

Performance evaluation of technical indicators for forecasting the moroccan stock index using deep learning

Ayoub Razouk¹, Moulay El Mehdi Falloul¹, Ayman Harkati¹, Fatima Touhami²

¹Economics and Management, Polydisciplinary Faculty of Beni Mellal, Sultan Moulay Slimane University, Beni Mellal, Morocco

²Economics and Management, Economics and Management Faculty, Sultan Moulay Slimane University, Beni Mellal, Morocco

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ABSTRACT

Navigating the complex terrain of financial markets requires accurate forecasting tools, underscoring the need for effective forecasting methods to assist investors and policymakers alike. This paper explores deep learning techniques for forecasting the Moroccan all shares index (MASI), a prominent indicator of the Moroccan stock market. The study aims to evaluate the performance of technical indicators in enhancing the accuracy of MASI predictions. A comprehensive dataset of daily closing prices of the MASI index is collected and 26 technical indicators are computed from the historical price data. Deep learning models based on artificial neural networks (ANNs) are trained and optimized using the dataset. The performance of the models is evaluated using standard metrics such as mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE). Additionally, feature selection techniques are employed to identify the subset of technical indicators that contribute most significantly to the prediction accuracy. The findings provide insights into the effectiveness of deep learning models and the impact of technical indicators on MASI prediction accuracy. This research has important implications for investors, financial analysts, and policymakers, enhancing investment strategies and risk management approaches.

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Corresponding Author:

Ayoub Razouk

Economics and Management, Polydisciplinary Faculty of Beni Mellal, Sultan Moulay Slimane University

Beni Mellal, Morocco

Email: ayoub.razouk@usms.ma

1. INTRODUCTION

The rapid advancements in artificial intelligence (AI) have revolutionized various domains, including finance and investment [1]. In recent years, the financial sector has undergone a fascinating and remarkable evolution, influenced by these transformative AI developments with its potential to significantly influence the entire financial ecosystem, the innovation of fintech has garnered substantial attention and discussions in recent years [2]. Particularly deep learning algorithms, have gained substantial attention for their potential in predicting stock market trends and facilitating informed decision-making [3]. By leveraging the power of deep neural networks, these algorithms can autonomously learn intricate patterns from vast amounts of data, providing a promising avenue for accurate stock market forecasting [4].

Artificial neural networks (ANNs) are a class of machine learning algorithms designed to emulate the structure and function of the human brain. These networks consist of multiple layers of interconnected nodes, starting with an initial input layer, followed by one or more hidden layers, and ending with an output layer. Data from external sources is received by the input layer and then processed through the hidden layers. Each node within these hidden layers uses an activation function to process the input it receives, thereby influencing

the resulting output. The final result of the network's computations is produced by the output layer. ANNs undergo a training process using the back-propagation method, which refines the connection weights between nodes with the aim of minimizing the discrepancy between the network's output and the intended result. The effectiveness of ANNs depends heavily on the role of activation functions, as they determine the degree of non-linearity apparent in the network's output. Notable and widely accepted activation functions include sigmoid, rectified linear unit (ReLU) and tanh. ANNs have a wide range of applications across various domains such as healthcare [5], food science [6], chemical engineering [7], renewable energy [8], construction management [9].

Within the realm of stock market prediction, several types of ANNs were used for the stock market forecasting, including multilayer perceptrons (MLPs) [10], recurrent neural networks (RNNs) [11], and convolutional neural networks (CNNs) [12]. RNNs, are well-suited for time-series data, as they possess a distinctive ability to adapt to irregular univariate and multivariate time series data by effectively utilizing missing value patterns, time intervals, and intricate temporal dependencies [13]. CNNs are mainly used for image processing, but they have also been applied to stock market forecasting by converting time-series data into images [14]. Based on stock market predictions, the incorporation of technical indicators has been a common practice. Technical indicators are mathematical calculations derived from historical price and volume data, providing insights into market trends, momentum, and volatility [15]. By combining deep learning algorithms with technical indicators, researchers and practitioners aim to enhance the predictive power of the models and capture both short-term fluctuations and long-term trends in stock prices. In research combining technical indicators with deep learning for stock market forecasting, ANNs outperform traditional methods such as regression, especially when the input horizon is matched [16], [17].

The Moroccan all shares index (MASI) is a prominent indicator of the Moroccan stock market's performance, accurately forecasting the MASI is crucial for investors, financial institutions, and policymakers. Various studies have explored the application of machine learning for forecasting purposes. For examples [18] compared support vector regression (SVR), XGBoost, long short-term memory (LSTM), and MLP models to predict daily MSI-20 prices, identifying SVR and MLP as superior performers. Ifleh and El-Kabbouri [19] assessed random forest (RF) and support vector machines (SVM) for Moroccan stock price prediction, favoring RF's consistent performance. Labiad *et al.* [20] demonstrated ANN's efficacy in intraday forecasting. Nahil and Lyhyaoui [21] harnessed SVM for regression and kernel principal component analysis (KPCA) with 23 technical indicators to predict Moroccan bank stocks. Labiad *et al.* [22] found RF and gradient boosted trees superior to SVM for predicting short-term stock movement. These studies collectively illuminate diverse facets of Moroccan stock market forecasting through machine learning approaches. However, predicting stock market movements is a complex task due to the presence of inherent uncertainties and the influence of numerous factors such as economic indicators, global events, and investor sentiment [23], [24]. This study focuses on predicting MASI using deep learning techniques and evaluates the performance of technical indicators in enhancing prediction accuracy. Additionally, the study aims to identify the technical indicators that contribute most significantly to the predictive performance of the models using feature selection techniques. To achieve these objectives, a comprehensive dataset of daily closing prices of the MASI index was collected. 26 technical indicators, such as relative strength index (RSI), moving average convergence divergence (MACD), and bollinger bands, were computed from the historical price data. These indicators were chosen based on their widespread use and recognized importance in technical analysis. The dataset was pre-processed using normalization techniques to ensure compatibility of the variables. It was then divided into training and test sets. The training set facilitated the development of deep learning models, with hyperparameter tuning and optimization to improve performance. Model evaluation used standard metrics including mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE), providing quantitative insights into prediction accuracy.

In the feature selection techniques, their application spans several domains, including the healthcare sector, as demonstrated by the study described in [25]. Furthermore, feature selection was employed to identify the subset of technical indicators that contribute most significantly to prediction accuracy. By understanding the importance and impact of individual indicators, investors and financial analysts can gain valuable insights into the key drivers of the Moroccan stock market, enabling them to make more informed decisions. These findings have important implications for academia and the financial industry, facilitating improved investment strategies and risk management practices. The rest of the paper is organized as follows: it begins with an explanation of the data sources, variables, and methodologies are then described in the data and methodology section. The experimentation and results discussion section presents and analyzes the experimental results. Additionally, this paper contributes to the field by conducting a performance evaluation of technical indicators for forecasting the MASI using deep learning techniques. The evaluation assesses the effectiveness of these indicators and their impact on MASI prediction accuracy.

2. METHOD

The methodology section is divided into several steps. Figure 1 provides a block diagram of these steps with a brief explanation. This diagram provides a visual overview of the process followed.

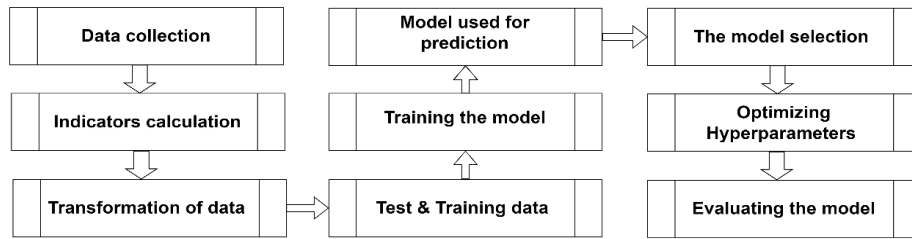


Figure 1. Key steps in forecasting the MASI index

2.1. 1st Step: collection of data

For this work, investing.com was used to gather daily closing stock index data for the MASI index. 2,492 observations were made between January 05, 2009 and January 01, 2019. These observations constitute the daily dataset used for this work.

2.2. 2nd Step: compute indicator variables

The TALIB package in Python is used to calculate 25 indicators as variables in total for the input variables. Table 1 contains information about these indicators. These technical indicators are crucial in forecasting the market index for stocks.

Table 1. Technical indicators and descriptions

Indicator	Description
RSI	Relative strength index measures the speed and change of price movements.
MACD	Moving average convergence divergence indicates the trend and momentum of an asset.
MACD_HIST	MACD histogram shows the difference between the MACD line and the signal line.
CCI	Commodity channel index identifies cyclical trends in an asset's price movement.
DX	Directional movement index measures the strength of the current trend.
SAR	Parabolic SAR (stop and reverse) determines potential reversal points in price direction.
BBAND	Bollinger bands represent volatility and potential price levels.
ADX	Average directional index quantifies the strength of a trend, regardless of its direction.
ADXR	Average directional movement rating is an extension of ADX, providing additional insights.
AROONOSC	Aroon oscillator identifies the strength and direction of a trend.
BOP	Balance of power measures the strength of buyers and sellers in the market.
CMO	Chande momentum oscillator calculates momentum based on price changes.
MINUS_DI	Minus directional indicator reflects the strength of downward price movement.
MINUS_DM	Minus directional movement measures downward price movement.
MOM	Momentum indicates the rate of change in an asset's price.
PLUS_DI	Plus, directional indicator represents the strength of upward price movement.
PLUS_DM	Plus, directional movement measures upward price movement.
ROC	Rate of change measures the percentage change in an asset's price.
ROCR	Rate of change ratio compares the current price to a previous one.
TRIX	Triple exponential average smoothes out price movements to identify trends.
ULTOSC	Ultimate oscillator combines various timeframes to determine momentum.
AD	Accumulation/distribution calculates the money flow into or out of an asset.
OBV	On-balance volume tracks the cumulative buying and selling pressure.
HT_DCPHASE	Hilbert transform-dominant cycle phase identifies dominant cycles in an asset's price.
HT_SINE	Hilbert transform-sine wave generates trading signals based on a sine wave.
HT_TRENDMODE	Hilbert transform-trend mode identifies trending or sideways markets.

2.3. 3rd Step: transformation of data

At this step, min-max normalization is used to execute data type conversions, scaling, and normalization. This process ensures data consistency and uniformity. To enact these transformations, we closely follow the formula outlined (1).

$$y = \frac{x - \text{Min}(x)}{\text{Max}(x) - \text{Min}(x)} \tag{1}$$

2.4. 4th Step: test and training data

The dataset is divided into two sets, namely the training and test data, following an 80:20 ratio. The training data, consisting of 1,993 observations, is exclusively utilized for training predictive models. The machine learning algorithm examines patterns and learns from diverse observations within this set. Conversely, the test data, comprising 500 observations, is employed to assess the accuracy of the trained model and generate predictions. By preserving the actual data for the forecast period, we can evaluate the precision of our predictions and compare them to the real values.

2.5. 5th Step: training the model

To develop the prediction model at this level, we used the ML ANN algorithms and provided them with the features of the training data. ANN consist of many layers that connect input to output. The three building blocks of ANNs are shown in Figure 2: the output layer comes after the input layer and the inner layer. The connections are how initial data is sent from the input layer to the hidden layers. The output layer receives the processed result from the hidden levels.

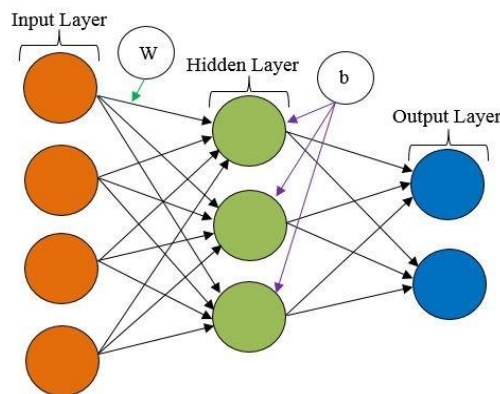


Figure 2. Layers making an ANN

2.6. 6th Step: model used for prediction

To complete the prediction challenge. We deployed a neural network model. This model served as the cornerstone of our approach.

2.7. 7th Step: choosing the model

Initially, the 25 features were utilized. In choosing the model, we selected the top 10 indicators from the many iterations of predictive models based on the highest accuracy. Feature selection aims to eliminate extraneous variables, reduce training time, and prevent overfitting. Recursive feature selection determines the relative relevance depending on prediction accuracy. Several studies employ feature selection algorithms to forecast changes in stock prices [26], [27].

2.8. 8th Step: optimizing hyperparameters

After selecting the relevant features, we aim to identify a collection of hyperparameters. These hyperparameters used by the model to maximize prediction accuracy and optimize overall model performance. This meticulous process of selecting hyperparameters plays an essential role in fine-tuning the model to obtain optimum results.

2.9. 9th Step: evaluating the model

In this study, MAE, MSE, and RMSE are used to evaluate the models performance. These metrics provide a comprehensive assessment of the model's predictive accuracy and robustness. The equations for calculating these metrics are as (2) to (4):

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

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \tag{3}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{4}$$

3. EXPERIMENTATION AND RESULTS DISCUSSION

In deep learning models, selecting the best model for our problem becomes critical. An important aspect to consider is the number of hidden layers required for our model. Therefore, exploring and determining the optimal model configuration that effectively captures the underlying patterns and relationships in the data is essential. Determining the optimal number of hidden layers for a deep learning model poses a significant challenge due to the absence of a definitive rule. Manual selection, in such cases, tends to be impractical and subjective. However, a promising solution emerges through automated techniques like the Keras Tuner library. This powerful tool enables efficient search space exploration, facilitating the identification of the most suitable model configuration through a series of systematic trials. The Keras Tuner empowers researchers to define the architecture of hidden layers by specifying the number of nodes in each layer.

Moreover, it facilitates fine-tuning critical hyperparameters, including learning rates and epochs. Leveraging the capabilities of the Keras Tuner, the model selection process can be streamlined, leading to the discovery of an optimized configuration tailored to the specific problem at hand. Following each trial, the Keras Tuner provides the best performing model, ensuring researchers are equipped with a highly effective deep learning model for their task. Now that our model is established, Figure 3 shows our proposed architecture for model 1, with an input layer of 26 nodes, 10 hidden layers, and an output layer. Our primary objective is to minimise the loss between the predicted and expected data. In order to achieve this objective, it is imperative to determine the optimal learning rate. In Figure 4, we present a detailed analysis of the optimal learning rate, which has been determined to lie within the interval of $[10^{-4}, 10^{-3}]$. This conclusion has been reached through a meticulous assessment of the best loss achieved on the training data. By carefully examining the model’s performance across various learning rates, we have identified this specific range as the most favorable for our objective of minimizing loss. This finding serves as a crucial insight in guiding our further optimization efforts and ensuring the efficacy of our model in accurately predicting the desired outcomes.

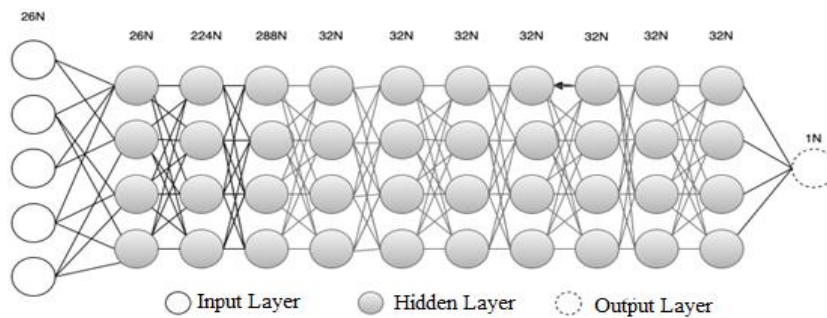


Figure 3. Model architecture

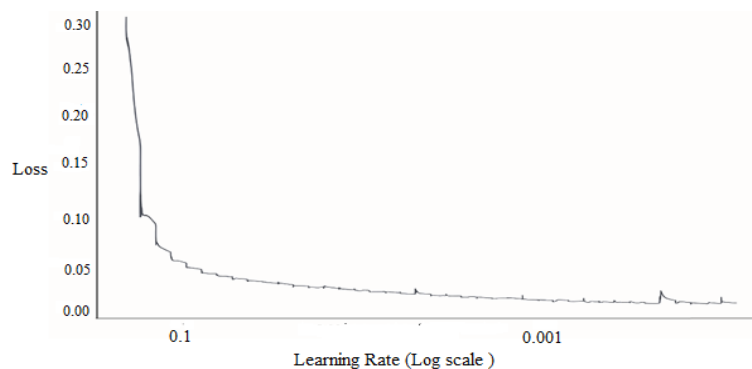


Figure 4. Learning rate interval

Having identified the optimal learning rate, our next step is implementing a scheduler that effectively adjusts the learning rate within the determined interval. To accomplish this, we employ callbacks, a powerful mechanism that allows us to modify the learning rate during training dynamically. By incorporating this technique into our model, we can iteratively update the learning rate at regular intervals, typically every n epoch. This adaptive learning rate scheduling shows a significant improvement in both the loss and validation loss metrics, as depicted in Figure 5. The observed trend reaffirms the effectiveness of our approach in fine-tuning the model's performance and achieving better overall results.

Upon completing the training phase and applying our model for forecasting purposes, we obtained remarkable results regarding MSE and RMSE. The calculated MSE, with a value of 0.046%, indicates the extent to which the predicted values deviate from the expected values. Similarly, the RMSE, computed at 2.1%, measures the average magnitude of these deviations. These evaluation metrics demonstrate our model's high accuracy and precision in capturing and predicting the underlying models within the data. As illustrated in Figure 6, the graph visually showcases the close alignment between the predicted and actual values, further solidifying the credibility and efficacy of our approach.

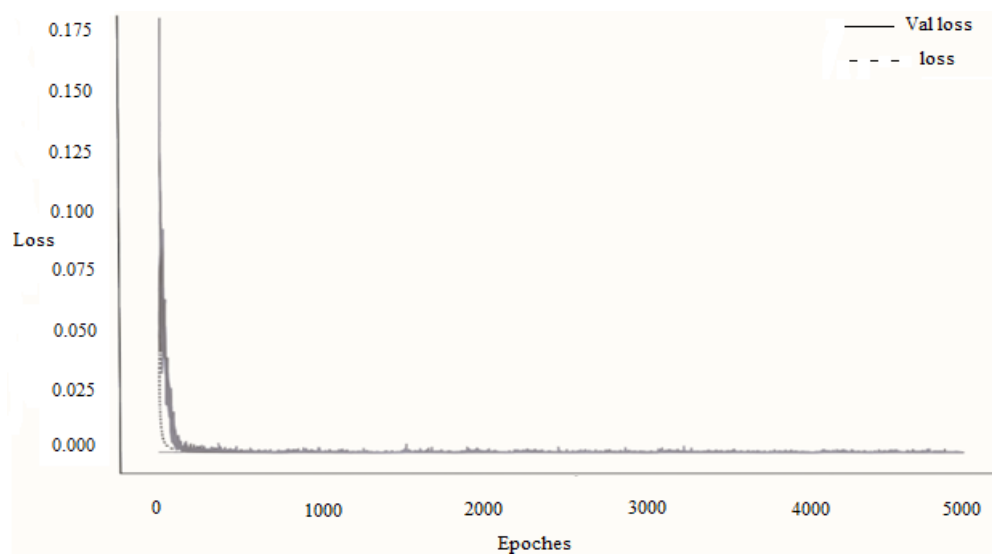


Figure 5. Training loss vs validation loss

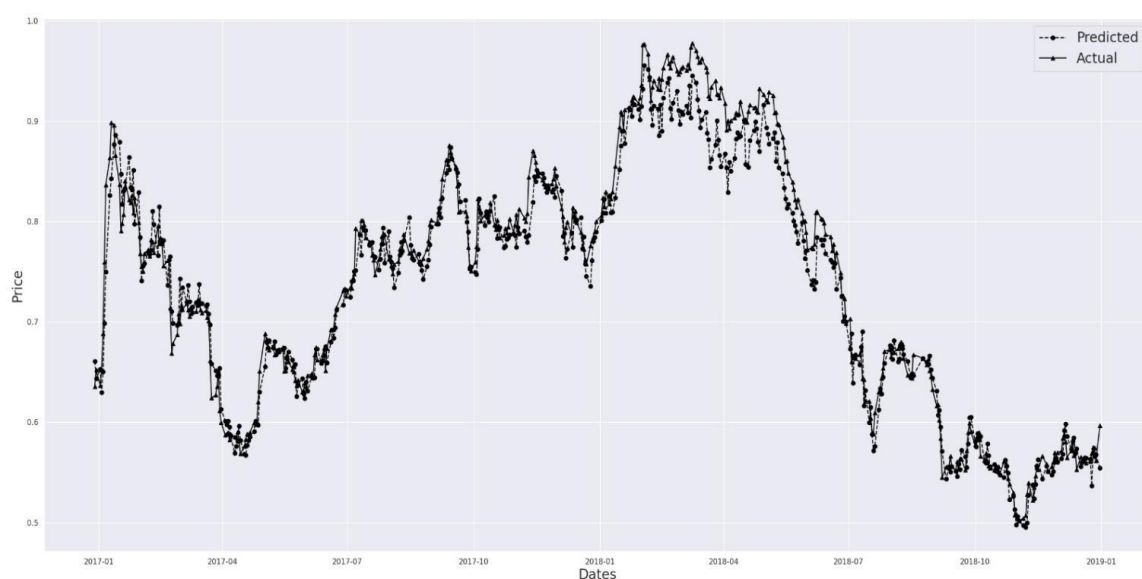


Figure 6. Model 1 results

Following the initial execution of our model, we proceed to perform feature selection by reducing the number of features. This step involves identifying and retaining only the top 10 features with the highest forecast accuracy based on their minimum error. By employing a meticulous evaluation process, we meticulously assess the performance of each feature and select those that yield the most precise and reliable forecasts. This focused selection strategy allows us to streamline the model and concentrate on the most influential and informative features, enhancing the efficiency and effectiveness of our predictive capabilities.

Figure 7 present the results of our feature analysis, showcasing the importance of each feature in relation to the output. Our analysis reveals that “bband” has the highest level of influence, followed by “macd”, “cmp”, “plus_dm”, “minus_dm”, “cci”, “bop”, “ad”, “rsi”, and “plus_di” exerting a substantial impact on the output. On the other hand, features such as “ht_dcphase”, “roc”, and “dx” exhibit relatively lower significance in terms of their contribution to the output. Interestingly, these findings align with the research conducted by [28] who also identified similar features, albeit with slight variations. While there may be subtle differences in the selected features, the overarching objective remains consistent: to identify the most relevant and impactful features that significantly contribute to achieving the desired outcome.

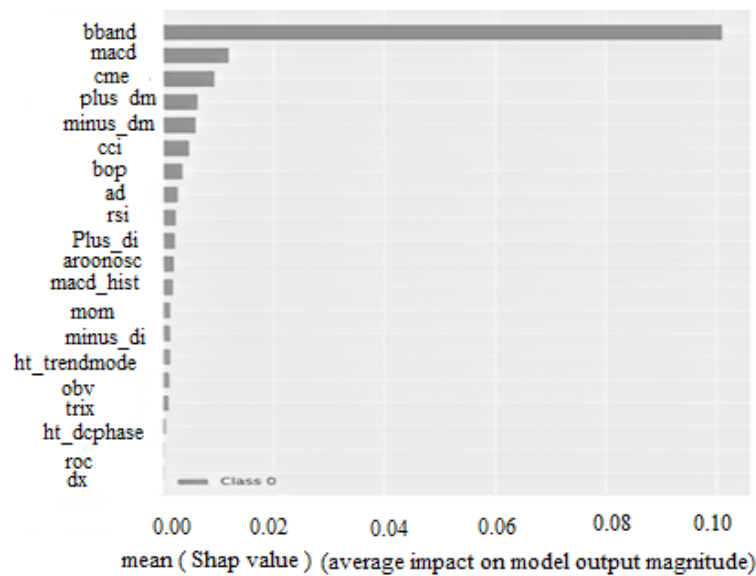


Figure 7. Most important features

In model II, we followed a similar methodology to model I, with the main difference being the alteration of features used in the model. Although the model’s architecture remained unchanged, we selected the top ten features based on their forecast accuracy. The results of model II demonstrated an improvement in performance metrics compared to model I. The MSE decreased from 0.046% to 0.035%, reducing the overall prediction error. Similarly, the RMSE decreased from 2.1% to 1.8%, further indicating improved accuracy in the model’s forecasts. These findings highlight the significance of feature selection in enhancing the model’s performance and achieving more accurate predictions. Table 2 show a summary of different metrics and the difference between model I and II.

Table 2. Metrics difference, model I vs. model II

Metrics	Model I	Model II
MSE	0.049%	0.032%
RMSE	2.2%	1.7%
MAE	1.6%	1.3%

Figure 8 provides a visualization of the model’s performance, highlighting its ability to detect and capture patterns in the data. The observed pattern indicates that the ANN model is learning from the training data and generalizing well to the testing data. This outcome supports the model’s reliability and indicates its potential to make accurate predictions in real-world scenarios.

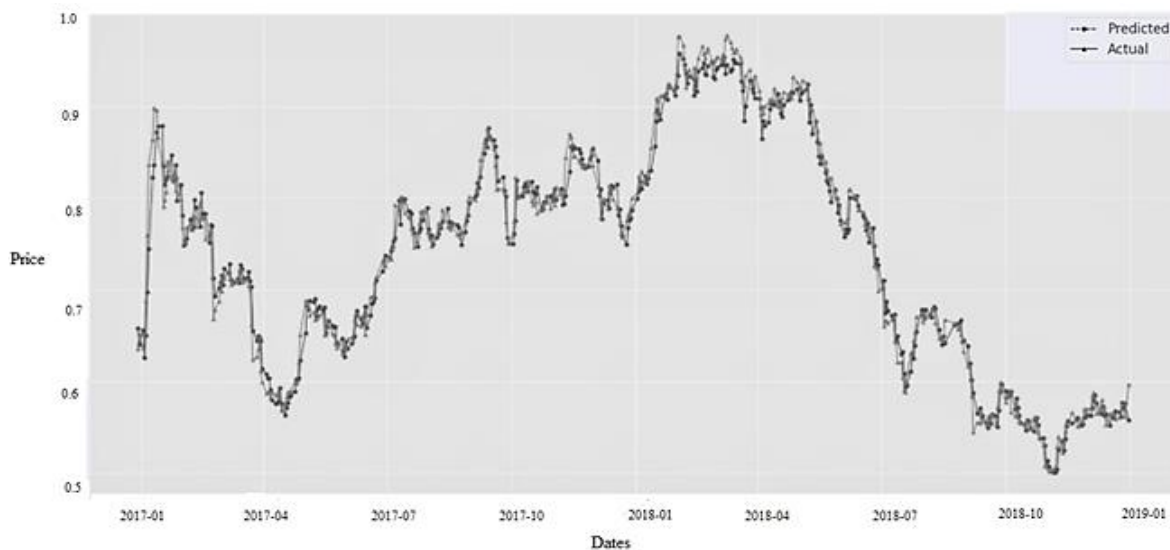


Figure 8. Model 2 results

4. CONCLUSION

In this study, we investigated the effectiveness of deep learning techniques, specifically ANNs, for forecasting the MASI using technical indicators. Our objective was to evaluate the performance of these indicators and their impact on the forecasting accuracy of the MASI. Using a comprehensive dataset of daily closing prices of the MASI index, we computed 26 technical indicators that are widely used and recognised in technical analysis. These indicators provide insights into market trends, momentum and volatility, which are valuable for stock market forecasting. We used deep learning algorithms based on ANNs to capture the complexity of the Moroccan stock market and generate reliable forecasts. The performance of the models was evaluated using standard metrics such as MAE, MSE, MAPE, and RMSE. These metrics provided quantitative measures of the predictive accuracy of the models and allowed us to compare their performance. We also used feature selection techniques to identify the subset of technical indicators that contribute most to predictive accuracy. By understanding the importance and impact of each indicator, investors and financial analysts can gain valuable insights into the key drivers of the Moroccan stock market and make more informed decisions. Our results show that deep learning models, particularly ANNs, show promising results in forecasting the MASI. The selected subset of technical indicators, determined by feature selection, contributed significantly to the predictive accuracy of the models. However, it's important to acknowledge that our study's reliance on historical data and technical indicators may not fully account for sudden market shifts or external events, potentially limiting the model's adaptability to unforeseen circumstances. Future research can explore additional deep learning architectures to further improve the accuracy of MASI prediction. In addition, the incorporation of other types of variables, such as economic indicators, financial performance data and textual data, can provide a more comprehensive analysis of the Moroccan stock market. We will delve into the field of sentiment analysis by incorporating sentiment variables extracted from social media platforms, such as Twitter, to obtain more accurate predictions and provide investors and analysts with timely and insightful information for decision making.





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BIOGRAPH BIOGRAPHIES OF AUTHORS






Ayoub Razouk     completed her studies at the National Higher School for Computer Science and System Analysis (ENSIAS), where she earned her degree in Finance. He is currently pursuing a Ph.D. at the Sultane Moulay Slimane University, with a focus on the exciting fields of AI and data science application in finance. Her research interests extend to the field of sentiment analysis, specifically in the context of stock market forecasting. By exploring the relationship between human emotions and financial trends, she aims to uncover valuable insights and enhance predictive models for stock market forecasting. He can be contacted at email: ayoub.razouk@usms.ma.






Prof. Dr. Moulay El Mehdi Falloul    Ph.D. in Economics and Applied Finance, Lecturer and Researcher in Applied Statistics and Strategic Studies at Hassan II-Mohammedia University, member of the ERMESIAD research team (Equipe de Recherche en Modélisation et Système Informatique d'Aide à la Décision), member of the French Association of Economic Sciences, member of the Moroccan Association of Economic Sciences, member of the International Association of Strategic Management of Rennes, member of the Moroccan Association of Islamic Economics, member of the Moroccan risk management association and chairman and founder of the think-tank CIESSA. He can be contacted at email: mymehdi.falloul@gmail.com.



Ayman Harkati    is a 23-year-old technologist from Khouribga, Morocco, with a Master's degree in Systems Engineering, specializing in Artificial Intelligence and Development from Sultane Moulay Slimane University. He is driven by a passion for technology and a desire to explore new advancements. Aymane's expertise lies in automating workflows to improve efficiency and productivity. Through innovative solutions, he simplifies complex processes and allows professionals to focus on strategic tasks. Aymane's goal is to make a lasting impact by integrating smart technologies into the lives of individuals and organizations, revolutionizing the way we work and operate in the digital age. He can be contacted at email: aymaneHarkati@gmail.com.



Prof. Dr. Fatima Touhami    Professor and Researcher in Economics and Management. She is currently Vice Dean of the Faculty of Economics and Management at Sultan Moulay Slimane University, Béni Mellal, Morocco. She has recognized expertise in the fields of economics and management, having conducted cutting-edge research and published academic works of the highest quality in various fields of economics and management. These include: ecotourism and cultural tourism, financial economics, banking and participatory finance, Islamic finance, marketing, digital marketing, territorial marketing-innovation and hr marketing. She can be contacted at email: f.touhami@usms.ma.