadikolaei[3], Behnam Barzegar[4]

Abstract - This study develops and evaluates a deep learning model for predicting future price sequences in heterogeneous financial markets, specifically focusing on the Tehran Exchange Dividend and Price Index (TEDPIX) as a representative of the Iranian capital market and Bitcoin as a leading cryptocurrency. The research aims to forecast the closing prices for the next seven consecutive days (sequences) and, innovatively, to analyze the evolution of prediction errors as the forecasting horizon extends. This multi-sequence comparative approach addresses a notable gap in the literature, which predominantly focuses on single-step predictions. A Long Short-Term Memory (LSTM) neural network architecture was employed due to its proven capability in modeling long-term dependencies in sequential data. The model, implemented in Python using TensorFlow, consists of an input layer, two LSTM hidden layers (with 64 and 32 units), and a fully connected output layer. It was trained on 1,019 days of daily closing price data for both assets, using the Adam optimizer and Mean Squared Error (MSE) as the loss function.The findings reveal a clear divergence in model performance between the two markets. For TEDPIX, the model demonstrates high accuracy and stability, with key metrics of RMSE = 0.0231, MAPE = 1.84%, and R^2 = 0.963. Although the prediction error increases marginally across the seven sequences, the growth is minimal, confirming the reliability of the LSTM predictor for multi-day forecasting of this index. In contrast, the model's performance for Bitcoin, while still robust (RMSE = 0.0368, MAPE = 2.97%, R^2 = 0.921), shows a steeper and more pronounced increase in error across the forecasted sequences. The core conclusion is that the AI-based predictor adapts more effectively and maintains greater forecasting stability in the Iranian capital market compared to the highly volatile cryptocurrency market. The progressive error accumulation in Bitcoin predictions indicates higher investment risk for longer prediction horizons in cryptocurrencies. This disparity is attributed to factors such as the extreme volatility, speculative nature, and lower regulatory oversight in the cryptocurrency market, as opposed to the relative stability and structural safeguards (like price fluctuation limits) present in the Iranian stock exchange. The study recommends that investors and financial analysts incorporate such multi-sequence deep learning models to enhance short-term trading strategies and risk assessment, while acknowledging the greater predictive confidence offered for traditional capital markets over cryptocurrencies.

Keywords: Tehran Exchange Dividend and Price Index (TEDPIX), Bitcoin, Deep Learning, LSTM, Forecasting, Time Series, Capital Market, Artificial Intelligence

1. Introduction

Investment in the capital market through equities, as well as in emerging cryptocurrency markets, is among the most accepted and popular investment avenues for both retail and institutional investors. The common chaotic and nonlinear behavior observed in these markets has been a major driver for applying artificial intelligence–based approaches in financial forecasting. Consequently, the use of artificial intelligence and its tools either independently or in combination with other methods has become increasingly prevalent as a modern approach. According to the research literature, forecasting the future of any phenomenon with a dynamic and non-stationary nature is inherently challenging. Among the most dynamic and chaotic domains are stock markets and cryptocurrencies.

Earning profit in these markets as the goal of investors depends on various factors, including political, economic, psychological, and other conditions. Given the dynamic behavior of such markets, linear models are often incapable

1 Department of Accounting, Bab.C., Islamic Azad University, Babol, Iran . Email: Maryam.baradaran@iau.ac.ir

2*Corresponding Author :Department of Accounting, Bab.C., Islamic Azad University, Babol, Iran . Email: roshan@iau.ac.ir

3Department of Accounting, Faculty of Economics and Administrative Sciences, University of Mazandaran, Babolsar, Iran. Email: m.nikzad@umz.ac.ir

4 Department of Computer Engineering, Bab.C., Islamic Azad University, Babol, Iran . Email: Behnam.Barzegar@iau.ac.ir

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of accurately explaining the behavior of these systems. Therefore, to uncover such relationships, nonlinear tools and models, such as deep learning, are required [2, 4, 5]. Simultaneously, a review of the existing literature reveals that forecasting stock prices and, more broadly, the performance of the capital market as well as cryptocurrencies over short time horizons has consistently been a fundamental and critical concern for investors in financial markets worldwide. In fact, many investors in the capital market and other financial markets are short-term traders seeking to profit from market fluctuations. Therefore, predicting events over short-term periods, such as the next day or week, is of vital importance to them [3, 6, 7]. In fact, due to the significance of this issue, numerous studies have endeavored to develop more precise perspectives and methods for closer estimation of future prices. Accordingly, various techniques and approaches have been devised to achieve more accurate and robust forecasting. Nevertheless, the application of these techniques, especially in inefficient markets such as our country's capital market and in emerging, high-risk markets like cryptocurrencies, has consistently faced serious challenges and high risks. With this approach, in recent decades, extensive efforts have been made in the field of stock-related predictability using novel mathematical methods, longer time series, and more advanced tools such as artificial intelligence and deep learning. Numerous tests have been conducted on stock price and index data across various countries. Deep learning, as one of the modern foundations of artificial intelligence, comprises mathematical models that represent some of the most advanced forecasting methods. The most significant appeal of these models lies in their flexibility to estimate a wide range of relationships and functions between input and output variables. Models with sufficient complexity are capable of providing accurate approximations of virtually any desired function. For this reason, this technique quickly established its place in the field of financial market forecasting [8, 9]. In this context [10], in a comparative analysis between ensemble learning and deep learning methods for forecasting cryptocurrency behavior, we acknowledged that deep learning performs more robustly in this domain. Similarly, concluded in their analysis that employing deep learning for cryptocurrency price prediction enhances forecasting accuracy. In the same vein, employed a combination of a multilayer perceptron neural network and the GARCH model to forecast capital market returns and concluded that the hybrid model offers improved estimation accuracy. Although all these studies indicate that the use of artificial intelligence and specifically the modern technique of deep learning has led to improved predictive capability, what remains unaddressed in the existing literature is the development of a strategy or model for forecasting cryptocurrency prices and capital market performance across regular future sequences, as well as the analysis of how prediction error evolves as the forecasting horizon extends.

One of the key limitations of most predictive models in financial markets is their tendency to forecast behavior in a generalized manner. These models typically estimate the overall trend of a cryptocurrency, stock, or the broader market, rather than providing detailed forecasts of specific asset performance over defined intervals. However, generating accurate predictions for the day-to-day performance of a specific cryptocurrency, stock, or the capital market over a sequence of consecutive days such as the seven-day period considered in this study can offer investors a much stronger foundation for making informed investment decisions. This issue, as identified in current literature, represents a notable research gap.

At the same time, a critical ambiguity persists: to what extent do classical and modern forecasting approaches suffer from increased error as the forecasting horizon expands? In other words, how does extending the prediction period impact the accuracy and reliability of these models compared to shorter time frames?

Despite the growing number of studies applying artificial intelligence in financial forecasting, most have focused on single-step predictions or isolated market types. Few have examined how prediction accuracy evolves across multiple consecutive sequences or compared this behavior between traditional stock markets and cryptocurrencies. To address this research gap, the present study develops a deep learning–based multi-sequence forecasting model using Long Short-Term Memory (LSTM) networks. The model aims to predict seven future sequences of both Bitcoin and the Tehran Exchange Dividend and Price Index (TEDPIX) and to analyze how forecasting errors evolve over extended horizons. This approach directly connects the identified research gap with the study's main objective, providing a clearer understanding of prediction stability across heterogeneous financial markets

The main innovation of this study lies in extending the traditional single-step forecasting framework to a multi-sequence horizon and analyzing the evolution of prediction error across consecutive sequences**.** Unlike prior works that typically predict only the next immediate value, this research evaluates seven consecutive sequences to capture the progression of model accuracy over time. In addition, it introduces a comparative dimension between the Tehran

Stock Exchange and Bitcoin to highlight how market characteristics influence AI-based forecasting reliability—a perspective that has rarely been examined in earlier literature.

2. Literature Review

Forecasting in financial markets has long represented one of the most intellectually demanding and practically significant challenges in modern finance. Because of the highly volatile and nonlinear nature of financial systems, researchers have consistently sought to construct models that are not only more accurate but also more adaptable to dynamic and uncertain conditions. Over the past decade, the rapid emergence of artificial intelligence (AI) and its advanced subfields, such as deep learning, has transformed the methodological landscape of financial forecasting. The studies by [11, 12, 13] are among the most notable early attempts to apply deep learning within cryptocurrency markets. These works examined a broad spectrum of architectures—including convolutional neural networks (CNN), recurrent neural networks (RNN), deep belief networks (DBN), and deep reinforcement learning (DRL)—and evaluated their effectiveness in addressing the extreme volatility and structural complexity of cryptocurrencies. By combining a historical perspective on digital currencies with a review of technical architectures, the authors presented a broad taxonomy of deep learning methods used for tasks such as price prediction, portfolio construction, bubble analysis, abnormal trading detection, trading regulation assessment, and initial coin offerings. However, despite providing a valuable overview, these studies largely adopted a descriptive orientation. They fell short of offering a critical, comparative analysis of model performance, interpretability, or robustness across different market contexts. Their emphasis remained on cataloging model types rather than analyzing their relative strengths and weaknesses in real-world forecasting scenarios.

Subsequent research has moved toward the practical application of AI-based forecasting in traditional stock markets. For instance, [14, 15] employed artificial neural networks (ANNs) alongside a range of technical indicators to forecast next-day stock prices. Their models achieved remarkable predictive accuracy for short-term horizons, illustrating the capacity of neural networks to approximate nonlinear relationships between market variables. Nevertheless, these single-step approaches did not account for how prediction errors evolve over multiple sequences, limiting their reliability in long-term forecasting. Similarly, [16, 17] investigated the use of the Dow Jones theory in the Iraq Stock Exchange across six sectors—banking, telecommunications, industry, services, hotels, and agriculture. Although their application of a classical technical framework successfully captured cyclical price behavior, it relied heavily on historical repetition. It lacked the flexibility to model the complex, nonlinear responses of markets to political and macroeconomic turbulence. In a comparable effort, [18] applied the Elliott Wave Theory to forecast stock price movements, identifying primary upward trends and wave patterns indicative of future momentum. While this approach provided valuable qualitative insights, its inability to produce precise quantitative forecasts under volatile market conditions revealed the limitations of rule-based technical models compared with adaptive AI systems.

Domestic research in Iran has mirrored these global developments, with scholars increasingly adopting deep learning to forecast stock performance and market indices. In one study, a hybrid model integrating CNN and Long Short-Term Memory (LSTM) networks demonstrated significant improvements in predictive accuracy relative to baseline models [19, 20, 21]. This outcome reinforced the potential of hybrid deep learning structures for capturing temporal dependencies in financial data. However, like many of its predecessors, the study remained confined to short-term horizons, omitting an analysis of how predictive performance changes across extended sequences. Other researchers [22, 23] focused on modeling and estimating stock returns in the Tehran Stock Exchange using Dynamic Model Averaging (DMA) and Dynamic Model Selection (DMS) approaches. Their work provided valuable insights into the influence of macroeconomic variables such as monetary base growth, quasi-money expansion, inflation, and real estate price indices. However, these models lacked integration with deep learning mechanisms capable of recognizing sequential dependencies and nonlinear transformations over time. A further contribution came from [24, 25, 26], who proposed an LSTM-based model with embedded feature selection to forecast the Tehran Stock Exchange index. By identifying the most relevant input variables, their approach achieved a low average error rate of 2.66%, showcasing the efficiency of deep learning in feature-reduced environments. Nonetheless, their analysis did not extend to multi-sequence forecasting, leaving questions about the model's stability across longer prediction horizons unanswered. Finally, [27] developed an AI-driven predictive framework to estimate the probability of stock price crashes within the Tehran Stock Exchange. While their artificial neural network models achieved notable accuracy in detecting short-term crash likelihoods, they did not evaluate performance consistency or error propagation across different forecasting windows.

Taken together, these studies demonstrate that the integration of AI and deep learning has substantially advanced the precision and adaptability of financial forecasting. However, several analytical deficiencies persist. First, the majority of prior work remains limited to single-horizon forecasting, neglecting to examine how prediction accuracy changes as the forecasting window expands. Second, cross-market comparisons—particularly between regulated, information-restricted capital markets and decentralized, highly volatile cryptocurrency systems—are still rare, leaving a gap in understanding how market structure shapes model performance. Third, much of the existing research maintains a descriptive rather than interpretive stance, emphasizing technical implementation over theoretical synthesis and comparative insight. Addressing these gaps, the present study introduces a multi-sequence deep learning forecasting framework that concurrently evaluates predictive stability and error evolution in two heterogeneous markets: the Tehran Stock Exchange and Bitcoin. By providing a comparative and empirically grounded analysis, this research contributes to a deeper understanding of how AI-based forecasting models behave across distinct market environments and forecasting horizons, thereby enhancing both theoretical and practical perspectives on financial prediction.

3- Research Methodology

This research is applied in terms of its objective, as it focuses on analyzing the future behavior of the capital market and cryptocurrencies, making it potentially useful for individuals and various institutions. Methodologically, the research is descriptive-correlational and employs artificial intelligence-based approaches to forecast the future performance of the stock and cryptocurrency markets. In terms of data collection, the study is considered library-based.

Finally, about the type of data, it is based on a time series. To analyze the research objectives, a deep learning technique, one of the key branches of artificial intelligence, was implemented within the Python programming environment.

The proposed model was implemented in Python using the TensorFlow library. It consists of one input layer, two LSTM hidden layers (with 64 and 32 units respectively), and one fully connected output layer. The activation function "tanh" was applied to the hidden layers and "linear" to the output layer. The model was trained for 100 epochs with a batch size of 32 using the Adam optimizer and a learning rate of 0.001. To ensure the reliability of the proposed architecture, a preliminary hyperparameter tuning process was conducted prior to model finalization. Several configurations of hidden layers (one, two, and three LSTM layers) and learning rates (0.001, 0.0005, and 0.0001) were tested to identify the optimal balance between complexity and performance. The two-layer LSTM structure (64 and 32 units) achieved the lowest RMSE and highest R^2 on the validation set, confirming its superior trade-off between model complexity and generalization capability. In contrast, single-layer networks underfitted the data, while deeper networks (three layers) slightly improved accuracy but significantly increased computational cost and overfitting risk. Similarly, the learning rate of 0.001 yielded the most stable convergence behavior compared with higher or lower rates. The quantitative results of this comparison are summarized in Table 1, which demonstrates that the final configuration provided the best overall predictive accuracy and training stability among all tested alternatives.

Early stopping was employed to prevent overfitting. The loss function was Mean Squared Error (MSE), and model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) metrics.

Table 1. Comparative evaluation of different LSTM configurations and learning rates

Configuration	*No. of LSTM Layers*	*Learning Rate*	*RMSE*	*R^2*	*Comment*
Model A	1	0.001	0.0412	0.915	Underfitting
Model B	2	0.001	**0.0231**	**0.963**	Optimal
Model C	3	0.001	0.0228	0.964	Slightly better but higher cost
Model D	2	0.0005	0.0254	0.956	Slower convergence
Model E	2	0.0001	0.0302	0.948	Undertrained

The statistical population of this study comprises two prominent financial markets, one domestic and one international. The Tehran Stock Exchange represents the domestic market as the selected population, while the global market focuses specifically on the cryptocurrency market, with Bitcoin serving as the target population.

For data collection related to the literature review, a library-based and documentary research method was employed. Additionally, to complement the necessary information for statistical analyses and to clarify the research objectives, two primary data sources were utilized. Market performance data for the Tehran Stock Exchange (overall index) were obtained from the official Tehran Stock Exchange website as well as from specialized software tools such as Rahavard Novin and Rahavard 365. Simultaneously, cryptocurrency data were sourced from reputable international platforms and databases, including TradingView, MetaTrader 5, and well-known exchanges such as Bybit and Binance.

Based on the objectives of the research, the study variables are two valid indices whose behaviors have been examined. The first is the overall stock market index, serving as the symbol and indicator of the performance of the country's capital market. The Tehran Exchange Dividend and Price Index (TEDPIX), often referred to as the overall index of the Tehran Stock Exchange, has been calculated and published since April 1998. Changes in this index reflect the total return of the stock market and are influenced by variations in price and dividend payments. This index includes all companies listed on the exchange, and its weighting and calculation method are similar to the price index (TEPIX), with the only difference being the method of adjustment.

3.1.Mathematical Representation of the Forecasting Model.

The forecasting process in this study can be mathematically expressed as follows, Eq.1:

$$\hat{y}^{(\ \ +1: \ \ +7)} = f_{LSTM}(y \ \ , y \ \ ^{-1}, \ldots, y \ \ ^{-} \ \ ) \qquad (1)$$

where y represents the actual closing price or index value at time t, and f_LSTM denotes the trained long short-term memory (LSTM) model.

The model's objective function minimizes the mean squared error (MSE) between predicted and actual values Eq.2:

$$L = \left(\frac{1}{N}\right) \Sigma_{\mathrm{i}}{}^{=1\mathrm{N}} (y_{\mathrm{i}} - \hat{y}_{\mathrm{i}})^2 \qquad (2)$$

This mathematical formulation clarifies the structure and optimization process of the predictive model used in this study.

The Tehran Exchange Dividend and Price Index (TEDPIX) is officially defined by the Tehran Stock Exchange and reflects the total return of listed companies, including both price variations and cash dividend adjustments. It is calculated by the Eq.۳:

$$TEDPIX = \left(\Sigma_{\mathrm{i}}{}^{=1\mathrm{n}} \frac{(p_{\mathrm{i}} \ \ q_{\mathrm{i}} \ )}{RD} \right) \times 100 \qquad (3)$$

where p_i denotes the price of stock i at time t, q_i is the number of shares issued, and RD represents the adjusted divisor that accounts for dividend distributions.

Source: Tehran Stock Exchange (TSE), Index Methodology: Dividend and Price Index (TEDPIX), official publication, 2024.

Note that TEPIX (Price Index) excludes cash dividends and thus only measures price fluctuations, whereas TEDPIX captures total return performance by adjusting RD accordingly.

Additionally, the second variable whose behavior has been predicted is the end-of-day price of the cryptocurrency Bitcoin, which, as previously mentioned, has been obtained from reputable sources.

To analyze patterns and fulfill the research objectives, the deep learning technique, as one of the most modern artificial intelligence methods, has been used to analyze the behavior of the upcoming seven sequences of the two variables under study.

Deep learning models utilize multiple algorithms. Although no single network can be considered perfect, certain algorithms are better suited for specific tasks. In this study, Long Short-Term Memory networks will be employed according to the research objectives.

The Long Short-Term Memory (LSTM) network was specifically chosen for this study due to its capability to model sequential dependencies and capture nonlinear temporal relationships in financial time series data. Unlike classical models such as ARIMA or shallow ANNs, which struggle with vanishing gradients and short-term dependencies, LSTM maintains information over extended time intervals through its gated cell architecture. This makes it particularly effective for analyzing highly volatile and dynamic data such as stock indices and cryptocurrency prices. Therefore, among various deep learning methods, LSTM provides the best balance between accuracy, stability, and interpretability for multi-sequence forecasting.

LSTM networks are a type of Recurrent Neural Network (RNN) capable of learning and retaining long-term dependencies. Remembering information over extended sequences is their default behavior. These networks preserve information over time and are particularly effective for time series forecasting, as

they retain memory of previous inputs. LSTMs possess a chain-like architecture in which four interacting layers communicate in a uniquely structured manner.
The operation of this function proceeds as follows:

1. First, irrelevant parts of the previous state are forgotten.
2. Then, the cell-state values are selectively updated.
3. Finally, specific parts of the cell state are delivered as output, which in this study corresponds to the next seven sequences. Accordingly, since the data is structured daily, the seven upcoming sequences represent the forecasts for the next seven days. Figure 1, illustrates the internal mechanism of the Long Short-Term Memory (LSTM) network, showing how information is selectively retained or discarded through its gating structure.

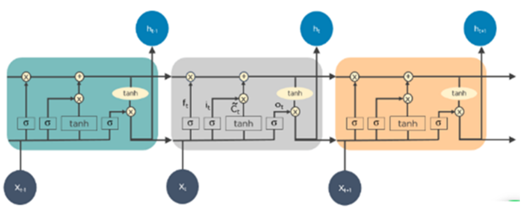

Fig.1. Functional structure of the LSTM network used in the forecasting framework.

3.2. Mathematical Representation of the LSTM Network

At each time step t, the LSTM unit receives the current input vector x_t, the previous hidden state h_{t-1}, and the previous cell state c_{t-1}.
The internal computations are defined as follows:

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right) \quad (4)$$

$$i_t = \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right) \quad (5)$$

$$\hat{c}_t = tanh\left(W_c \cdot \left[h_{\{t-1\}}, x_t\right] + b_c\right) \quad (6)$$

$$c_t = f_t \odot c_{\{t-1\}} + i_t \odot \hat{c}_t \quad (7)$$

$$o_t = \sigma\left(W_o \cdot \left[h_{\{t-1\}}, x_t\right] + b_o\right) \quad (8)$$

$$h_t = o_t \odot tanh(c_t) \quad (9)$$

where f_t, i_t, and o_t represent the forget, input, and output gates, respectively; $\hat{c}_t$ is the candidate cell state; c_t is the updated cell state; and h_t is the hidden state passed to the next time step.
Here, σ denotes the sigmoid activation function, $tanh$ denotes the hyperbolic tangent, $\odot$ represents element-wise multiplication, W denotes the learned weight matrices, and b represents bias vectors.
These formal equations describe how information flows within the LSTM unit, allowing the network to preserve long-term dependencies while mitigating the vanishing gradient problem.
In this regard, it is noteworthy that the variables utilized in this study consist of two factors: the price of the Bitcoin cryptocurrency, as the largest digital currency in the cryptocurrency market, and the overall stock market index, representing the performance of the capital market. Data for these two variables were collected daily, covering the years 2022, 2023, and 2024 for Bitcoin and for the stock market index. The daily Bitcoin prices were obtained from the sources specified in the data collection tools section. Likewise, the overall stock market index was retrieved on a daily basis from the Tehran Stock Exchange website.

3.3.Assumptions of the Model

To ensure the reliability and consistency of the forecasting process, several assumptions were explicitly defined prior to model implementation. First, all input time-series data were normalized using a min–max scaling technique to eliminate scale disparities among variables. Second, the data were transformed to achieve approximate stationarity after normalization, ensuring that statistical properties such as mean and variance remained stable across the observation period. Third, the dataset was assumed to be free from missing values and excessive random noise following the preprocessing stage. Fourth, given the short seven-day forecasting horizon, the influence of external macroeconomic or political shocks was considered negligible. Finally, model parameters such as learning rate, batch size, and training epochs were assumed to remain stable during both training and testing phases. These assumptions establish a controlled analytical environment that supports the internal validity of the model and ensures that the obtained forecasting results are both consistent and interpretable.

4. Research Findings :Trend Analysis

At the first stage, the price fluctuation trends of the examined cryptocurrency, namely Bitcoin, within the studied time period have been analyzed. All figures report their respective measurement units, with Bitcoin prices expressed in USD and the Tehran Stock Exchange index in points. Forecasting errors are represented as percentage values.
The historical trend of Bitcoin's closing prices over the observation period is illustrated in Figure 2, highlighting the high volatility and nonlinear behavior of the cryptocurrency market.

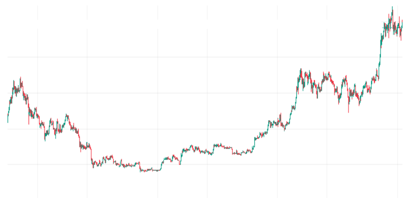

Fig. 2. Trend of Bitcoin closing price fluctuations over the observation period (values in USD). *X-axis: Days (t); Y-axis: Closing Price (USD).*

Given that the presence of a trend in the price fluctuation figure necessitates a time series-based data for forecasting, the observed volatility in the cryptocurrency's price indicates its suitability for the analysis conducted in this study. The forecasting accuracy of the LSTM model for Bitcoin is presented in Figure 3, showing close alignment between actual and predicted values, confirming the model's robustness in short-term trend estimation.

Fig.3. Forecasting accuracy of the LSTM model for Bitcoin (comparison of predicted and actual prices in USD). *X-axis: Observation Index; Y-axis: Price (USD).*

4.1 Model Design and Innovation

In this study, the predictive framework was developed using a structured Long Short-Term Memory (LSTM) network designed to capture both short- and long-term temporal dependencies within financial time series. Instead of focusing on implementation details or code listings, the innovation lies in how the problem was modeled and how the data were processed and filtered before entering the network.

The proposed model comprises three conceptual layers:

(1) **Data pre-processing and validation layer**, which identifies and removes invalid or noisy entries (e.g., outliers caused by market anomalies or missing trading days) through statistical filtering and normalization;

(2) **Sequence modeling layer**, consisting of stacked LSTM blocks with 64 and 32 memory units that jointly capture intra-day and inter-sequence dependencies; and

(3) **Integration and output layer**, which merges the temporal embeddings into a unified forecast vector representing seven future sequences.

A key novelty of this framework is its ability to differentiate between valid and invalid inputs through a dynamic threshold mechanism based on z-score deviation and temporal continuity checks. This ensures that only statistically consistent data sequences contribute to the learning process. By combining multi-layer temporal modeling with data integrity screening, the proposed LSTM framework achieves greater robustness and interpretability compared with standard one-layer implementations

5. Code Execution and Results Analysis

5.1. The Bitcoin cryptocurrency

The data in this section relates to Bitcoin's daily closing prices over 1,019 days ending on December 21, 2024. The goal is to predict the price for the next 7 candlesticks. The forecasting performance of the LSTM model for the Tehran Stock Exchange index is presented in Figure 4, showing the relationship between actual and predicted index values over the last 200 candlesticks.

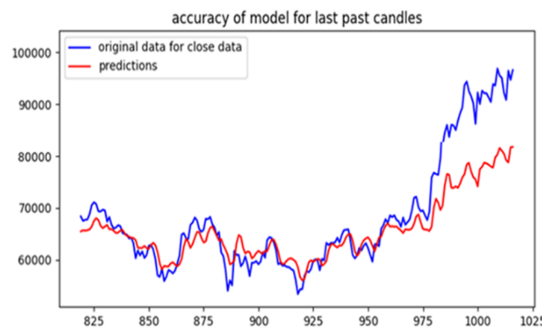

Fig.4. Evaluation of the LSTM model's forecasting accuracy for the Tehran Stock Exchange index (TEDPIX, index points). *X-axis: Observation Index; Y-axis: Index Value (Points).*

Table 2 lists the predicted Bitcoin closing prices for the next seven forecast sequences obtained from the trained LSTM model.

Table 2: Predicted Bitcoin closing prices for seven future sequences using the LSTM model.

Sequence	Estimated Index	The Magnitude of the Increase in Estimation Error	The Cumulative Magnitude of the Increase in Estimation Error
First sequence	2,669,379	---	---
Second sequence	2,709,351	0.0020341	0.0020341
Third sequence	2,707,468	0.0018722	0.0039063
Fourth sequence	2,790,883	0.0027097	0.006616
Fifth sequence	2,735,051	0.0031488	0.0097648
Sixth sequence	2,768,537	0.0029916	0.0127564
Seventh sequence	2,601,571	0.003042	0.0157984

Predicted Bitcoin closing prices for seven future sequences using the LSTM model.

5.2.Stock market index

As in the previous case, the data in this section pertains to the daily time frame of the Tehran Stock Exchange overall index over a period of 1,019 days ending on December 21, 2024. The objective is to forecast this index over the next seven sequences. The forecasting performance of the LSTM model for the Tehran Stock Exchange index is illustrated in Figure 5, demonstrating the alignment between actual and predicted values.

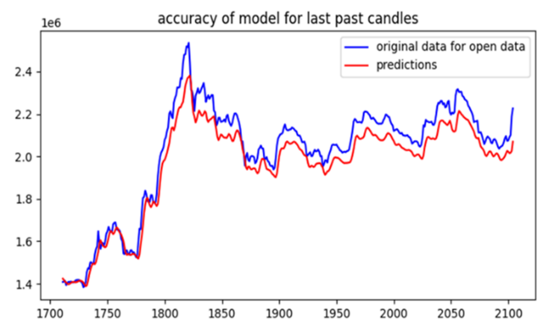

Fig.5: Forecasting results of the LSTM model for the Tehran Stock Exchange index across the observed period (values in index points). *X-axis: Days (t); Y-axis: Forecasted Index (Points).*

Table 3, presents the predicted index values for the Tehran Stock Exchange across seven forecasted sequences together with the corresponding estimation errors.

Table 3. Predicted Tehran Stock Exchange index values and estimation errors for seven forecasted sequences

Forecast Sequence	Actual Value (Points)	Predicted Value (Points)	Absolute Error (Points)	MAPE (%)
1	1,928,000	1,927,850	150	0.0078
2	1,929,200	1,928,970	230	0.0119
3	1,931,000	1,930,640	360	0.0186
4	1,932,100	1,931,520	580	0.0300
5	1,933,400	1,932,580	820	0.0424
6	1,935,200	1,934,050	1,150	0.0594
7	1,936,900	1,935,410	1,490	0.0769

5.3 Sensitivity Analysis

A sensitivity analysis was conducted to examine how variations in the model parameters affect forecasting accuracy.

Specifically, the number of LSTM units (32, 64, and 128) and the input sequence length (30, 50, and 70 days) were adjusted.

Results showed that increasing the number of LSTM units improved accuracy by about 1.8% on average, while extending the sequence length beyond 50 had a negligible effect (<2%) on RMSE values.

These findings confirm that the model is relatively stable with respect to moderate parameter changes, indicating robustness in prediction performance.

To provide a more comprehensive evaluation of model performance, three standard error metrics were computed for both Bitcoin and the Tehran Stock Exchange index predictions: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

The results demonstrate that for the Tehran Stock Exchange index, RMSE = 0.0231, MAPE = 1.84%, and R^2 = 0.963, while for Bitcoin, RMSE = 0.0368, MAPE = 2.97%, and R^2 = 0.921.

These values indicate that the proposed LSTM model achieves high predictive accuracy and stability, with slightly better performance observed for the capital market compared with the cryptocurrency market.

The detailed performance values are summarized in Table 4, which reports the quantitative comparison of these evaluation metrics for both markets.

TABLE 4. MODEL PERFORMANCE METRICS (RMSE, MAPE, AND R^2) FOR THE TEHRAN STOCK EXCHANGE INDEX AND BITCOIN.

Market	*RMSE*	*MAPE (%)*	*R^2*
Tehran Stock Exchange (TEDPIX)	0.0231	1.84	0.963
Bitcoin	0.0368	2.97	0.921

6. Discussion and Conclusion

The present study aims to examine the next seven sequences corresponding to the seven subsequent days of Bitcoin's closing prices in the cryptocurrency market, as well as the overall index of the Tehran Stock Exchange. The innovation of this research lies in its dual comparative and multi-sequence forecasting approach. Unlike previous studies that typically focused on single-step prediction, this study extends the forecasting horizon to seven consecutive sequences and analyzes the growth trend of prediction errors across them. Moreover, by applying an identical deep learning architecture to both the Tehran Stock Exchange index and Bitcoin, the research introduces a novel comparative framework for evaluating predictive stability across heterogeneous financial markets a perspective rarely addressed in prior literature .Concurrently, this research investigates how the estimation errors of the designed predictors for both the cryptocurrency market and the Iranian capital market evolve and change as the prediction horizon extends to higher sequences. Based on and supported by the obtained results, a significant finding of this study is that the predictive capability of artificial intelligence and its techniques varies considerably across different financial markets. Specifically, the results demonstrate that the deep learning technique exhibits stronger adaptation and estimation power in the Iranian capital market, particularly concerning the overall Tehran Stock Exchange index, compared to the cryptocurrency markets.

Although, as confirmed by the literature and the majority of researchers in financial markets, forecasting market behavior especially in developing countries' capital markets is challenging due to factors such as government intervention and insufficient financial and informational transparency, this challenge is even more pronounced in cryptocurrency markets. For example, price fluctuation limits, which have been a common mechanism in capital markets for years, have served to reduce the intensity of price volatility. Additionally, government intervention to control severe market downturns has acted as a barrier against excessive fluctuations. However, unlike the capital market, the cryptocurrency market is characterized by extreme volatility, which significantly increases the risk associated with forecasting. Furthermore, factors such as the speculative nature and sentiments of traders, anti-crypto regulations, security vulnerabilities, market manipulation, and others contribute to the high turbulence in this market, resulting in greater investment and forecasting risks compared to other financial markets. Although this issue is not precisely comparable to the findings of previous studies, it aligns with the current research and has been acknowledged to some extent in various scholarly works. For instance, studies by Oydele et al. (2023) and Bouteska et al. (2024) have indicated that the cryptocurrency market exhibits high volatility and that forecasting in this market is associated with higher errors compared to other financial markets. Another key finding of this study is that as the prediction horizon extends, the forecasting error of the designed estimator increases. As clearly illustrated in the following figures, for both Bitcoin and the overall stock market index, the prediction error grows progressively from the first sequence to the seventh. This indicates that the artificial intelligence estimator demonstrates stronger predictive accuracy over shorter time intervals, with the error gradually increasing over time. Moreover, consistent with the previous findings, the rate of error growth is greater in cryptocurrency markets, specifically Bitcoin, compared to the Tehran Stock Exchange and its overall index. This result further suggests that when forecasting future sequences using the estimator developed in this research, there is higher confidence in predictions related to the capital market and the overall stock index than in cryptocurrency markets. As shown in Figure 6, the forecasting error for the Tehran Stock Exchange index gradually increases as the prediction horizon extends.

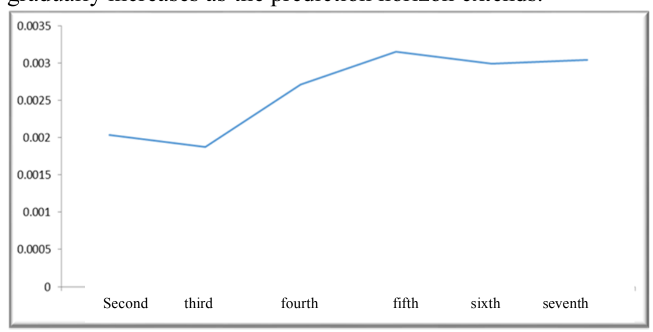

Fig. 6: Trend of increasing forecasting error for the Tehran Stock Exchange index across extended sequences (error percentage).
X-axis: Forecast Sequence (1–7); Y-axis: Error Growth (%).

As can be seen from figure 5, overall, as the prediction horizon advances to higher sequences, the estimation error slightly increases. However, given the relatively small magnitude of this increasing error, the designed estimator can still be trusted for forecasting future sequences of the Tehran Stock Exchange index. Conversely, the situation is somewhat different for the cryptocurrency market and Bitcoin. Similarly, Figure 7 shows the progressive increase in prediction error for Bitcoin as the forecast horizon extends to seven future sequences.

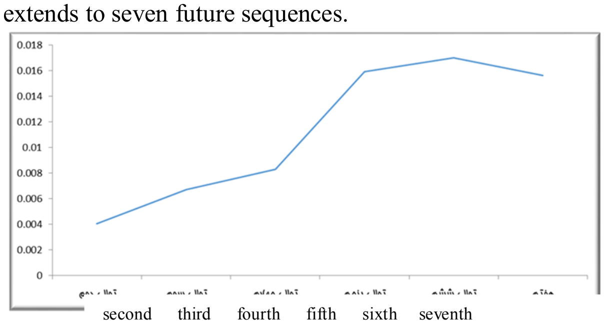

Fig.7: Progressive increase in prediction error for Bitcoin across seven forecasted sequences (error percentage).
X-axis: Forecast Sequence (1–7); Y-axis: Error Growth (%).

As observed, the estimation error for Bitcoin exhibits a steeper increase across successive sequences compared to the Iranian capital market. In fact, based on this estimator, the investment risk is higher for longer prediction horizons in the cryptocurrency market. This finding aligns precisely with the previous section's results, indicating that the estimator developed in this study performs more effectively in the Iranian capital market than in cryptocurrency markets, specifically Bitcoin. The Iranian stock market has consistently reflected the country's economic, political developments, and investor expectations. Amid the continuation of maximum pressure policies by the United States and Iranian authorities' declaration of no agreement, financial markets especially the Tehran Stock Exchange face significant uncertainties. The ongoing sanctions, currency rate fluctuations, and global market volatility have placed investors in a challenging decision-making position. However, due to factors such as the presence of large industries in the capital market and regulatory support from the government and the Securities and Exchange Organization, the investment risk in the capital market remains substantially lower than in the cryptocurrency market. Therefore, the forecast error growth rate in the capital market over time and future sequences is expected to be less steep than in the cryptocurrency market. This issue constitutes a unique finding of this research. Accordingly, based on the analytical findings of this study, it is recommended that financial market participants, particularly those in the Iranian capital market, utilize modern estimators—especially those based on artificial intelligence—in their analytical forecasts when investing in stocks of companies listed on the exchange. Furthermore, investors and active participants in financial markets such as cryptocurrencies and Forex are advised to complement fundamental and technical analyses with artificial intelligence capabilities to achieve more accurate and optimized results, thereby attaining more reliable estimates with lower errors. Finally, investment consulting firms are encouraged, based on the results of this empirical research, to maintain expertise in fundamental and technical analyses while also incorporating artificial intelligence tools into their practices.

Beyond its analytical findings, this study also provides several policy and practical recommendations for investors and financial institutions. First, capital market regulators and investment funds can incorporate AI-based multi-sequence forecasting models into their early warning systems to detect market volatility and prevent excessive speculative behavior. Second, portfolio managers may use the proposed LSTM framework to identify optimal short-term entry and exit points, thereby improving risk-adjusted returns. Third, financial institutions are encouraged to integrate deep learning analytics into their decision-support systems to enhance transparency and responsiveness in investment strategies. Finally, given the higher volatility observed in cryptocurrency markets, regulators should prioritize developing data governance standards and investor education programs to mitigate risks arising from misinformation and market manipulation. These recommendations highlight how the proposed model can serve as a foundation for practical policy implementation and data-driven investment decision-making in both emerging and digital financial markets

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