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Stock Price Forecasting in Iran Stock Market: A Comparative Analysis of Deep-learning Approaches

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ABSTRACT

The capital market plays a crucial role within a country's financial structure and is instrumental in funding significant, long-term projects. Investments in the railway transport industry are vital for boosting other economic areas and have a profound impact on macroeconomic dynamics. Nonetheless, the potential for delayed or uncertain returns may deter investors. Accurate predictions of rail company stock prices on exchanges are therefore vital for making informed investment choices and securing sustained investment. This study employs deep learning techniques to forecast the closing prices of MAPNA and Toucaril shares on the Tehran Stock Exchange. It utilizes deep neural networks, specifically One-dimensional Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM) networks, and a combined CNN-LSTM model, for stock price prediction. The effectiveness of these models is measured using various metrics, including MAE, MSE, RMSE, MAPE, and R^2. Findings indicate that deep learning methods can predict stock prices effectively, with the CNN-LSTM model outperforming others in this research. According to the results, The CNN-LSTM model reached the highest R^2 of 0.992. Also, based on criteria such as MAE, MSE, RMSE, and MAPE the best results belong to LSTM (Kaggle-modified) with 521.715, 651119.194, 806.920, and 0.028, respectively.

Keywords—*Time Series Prediction, Iran Stock Market, Railway Stock, Deep Learning, Wavelet Transformation.*

1. Introduction

Transportation is a key factor in the commercial sphere, influencing both the economic expansion of a country and the cost of products. Countries recognize the importance of expanding their railway networks to foster economic prosperity. This is especially true for transit economies like India, China, and Russia, which heavily rely on their railway systems [1]. In general, the standard methods of financing railway projects can be divided into the following four categories:

- Budget allocation by the government
- Financing from the capital market
- Borrowing from the International Monetary Fund (IMF) and development banks
- Private sector investment

Since the railway is an asset-intensive industry, its development requires significant investments. This issue, along with the long payback period, has caused the private sector to be reluctant to invest in the railway industry. Also, sanctions and reducing the government's budget have prevented Iran from benefiting from the long-term loans provided by the International Monetary Fund. Considering these conditions, the capacity of the capital market should be used to complete the various infrastructures of the country, including the railway infrastructures. Moreover, the country's general policy is to reform the financing system and move from bank-based to capital market-based financing.

Investing in rail transportation is vital for boosting the economy and increasing production. When individuals allocate financial resources to productive ventures, it has the potential to enhance personal income and company productivity. It is essential to

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have a long-term perspective when investing, focusing on anticipating economic activities rather than short-term speculation. This predictive capability is particularly significant for emerging economies, as it ensures steady progress in stock market governance, leading to sustained development [2].

The primary objective of this project is to develop a deep learning-based model capable of accurately predicting the stock values of railway companies. After a comprehensive evaluation and comparison of the proposed models, the optimal model will be selected. By utilizing deep learning models and frameworks, it is intended to forecast the share values of the MAPNA and Toucaril on the Tehran Stock Exchange. The objective is to carefully evaluate the potency and accuracy of these models in correctly projecting the latest stock market prices. On the other hand, we expect shares in the industry to behave similarly (considering sanctions and mandated prices in Iran's economy). Our review of existing literature indicates a lack of a deep learning model with the ability to generalize across different scenarios. By concentrating on the rail industry specifically, we aim to address this gap in research.

The paper is organized into five sections. The initial section serves as an introduction, offering a comprehensive overview of the subject matter and establishing a broader context. The subsequent section provides a comprehensive review of previous research, highlighting the strengths and limitations of each study and drawing significant conclusions. This evaluation aims to stimulate innovation and enhance results within the field. The methods used for data collection and the statistical approaches used for data preprocessing are explained in the third part. The fourth section then displays the findings from the constructed models, notably how well they performed in predicting the share prices of MAPNA and Toucaril. Finally, the summary of the study's major conclusions is provided in the concluding part, along with further suggestions based on the learnings.

2. Backgrounds

The analysis of stock markets typically involves two main approaches: technical analysis and fundamental analysis. However, recent developments in stock market analysis and forecasting have given rise to the following four separate categories of cutting-edge methodologies [3]:

- Statistical methods,
- Artificial Intelligence methodologies,
- Pattern Recognition, and
- Sentiment Analysis.

In this section, we will delve into relevant studies within each of these categories. The categorization of articles concerning the prediction of stock prices revolves around two main aspects: models and features. These can be further subdivided into statistical analysis, conventional machine learning, and deep learning techniques, as mentioned in [4]. Furthermore, an alternative classification of these methods for predicting stock prices is based on either numerical data exclusively or a combination of text and numerical data. Additionally, the research hurdles associated with forecasting stock prices are addressed, and potential directions for future research are provided toward the conclusion.

2.1. Statistical Methods

In a comparative study undertaken in 2020 [5], three different approaches were investigated to predict stock prices: AutoRegressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), and Stochastic Process-Geometric Brownian Motion model. Using historical stock data as input, the predicted values for each of the three methods were contrasted with the actual prices. The findings revealed that in contrast to the ANN model, the ARIMA and stochastic models exhibited greater accuracy in predicting stock prices. These results are intriguing, as they contradict the findings of a previous study from 2010 [6], which concluded that the ANN model outperformed the ARIMA model in time series prediction.

2.2. Artificial Intelligence Methods

Deep learning techniques were used to predict the price of Apple's shares as well as the trend of the S&P 500 index in a study by Mehrnaz Faraz [7]. Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and hybrid models were some of the techniques used. To add new features to these models, technical analysis was applied. The outcomes showed the efficacy of deep learning techniques, with CNN-LSTM, 1D-CNN, and 2D-CNN being the most successful networks for producing forecasts of stock prices one day ahead. In the study conducted by Aminimehr et al. [8], a Multivariate Time Step CNN-LSTM model was utilized to analyze historical market data patterns. The model was applied to study price fluctuations in the stocks of five prominent companies listed on the Tehran Stock Exchange over a period of ten years, from 2010 to 2020. The results showed that among the several companies, the stock prices of Ghadir Inv were forecasted using this model more accurately. This suggests that it is not feasible to make precise predictions for every stock in the market using a single model, as the performance may vary depending on the specific company and its characteristics.

Regression-based machine learning algorithms were used to assess data pertaining to the stocks of two companies on the Tehran Stock Market in the study mentioned in reference [2]. According to the evaluation's technical analysis findings, the decision tree technique performed better than the MLP and Support Vector Regression (SVR) algorithms for 23 features, including the total price index, industry index, and equal weight price index. Four Tehran Stock Exchange sectors, including Diversified Financials, Oil, Materials, Non-Metallic Minerals, and Metals, were evaluated in a different study by Nabipour et al. [9]. The study utilized data spanning a decade to examine the price fluctuations in these sectors. The study's findings revealed that the LSTM model exhibited the highest fitting capability and outperformed other models in terms of performance. Among the tree-based models, Adaboost, Gradient Boosting, and XGBoost demonstrated fierce competition. A different study published in 2019 [10] used recent iShares MSCI British stock prices from 2015 to 2018 to anticipate share values using machine learning techniques. The LSTM method outperformed other methods in terms of predictive accuracy, with the SVR method ranking second and achieving a lower Mean Absolute Error (MAE). In a study conducted by Faraz et al. [11], the authors utilized Long Short-Term Memory (LSTM) and Autoencoder LSTM models for predicting end-of-day stock market values. To enhance the core dataset, additional features such as technical indicators and oscillators were incorporated, combining deep learning techniques with technical analysis. The initial training of Autoencoders on the data enabled the extraction of features that were subsequently employed by the LSTM network for stock price prediction. The study outcomes indicated that the AE-LSTM model outperformed the GAN model in effectively forecasting prices. In another study conducted by the same researchers [12], a comparison was made between two networks, namely GAN and Least Squares Generative Adversarial Network (LSGAN). The findings revealed that the LSGAN technique exhibited superior performance over the GAN network model in terms of predicting stock prices.

A comprehensive survey study [13] was conducted to analyze research papers published between 2005 and 2019 that employed deep learning methods for forecasting financial time series. Among the various techniques explored, researchers displayed a higher level of interest in Recurrent Neural Networks (RNN), specifically the LSTM network. A review of 86 papers published from 2015 until 2021 [14] highlighted that the LSTM method was the most frequently utilized approach for financial time series analysis and forecasting. However, the study also emphasized the limited number of studies focusing on hybrid approaches that combine multiple deep-learning techniques. Another research [15] that covered the years 2017 to 2019 and examined more than 100 publications, mostly using deep learning, machine learning, and linear models, found that Python had overtaken MATLAB as the most widely used programming language. The optimizers Adam and SGD were the most commonly used. Approximately 60% of the publications incorporated technical analysis indicators either alone or in conjunction with stock history data as inputs for their models.

The accurate prediction of share prices is explored in [16] using machine learning algorithms. Statistical data sourced from a Kaggle dataset is utilized, and sampling techniques such as SVM, Forest Algorithm, and LSTM are employed. The data preprocessing stage is performed using the Pandas library. Cross-validation is employed to train the data, and various machine-learning algorithms are applied. Among these fundamental machine learning algorithms, the Random Forest Classifier achieves an accuracy of 80.8%. Moreover, artificial intelligence methods extend beyond stock market prediction to include the forecasting of market risks and prices in the futures and forward markets.

Hence, within the article [17], deep learning techniques are employed to achieve precise predictions of methanol prices, thereby facilitating intelligent production planning in coking plants. The proposed method revolves around utilizing multiple iterations of CNN-GRU, which excel in extracting temporal and spatial features. This approach is further enhanced by incorporating the attention mechanism, which combines the spatiotemporal static and dynamic features obtained from CNN and GRU, resulting in a methodology called MCGAT. The utilization of the attention mechanism allows for discerning the varying contributions of individual input features toward predicting methanol prices. When predicting the future settlement prices of methanol, the foremost factors with a substantial influence are the upstream products and fuel substitutes. On the other hand, the prediction of the methanol price index heavily relies on the import and export of methanol, as well as the upstream and downstream products. Through experimentation on two datasets spanning six years, the MCGAT method proposed in this study surpasses other advanced techniques, demonstrating its superiority. As a result, MCGAT proves to be a valuable forecasting tool for smart coking plants, providing insightful predictions for future methanol prices.

Given the significance of the Chinese stock market as the second-largest globally, after the United States, it is crucial to conduct thorough investigations. Consequently, in [18], machine learning algorithms are employed to analyze the Chinese stock market. This study unveils distinctive findings that differentiate this market from the American stock market. Notably, liquidity emerges as the most critical predictor, and the dominant presence of retail investors positively impacts short-term predictability, particularly for small stocks. Moreover, stocks belonging to large companies and public companies exhibit a high level of predictability over longer time horizons.

The exploration of the importance of data labeling in trading system development is discussed in [19]. With stock prices exhibiting a non-linear and seemingly unpredictable behavior, accurately forecasting their precise trends presents a formidable challenge. Previous research on predicting stock price trends typically adopts a top-down labeling strategy that encompasses all timeframes. Nevertheless, this labeling technique proves vulnerable to even minor fluctuations in prices. To overcome this drawback, the study proposes an alternative method known as N-term min-max labeling (NPMM). NPMM exclusively assigns labels at the minimum and maximum points within a specified period, thereby reducing susceptibility to minor alterations. The model proposed in this research implements XGBoost to develop an automated trading system. The system's performance is assessed through an empirical analysis conducted on a specific group of 92 companies listed on NASDAQ. It is worth noting that this empirical study exclusively focuses on high-value stocks from the NASDAQ list. The research findings highlight that as the value of N in NPMM labeling increases, the amount of training data decreases, leading to enhanced transaction performance. The application of NPMM labeling, which extracts significant insights from the original data, proves to be more effective than other labeling methods when it comes to predicting stock price trends. Furthermore, a comparison between Sezer labeling and NPMM demonstrates that improving forecasting performance does not necessarily guarantee superior performance in trend forecasting.

By analyzing three Chinese stock indices and eight overseas stock indices, the research done in [20] focuses on increasing the accuracy of stock price and index prediction. In order to achieve this, a Convolutional Neural Network (CNN) and a Bidirectional Long Short-Term Memory (BiLSTM) network are used to extract the temporal features of sequential data. The whole forecasting process is improved by adding an attention mechanism, which automatically modifies the weight allocation for information features. Prior studies have shown that the addition of an attention layer, positioned as the model's last layer after the LSTM layer and before the final activation, improves metrics and boosts model performance as a whole. Therefore, the dense layer is in charge of producing the final forecast outcomes. The study starts by using the suggested technique to forecast the value of China's CSI300 stock index. It is clear from a comparison with various models, including LSTM, CNN-LSTM, and CNN-LSTM-Attention, that the CNN-BiLSTM-Attention model outperforms them all in terms of projecting stock values.

Machine learning techniques have been applied to predict cryptocurrency prices, particularly Bitcoin. According to [21], the goal was to find an algorithm that could predict Bitcoin's price for the following day. In order to identify the factors that affect Bitcoin's price, Random Forest Regression and LSTM (Long Short-Term Memory) were used for this purpose. Three important US stock market indices (NASDAQ, DJI, and S&P 500), the price of oil, and the price of ETH (Ethereum) were all included in the study, which covered the years 2015 to 2018 and found them as influences on Bitcoin's price. Since 2018, the price of ETH (Ethereum) and the Japanese stock index JP225 have become the main factors influencing the price of Bitcoin. However, directly comparing the precision of Bitcoin price prediction is challenging given the possibility of several price bubbles in Bitcoin and the difficulty in determining if the experimental data falls within a bubble period. The research's findings also highlight how the prediction accuracy of both the Random Forest Regression and LSTM algorithms decreases when the number of prior periods with alternative explanatory factors rises. The model that contains only the explanatory factors from the preceding period performs with the maximum accuracy. Random Forest Regression is unable to produce predictions that transcend the prior historical peak when the price of Bitcoin does not reach a new all-time high. However, as Bitcoin's transaction history grows and its price stabilizes, the model's performance tends to improve.

The work described in [22] makes use of keyword proxies that were taken from three datasets, including a combined dataset that contained both the technical indicators dataset and the Google Trends dataset. The study's main goal is to investigate and characterize the variables that affect stock selection in Thailand. The study also includes the creation and assessment of models for choosing a portfolio. Particular focus is placed on stock market technical indicators throughout the data preparation step. These indicators consist of mathematical formulas that take into account variables like prices and volumes while analyzing shifts in the market and their direction. The study focuses on finding phrases often used by stock market investors and those used by internet users while looking for information about securities throughout the keyword selection process. Extreme Gradient Boosting (XGBoost), Random Forest, and Logistic Regression techniques were used in the forecasting step in conjunction with Google Trends search phrases. The ROC curves that resulted showed that this combination produced the best performance.

In terms of success rates and annualized returns, XGBoost had a greater average success rate under challenging market conditions (like the COVID-19 period), but Random Forest outperformed itself under more favorable market circumstances. The difficulty of extrapolating the results to other stock markets is a key caveat of this study.

2.3. Pattern Recognition Methods

A 2018 study's [23] main goal was to evaluate how well CNN and LSTM algorithms could spot repeating patterns in historical stock data charts. The double bottom pattern and the flag pattern, two often seen patterns produced by technical analysis methods, were used to train the deep neural network model. The model was then used to forecast stock trends. The results showed that the LSTM model had the highest detection rate, while the accuracy of the 1D-CNN and 2D-CNN models did not match.

2.4. Sentiment Analysis Methods

The Efficient Market Hypothesis (EMH), which was proposed in 1970, posits that stock prices reflect all available market information [24]. According to this hypothesis, price fluctuations are not influenced by the previous day's changes but rather respond to daily market news and information. Consequently, price movements are deemed unpredictable and do not follow discernible patterns. However, some academics have looked into how news and market data affect stock values, with an emphasis on sentiment analysis methods in particular. Notably, recent improvements in Natural Language Processing (NLP) have enabled deep learning techniques to boost sentiment analysis significantly. A deep learning method for sentiment analysis using multiple recurrent neural networks was introduced by the authors in a specific study [25] by training them on financial news. The suggested approach sought to forecast market mood changes and the behavior of sector Exchange-Traded Funds (ETFs).

Sentiment Analysis plays a pivotal role in evaluating the informational content and investor sentiment surrounding events, categorizing them as positive, negative, or neutral. However, relying exclusively on news information for forecasting purposes may lead to inaccurate outcomes due to the presence of non-factual and deceptive news sources. Consequently, it becomes essential to integrate sentiment analysis techniques with other advanced learning approaches to enhance accuracy. The study conducted by Li et al. [26] demonstrated the effectiveness of the joint Differential Privacy-inspired LSTM (DP-LSTM) model in reducing forecast errors and enhancing robustness. The research provided evidence that the DP-LSTM model has the capability to decrease errors and improve the robustness of the forecasting process.

Due to the complexity of accurately predicting share prices or providing point estimations, recent articles, such as [27], have explored the application of various Natural Language Processing (NLP) and Sentiment Analysis methods to forecast market trends or predict whether shares will experience upward or downward movements (profitable or unprofitable). The primary focus of this article is to examine the correlation between news articles and the movement of the stock market's closing prices. The impact of news headlines on stock prices is examined in this study using a variety of deep-learning models. The goal is to assess the propensity of news headlines to predict stock prices over a seven-day period using stock price data from 2010 to 2021 and associated news headlines about those stocks. Based on the results, it can be seen that the FinBERT + parallel CNN model performs better than other models at predicting the general direction of stock price changes.

In a study conducted by [28], LSTM and GRU models were employed to predict stock prices by leveraging stock characteristics. The research also examined the effectiveness of incorporating financial news data alongside stock characteristics. The dataset utilized in this study consisted of the S&P 500 stock market index and financial news data. The findings indicate that the inclusion of financial news data improves the accuracy of stock price forecasting compared to relying solely on fundamental stock characteristics. Additionally, statistical tests were conducted to validate the models, revealing no significant difference in performance between LSTM and GRU. However, GRU exhibited slightly superior performance metrics compared to LSTM.

Considering the arguments presented, artificial intelligence methods, particularly deep learning techniques, play a significant role in financial time series forecasting. Among these techniques, Recurrent Neural Networks (RNN), and specifically LSTM networks, have gained immense popularity due to their remarkable predictive capabilities. Previous research has shown that LSTM networks are effective at forecasting a variety of variables, including the S&P 500 index, Hong Kong stocks, and US market data. Similar successful outcomes have been noted in Turkey [29] and the Australian stock market [30]. In addition to LSTM networks, Convolutional Neural Networks (CNN) and hybrid CNN-LSTM models have also been investigated in recent research for their potential use in financial forecasting. These alternative models offer different strategies and have shown promising results. Furthermore, most studies have focused on incorporating technical analysis indicators and stock price histories as input variables in forecasting models, indicating the significance of these factors in capturing relevant patterns and trends.

Nonetheless, the introduced models exhibit constrained generalization capabilities, and the comprehensive exploration of hybrid models remains relatively scarce. Furthermore, the application of Deep Learning methods in the context of the Tehran Stock Market has received limited attention from researchers.

3. Methods and Materials

In this section, we will offer an overview of the data collection procedure and delve into the accompanying data preprocessing techniques. Following that, we will present a range of deep learning models proposed for this study.

3.1. Data Collection of the Tehran Stock Market

Two railroad firms, MAPNA and Toucaril, whose stock prices will be analyzed and predicted, will be the subject of the study. Several resources, including the Python Pytse-client package, can be used to get historical information about the Iranian stock market. This library makes it easier to retrieve thorough daily share history from the stock market. Additionally, data can be downloaded directly in .csv format from the Tehran Securities Exchange Technology Management Company (TSETMC)[1] website.

According to the calendar date, the aforementioned website offers daily information on each share. However, the dates were changed from Gregorian to Solar calendar dates for better visibility. The data gathering procedure included 2,770 data points from MAPNA shares recorded on the TSETMC portal between September 1386 and September 1400. Figure 1 shows the history chart of the closing price of MAPNA shares.

3.2. Preprocessing Data

After collecting the data, a four-step preprocessing stage is applied, as shown in Figure 2 and described in the following paragraphs.

Figure. 1. The TSETMC website provided the closing price history chart of MAPNA shares (in Rials).

[1] http://tsetmc.com

Missing Values

When working with stock market data, handling missing values is a crucial preprocessing step. Missing values occur when an attribute in the dataset lacks a value or is represented as NaN, and this issue is common in raw data. In the Iranian Stock Market, missing data can be categorized into two types:

- Missing data due to a complete market shut down, such as on public holidays. Some researchers suggest entirely excluding data from such days in computations [31].
- Data scarcity arises when a particular stock is suspended, usually due to events like an Annual General Meeting (AGM). In such cases, one suggested approach for handling missing values is to estimate them using the Geometric Average technique, as mentioned in [31]. This technique involves calculating the average between the preceding and succeeding values. Another method involves utilizing the mean of the preceding and succeeding values, which has the potential to underestimate stock volatility [32].

Irrespective of whether the absence of data is caused by a market shutdown or stock suspension, [33] proposes several remedies to address the issue:

- Eliminating missing values if they constitute less than 10% of the overall data.
- Employing regression computations.
- Utilizing stochastic regression techniques.
- Substituting missing values with zero, mean, median, the most frequent data, or preceding/subsequent values.

Time Series Stationary

To establish the stationarity of a time series, which comprises data collected over a specific time period, four categories of time series structures are generally recognized:

- **Trend:** Refers to the overall tendency of a time series to exhibit a pattern of rising, falling, or remaining relatively constant over a longer period.

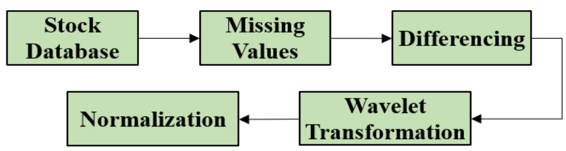

Figure. 2. Data Preprocessing steps.

- **Cyclic:** Describes regular and consistent medium-term fluctuations or oscillations observed in a time series that do not conform to a specific seasonality pattern.
- **Seasonal:** Relates to recurring and predictable changes in a time series that occur over shorter timeframes, often corresponding to specific seasons, months, or days of the week.
- **Unexpected Shifts:** The impact of unforeseen random factors on a time series, often referred to as residual or unexpected changes. Analysts typically identify and remove these changes from the time series to prevent biased results in time series analysis.

To identify trends, cyclical patterns, seasonal fluctuations, and unexpected shifts in time series analysis employs various techniques. In this study, two traditional approaches are utilized [34]:

- The utilization of moving averages.
- Employing the Statsmodels.tsa module in Python to decompose trend and seasonal components.

In this section, the Statsmodels module in Python is employed to extract the structural components of the MAPNA stock data using the seasonal_decompose function. Additionally, the Dickey-Fuller test is conducted on the MAPNA stock data using the Adfuller function from the statsmodels module. The resulting p-value from the test is calculated to be 0.120183. Since this value exceeds the significance level of 0.05, it confirms the nonstationarity of the MAPNA stock.

To tackle the current issue, we will employ a combination of the Differencing method and Logarithm technique for assessment. To address the issue at hand, the differencing technique is employed, which allows us to remove the trend from time series data or isolate the underlying pattern within it. This approach is particularly useful when the data exhibit random walk behavior. The differencing process begins by subtracting the data, and this step is repeated until the data becomes stationary.

However, it's important to note that this approach comes with a drawback: with each differentiation, one data row is lost. While this may present challenges for future analysis with small datasets, it isn't very important when working with large volumes of data.

The steps involved in the logarithm approach are as follows: In order to remove the exponential trend from the dataset, a logarithm is first applied. The differentiation process is then used to improve the outcomes further. The first-order differentiation chart's sharp oscillations, which are shown in Figure 3, demonstrate how the stock price of MAPNA increased significantly in 1399. We accomplish data stationarity while maintaining a precise line chart depiction of the MAPNA stock data without any information loss by using the first-order differentiation method. It is critical to remember that using logarithms may leave out important stock information and volatility.

The results of the Dickey-Fuller test for the Toucaril shares' initial closing price data are shown in Table 1, along with the test results following the application of the differentiation and logarithm procedures. The deployment of the logarithm approach is not essential because the differentiation method creates stationary data successfully.

Figure 4 illustrates the comparison between the data obtained using the differentiation and logarithm approaches with the historical closing price of Toucaril shares. It is evident that the data derived from the logarithm approach fails to accurately represent the information regarding the price of Toucaril stock. The logarithm transformation does not capture extreme price movements and omits certain information in the original data.

Remove Noise and Outliers

Reducing noise and outliers is important in financial data analysis, as they can compromise the

Table 1. P-value of Toucaril stock data, before and after stationary

Close Price	***Toucaril***		
	Raw Data	***After 1st Differencing***	***After Log & 1st Differencing***
P-value	0.551691	0.000000	0.000000

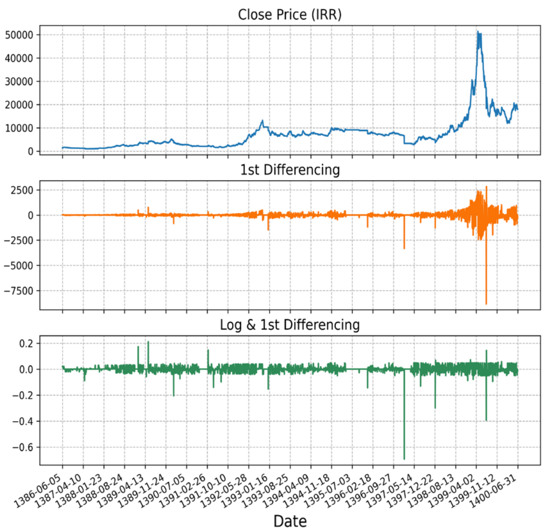

Figure. 3. Along with the data derived from first-order differentiation and the logarithm with first-order differentiation, this figure shows a line chart displaying the closing price of MAPNA shares.

accuracy of deep neural networks in predicting stock prices. To address this, the wavelet transform can be used to remove noise during the preprocessing of training data. Wavelet transform is an extensively utilized method for signal denoising [35], and it can effectively mitigate the risk of overfitting.

To eliminate noise from the dataset, the Discrete Wavelet Transform (DWT) is applied. The PyWavelets library in Python offers a range of wavelet transforms, and this study specifically utilizes the Daubechies family wavelet transforms, particularly db4, with eight decomposition levels. Figure 5 and Figure 6 illustrate the original signal of MAPNA and Toucaril shares' closing price alongside the smoothed signal obtained through wavelet transformation.

We know that the range of stock fluctuations in the Tehran Stock Exchange is controlled. On the other hand, by removing outlier data, we may lose helpful information and be unable to predict the future sharp growths and declines of the stock market. Therefore, in this article, we have avoided removing outlier data.

Re-scaling Data

To prevent larger values from overshadowing the significance of more minor data, it is crucial to standardize the data scale. This can be achieved through normalization and standardization methods, as shown in Equ(1) and Equ(2). Various techniques for data preprocessing, including normalization and standardization, are available. In this study, the MinMaxScaler approach is utilized as a normalization technique to ensure uniformity in the scale of all features. This method scales the data values between 0 and 1. However, it is essential to note that the MinMaxScaler approach may not effectively handle outliers in the data.

$$x_{normalized} = \frac{(x - \min(x))}{(\max(x) - \min(x))} \tag{1}$$

$$x_{standardized} = \frac{(x - mean(x))}{std(x)} \tag{2}$$

3.3. Split Train and Test Data

The data is initially divided into two parts using the Hold-out method, with 80% allocated for training data and 20% for testing data. Subsequently, the training data is further divided using the Cross-validation technique, where Three-fold is used for training, and One-fold serves as a validation set. Table 2 presents a comprehensive overview of the segmentation of the MAPNA and Toucaril stock data.

3.4. Deep Learning Methods

Three neural network models are created using MAPNA stock data in the first step. Each model is assessed for performance and generalizability, and the Toucaril stock data is then applied using the top-performing architecture. These models were created exclusively to forecast the price of the 61st day using information from the 60 days prior. Using the Python programming language and the Keras package, the

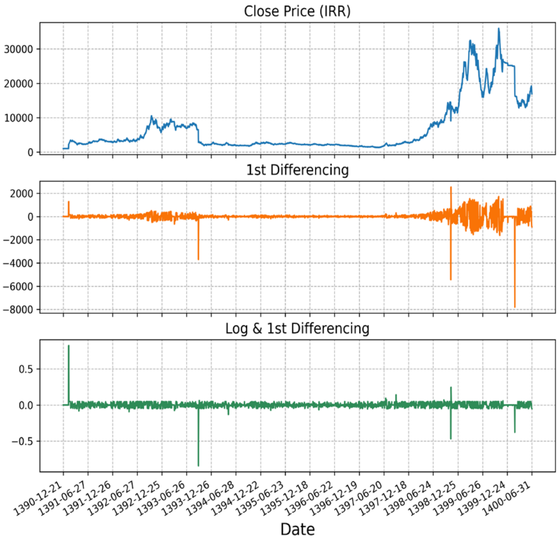

Figure. 4. A comparison between the close price of Toucaril shares and the data obtained using the first-order differentiation and logarithm with first-order differentiation methods.

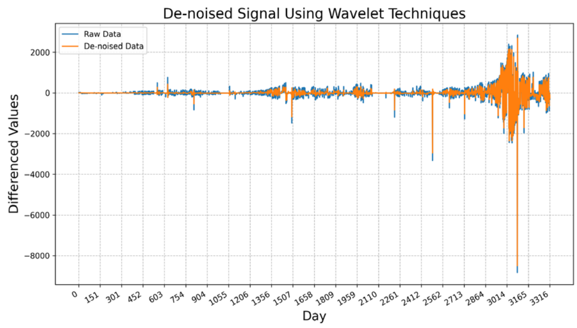

Figure. 5. The denoised signal produced using the wavelet transform approach is shown next to the closing price of the MAPNA stock (post-differentiation).

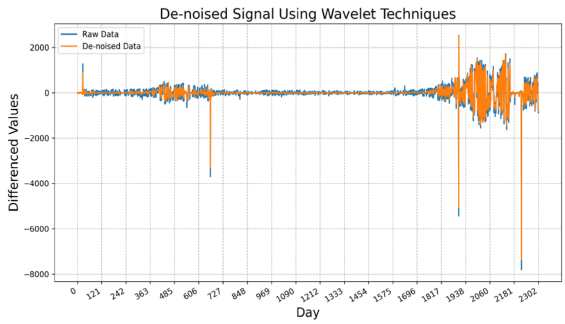

Figure. 6. Comparing the closing price of Toucaril stock (post-differentiation) to the denoised signal obtained using the wavelet transform approach.

models are gradually implemented. Furthermore, to achieve uniform scaling across all features, the data is normalized using the MinMaxScaler technique.

LSTM

In this research, we apply the Mehrnaz Faraz [7] LSTM model, which has been successfully applied to forecasting Apple Inc. stock price. The model architecture consists of three LSTM layers with 32, 16, and 16 neurons, respectively, and a fully connected layer with a single neuron. A random dropout mechanism is utilized, and batch normalization is applied following each LSTM layer. Adam serves as the optimizer function, and ReLU is the activation function.

CNN

In this investigation, a CNN model with a Conv1D layer comprising 30 filters of size 3 is used. ReLU has been selected as this layer's activation function. After this layer, an AveragePooling1D layer with a pool size of 2 is utilized, and then a Flatten layer is used. Last but not least, a Dense layer with a single neuron and ReLU activation function is used. The optimizer function is also of Adam type.

CNN-LSTM

The suggested model, based on research by [36], has a Conv1D layer with 32 filters of size 2. This layer is given the ReLU activation function, and the Padding parameter is set to "Same". After that, a MaxPooling1D layer with a pool size of 2 and the Padding parameter set to "Same" follows. The LSTM layer with 64 neurons and a ReLU activation function is then used. The model architecture is finished by adding a fully connected Dense layer with a single neuron and a ReLU activation function. The Adam optimizer is used for optimization. The CNN-LSTM model is illustrated in Figure 7, and a list of its component layers is given in Table 3.

4. Results and Discussions

The evaluation criteria serve as markers to examine the efficiency and forecast precision of the models. We employ five statistical metrics to assess the accuracy of our models, computing them with Equ(3)–Equ(7).

$$\text{MAE} = \frac{1}{\text{N}}\sum_{\text{d}=1}^{\text{N}} \left|a_{\text{d}} - \text{p}_{\text{d}}\right| \tag{3}$$

$$\text{MSE} = \frac{1}{\text{N}}\sum_{\text{d}=1}^{\text{N}} \left(a_{\text{d}} - \text{p}_{\text{d}}\right)^2 \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{\text{N}}\sum_{\text{d}=1}^{\text{N}} (a_{\text{d}} - \text{p}_{\text{d}})^2} \tag{5}$$

$$\text{MAPE} = \frac{1}{\text{N}}\sum_{\text{d}=1}^{\text{N}} \frac{\left|a_{\text{d}} - \text{p}_{\text{d}}\right|}{a_{\text{d}}} \tag{6}$$

$$R^2 = 1 - \frac{\sum_{\text{d}=1}^{\text{N}} \left(\text{a}_{\text{d}} - \text{p}_{\text{d}}\right)^2}{\sum_{\text{d}=1}^{\text{N}} (\text{a}_{\text{d}} - \bar{\text{a}})^2} \tag{7}$$

In the above formulas, $\bar{a} = \frac{1}{N}\sum_{d=1}^{N} a_d$, p_d is the predicted price, and a_d is the actual share price on day d. Although the LSTM model [7] has had promising results on the Apple stock, its performance on the MAPNA stock data is not suitable and defensible in any way. Figure 8 shows the result of applying this model to our data. Then, inspired by another LSTM model that has been used on the Kaggle site [37] to predict the stock price of Apple Inc., we predict MAPNA stocks. This model consists of two LSTM layers with 128 and 64 neurons and two fully connected (Dense) layers containing 25 and 1 neurons, respectively. Figure 9 represents the result of the LSTM (Kaggle) model trained on our data.

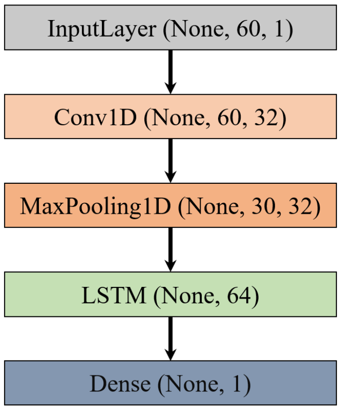

Figure. 7. The architecture of the CNN-LSTM model.

Table 2. Division of MAPNA and Toucaril stock data

Ticker	*Data Volume*	*Validation & Train Data*	*Train Data*	*Test Data*
MAPNA	3317	2654	(2594,60,1)	(663,60,1)
TOUCARIL	2303	1843	(1783,60,1)	(460,60,1)

Table 3. Summary of layers characteristics in the CNN-LSTM model

Layer (Type)	*Output Shape*	*Parameters*
Layer_1 (Conv1D)	(None, 60, 32)	96
Layer_2 (MaxPooling1D)	(None, 30, 32)	0
Layer_3 (LSTM)	(None, 64)	24832
Layer_4 (Dense)	(None, 1)	65
Total Parameters: 24,993 Trainable Parameters: 24,993 Non-trainable Parameters: 0		

The performance of each model according to various criteria is shown in Table 4.

The outcomes from applying the CNN-LSTM model to the analysis of MAPNA stock data are shown in Figure 10. Figure 11 offers a magnified image for a more in-depth examination.

Due to high errors, this study did not report the CNN-LSTM model's results when applied to Toucaril stock data. The large batch size was found to be the cause of these issues; hence, it was decided to reduce the batch size from 64 to 32. The results of using the updated CNN-LSTM model on Toucaril

Table 4. Investigating the models based on different evaluation criteria

Model	*Ticker*	*MAE*	*MSE*	*RMSE*	*MAPE*	*R^2*
LSTM (M. Faraz)	MAPNA	2656.884	22633458.096	4757.463	0.114	0.796
LSTM (Kaggle)	MAPNA	583.300	1231854.753	1109.890	0.029	0.989
LSTM (Kaggle)	Toucaril	1024.118	1922590.192	1386.575	0.047	0.958
LSTM (Kaggle-modified)	Toucaril	521.715	651119.194	806.920	0.028	0.986
1D-CNN	MAPNA	637.879	1067928.355	1033.406	0.036	0.990
1D-CNN	Toucaril	887.982	1550356.290	1245.133	0.045	0.966
CNN-LSTM	MAPNA	558.574	867382.887	931.334	0.031	0.992
CNN-LSTM (modified)	Toucaril	612.303	928081.806	963.370	0.032	0.980

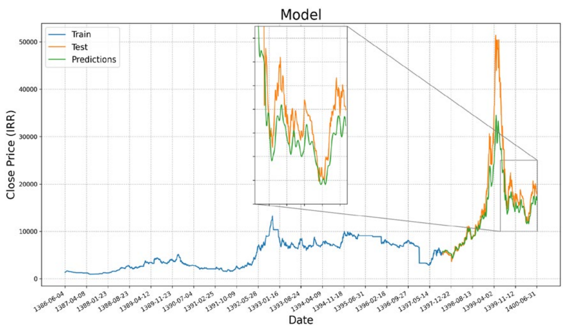

Figure. 8. The predicted price chart of MAPNA shares by LSTM (M. Faraz [7]).

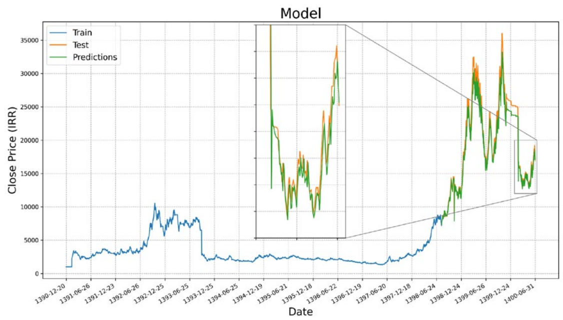

Figure. 9. The predicted price chart of Toucaril shares by LSTM (Kaggle) [37].

stock data are shown in Figure 12. Figure 13 offers a zoomed-in perspective of the findings for a more thorough analysis.

Comparing models using metrics like MAE, MSE, and RMSE is unrealistic due to the disparities in price scales between distinct equities, such as Rials for the Tehran Stock Exchange and Dollars for other markets. To validate the results of this study, R^2 and MAPE were used in Tables 5 and 6. A comparison of the existing literature and our suggested method based on MAPE is shown in Figure 14.

The time required to implement the learning process of each model is shown in Figure 15. It should be noted that all the codes were executed on the Google Colab environment and using the CPU.

4.1. Challenges and Vulnerabilities

- The first challenge is obtaining correct information. On the other hand, the data must be sufficient and valuable because deep learning methods require a large amount of data to achieve accurate and reliable results.
- Regarding the structure of neural networks, the researcher should overcome the limitation of adjusting the parameters and design of the appropriate input and output to obtain the proper relationship between the existing inputs and the expected output and prevent the network from becoming complicated to avoid diverging results.

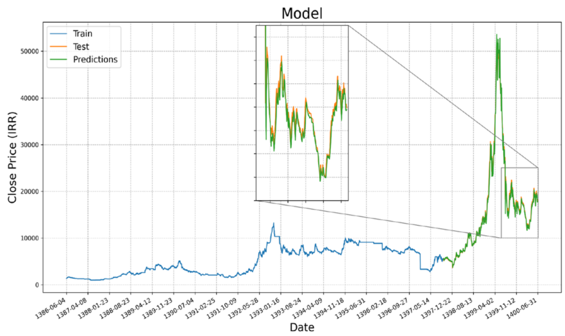

Figure. 10. The predicted price chart of MAPNA shares is generated by the CNN-LSTM model.

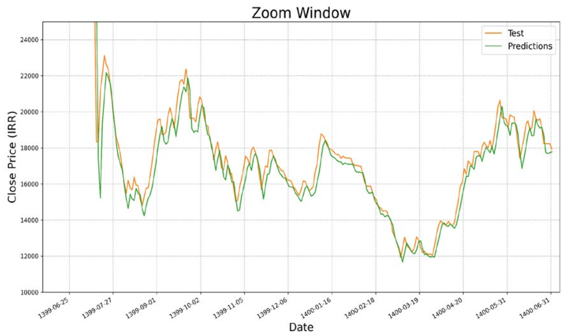

Figure. 11. A zoomed-in view of the predicted price chart of MAPNA stock produced by the CNN-LSTM model.

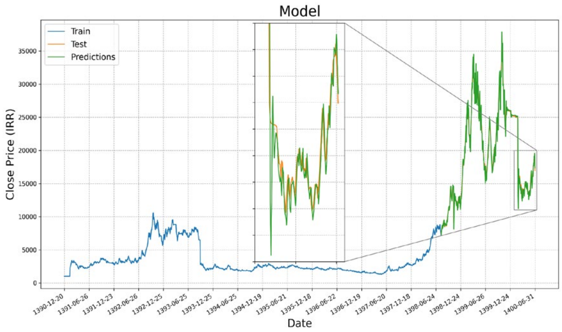

Figure. 12. The predicted price chart of Toucaril shares is generated by the modified CNN-LSTM model.

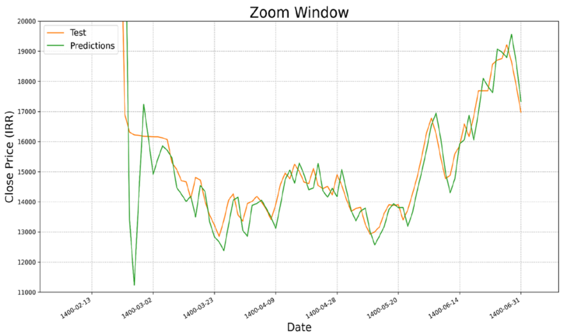

Figure. 13. A close-up look at the forecasted price chart for Toucaril stock was created using the modified CNN-LSTM model.

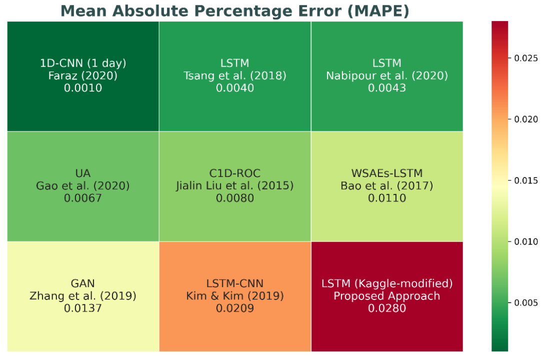

Figure. 14. Heat map of MAPE for different papers and our proposed method.

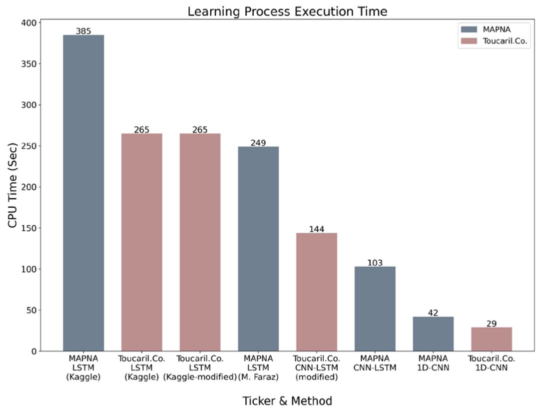

Figure. 15. Comparison of the duration of the learning process in different models.

Table 5. Comparing the results based on the coefficient of determination (R^2)

Reference No.	*Model*	*R^2*
[5]	ANN (7-15-1)	0.6216
[8]	CNN-LSTM	0.8739
[36]	CNN-LSTM	0.9646
[38]	LSTM-News	0.979
[39]	LSTM Advanced + MV	0.83
Proposed Approach	**CNN-LSTM**	**0.992**

Table 6. Comparing the outcomes of 11 papers with our proposed approach using MAPE as the metric

Reference No.	*Model*	*MAPE*
[7]	1D-CNN (1 day)	0.001
[8]	CNN-LSTM	5.7074
[9]	LSTM	0.0043
[39]	LSTM Advanced + MV	1.03
[40]	LSTM	0.004
[41]	UA	0.0067
[42]	C1D-ROC	0.008
[43]	WSAEs-LSTM	0.011
[44]	GAN	0.0137
[45]	LSTM-CNN	0.0209
[46]	LSTM-GRU	0.0413
Proposed Approach	**LSTM (Kaggle-modified)**	**0.028**

- Another limitation of deep learning methods is the weak theoretical support and the lack of a specific formula and approach for using its functions, which must be done by trial and error on each data series.

4.2. The Case Study: Tehran Stock Exchange

Since the current research has focused on the Tehran Stock Exchange market, to understand the obtained results better, we compare our proposed method with the best results reported by Aminimehr et al. [8], relying on the evaluation criteria introduced before. As seen in Figure 16, the graph is drawn semi-logarithmically due to the big difference between the values of different criteria.

5. Conclusions

In this research, data were collected from the TSETMC website, with the initial step involving data preparation through standard techniques. The LSTM model, previously successful in predicting Apple stock prices as per M. Faraz's findings, performed poorly in predicting MAPNA and Toucaril stock prices. A significant challenge encountered was the insufficiency of reliable data, which is critical for deep learning techniques to provide accurate forecasts. To mitigate noise in the data, the wavelet transform method was employed. The research's concluding phase introduced deep learning models to forecast the latest prices of MAPNA and Toucaril stocks on the Tehran Stock Exchange. Different deep neural network (DNN) models, including LSTM, 1D-CNN, and CNN-LSTM hybrids, were utilized in the prediction process. The models were evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2. The results indicated that while deep learning models are capable of making precise predictions for specific stock prices, their ability to generalize may be limited. The CNN-LSTM model emerged as the most effective among the models tested, with the highest R^2 value of 0.992. Furthermore, the best outcomes in terms of MAE, MSE, RMSE, and MAPE were achieved by the LSTM (Kaggle-modified), with scores of 521.715, 651119.194, 806.920, and 0.028, respectively.

5.1. Open Issues

This study attempts to accurately predict the stock prices of two railway companies, MAPNA and Toucaril, by using deep learning methods. Therefore, based on the conducted research, to develop the proposed method, the following are suggested:

Generalization Capability

Models proposed in this study have been evaluated only on two shares of the Iranian Capital Market. It is better to ensure that the results are not random and to detect the scope of using them on more shares or other financial markets, including forex and cryptocurrencies.

Feature Selection Methods

Excluding stock history, more factors in stock market forecasting could be considered, including sentiment analysis. For this purpose, we can use web scraping methods to collect financial news. Using econometric tests to choose suitable inputs for neural networks is also suggested.

Transformers

Transformers can be operated for prediction to avoid computational costs and waste of time.

Designing Trading Strategies for Stock Markets

Currently, trading strategies, such as Simple Moving Average (SMA), are expected in the stock market. In future works, learning with the help of Deep Q Network as a Reinforcement Learning (RL) method can be used to design a trading strategy based on generating buy, sell, or hold signals.

Hybrid Methods

Research results show the efficiency of the hybrid models. Therefore, it is suggested to focus more on these models in future studies. It is also recommended to use the Bidirectional LSTM and CNN-BiLSTM models.

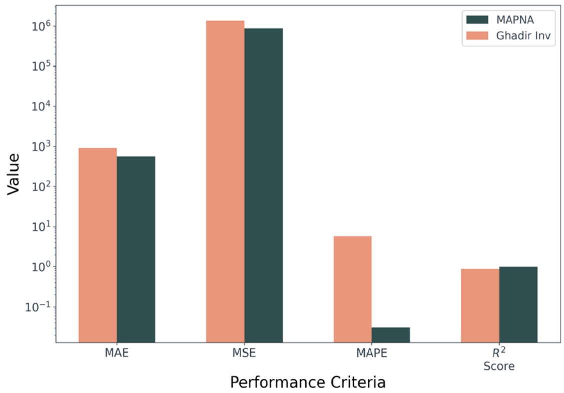

Figure. 16. Comparing our proposed approach and the results of Aminimehr et al. [8].

Declarations

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Authors' contributions

FB: Study design, acquisition of data, interpretation of the results, statistical analysis, literature review, drafting the manuscript;

AO: Idea generating, interpretation of the results, revision of the manuscript, supervision;

AKN: Research methodology, supervision, drafting the manuscript, revision of the manuscript;

MKS: Interpretation of the results, revising the manuscript, supervision.

Conflict of interest

The authors declare that there is no conflict of interest.

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