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APPLICATION OF MULTILAYER PERCEPTRON MODEL IN PREDICTING DIRECTION OF G7 STOCK INDICES

Nazif AYYILDIZ[1]

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ABSTRACT

The aim of this study is to evaluate the prediction performance of the Multilayer Perceptron (MLP) model, one of the deep learning methods, on the stock indices of G7 countries, namely NYSE 100 (USA), FTSE 100 (UK), NIKKEI 225 (Japan), CAC 40 (France), FTSE MIB (Italy), DAX 30 (Germany), and TSX (Canada). In addition to daily data from January 1, 2014, to December 31, 2023, ten technical indicators, widely used in the literature and selected for their ability to enhance prediction performance and provide statistically significant contributions to the model, were included as input variables. The analysis results showed that the directional movements of the NYSE 100, FTSE 100, NIKKEI 225, CAC 40, FTSE MIB, DAX 30, and TSX indices were predicted with accuracies of 74.75%, 92.28%, 77.58%, 79.10%, 82.58%, 88.83%, and 77.49%, respectively. The obtained average accuracy of 81.80% demonstrates that the Multilayer Perceptron (MLP) model is an effective method for stock index prediction.

Keywords: Financial Markets, Deep Learning, Multilayer Perceptron, Classification

JEL Codes: C45, C53, G15, G17

G7 BORSA ENDEKSLERİNİN YÖN TAHMİNİNDE ÇOK KATMANLI ALGILAYICI MODELİNİN UYGULANMASI

ÖZ

Bu çalışmanın amacı, derin öğrenme yöntemlerinden biri olan çok katmanlı algılayıcı (MLP) modelinin, G7 ülkelerine ait borsa endeksleri olan NYSE 100 (ABD), FTSE 100 (İngiltere), NIKKEI 225 (Japonya), CAC 40 (Fransa), FTSE MIB (İtalya), DAX 30 (Almanya) ve TSX (Kanada) üzerindeki tahmin performansını değerlendirmektir. 01 Ocak 2014 ile 31 Aralık 2023 tarihleri arasında günlük verilere ilave olarak literatürde yaygın olarak kullanılan teknik göstergeler arasından modelin tahmin performansını artıran ve modele istatistiksel olarak anlamlı katkı sağlayan on adet teknik gösterge seçilerek modelde giriş değişkeni olarak kullanılmıştır. Gerçekleştirilen analizler sonucunda, NYSE 100, FTSE 100, NIKKEI 225, CAC 40, FTSE MIB, DAX 30 ve TSX endekslerinin hareket yönlerinin sırasıyla %74,75, %92,28, %77,58, %79,10, %82,58, %88,83 ve %77,49 oranında doğrulukla tahmin edildiği görülmüştür. Elde edilen %81,80 ortalama doğruluk oranı, çok katmanlı algılayıcı (MLP) modelinin borsa endeksi tahmininde etkili bir yöntem olduğunu göstermektedir.

Anahtar Kelimeler: Finansal Piyasalar, Derin Öğrenme, Çok Katmanlı Algılayıcı, Sınıflandırma

JEL Kodları: C45, C53, G15, G17

[1] Lecturer Dr., Harran University, Suruç Vocational School, 63800, Şanlıurfa, nazifayyildiz@harran.edu.tr, ORCID: 0000-0002-7364-8436

1. Introduction

Stock market indices play a pivotal role as essential benchmarks, serving as reliable indicators to assess the overall trajectory of financial markets. The ability to accurately predict these indices holds paramount significance for various stakeholders, including investors, decision-makers, and regulatory authorities. Such predictions aid in making well-informed investment choices, conducting effective risk assessments, and analyzing broader fiscal policies (Kanwal et al., 2022). The ongoing and extensive exploration of accurately anticipating the future trajectory of stock market indices reflects the continuous efforts of both industry practitioners and researchers. However, the intricate nature of stock values, influenced by a myriad of factors encompassing internal company operations and external market dynamics, poses a formidable challenge in the realm of stock price prediction (Cui et al., 2023).

The advantages of predicting price trends in the stock markets extend beyond the financial realm, benefiting not only the markets themselves but also investors, stock market regulators, and business managers. Anticipating the direction of stock prices can contribute to economic growth by stimulating increased investment flow into the market. Furthermore, it empowers investors to make informed adjustments in their portfolios, enabling the formulation of effective buying and selling strategies to maximize returns. The implications are far-reaching, providing valuable guidance for market regulators to make accurate decisions and implement corrective measures, thereby fostering the fair and efficient operation of the market. Additionally, the ability to predict stock prices presents a unique opportunity for business managers to navigate the markets strategically, taking the right steps to maximize firm values (Mallikarjuna and Rao, 2019). This predictive capability becomes a crucial tool in the hands of decision-makers, allowing them to steer their companies through dynamic market conditions and capitalize on emerging opportunities.

The predictability of price trends in stock markets depends on determining the most suitable analysis method for the market and accurately forecasting trends. However, the predictability of stock prices is a controversial topic in the literature, discussed through the Efficient Market Hypothesis (EMH) introduced by Eugene Fama in 1970. EMH argues that stock prices are determined by new information, prices are unpredictable with past information, and follow a random walk. Since its inception, EMH has been consistently criticized, and its validity has been questioned. On the other hand, in capital markets, two main methods, fundamental and technical analysis, are employed for predicting stock prices. Fundamental analysis involves the analysis of financial statements and economic indicators. On the flip side, technical analysis hinges on the examination of historical prices as a means to forecast future price movements. Beyond these traditional approaches, the realm of predicting time series in securities markets incorporates econometric and statistical methods. Techniques like Auto Regressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR), and Seasonal Auto Regressive Integrated Moving Average (SARIMA) are employed to enhance the accuracy of projections in this domain. Nevertheless, linear approaches might encounter difficulties in capturing intricate and nonlinear connections among variables that impact stock prices. In recent times, there has been a development of potent tools for stock market analysis through the application of machine learning techniques. Prediction-based models created by machine learning methods exhibit elevated accuracy by effectively addressing the nonlinear and non-stationary attributes of financial series (Kumbure et al., 2022; Ayyildiz and Iskenderoglu, 2023). In recent years, the application of machine learning techniques has led to the development of powerful tools for stock market analysis. Prediction models created using machine learning methods provide high accuracy by effectively handling the nonlinear and non-stationary characteristics of financial series (Kumbure et al., 2022; Ayyildiz and Iskenderoglu, 2023). Recently, deep learning has emerged as the most effective prediction method in the field of machine learning and has been applied across various domains. This continuously evolving field has seen the development and implementation of new deep learning-based prediction models (Sezer et al., 2020). Deep learning models utilize algorithms designed to capture high-level abstractions in data through multilayer structures involving numerous linear and nonlinear transformations (Lecun et al., 2015; Zhong and Enke, 2019). One of the key characteristics of deep learning models is their ability to efficiently process large datasets, enabling the identification of intricate nonlinear relationships among input features (Najafabadi et al., 2015; Beniwal et al., 2024). Among deep learning models, the Multilayer Perceptron (MLP) stands out due to its strong learning capacity, flexibility, and ability to model complex relationships in financial time series. MLP, as a fully connected feedforward neural network, can effectively capture nonlinear relationships in financial data, enhancing prediction accuracy (Hornik et al., 1989). Compared to other deep learning methods such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), MLP offers a simpler yet effective architecture that is computationally more efficient while still achieving high prediction accuracy. Moreover, the flexible structure of MLP allows for hyperparameter optimization, making it adaptable to different market conditions and more efficient compared to other deep learning models (Guresen et al., 2011).

The aim of this study is to measure the prediction performance of the Multilayer Perceptron (MLP) method, one of the deep learning models, on the stock market indices of developed countries. In line with this objective, daily data sets and technical indicators were utilized to predict the directional movements of the main stock market indices of G7 countries; NYSE 100 (USA), FTSE 100 (UK), NIKKEI 225 (Japan), CAC 40 (France), FTSE MIB (Italy), DAX 30 (Germany), and TSX (Canada) indices between January 1, 2014, and December 31, 2023, using the deep learning method.

In this study, stock indices of G7 countries, representing developed nations, have been predicted. As G7 countries hold some of the largest and most influential markets in the global economy, accurate prediction of these indices is crucial as their movements have a direct impact on worldwide markets. Successfully forecasting the movements of G7 indices plays a critical role in strategic decision-making for global investors and is essential for anticipating potential market fluctuations on an international scale. These predictions are not only significant for national-level investment strategies but also crucial for maintaining global economic balances. Therefore, the aim of this study is not only to contribute academically but also to provide valuable insights for investors and policymakers by considering the global impact of G7 stock markets.

In the literature, studies focusing on predicting the directions of stock market indices using deep learning methods have been observed, where one or more different stock market indices are predicted. However, there is no study that specifically examines the stock market indices of countries belonging to a particular economic group or category using deep learning algorithms, such as Multilayer Perceptron. Therefore, it is expected that this study will contribute to the existing literature in terms of its scope, the method used, and the findings obtained.

The next section of the study provides a summary of the literature focusing on deep learning models for predicting stock market indices in developed countries. In the third section, the dataset used in the research is explained, and the fourth section details the deep learning method employed in the application. The findings obtained from the research are presented and compared with similar studies in the literature in the fifth section. In the conclusion part of the study, the overall results are evaluated, and recommendations are provided for market participants, regulators, and researchers who may conduct similar studies in the future.

2. Literature Review

Within the scope of the study, research focusing on the prediction of stock market index movements of developed countries using the deep learning method has been reviewed. In this section, the studies examined within the literature review are presented in two parts. The first part covers studies that concentrate on the directional movements of stocks in developed country stock markets using the deep learning method, while the second part summarizes studies that investigate the stock market indices of developed countries.

In the pioneering study by Takeuchi and Lee (2013), which focuses on predicting the directional movements of stocks traded on NYSE, AMEX, and Nasdaq stock exchanges in the United States using the deep learning method, stock movements were forecasted for the period 1990-2009. Stocks with a monthly closing price below $5 were excluded from the analysis. According to the analysis results, an average accuracy rate of 53.36% was achieved. In the study by Karmiani et al. (2019), the directional movements of stocks such as Google, Microsoft, Apple, Acer, IBM, Amazon, HP, Sony, and Intel were predicted using the Long Short-Term Memory (LSTM) model with daily data and six technical indicators between January 2009 and October 2018. The study reported an average accuracy rate of 68.5%. Şişmanoğlu et al. (2020) focused on IBM stock on the New York Stock Exchange, using three different deep learning models—LSTM, GRU, and BLSTM—with daily data from 1968 to 2018. The analysis determined that the direction of IBM stock was predicted with an accuracy of 63.54%. In the study by Karlis et al. (2021), attention was given to stocks of firms in the technology index in the United States, including APPLE, NVIDIA, TESLA, and IBM. Using daily data from 2011 to 2015 and input data from Standard & Poor's 100, DJI, and NASDAQ100 indices, predictions were made with the LSTM model. The results showed accuracy rates of 84%, 61%, 68%, and 69% for the direction of APPLE, NVIDIA, TESLA, and IBM stocks, respectively. Gudelek et al. (2017) focused on ETFs (Exchange Traded

Funds), consisting of commodities, bonds, and index funds, which have had a significant impact on financial markets in recent years. The study predicted the directional movements of the 17 most frequently traded ETFs on the New York Stock Exchange using the LTSM model. The model utilized daily data, trend indicators, and momentum indicators between 2000 and 2017, achieving a prediction accuracy of 72%.

In the study by Li and Tam (2017), considered a pioneering effort in predicting directional changes in stock market indices of developed countries through the application of deep learning methodologies, the Long Short-Term Memory (LSTM) model was specifically employed to forecast the directional movements of the NIKKEI 225 index. Daily data spanning from January 1, 2010, to December 31, 2016, along with nine technical indicators, were utilized, resulting in an accuracy of 61.07% in predicting the directional trends of the NIKKEI 225 index. Oncharoen and Vateekul (2018) utilized the LSTM model with daily data from October 20, 2006, to December 12, 2017, and seven different technical indicators to predict the directional movements of the DJIA and S&P500 indices. The study achieved a 63.01% accuracy in predicting the movement directions of the examined indices. In a study by Noh et al. (2023), which examined S&P500 and DJIA indices together, daily data from 2021 to 2022 were used to predict the movement directions of these indices. The F1 score was used as the main measurement for model performance, and the prediction performance was found to be 64.07%. Lei (2018) focused on NIKKEI 225 and DJI indices, using daily price and trading volume data from March 15, 2009, to May 24, 2014, for NIKKEI 225 and from October 22, 2009, to July 18, 2014, for DJI. The NIKKEI 225 and DJI indices were predicted with accuracies of 65.41% and 66.12%, respectively. Minh and others (2018) achieved a 60.98% accuracy in predicting the direction of the S&P 500 using daily data between October 1, 2001, and January 1, 2015, and three technical indicators on an LSTM model. In a similar study by Saxena (2023), the direction of the S&P 500 index was predicted with a 62% accuracy using daily data from January 1, 2000, to December 31, 2019. Damrongsakmethee and E. Neagoe (2020), examining S&P 500 and DJI indices together, used daily data between February 11, 2010, and February 10, 2020, achieving prediction accuracies of 85.86% for the S&P 500 index and 83.62% for the DJI index. Yang et al. (2020) proposed a deep learning model focusing on five different stock indices, namely CAC40, DJIA, S&P 500, NASDAQ, and DAX. Daily data and ten technical indicators between January 4, 2010, and December 29, 2017, were used. The S&P 500 index achieved the highest accuracy at 65%, and the suggested deep learning model demonstrated prediction performance ranging from 50% to 65%. Derbentsev et al. (2021) focused on five different stock market indices, including S&P500, DJI, NASDAQ, NIKKEI 225, and DAX. Daily data from January 1, 2015, to June 1, 2021, were used to predict the indices using Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and CNN-RNN hybrid models. The obtained prediction accuracy rates were 62% for DJI, 60.9% for NIKKEI 225, 60.8% for S&P500, 57.6% for NASDAQ, and 56.4% for DAX.

In the literature, various studies focus on predicting stock market index directions using deep learning methods; however, these studies often overlook stock indices belonging to specific economic groups. Most studies prefer LSTM and CNN models due to their ability to capture sequential dependencies. However, LSTM requires high computational power and carries the risk of overfitting, while CNN is primarily designed for spatial data analysis and is limited in directly capturing sequential patterns in financial time series. Compared to these models, MLP is computationally more efficient, has strong generalization ability, and is more suitable for structured financial data (Guresen et al., 2011). Additionally, this study differs from previous research in terms of technical indicator selection, as the indicators used were not chosen arbitrarily but were carefully selected based on their statistical significance and contribution to prediction accuracy. Furthermore, the dataset used in this study is broader in scope, focusing on the stock indices of G7 countries rather than individual stocks or isolated indices, allowing for a more comprehensive analysis of global market trends. Due to these differences in dataset composition, accuracy comparisons with previous studies should consider variations in market conditions, time frames, and data processing methods. The preference for MLP over more complex models and the meticulous selection of technical indicators make this study a significant contribution to the literature in terms of both methodology and findings.

3. Data Set

This study aims to predict the directional movements of stock market indices in developed countries using the Multilayer Perceptron method. In this context, the focus is on the Group of Seven (G7) countries, which are considered developed nations. The selection of stock market indices is based on the countries with the highest market capitalization and their main stock indices. Accordingly, the following indices are considered: NYSE 100 (USA), FTSE 100 (United Kingdom), NIKKEI 225 (Japan), CAC 40 (France), FTSE MIB (Italy), DAX 30 (Germany), and TSX (Canada). Subsequently, an appropriate research period for the application is determined. Similar studies in the literature are reviewed to identify the research periods used, and it is observed that research periods covering ten years, such as in the studies by Damrongsakmethee and E. Neagoe (2020) and Saxena (2023), are more commonly employed. Therefore, a ten-year period from January 1, 2014, to December 31, 2023, is chosen as the research period. Daily data for stock indices has been obtained from www.investing.com. The number of days the stock markets are open during the determined research period varies due to national and official holidays. In this context, during the examined period, there are 2,516 daily data points for NYSE 100, 2,525 for FTSE 100, 2,473 for NIKKEI 225, 2,560 for CAC 40, 2,556 for FTSE MIB, 2,536 for DAX 30, and 2,508 for TSX. Considering the ten-year analysis period, these data points are directly used in the analyses, assuming no significant imbalance that could potentially affect the analysis results. To assess the reliability of the dataset, tests for normality, autocorrelation, multicollinearity, and heteroscedasticity were conducted. The normality test indicated that the data followed a normal distribution; the autocorrelation analysis showed that the error terms were independent; the multicollinearity test confirmed that there was no high correlation among the independent variables; and the heteroscedasticity analysis demonstrated that the error terms had a constant variance.

Technical indicators used in studies focusing on index direction prediction with Multilayer Perceptron models were examined for the selection of technical indicators in this study. In this context, the technical indicators used in Li and Tam (2017), Oncharoen and Vateekul (2018), and Yang et al. (2020) studies were initially calculated. Following this, specific indicators that enhance prediction performance—those demonstrating a statistically significant contribution to the model—were subsequently incorporated into the analysis as input variables.

Table 1 presents the technical indicators used as input variables along with their calculation methods.

Table 1: Technical Indicators and Calculations

Technical Indicators	Calculation Method
Simple Moving Average (MA)	$\frac{\mathbf{C_t + C_{t-1} + \cdots + C_{t-30}}}{\mathbf{n}}$
Weighted Moving Average (WMA)	$\frac{((\mathbf{n}) * \mathbf{C_t} + (\mathbf{n-1}) * \mathbf{C_{t-1}} + \cdots + \mathbf{C_{t-14}}}{(\mathbf{n} + (\mathbf{n-1}) + \cdots + \mathbf{1})}$
Exponential Moving Average (EMA)	$\mathbf{EMA(k)_t = EMA(k)_{t-1} + a * (C_t - EMA(k)_{t-1}}$
Stochastic D% (D%)	$\frac{\sum_{\mathbf{I=0}}^{\mathbf{n-1}} \mathbf{K_{t-I}}\%}{\mathbf{n}}$
Stochastic K% (K%)	$\frac{\mathbf{C_t - LL_{t-n}}}{\mathbf{HH_{t-n} - LL_{t-n}}} * \mathbf{100}$
Momentum (Mom)	$\mathbf{C_t - C_{t-n}}$
Relative Strength Index (RSI)	$\mathbf{100} - \frac{\mathbf{100}}{\mathbf{1} + (\sum_{\mathbf{I=0}}^{\mathbf{n-1}} \mathbf{Up_{t-i}} / \mathbf{n}) / (\sum_{\mathbf{I=0}}^{\mathbf{n-1}} \mathbf{Dw_{t-i}} / \mathbf{n})}$
Moving Average Convergence/Divergence (MACD)	$\mathbf{MACD(n)_{t-I}} + \frac{\mathbf{2}}{\mathbf{n+1}} * \mathbf{DIFF_t - MACD(n)_{t-1}}$
Commodity Channel Index (CCI)	$\frac{\mathbf{M_t - SM_t}}{\mathbf{0,015D_t}}$
Larry William's R% (LW)	$\frac{\mathbf{H_n - C_t}}{\mathbf{H_n - L_n}} * \mathbf{100}$

*$\mathbf{C_t}$: Closing Price
$\mathbf{H_t}$: Highest Price
$\mathbf{L_t}$: Lowest Price
$\mathbf{DIFF_t = EMA(12)_t - EMA(26)_t}$
a: Adjustment Factor
$\mathbf{HH_t}$: Highest of the highest within last *t* days

$\mathbf{LL_t}$: Lowest of the lowest within the last *t* days
$\mathbf{M_t = (H_t + L_t + C_t)/3}$
$\mathbf{SM_t = \sum_{I=0}^{n} M_{t-I+1}/n)}$
$\mathbf{D_t = \sum_{I=1}^{n} | M_{t-I+1} - SM_t|/n}$
$\mathbf{DV_t}$: Downward price at time *t*
$\mathbf{UP_t}$: Upward price at time *t*

Source: Yang et al, (2020).

In this study, input variables aimed at enhancing the performance of the Multilayer Perceptron model include indicators such as Simple Moving Average, Weighted Moving Average, Exponential Moving Average, Stochastic D, Stochastic K, Momentum, Relative Strength Index, Moving Average Convergence Divergence, Commodity Channel Index, and Larry William's R. These indicators are calculated based on past closing data. In the analysis, the next day's directional movement, expressed as 'rise' or 'fall' based on the closing prices of stock indices, is utilized as the output data.

During the implementation phase of the Multilayer Perceptron model, it becomes important to partition the dataset into distinct segments, specifically as training and test datasets, in an appropriate proportion. The Multilayer Perceptron model is trained on the designated training dataset, and the predictions are then compared with the test dataset to evaluate the model's predictive performance. While there is no general consensus in the literature regarding the optimal dataset split ratio, a commonly recommended ratio for classification processes involving large datasets is 80% for training and 20% for testing (Racz, 2021). Similarly, in related studies such as Karmiani et al. (2019), Damrongsakmethee and E. Neagoe (2020), Yang et al. (2020), and Derbentsev et al. (2021), an 80:20 ratio is observed. Based on literature recommendations and similar studies, the dataset used linearly was divided into two parts: the first 80% covering the initial eight years was used as training data, and the remaining 20% covering the last two years was used as test data. An optimization process was conducted to determine the hyperparameters used in the model. After optimization, the model was trained, and the predictions were compared with the test dataset to measure the accuracy of the Multilayer Perceptron model's predictions. In the scope of the application, all modeling and data analysis tasks were performed using RapidMiner, version 10.3.

4. Method

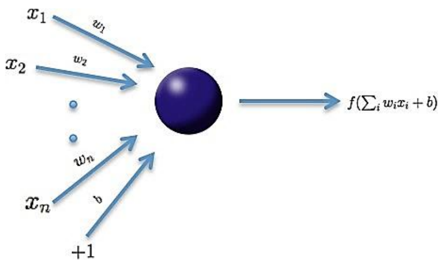
Multilayer Perceptron (MLP) models are based on multilayer feedforward artificial neural networks trained using stochastic gradient descent and the backpropagation method. These networks can contain multiple hidden layers, each composed of neurons with activation functions like tanh, rectifier, and maxout. Advanced techniques such as adaptive learning rate, learning rate annealing, momentum-based learning, and dropout play a crucial role in enhancing prediction accuracy. During training, each node independently trains a copy of the model parameters on local data asynchronously using multiple threads. At regular intervals, these nodes contribute to the global model through model averaging (Goodfellow et all., 2016: 210).

The MLP model follows a feedforward architecture. At its core lies the neuron, a unit modeled after the biological structure of human nerve cells. In the human brain, neurons transmit output signals of different strengths through synapses, which are then combined as inputs to trigger a connected neuron. The equation for computing these weighted combinations is provided in Equation (1) (Stetsenko, 2017).

$$\alpha = \sum_{i=1}^{n} w_i x_i + b \quad (1)$$

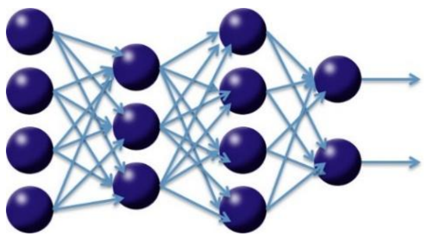
As shown in Equation (1), the model calculates a weighted sum of input signals, which is then passed through the connected neuron to produce an output signal, f(α). Figure 1 graphically represents the function f, which refers to the non-linear activation function used in the network, and the bias term b, which indicates the neuron's activation threshold, as illustrated in Figure 1 (Arora et al., 2015).

Figure 1: Activation Function



Multilayer feedforward neural networks consist of interconnected neuron units, starting with an input layer that represents the feature space, as shown in the accompanying diagram. Following this, several layers introduce nonlinearity, leading to a final classification layer that represents the output space. The inputs and outputs of the units in the model follow the basic principles of a single neuron, as explained earlier (Stetsenko, 2017).

Figure 2: Multilayer Perceptron



Bias units are included beneath each output layer. The weights, which define the relationships between neurons and their connections, directly influence the network's final output. During training, these weights are adjusted to reduce the error on labeled data. As shown in Equation (1), the objective for each training example j is to minimize a loss function (Arora et al., 2015).

$$L(W, B \mid j) \tag{2}$$

Here, W represents the collection $\{W_i\}_{1:N-1}$ denoting the weight matrices connecting the layers between *i* and *i+1* for a network with N layers. Similarly, B is the collection $\{b_i\}_{1:N-1}$ representing the bias column vectors for the *i+1* layer. This basic framework of multilayer neural networks is utilized to perform deep learning tasks (Candel and Ledel, 2023).

The parameters utilized during the training and implementation processes of the Multi-layer Perceptron (MLP) model are presented in detail below (RapidMiner, 2024):

- Activation Function for Hidden Layers: The hidden layers of the model utilize the ReLU (Rectified Linear Unit) activation function. ReLU is favored for its ability to effectively capture nonlinear relationships. In classification tasks, the output layer employs the softmax activation function, which transforms the model's output into a probability distribution across different classes, thereby improving classification performance.
- Learning Rate: The learning rate is set to 0.01. This parameter is crucial as it dictates the extent to which the weights are adjusted during each training iteration. A smaller learning rate promotes more careful adjustments but may necessitate a greater number of epochs for convergence.
- Number of Epochs: The model is trained over 10 epochs. The number of epochs represents how many times the model goes through the entire training dataset, influencing its overall performance.
- Batch Size: The batch size is set to 32. This refers to the number of training examples used to update the model's weights during each iteration, impacting the training efficiency.
- Dropout Rate: The dropout rate is set to 0.5. This technique is employed to mitigate overfitting by randomly disabling neurons during training, which aids the network in generalizing more effectively.
- Momentum: Momentum is set to 0.9. This parameter helps accelerate the learning process by pushing the gradient vectors in the correct direction, thus speeding up convergence.
- Optimization Algorithm: The Stochastic Gradient Descent (SGD) algorithm is employed. SGD updates the model weights incrementally based on each batch of data, enhancing computational efficiency and reducing the likelihood of getting stuck in local minima.

- Hyperparameter Optimization and Cross-Validation: To enhance model performance and prevent overfitting, hyperparameter optimization was performed using the Grid Search method. Grid Search systematically explores predefined hyperparameter combinations to determine the optimal model configuration. Additionally, 10-fold cross-validation (k=10) was applied to improve the model's generalization ability and further mitigate overfitting.

5. Findings and Discussion

In the context of binary classification through deep learning methods, the assessment of classification performance is conducted using a confusion matrix. The specific confusion matrix employed for binary classification is outlined in Table 3 (Han et al, 2012).

Table 2: Binary Classification Confusion Matrix

	True Positive Value	***True Negative Value***
Predicted Positive Value	*True Positives*	*False Negatives*
Predicted Negative Value	*False Positives*	*True Negatives*

Evaluating the performance of classifiers is a crucial step in developing and selecting effective and accurate classification models. This process requires the use of various performance metrics to measure the success of the classifier. However, there is no universal guideline for selecting the most appropriate metric (Liu et al., 2014). Four key metrics are commonly employed to assess classification performance: accuracy, precision, recall, and F1 score. Accuracy, the most frequently used metric, is calculated as the ratio of correctly classified instances to the total dataset, providing an overall success rate of the model. When predicting the directional movements of stock indices, accuracy reflects how often the model correctly predicts whether the market will rise or fall. High accuracy means the model often predicts market trends correctly. Precision refers to the proportion of true positive instances among those predicted as positive by the model. In the context of stock index movement predictions, precision indicates how reliable the model is when forecasting an upward trend. High precision suggests that when the model predicts a rise, it is likely to be accurate, thereby reducing false alarms. Recall measures how well the model captures all actual positive instances. For stock market movements, recall shows how effectively the model detects real upward trends. High recall means the model successfully identifies actual upward trends, though it may still misclassify some instances. The F1 Score provides a harmonic mean of precision and recall, balancing these two metrics. In the case of predicting stock index movements, the F1 Score evaluates the model's ability to make accurate positive predictions while also identifying all true positive cases. A high F1 Score signifies that the model performs well in both accuracy and comprehensiveness. The formulas for these metrics are provided in Equations (3), (4), (5), and (6) (Sokolova and Lapalme, 2009).

$$Accuracy = \frac{True\ Pozitive + True\ Negative}{Pozitive + Negative} \tag{3}$$

$$\text{Precision} = \frac{True\ Pozitive + \text{False Positives}}{True\ Pozitives} \tag{4}$$

$$\text{Recall} = \frac{True\ Pozitive + False\ Negatives}{True\ Pozitives} \tag{5}$$

$$F1\ Score = 2x \frac{Precision\ x\ Recall}{Precision\ +\ Recall} \tag{6}$$

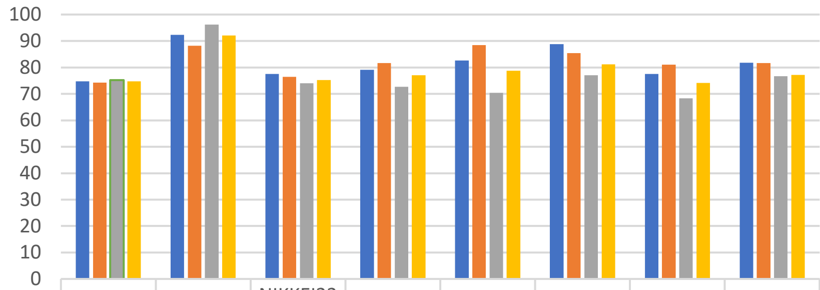
In this study, while the overall evaluation is based on accuracy, the model's performance has also been further examined by calculating additional metrics such as precision, recall, and F1 score. To better understand the performance of the MLP model in predicting the directional movements of stock indices, the confusion matrices, are presented in Table 3.

Table 3: Confusion Matrix

Stock Index	Movement Direction	Actual Rise	Actual Fall	Total
NYSE 100	Predicted Rise	187	65	252
	Predicted Fall	62	189	251
	Total	249	254	503
FTSE100	Predicted Rise	223	30	253
	Predicted Fall	9	243	252
	Total	232	273	505
NIKKEI225	Predicted Rise	167	52	219
	Predicted Fall	59	217	276
	Total	226	269	495
CAC 40	Predicted Rise	179	40	219
	Predicted Fall	67	226	293
	Total	246	266	512
FTSE MIB	Predicted Rise	162	21	183
	Predicted Fall	68	260	328
	Total	230	281	511
DAX 30	Predicted Rise	175	30	205
	Predicted Fall	52	250	302
	Total	227	280	507
TSX	Predicted Rise	162	38	200
	Predicted Fall	75	227	302
	Total	237	265	502

Upon examining the confusion matrix in Table 3, it is observed that the MLP model correctly predicted the movements of the NYSE 100 index with 187 rises and 189 falls out of 503 daily movements, the FTSE 100 index with 223 rises and 243 falls out of 505 daily movements, the NIKKEI 225 index with 167 rises and 217 falls out of 495 daily movements, the CAC 40 index with 179 rises and 226 falls out of 512 daily movements, the FTSE MIB index with 162 rises and 260 falls out of 511 daily movements, the DAX 30 index with 175 rises and 250 falls out of 507 daily movements, and the TSX index with 162 rises and 227 falls out of 502 daily movements. Based on these results, the calculated binary classification metrics can be examined in detail in Figure 1.

Figure 3: Classification Performance Metrics of the MLP Model



	NYSE 100	FTSE 100	NIKKEI225	CAC 40	FTSE MIB	DAX 30	TSX	Average
Accuracy (%)	74,75	92,28	77,58	79,10	82,58	88,83	77,49	81,80
Precision (%)	74,30	88,20	76,40	81,70	88,50	85,40	81,00	81,70
Recall (%)	75,20	96,20	74,00	72,70	70,40	77,10	68,30	76,70
F1 Score *100	74,70	92,10	75,20	77,00	78,70	81,20	74,10	77,20

As shown in Figure 3, the classification performance of the MLP model for stock indices achieved accuracy rates of 74.75% for the NYSE 100 index, 92.28% for the FTSE 100 index, 77.58% for the NIKKEI 225 index, 79.10% for the CAC 40 index, 82.58% for the FTSE MIB index, 88.83% for the DAX 30 index, and 77.49% for the TSX index. The directional movements of the main stock indices of the G7 countries were predicted with an average accuracy of 81.80%, indicating a high level of predictive success for the MLP model.

Although accuracy was the primary metric in this study, the model's performance was also evaluated using other key classification metrics, including precision, recall, and F1 score. As shown in Figure 3, the average precision was calculated as 81.7%, recall as 76.7%, and the F1 score as 77.2%. These values confirm the model's strong overall classification performance. The precision rate of 81.7% suggests that investors can rely on the model's ability to correctly predict upward movements. The recall rate of 76.7% indicates that the model successfully captures most upward signals, while the F1 score of 77.2% highlights the model's balanced classification ability between precision and recall. Considering the diverse characteristics of stock indices, such as market value, trading volume, and technical market structures, these high-performance metrics suggest that the model consistently delivers accurate predictions across different indices.

The differences in accuracy rates among the stock indices should also be evaluated. For instance, while the FTSE 100 index achieved a high accuracy rate of 92.28%, the NYSE 100 index had a relatively lower accuracy of 74.75%. This discrepancy may be related to factors such as market structure, trading volume, and volatility levels. As the U.S. markets are characterized by high-frequency trading activities and a strong sensitivity to news flow, the model's predictive performance may have been affected by these elements. Conversely, the more stable price movements observed in European markets, such as the FTSE 100, may have allowed the MLP model to make more accurate predictions. Moreover, the effectiveness of technical indicators may vary across different market structures. For example, in more volatile markets such as the NYSE 100 and NIKKEI 225, the predictive power of technical indicators may sometimes be limited. Momentum indicators and moving averages, in particular, may produce less meaningful signals in highly fluctuating markets, which could have contributed to the lower accuracy rates observed for certain indices.

The performance of the MLP model becomes more meaningful when compared to previous studies in the literature. This study achieved accuracy rates of 74.75% for the NYSE 100 index, 92.28% for the FTSE 100 index, 77.58% for the NIKKEI 225 index, 79.10% for the CAC 40 index, 82.58% for the FTSE MIB index, 88.83% for the DAX 30 index, and 77.49% for the TSX index. Additionally, the directional movements of the main stock indices of the G7 countries were predicted with an average accuracy of 81.80%. When compared to similar deep learning-based stock market prediction studies in developed countries, the results show a relatively higher predictive success. For instance, previous studies reported the following accuracy rates: Takeuchi and Lee (2013): 53.36%, Karmiani et al. (2019): 68.5%, Şişmanoğlu et al. (2020): 63.54%, Karlis et al. (2021): 70.5%, Gudelek et al. (2017): 72%, Li and Tam (2017): 61.07%, Oncharoen and Vateekul (2018): 63.01%, Lei (2018): 65.76%, Minh et al. (2018): 60.98%, Saxena (2023): 62%, Damrongsakmethee and Neagoe (2020): 84.74%, Yang et al. (2020): 65%, and Derbentsev et al. (2021): 60%. Thus, the 81.80% average accuracy achieved in this study represents a relatively higher success compared to similar research in the literature. This predictive success can be attributed to the effectiveness of the deep learning model and the technical indicators used as input data.

The predictive performance of the MLP model can also be compared with previous studies on stock index forecasts. For instance, Yang et al. (2020) used various hybrid deep learning models to predict the NYSE 100 index, obtaining accuracy rates ranging from 50% to 65%. Therefore, the 74.75% accuracy rate achieved for the NYSE 100 index in this study indicates a superior performance. Similarly, studies focusing on the NIKKEI 225 index reported accuracy rates of 61.07% (Li and Tam, 2017), 63.01% (Oncharoen and Vateekul, 2018), 65.41% (Lei, 2018), and 60.9% (Derbentsev et al., 2021). The accuracy rate of 77.58% for the NIKKEI 225 index in this study surpasses these previous results. Likewise, for the DAX 30 index, Derbentsev et al. (2021) obtained an accuracy of 56.4%, while this study achieved an accuracy rate of 88.83%, indicating a significantly higher predictive performance.

6. Conclusion

G7 stock indices reflect global economic developments and influence international investment flows. Therefore, applications made in these markets are of great importance for shaping economic trends and investment decisions. It has become a vital necessity for investors and regulators to accurately analyze the movements of these indices in order to enhance economic stability and develop more informed investment strategies. These predictions enable investors to make informed decisions, manage risks more effectively, and seize opportunities. Additionally, since these exchanges form the backbone of the global economic system, accurate directional forecasts are crucial for regulators to ensure market stability and take preventive measures against potential economic fluctuations.

The aim of this study is to assess the predictive performance of a type of deep learning method known as the Multi-Layer Perceptron (MLP) model on the stock indices of G7 countries. In this context, daily data from January 1, 2014, to December 31, 2023, along with technical indicators such as Moving Average, Exponential Moving Average, Weighted Moving Average, Stochastic %D, Stochastic %K, Momentum, RSI, MACD, CCI, and William's %R were calculated and used as input features. The performance of the MLP predictive model in forecasting the directional movements of the indices was examined. The analysis results indicate the following prediction accuracy rates for G7 stock indices: 74.75% for the NYSE 100 index, 92.28% for the FTSE 100 index, 77.58% for the NIKKEI 225 index, 79.10% for the CAC 40 index, 82.58% for the FTSE MIB index, 88.83% for the DAX 30 index, and 77.49% for the TSX index. Consequently, it was concluded that the directional movements of the main stock indices of G7 countries were successfully predicted with an average accuracy of 81.80%.

The results of the study demonstrate that the movements of stock indices can be predicted to a certain extent using deep learning methods based on historical stock index data and technical indicators. The predictability of stock prices can offer various advantages to market participants and regulators. Predictability can primarily support economic growth by increasing investment flows into the market. It can also provide significant benefits to investors, such as wealth preservation, minimizing transaction costs, evaluating investment opportunities, and taking proactive measures against potential risks. This situation is also crucial for market regulators. Accurate predictions can guide regulators in making informed decisions and taking timely corrective actions. Furthermore, accurate analyses based on historical data can assist business managers in enhancing firm values and making strategic decisions. In conclusion, accurately predicting stock market indices can contribute to enhancing the efficiency of financial markets, thereby supporting overall economic stability and business success.

In addition to the obtained results, certain limitations of the study can be discussed. These limitations include the fact that the application is restricted to a specific time period, the lack of macroeconomic variables, and the use of a single deep learning model for predictions. Future studies could enhance the accuracy of prediction models by incorporating macroeconomic data (such as interest rates, inflation, and exchange rates) along with various technical indicators found in the existing literature. The use of hybrid models in prediction processes could also contribute to the development of more effective trading strategies. Additionally, exploring applications on different periods and various stock indices could provide new perspectives for obtaining more reliable and context-specific predictions in financial markets.

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