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Harnessing Convolutional Neural Networks for Accurate Stock Price Prediction: A Case Study of Hellenic Telecommunications Organization (HTO.AT)

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ABSTRACT

This study presents a novel approach to stock price prediction by employing Convolutional Neural Networks (CNNs) to forecast the stock prices of the Hellenic Telecommunications Organization (HTO.AT). The CNN model demonstrated exceptional predictive performance, achieving a Root Mean Squared Error (RMSE) of 0.22859211 and a Mean Absolute Percentage Error (MAPE) of 1.2041852, indicating a high level of accuracy. By effectively capturing complex and non-linear patterns in historical stock price data, the model surpasses traditional forecasting methods, thus offering significant advantages for investors and financial analysts. This research emphasizes the importance of integrating external data and exploring alternative deep learning architectures, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, to further enhance prediction capabilities. Overall, the findings underscore the potential of CNNs as powerful tools in financial market analysis, providing actionable insights for more informed investment decisions.

1. INTRODUCTION

The stock market is a crucial component of the global economy, drawing interest from a wide range of stakeholders, from individual investors to large financial institutions [1], [2]. Due to its inherent volatility and dynamic nature, stock price prediction remains a highly sought-after topic in both academic and practical spheres[3], [4]. Numerous methods have been employed to forecast stock price movements, ranging from traditional technical and fundamental analysis to advanced techniques such as machine learning and deep learning [5].

The Hellenic Telecommunications Organization (HTO.AT), as Greece's largest telecommunications company, exerts substantial influence on the stock market. The fluctuations in HTO.AT's stock price are influenced not only by the company's own performance but also by broader economic and political conditions in Greece, as well as advancements in the telecommunications sector. Consequently, predicting HTO.AT's stock price represents a complex but critical challenge for investors and market analysts[6].

With technological advancements, deep learning methods, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential across various applications, including stock price prediction [7], [8]. Originally designed for pattern recognition in image data, CNNs have been successfully adapted to address sequential data problems such as stock price series[9]. The capability of CNNs to capture local features and intricate patterns in data renders them a highly effective tool for stock market analysis[10].

This research aims to develop a stock price prediction model for HTO.AT utilizing CNNs. The study will provide a comprehensive examination of how CNNs can be applied to stock price prediction and will evaluate the performance of the proposed model [11], [12]. Using historical stock price data of HTO.AT, the CNN model will be trained and tested to assess its accuracy in forecasting future stock price movements [13].

Previous research has demonstrated that deep learning methods, including CNNs, offer advantages over traditional prediction methods [14]. However, there remains a notable gap in the literature concerning the application of CNNs to HTO.AT's stock and the Greek stock market at large [15]. This study seeks to address this gap and make a significant contribution to the field of stock price prediction through advanced deep learning techniques[16].

The methodology of this research will be detailed, encompassing data collection and preprocessing, the architecture of the CNN model employed, and the techniques used for evaluating model performance [17]. The results of this study are anticipated to provide valuable insights for both researchers and practitioners in applying CNNs for stock price prediction, particularly within the context of the Hellenic Telecommunications Organization and the broader Greek stock market[18].

In summary, this research not only aims to advance academic knowledge but also to offer practical guidance for investors and market analysts in making informed investment decisions based on accurate predictions generated by CNN models.

2. METHOD

2.1. Data Collection

For this study, we utilized stock price data for the Hellenic Telecommunications Organization (HTO.AT), which is the largest telecommunications service provider in Greece. This data was sourced from Yahoo Finance, a widely recognized and reliable platform for financial data.

2.1.1 Data Source

The data was obtained from Yahoo Finance, which provides comprehensive historical financial data, including stock prices, trading volumes, and other relevant metrics. Yahoo Finance is commonly used in financial research due to its accessibility and the reliability of its data. The dataset includes historical stock price information for HTO.AT. Specifically, we used the "Close" prices, which represent the last price at which the stock traded during a regular trading session. The "Close" price is a crucial indicator as it reflects the stock's value at the end of each trading day and is widely used in financial analysis and forecasting models. The data spans from April 19, 1996, to April 19, 2023. This period encompasses a broad range of market conditions and economic environments, providing a comprehensive dataset for analyzing trends and patterns in HTO.AT's stock price. The chosen timeframe ensures that the model can capture long-term trends and respond to various market cycles, which enhances the robustness and reliability of the predictions.

2.1.4. Data Characteristics

Frequency: The data is collected on a daily basis, providing a granular view of the stock's performance over time. Format: The data was downloaded in CSV (Comma-Separated Values) format, which is a standard format for data manipulation and analysis. Each row in the dataset represents a single trading day and includes columns for the date, closing price, and potentially other metrics like opening price, high, low, and volume. Preprocessing: Prior to analysis, the data underwent preprocessing steps to handle missing values, outliers, and ensure consistency in the format. This might include interpolation for missing values, normalization, or scaling of the data. By leveraging this extensive dataset, the study aims to develop and evaluate a Convolutional Neural Network (CNN) model for predicting future stock price movements of HTO.AT. The use of historical closing prices allows for the analysis of price trends and patterns that are critical for forecasting stock prices accurately.

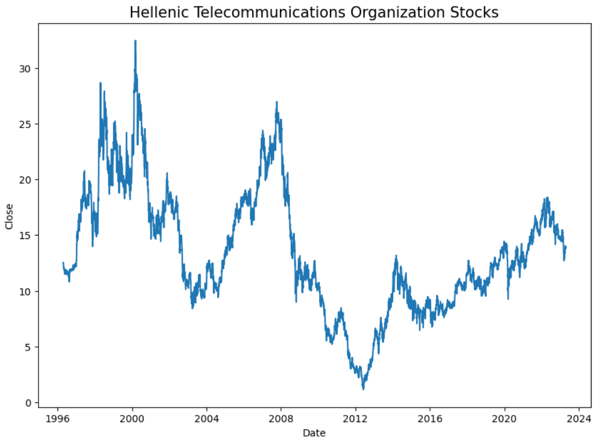

Figure 1. Hellenic Telecommunications Organization stock chart

2.2. Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for analysis and modelling [8]. In this study, the preprocessing phase involves several key activities to ensure that the data is clean, structured, and suitable for training and testing the Convolutional Neural Network (CNN) model.

2.2.1. Data Cleaning

The first step in preprocessing is data cleaning. This involves identifying and addressing any issues within the dataset, such as missing values or inconsistencies[19].Handling Missing Values: Missing data can occur for various reasons, such as incomplete data records or issues during data collection. In this study, missing values are managed through interpolation or imputation methods. Interpolation involves estimating missing values based on existing data points, while imputation involves filling in missing values with statistical measures such as the mean or median of the available data. Removing Duplicates: Duplicate entries, if any, are identified and removed to ensure the integrity of the dataset. This step is crucial to avoid redundant information that could skew the results of the analysis. Outlier Detection: Outliers, or data points that significantly deviate from other observations, are identified and addressed. Outliers can distort statistical analyses and model training, so they are either adjusted or removed based on their impact and relevance.

2.2.2. Data Splitting

Once the data is cleaned, it is split into training and testing datasets. This division is essential to evaluate the performance of the model effectively[4], [10]. Training Data: 80% of the data is allocated for training purposes. This subset is used to train the CNN model, allowing it to learn the patterns and relationships within the historical stock price data. Test Data: The remaining 20% of the data is reserved for testing. This subset is used to evaluate the model's performance on unseen data, providing an indication of how well the model generalizes to new, unseen stock price movements.

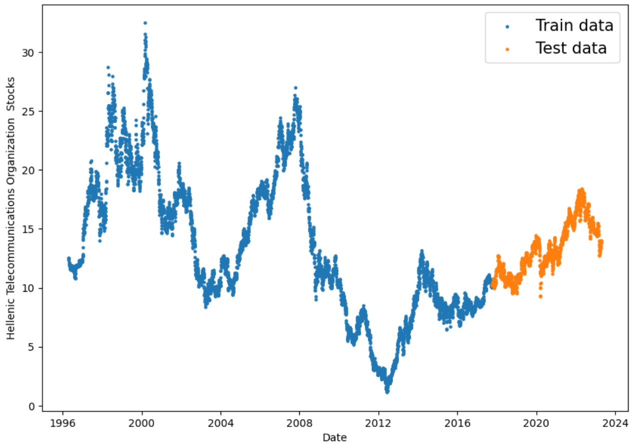

Figure 2. Graph of train and test data split

2.2.3. Time Series Split

Given the nature of stock price data, which is sequential and time-dependent, a time series split is employed [20], [21]. Unlike random splitting, which may disrupt the temporal order of the data, the time series split maintains the chronological order of the data.

1. Process: The dataset is divided into training and testing sets based on time. The training set includes all data up to a certain point in time, while the test set consists of data following that point. This approach ensures that the model is trained on past data and tested on future data, reflecting a real-world scenario where future stock prices are predicted based on historical trends.
2. Visual Representation: An illustrative diagram or image of the time series split can be provided to visually depict how the data is divided. This image helps in understanding the chronological separation between training and testing periods.

By performing these preprocessing steps, the data is prepared in a manner that supports accurate and effective training and evaluation of the CNN model. Proper preprocessing ensures that the model can learn from high-quality data and provides reliable predictions for future stock price movements.

2.3. Creating Sequences

To effectively utilize Convolutional Neural Networks (CNNs) for stock price prediction, the input data must be formatted into sequences. CNNs are adept at handling sequential data due to their ability to capture patterns across multiple time steps. In this context, creating sequences involves defining how past data points are used to predict future stock prices. Two key concepts in sequence creation are the horizon and the window.

2.3.1. Horizon

The horizon refers to the number of future time steps that the model aims to predict. It represents the forecasting goal of the model. For this study, the horizon is set to 1, which means that the model will predict the stock price for the next day. In other words, given historical data, the CNN will learn to forecast the stock price one day into the future.

2.3.2. Window

The window specifies the number of past time steps used to make predictions. It defines the extent of historical data that the model considers when generating forecasts. In this study, the window is set to 7. This means that the model will use the stock price data from the past 7 days to predict the price for the next day.

2.3.3. Sequence Creation Process

For time-series stock price forecasting using a Convolutional Neural Network (CNN), it is essential to structure the input data into sequences, given the model's design to handle sequential dependencies. Two critical parameters in sequence formation are the horizon and the window. The horizon refers to the number of future timesteps the model aims to predict, while the window defines the number of past timesteps used as input to make these predictions. In this study, a horizon of 1 and a window of 7 were employed, which means the model predicts the next day's stock price for Hellenic Telecommunications Organization (HTO) based on the previous seven days of price data.

2.4. CNN Model Development

The CNN model architecture is specifically designed to capture temporal patterns within the stock price data. The architecture consists of the following core components:

1. Input Layer: The input layer accepts sequences of stock price data with dimensions (sequence_length, features), where sequence_length corresponds to the window size, and features represent the attributes of the data.
2. Convolutional Layer: This layer applies several filters with specified kernel sizes to extract local temporal features from the input sequence. These filters scan over the input data, capturing short-term patterns that may influence future stock price movements.
3. Activation Layer: The Rectified Linear Unit (ReLU) activation function is employed to introduce non-linearity into the model, enhancing the network's ability to model complex relationships between input variables.
4. Pooling Layer: A Max Pooling layer is used to downsample the feature maps produced by the convolutional layer, reducing the dimensionality while preserving essential features. This reduces computational cost and helps prevent overfitting.
5. Flatten Layer: The flatten layer transforms the output of the pooling layer into a one-dimensional vector, enabling its integration with fully connected layers for further processing.
6. Dense Layer: Multiple fully connected (dense) layers follow, which combine the learned features to form higher-level representations. These layers enable the model to make refined inferences about future stock prices based on the extracted features.
7. Output Layer: The final output layer consists of a single neuron, which generates the predicted stock price for the next timestep.

The model is compiled using the Adam optimizer, known for its efficiency in adjusting learning rates dynamically, and the Mean Squared Error (MSE) as the loss function, which is commonly used in regression tasks due to its ability to penalize larger errors more heavily.

To enhance generalization and mitigate overfitting, an early stopping mechanism is employed. This approach monitors the validation performance during training and halts the process if no improvement is observed after a specified number of epochs

2.5. Model Training and Evaluation

The training process involves updating the model's weights over multiple epochs, using a defined batch size, with the goal of minimizing the MSE loss function. The training dataset is used to optimize the model, while early stopping helps ensure that the model does not overfit on the training data.

Once training is complete, the model is evaluated using an independent test dataset. To assess the model's forecasting accuracy, two key performance metrics are employed:

1. Root Mean Squared Error (RMSE): This metric calculates the square root of the average squared differences between predicted and actual values, providing an indication of the typical magnitude of forecast errors.
2. Mean Absolute Percentage Error (MAPE): This metric evaluates the percentage difference between predicted and actual values, offering insight into the relative accuracy of the predictions.

These evaluation metrics provide a comprehensive understanding of the model's performance in predicting future stock prices and are essential in comparing the effectiveness of different forecasting approaches.

3. RESULTS AND DISCUSSION

3.1. Result

The Convolutional Neural Network (CNN) model developed in this study was trained and evaluated using historical stock price data of Hellenic Telecommunications Organization (HTO.AT). Two key performance metrics were employed to assess the model's predictive capabilities: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The evaluation results demonstrate that the CNN model exhibits strong performance in forecasting HTO.AT stock prices, as indicated by the following values:

Table 1. Evaluation result table of CNN model

Evaluation Method	Value
RMSE	0.22859211
MAPE	1.2041852

A low RMSE value suggests that the model's absolute prediction error is relatively small, indicating good fit to the actual data. Meanwhile, the low MAPE value highlights that the model's prediction error, when expressed as a percentage of the actual stock price, is minimal, signifying high accuracy in the model's forecast.

To further illustrate the model's performance, the figure below presents a comparison between the actual stock prices and those predicted by the CNN model for the test dataset. This comparison visually depicts the alignment between predicted and observed stock price movements, offering insight into the model's effectiveness.

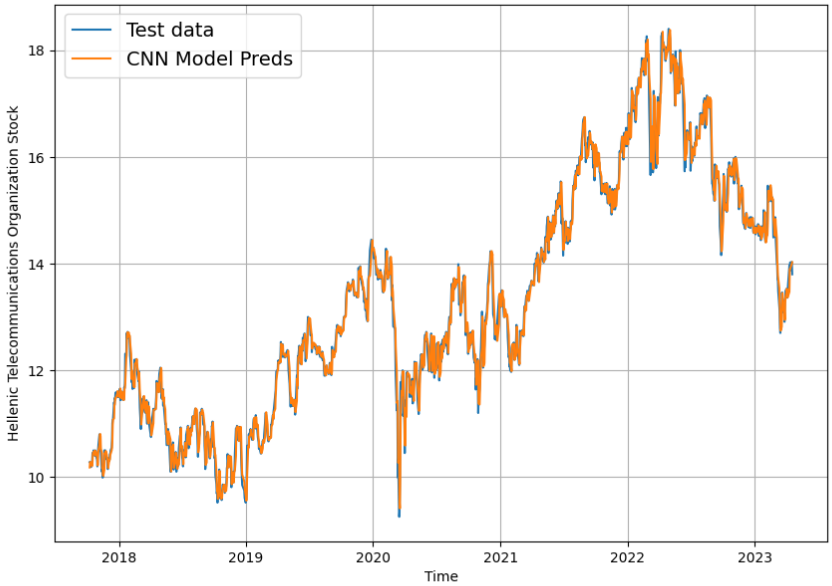

Figure 3. Comparison graph between test data and CNN prediction model

3.2. Discussion

The results of this study highlight the significant effectiveness of the Convolutional Neural Network (CNN) model in predicting stock prices for the Hellenic Telecommunications Organization (HTO.AT). The low values of Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) indicate the model's high accuracy and reliability, demonstrating its ability to capture complex patterns and non-linear relationships in stock price data that traditional forecasting methods, such as AutoRegressive Integrated

Moving Average (ARIMA) or linear regression, often struggle to address. This capability is consistent with previous research that emphasizes the superiority of deep learning techniques in financial forecasting. The CNN model's high predictive accuracy offers practical implications for investors and financial analysts, enabling them to make informed decisions and effectively manage risks based on anticipated stock price movements. Nevertheless, the model does face certain limitations, including the need for substantial datasets and considerable computational resources for effective training. Future research directions may include optimizing the CNN architecture and incorporating external variables, such as economic indicators and market sentiment, which could enhance the model's predictive performance. Overall, this study underscores the potential of CNNs as valuable tools in stock price forecasting, contributing to the broader field of financial analytics and providing actionable insights for market participants.

4. CONCLUSION

This research successfully developed a Convolutional Neural Network (CNN) model for predicting stock prices of the Hellenic Telecommunications Organization (HTO.AT), achieving a Root Mean Squared Error (RMSE) of 0.22859211 and a Mean Absolute Percentage Error (MAPE) of 1.2041852, indicating high predictive accuracy. The model's ability to capture complex and non-linear patterns in stock price data highlights its advantages over traditional methods, making it a valuable tool for investors and analysts in decision-making. While the results are promising, future research should focus on integrating external data and exploring other deep learning architectures, such as Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) networks, to further enhance prediction accuracy. Overall, this study demonstrates the potential of CNNs in financial market analysis and their practical application in improving investment strategies.

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