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Artificial Intelligence for Financial Market Forecasting: Comparative Assessment of ARIMA, ANN, and Hybrid ARIMA–ANN Approaches on Morocco and South Korea

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Abstract

Over the past few years, hybrid modeling approaches have attracted growing interest in financial forecasting due to their ability to capture both linear and nonlinear dynamics. This study proposes a data-driven hybrid model combining Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN) to forecast stock market indices in Morocco (MSI20) and South Korea (KOSPI).

The empirical results show that the ARIMA model exhibits weak predictive performance, characterized by high error rates and very low explanatory power. The ANN model significantly improves forecasting accuracy, particularly for the Moroccan market, although it remains limited in highly volatile environments. In contrast, the hybrid ARIMA–ANN model clearly outperforms both standalone models, achieving substantial error reductions and high coefficients of determination ($R^2 = 0.888$ for MSI20 and 0.975 for KOSPI).

These findings confirm that hybrid ARIMA–ANN models provide a robust and reliable framework for financial market forecasting by effectively capturing both linear and nonlinear structures, with superior performance observed in more liquid and stable markets such as South Korea.

Keywords : Financial forecasting, Time series, Artificial Neural Networks, Volatility, Non-linearity, Predictive performance, Econometric modeling

1 Introduction

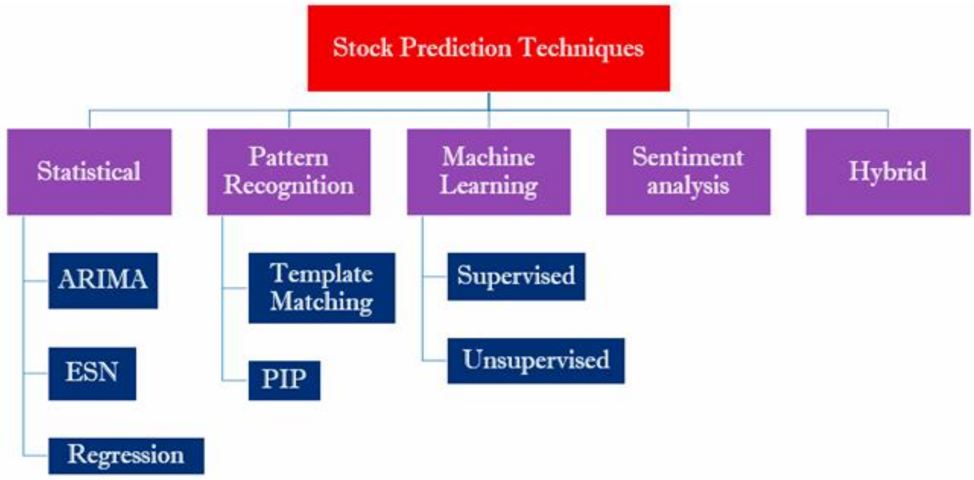
The estimation and forecasting of stock prices have long been central topics of interest for investors, traders, financial analysts, and academic researchers. To anticipate future market movements with the highest possible accuracy, numerous forecasting approaches have been developed. Among these, autoregressive integrated moving average (ARIMA) models and artificial neural networks (ANN) play a prominent role in the modeling of financial time series. (Hassanien, 2025)

Traditional time-series models, particularly the ARIMA framework introduced by Box and Jenkins, rely on the assumption of linearity. However, economic and financial data typically exhibit both linear and nonlinear structures. This mixed behavior limits the performance of purely linear models, which often fail to capture the full complexity and irregular dynamics of financial markets. In contrast, artificial neural networks provide a flexible alternative capable of modeling nonlinear patterns and adapting to the volatile nature of financial data.

The emergence of hybrid models—especially the ARIMA–ANN approach—offers an effective response to this duality. By combining ARIMA's ability to model linear components with the nonlinear learning capacity of ANN's, hybrid approaches often achieve superior predictive accuracy compared with individual models used in isolation.

Stock price forecasting remains a critical challenge, even though certain theories—such as the Efficient Market Hypothesis—suggest that future price movements are fundamentally unpredictable. Nevertheless, empirical evidence shows that well-designed statistical and computational models can yield meaningful predictions. Beyond ARIMA and ANN, more recent architectures such as Long Short-Term Memory (LSTM) networks have been explored to capture long-range temporal dependencies. However, their practical adoption remains relatively limited due to complex preprocessing requirements and the scarcity of extensive empirical studies.

Figure 1: Stock Prediction Techniques



Source : Authors' elaboration based on the literature (Box & Jenkins, 1976; Adebiyi et al., 2014; Sezer et al., 2020).

In today's global context, marked by the growing integration of artificial intelligence in financial decision-making, cooperation between Morocco and South Korea presents significant potential. Morocco, through Casablanca Finance City, aims to position itself as a leading financial hub in Africa, while South Korea stands as a global pioneer in technological innovation and AI-driven financial solutions. Strengthening collaboration between the two countries could foster valuable synergies to enhance financial stability across both the African and Asian regions.

This article pursues a twofold objective. First, it evaluates the predictive performance of ARIMA, ANN, and hybrid ARIMA–ANN models in forecasting stock market prices. Second, it highlights the opportunities offered by artificial intelligence for financial modeling, while proposing strategic avenues for cooperation between Morocco and South Korea to support market resilience and financial development.

This study aims to provide a comparative assessment of the forecasting performance of linear, nonlinear, and hybrid models—namely ARIMA, ANN, and hybrid ARIMA–ANN—applied to stock market indices from two structurally different financial markets: Morocco (MSI20) and South Korea (KOSPI). By comparing an emerging market with a developed and highly liquid market, this research seeks to highlight how market structure, volatility, and data quality influence the effectiveness of artificial intelligence–based forecasting models.

The remainder of this work presents a detailed overview of the theoretical foundations of each model, followed by a comparative analysis of their forecasting performances applied to the same stock market index over a defined period. This comparison aims to identify the strengths and limitations of each approach and to provide insights for future research in financial prediction.

The remainder of this paper is organized as follows. Section 2 presents a review of the related literature on stock market forecasting using econometric and artificial intelligence models. Section 3 describes the methodological framework, including the ARIMA, ANN, and hybrid ARIMA–ANN models, as well as the data and evaluation criteria. Section 4 reports and discusses the empirical results obtained for the Moroccan and South Korean stock markets. Finally, Section 5 concludes the paper and outlines directions for future research.

2 Literature Review :

The application of artificial intelligence (AI) techniques—and more specifically Machine Learning—to the detection and forecasting of financial dynamics has become a rapidly expanding research field. This evolution stems from the ability of these techniques to process large datasets and uncover complex, often nonlinear relationships between economic and financial variables.

Financial crises and market fluctuations typically arise from a combination of macroeconomic, structural, and behavioral factors, which makes forecasting particularly challenging for policymakers and financial institutions. Within this context, Machine Learning provides innovative analytical tools that not only improve the prediction of market movements but also enhance the understanding of the mechanisms underlying financial volatility.

Recent studies highlight the importance of accurate forecasting for financial time series, given their high volatility and sensitivity to macroeconomic conditions (Mustapa FH, 2019). While traditional linear models such as ARIMA and GARCH remain widely used, contemporary research increasingly favors advanced Machine Learning and Deep Learning approaches—including Support Vector Regression (SVR), XGBoost, Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM) networks. These techniques stand out for their ability to effectively model nonlinear patterns in financial data. Comparative studies in quantitative finance consistently demonstrate the superior performance of these modern methods over traditional approaches.

Nonlinear stochastic models like GARCH also offer greater flexibility than ARIMA in capturing the complexity of financial dynamics (Rundo F, 2019) (Cocianu C-L, 2016) (Li Z,

2018) (Sezer OB, 2020). For example, Adebiyi et al. (Adebiyi AA, 2014) compared the predictive performance of ARIMA and ANN models using New York Stock Exchange (NYSE) data and found that artificial neural networks delivered more accurate forecasts. Similarly, (Wijaya YB, 2010) showed that ANN models produced lower forecasting errors than ARIMA for the Indonesian stock market. In another study, (Falloul MEM, 2014) examined the MASI index and concluded that the GARCH model offered the best predictive performance after empirical testing.

Other research by Hossain and Nasser (2011) (Hossain A, 2011) compared SVM with ARMA-GARCH and GARCH models, revealing that the long-memory property of SVM provided a clear predictive advantage for financial returns. Ping-Feng Pai also introduced a hybrid ARIMA–SVM methodology for stock price forecasting, demonstrating that optimal parameter tuning significantly enhances predictive accuracy. (Kumar M, 2014) further confirmed that ARIMA–SVM models outperform standalone approaches in forecasting stock returns due to their high accuracy. More recent empirical work has also validated the effectiveness of the XGBoost algorithm in predicting stock prices.

Weiss (AA, 1986) expanded the ARMA framework by incorporating bilinear components and ARCH-type errors, examining their interactions through specific hypothesis tests and parametric estimation methods. The study demonstrated that jointly accounting for bilinearity and ARCH effects is essential for accurate modeling, and highlighted the limitations of relying solely on classical ARMA specifications—especially when applied to empirical time series.

Bilinear models have shown strong capabilities in capturing atypical patterns and extreme-value sequences (Lmakri A, 2021). Bibi et Gheza (Bibi A, 2018) extended this framework by proposing Markov-switching bilinear GARCH (MS-BLGARCH) models, which integrate regime changes and interaction terms between observed series and their volatility processes. These models aim to better capture structural breaks and asymmetric behaviors, such as leverage effects. Their study formalized key structural properties—stationarity, causality, covariance functions, and higher-order structures—to facilitate identification and estimation.

Panel regression models with bilinear errors have also been explored within hybrid frameworks, where optimized tests for bilinear dependence and adaptive estimation techniques demonstrated strong robustness and efficiency efficacité (Lmakri A A. A., 2020) (Lmakri A A. A., Estimation in short-panel data models with bilinear errors, 2023).

Further advances have been made by (Yuan G, 2021) , who developed a predictive model using XGBoost combined with GridSearchCV. Their findings indicate performance improvements over traditional ML methods, with RMSE reductions of 1.39%, 2.43%, and 8.33% compared with SVM, neural networks, and LightGBM, respectively. Their study also identified key determinants influencing stock closing prices, highlighting the benefits of ML for financial market forecasting.

In another example, (Siami-Namini S, 2018) examined financial market data from January 1985 to August 2018 and demonstrated the significant superiority of LSTM over traditional ARIMA models, with forecasting error reductions ranging from 84% to 87%. (Rhanoui M, 2019) similarly validated the enhanced predictive performance of LSTM compared with ARIMA for budgeting and financial series. These findings confirm the growing relevance of Deep Learning techniques in financial forecasting.

Evaluating forecasting models is essential for ensuring reliable prediction accuracy. Deep Learning models can be optimized using techniques such as Grid Search to improve predictive performance. Performance metrics play a crucial role in objectively assessing models, allowing researchers, investors, and financial decision-makers to identify the most effective predictive tools. These quantitative indicators help guide investment strategies and support efficient portfolio management. (ALIMOUSSA, 2023)

Summary of Selected Studies on the State of the Art

Recent academic literature emphasizes the increasing effectiveness of AI and Machine Learning techniques for stock market forecasting. Classical models such as ARIMA and GARCH are now complemented by hybrid approaches and neural networks capable of capturing nonlinearities and the inherent complexity of financial markets.

In South Korea, numerous studies apply Deep Learning and evolutionary algorithms to forecast KOSPI fluctuations and enhance risk management. In Africa—particularly in Morocco—research in this field is still emerging but is expanding rapidly, especially concerning the MASI and MSI20 indices.

Collectively, these studies converge toward a common conclusion: AI significantly improves the accuracy of stock market predictions and provides more robust decision-support tools for regulators, investors, and portfolio managers

The evolution of financial forecasting can be understood as a progression from models designed primarily to capture linear temporal dependence toward increasingly flexible approaches capable of representing nonlinear relationships. Classical econometric models such as ARIMA remain valuable because of their parsimonious structure, interpretability, and ability to represent temporal dependence. However, their linear formulation can become restrictive when financial series exhibit nonlinear and irregular dynamics.

Machine-learning approaches address part of this limitation by allowing more flexible functional relationships between past observations and future outcomes. In particular, ANN models can approximate nonlinear relationships and have therefore been increasingly applied to financial forecasting. The literature reviewed in this study illustrates this transition from traditional statistical models toward neural and deep-learning architectures.

However, the superiority of nonlinear models should not be interpreted as universal. Their performance may depend on the amount and quality of available data, the selected architecture, the forecasting horizon, and the statistical properties of the financial series. This explains the continued interest in hybrid approaches, which attempt to combine the interpretability and linear structure of econometric models with the nonlinear learning capacity of artificial neural networks.

The ARIMA–ANN framework represents this intermediate approach. Instead of requiring one model to reproduce all characteristics of the series, the hybrid strategy decomposes the forecasting problem into a linear component and a nonlinear residual component. In the present study, ARIMA first captures the linear component and ANN subsequently models the residual structure.

This theoretical progression identifies an important empirical question: whether the relative advantage of linear, nonlinear, and hybrid models remains similar across different market environments. The present study addresses this question by comparing the MSI20 in Morocco with the KOSPI in South Korea, thereby linking the methodological debate on linear versus nonlinear forecasting to differences in financial-market structure

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Table 1: Summary of Selected Studies

Models Used	Dataset	Methodology	Conclusion	Reference
LSTM, MLP, SVM	Eleven Brazilian stocks from the 2016 Brazilian stock market, totaling 250 daily observations. Most were part of the BOVA11 index.	Data split into 166 training days and 84 testing days. The LSTM network consisted of four layers with 8, 4, and 2 LSTM units, followed by an output layer.	LSTM outperformed MLP and SVM, though the performance gap remained small due to limited data. With a longer dataset (e.g., 2000 days), LSTM would likely show a significantly larger advantage.	Mesquita et al. (2020). *Combining an LSTM Neural Network with the Variance Ratio Test for Time Series Prediction…*
LSTM vs. SVM, CNN, NFNN, and Pipeline Models	S&P 500 index prices from January 1999 to January 2019 (20 years).	Multiple LSTM networks were trained to capture multi–time scale dependencies. The extracted features were combined to predict future closing prices.	LSTM achieved superior performance thanks to its strong ability to model temporal dependencies. It reached an accuracy of 74.55% over a one-month horizon.	Hao & Gao (2020). *Predicting the Trend of Stock Market Index Using Hybrid Neural Networks…*
LSTM, CNN, SACLSTM	Stocks from the U.S. market (AAPL, IBM, MSFT, FB, AMZN) and Taiwan market (CDA, CFO, DJO, DVO, IJO) from Oct. 2018 to Oct. 2019.	Dataset split into 60% training, 20% testing, and 20% validation. Models implemented using TensorFlow.	The SACLSTM model achieved the best performance with lower errors and more accurate directional movements. Standard CNN and LSTM models underperformed.	Wu et al. (2021). *A Graph-Based CNN-LSTM Stock Price Prediction Algorithm…*
ANN vs. LSTM (RMSE comparison)	Dixon Hughes, Cooper Tire, PNC Financial, CitiGroup, Alcoa Corp.; forecasting 10-day stock prices.	LSTM network: 1 input layer (5 neurons), several hidden layers, and 1 output layer. RMSE used as main evaluation metric.	LSTM consistently produced lower RMSE than ANN for all companies, demonstrating higher predictive accuracy. GASVM models also performed competitively in some cases.	Nandakumar et al. (2018). *Stock Price Prediction Using Long Short-Term Memory.*

Source : : Authors

3 Methodological approach:

3.1 Definition and presentation of models:

3.1.1 Conceptual rationale for model selection:

The selection of ARIMA, ANN, and the hybrid ARIMA–ANN framework is motivated by the assumption that financial time series may simultaneously contain linear temporal dependence and nonlinear dynamics. These characteristics make a comparison between classical econometric and artificial intelligence approaches particularly relevant.

ARIMA is used as a linear benchmark because it provides a well-established framework for capturing autoregressive dependence, moving-average effects, and temporal persistence. Its role in the present study is therefore not only to provide a forecasting model but also to establish a reference point against which the contribution of nonlinear and hybrid approaches can be evaluated.

ANN is selected because financial market dynamics may involve nonlinear relationships that cannot be adequately represented by a purely linear specification. By using lagged observations as inputs, ANN can approximate complex nonlinear relationships and potentially capture patterns that remain unexplained by ARIMA.

The hybrid ARIMA–ANN model is motivated by the possibility that linear and nonlinear structures coexist within financial time series. In the proposed framework, ARIMA captures the linear component, while ANN is applied to the residual component in order to model nonlinear information that remains after the linear structure has been extracted. This allows the hybrid framework to exploit the complementary strengths of statistical and machine-learning approaches. The manuscript already implements this decomposition explicitly in the hybrid-model construction.

The comparison between Morocco and South Korea provides an additional dimension to this methodological framework. The MSI20 represents an emerging-market environment, whereas the KOSPI represents a substantially more mature and internationally integrated market. Differences in liquidity, trading activity, investor composition, information availability, and market depth may theoretically affect the degree to which linear and nonlinear patterns can be identified and learned by forecasting models. However, these characteristics are not directly modeled in the present study. Therefore, they are treated as potential explanatory mechanisms rather than as causal determinants of model performance.

This comparative design makes it possible to examine whether the relative forecasting performance of linear, nonlinear, and hybrid approaches remains stable across structurally different financial environments.

3.1.2 Autoregressive Integrated Moving Average (ARIMA) model:

This research adopts a positivist epistemological stance grounded in an empirical and quantitative research paradigm. The methodological reasoning follows a deductive and comparative approach, aiming to evaluate the forecasting performance of linear, nonlinear, and hybrid models under identical data conditions. The selection of the ARIMA model is motivated by its effectiveness in capturing linear dependencies and short-term dynamics in stationary financial time series. In contrast, Artificial Neural Networks (ANN) are employed for their ability to approximate complex nonlinear relationships and adapt to highly volatile market behavior. The hybrid ARIMA–ANN framework is therefore justified by the coexistence of linear and nonlinear structures in stock market data, allowing the model to integrate complementary strengths from both approaches. This methodological design ensures robust performance evaluation and provides a comprehensive framework for forecasting financial markets characterized by uncertainty, volatility, and structural complexity.

ARIMA model extends the ARMA framework by incorporating differencing into the modeling process. Differencing transforms a non-stationary time series into a stationary one by subtracting the previous observation from the current value. For instance, first-order differencing removes linear trends using the transformation $z_i = y_i - y_{i-1}$. Second-order differencing eliminates quadratic trends by applying first-order differencing twice, leading to $z_i = (y_i - y_{i-1}) - (y_{i-1} - y_{i-2})$, and higher-order differencing can be applied similarly when necessary.

ARIMA models are generally characterized by three integers (p, d, q):

- **p**: number of autoregressive terms (AR order)
- **d**: number of non-seasonal differences (order of integration)
- **q**: number of moving average terms (MA order)

The full name of the model, *Autoregressive Integrated Moving Average*, reflects these components. In the forecasting equation, lagged values of the differenced series serve as autoregressive terms, while lagged forecast errors constitute the moving average terms. Once the series has been differenced to achieve stationarity, the number of differences represents the integration order. An ARIMA model is commonly denoted ARIMA(p, d, q), where **p**

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corresponds to the AR part, **d** indicates the integration degree, and **q** represents the MA component.

According to the Box–Jenkins methodology, selecting the optimal ARIMA model involves three main stages. First, a preliminary model is identified based on initial data characteristics. Second, the model parameters are estimated. Finally, the adequacy of the model fit is assessed. Several combinations of p, d, and q are usually tested to determine the model that best satisfies statistical and diagnostic criteria.

<u>Steps for Building an ARIMA Model:</u>

a) Identification

The initial step in ARIMA modeling consists of verifying whether the series is stationary, which is typically true for stock returns. Autocorrelation (ACF) and partial autocorrelation (PACF) plots are then examined to determine appropriate values for **p** and **q** in the general ARMA specification.

b) Parameter Estimation

Once one or more candidate models have been selected, their parameters are estimated using suitable estimation techniques, such as Maximum Likelihood Estimation (MLE) or other numerical optimization methods.

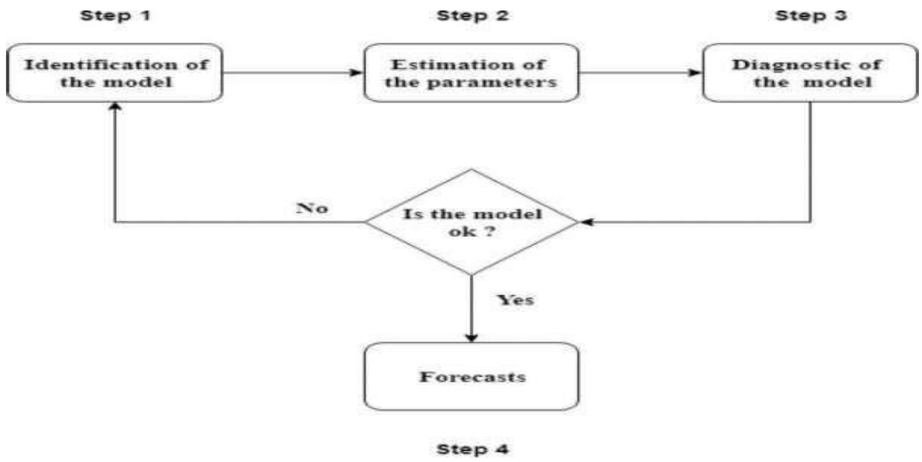
c) Model Diagnostics

This constitutes the most critical phase of ARIMA modeling. Diagnostic checks assess whether the residuals and estimated parameters are statistically significant. If the model is properly specified, the residuals should resemble white noise, exhibiting no autocorrelation and following an approximately normal distribution.

a) 4. Forecasting

After validating the model, the final ARIMA specification is used to generate future forecasts. Forecasting accuracy is subsequently evaluated by calculating prediction errors.

Figure 2:Box-Jenkins Modeling Approach



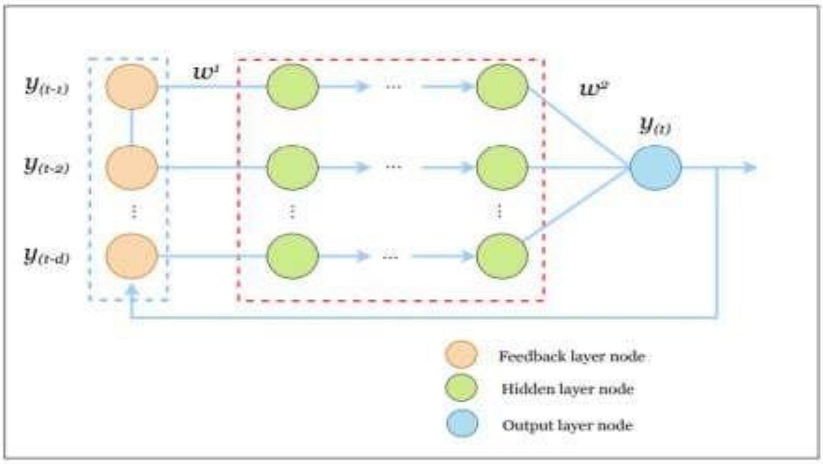
Source: Authors' elaboration based on Box and Jenkins (1976).

3.1.3 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are nonlinear modeling techniques widely used for forecasting time-series data. They have attracted significant attention across various fields, including medicine, biology, psychology, computer science, mathematics, economics, and statistics. This growing interest stems from the flexibility of ANNs, as they can approximate highly complex and nonlinear functional relationships, making them suitable for a broad range of predictive tasks. (Jawaria Nasir Hasnain Iftikhar 2, 2025)

The architecture of an ANN is inspired by the structure of the human brain, where information is processed through interconnected units called neurons. A typical ANN consists of multiple layers of neurons, commonly organized into an input layer, one or more hidden layers, and an output layer. Figure 2 illustrates an example of a three-layer neural network, composed of an input layer (possibly including feedback connections), a hidden layer, and an output layer.

Figure 3:Architecture des Réseaux de Neurones Artificiels (RNA).



Source : Authors' elaboration based on Haykin (1999) and Sezer et al. (2020).

For time series forecasting problems, it is particularly appropriate to use Dynamic Neural Networks (DNN), in which the output of the network depends on both current and past values. This structure allows the DNN to generate future predictions by exploiting the lagged observations of the series. The general form of a DNN model can be expressed as follows:

$$\boldsymbol{y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \dots \dots, y_{t-d}) + \varepsilon_t}$$

Where y_t is the original series, εt\varepsilon_tεt is the error term, $f(.)$ is a non linear function, and, et $y_{t-1}, y_{t-2}, y_{t-3}, \dots \dots, y_{t-d}$ represent the feedback lags.

❖ **The basic structure of an Artificial Neural Network (ANN) generally consists of three main layers:**

- Input layer, where the raw data are fed into the network;
- Hidden layers, where neurons process the inputs using nonlinear activation functions;
- Output layer, which produces the final prediction or estimated value.
- The output of each neuron is obtained by applying an activation function to the weighted sum of its inputs. A typical neuron can be described by the following equation:

The output of each neuron is obtained by applying an activation function to the weighted sum of its inputs. A typical neuron can be described by the following equation:

$$a_j = f(\sum w_i x_i + b_j) \qquad \boldsymbol{i=1}$$

where:

aj : is the activation of neuron j

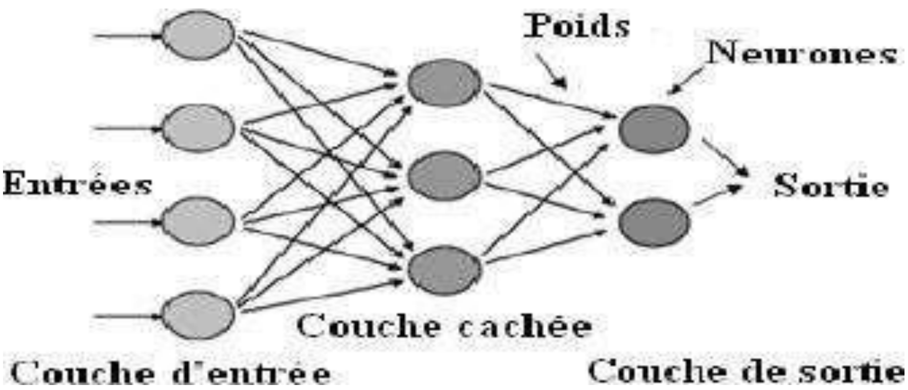
f : denotes the activation function (e.g., ReLU, sigmoid, tanh),

wij : is the weight connecting input xi to neuron j i et j

xi : input i

bj : is the bias associated with neuron j.

This architecture enables neural networks—particularly DNNs—to capture complex nonlinear relationships and enhance forecasting accuracy for time series data.



3.1.4 ARIMA-ANN Hybrid Model:

To construct our hybrid ARIMA–ANN model, we follow a methodology that acknowledges the coexistence of linear and nonlinear patterns within time series data. In the existing literature, hybrid approaches have consistently demonstrated superior performance in time series forecasting, as they successfully combine linear modeling techniques with nonlinear learning methods. This combination allows the model to capture both the linear structures described by ARIMA and the nonlinear dynamics learned by the ANN, resulting in more accurate and robust predictions.

❖ **Steps to build a hybrid ARIMA-ANN model: :**

a. Application of the ARIMA model:

We begin by applying an ARIMA model to the time series Y_t to capture its linear component L_t. The linear predictions $\widehat{L_t}$ of the ARIMA are obtained as follows:

Extraction of residuals:

$$\widehat{L_t} = ARIMA(Y_t)$$

By subtracting the linear predictions from the original series, we obtain a series of residuals et, which represents the nonlinear component of the series:

$$\boldsymbol{\varepsilon_t = Y_t - \widehat{L_t}}$$

b. <u>Residue modeling with ANN</u>:

These residuals are then used as inputs for an artificial neural network (ANN) to model the nonlinear component N_t of the time series..

The nonlinear predictions $\widehat{N_t}$ are obtained from the ANN based on the previous residual values:

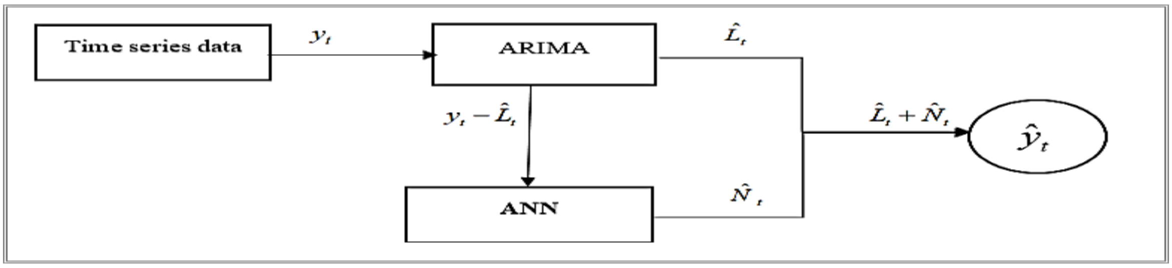
$$\widehat{N_t} = f(e_{t-1}, e_{t-2}) + \varepsilon_t$$

In this equation, f represents a nonlinear function of past residuals, and ε_t is the error term used in ANN.

c. <u>Combination of forecasts:</u>

Finally, the final forecasts of our hybrid model are obtained by combining the ARMA $\widehat{L_t}$ and ANN $\widehat{N_t}$ forecasts : $\widehat{Y_t}$= $\widehat{L_t} + \widehat{N_t}$

This approach allows us to model both the linear and nonlinear aspects of time series data, thereby improving the accuracy of our forecasts. The following figure illustrates this process graphically: (Onalenna Moseane, 2024)

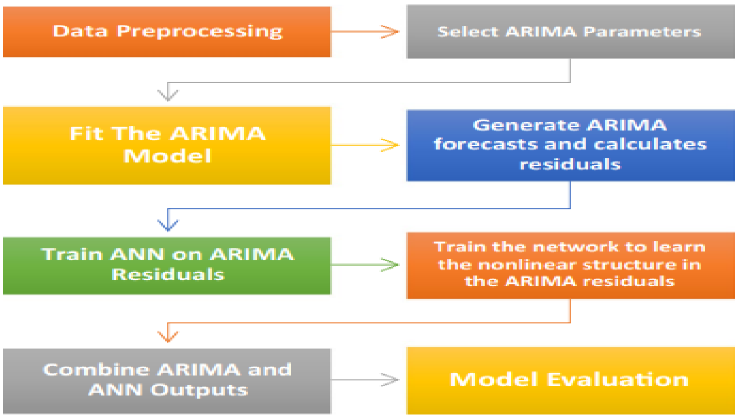


3.2 Model evaluation methods :

3.2.1 Model Evaluation :

It is important to find the best prediction model that produces the most accurate results during the evaluation process. Error metrics define "error" and ε_t as the difference between the actual observed value Y_t and its prediction $\widehat{Y_t}$ at time t. This difference refers to the unpredictable part of the corresponding observation. Well-known error metrics are described below in the literature.

<u>Figure 4:General flowchart of constructing hybrid models.</u>



Source: Authors' elaboration based on Kumar et al. (2014) and Mustapa et al. (2019).

3.2.2 Statistical criteria (RMSE, MAE, MAPE, etc.) :

Equation 1:Mean Square Error (MSE)

Mean Square Error (MSE) is defined by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_t)^2 \qquad i = 1$$

MSE (Mean Squared Error) measures the average of squared prediction errors. Since this error metric squares the errors, information about the direction of the overall error is lost. For the same reason, MSE emphasizes large errors, which means that it penalizes extreme prediction errors more heavily than other error metrics. MSE is not scale-independent and is even very sensitive to small differences in scale.

Equation 2:RMSE (root mean square error)

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \widehat{x_t})^2}$$

RMSE measures the average magnitude of errors between predicted values and actual values, with a higher penalty for larger errors. It is estimated by the following relationship.

Equation 3:MAE (mean absolute error):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|x_t - \widehat{x_t}|$$

MAE evaluates the average of the absolute differences between predicted values and actual values. It is estimated by the following equation.

Equation 4:MAPE

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - \widehat{x_t}}{x_t}\right| * 100$$

MAPE evaluates model accuracy as a percentage by comparing absolute errors to actual values, providing a normalized error measure. A lower MAPE indicates a more accurate model. It is estimated by the following equation.

Equation 5: R^2 (coefficient of determination)

$$R^2 = \frac{\sum_{i=1}^{n}(y_t - \widehat{y_t})}{\sum_{i=1}^{n}(y_t - \overline{y_t})}$$

4 Results and discussion :

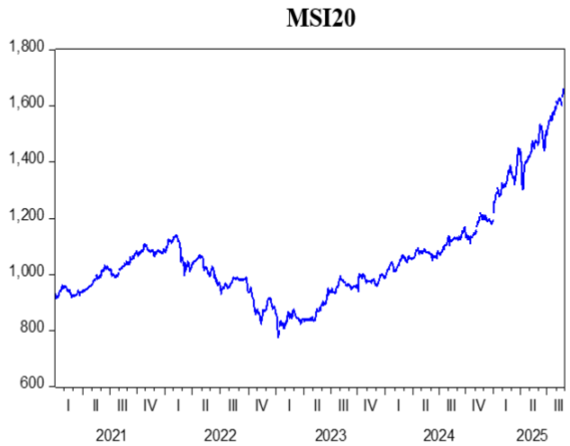
4.1 Data présentation :

The period covered extends from January 4, 2021, to August 29, 2025, for a total of 1160 observations.

Figure 4 shows that both price series exhibit marked irregularity and fluctuations of varying amplitudes.

4.1.1 Test de racine unitaire :

The graphs of the two-time series clearly indicate that the mean and variance are not constant, revealing the non-stationarity of the data.



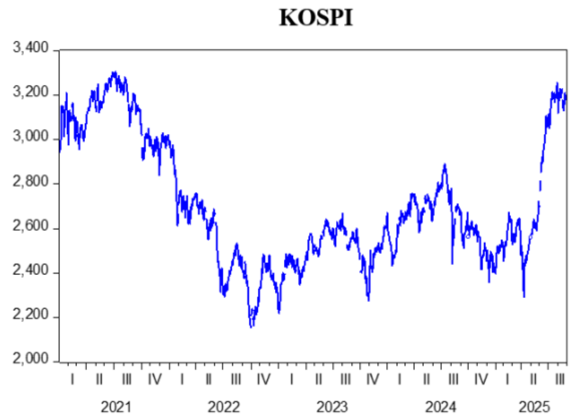


Figure 5:MSI 20 index et KOSPI index

Source: Eviews 12 outputs.

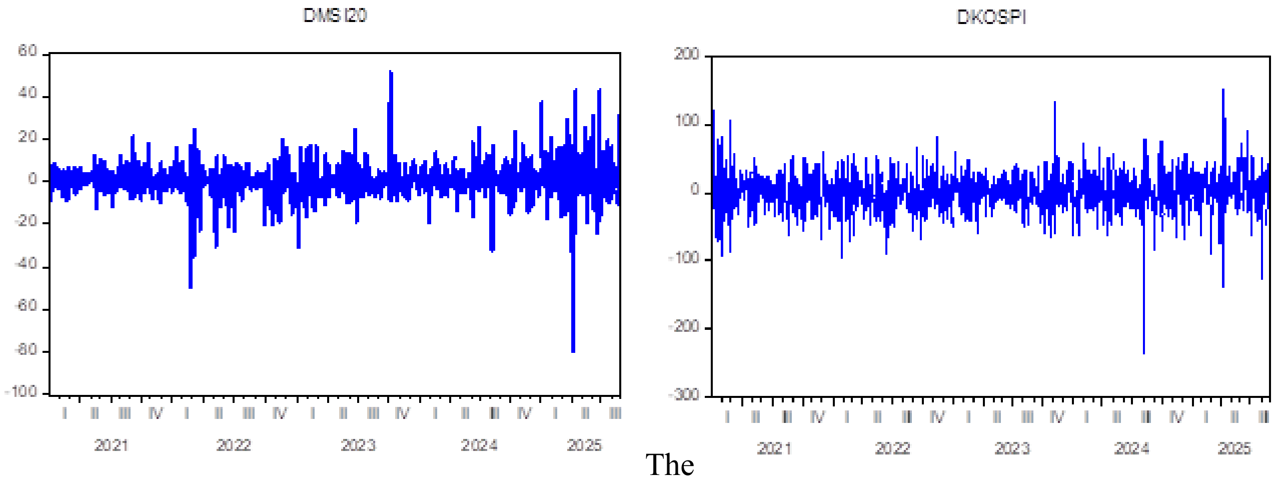
The returns were plotted using EViews 12 software.

Figure 4 shows that the two series of returns are stationary, show no trend, and vary in amplitude over time.Volatility clustering can also be observed.

We will verify this finding using the Augmented Dickey-Fuller (ADF) test.

Figure 6:Morocco's & COREE SUD returns plot

Source : Eviews 12 outputs.



The augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), presented in Table 1, indicates that both series of returns are stationary, as the absolute value of the test statistic is greater than the critical value.

Thus, the Moroccan and Korean time series are appropriate for modeling.

Table 2:Augmented Dickey Fuller test statistic for return series

Niveau de test	ADF statistic		p-value		Conclusion
	MSI20	**KOSPI**	**MSI20**	**KOSPI**	
Niveau (avec tendance et constante)	+0.2765	–1.0989	0.9985	0.9275	Non stationnaire
Niveau (avec constante seule)	+1.5464	–1.4882	0.9994	0.5395	Non stationnaire
Niveau (sans constante)	+2.3048	+0.0812	0.9953	0.7084	Non stationnaire
1ère différence	**–20.4463**	**–33.8398**	**0.0000**	**0.0000**	**Stationnaire**

Source: Auteurs (output Eviews 12)

The augmented detrended commonality (ADF) test applied to the MSI20 and KOSPI indices reveals that both series are non-stationary in level, meaning that their values evolve according to a trend over time, probably under the influence of macroeconomic, political, and global factors. After initial differentiation, both series become stationary, indicating that their variations (or returns) are stable around a constant mean. This result is consistent with the typical characteristics of financial series, which are generally first-order integrated (I(1)), i.e., non-stationary in level but stationary in first difference.

In terms of modeling, this diagnosis of stationarity is fundamental. It justifies the use of ARIMA models in differences rather than levels in order to avoid spurious regressions. In addition, it allows the use of hybrid ARIMA-ANN models, which are capable of simultaneously capturing the linear and nonlinear components of stock market returns. Finally, before any causality or cointegration analysis, it is essential to test for the existence of a long-term relationship between the two markets using a Johansen or Engle-Granger test to determine whether they evolve jointly over time.

4.1.2 Descriptive analysis:

Table 3:Statistique Descriptive.

Statistics	**MSI20**	**KOSPI**
Mean	1063.929	2702.498
Median	1023.060	2620.420
Maximum	1659.560	3305.210
Minimum	775.3800	2155.490
Std. Dev.	178.9528	283.7141
Skewness	1.353634	0.564940
Kurtosis	4.546726	2.186683
Jarque-Bera	469.8802	92.46421
Probability	0.000000	0.000000
Sum	1234158.	3094360.
Sum Sq. Dev.	37115936	92084769
Observations	1160	1145

Source : Eviews 12 outputs.

The descriptive statistics table provides a comparative overview of the Moroccan stock index MSI20 and the South Korean KOSPI index over the study period.

An examination of the central tendency measures shows that both the mean and the median of the KOSPI (2702.50 and 2620.42) are significantly higher than those of the MSI20 (1063.93 and 1023.06). This reflects the difference in scale and level of development between the two stock markets. In both cases, the mean slightly exceeds the median, indicating a positive skewness confirmed by the skewness coefficients (1.35 for MSI20 and 0.56 for KOSPI). This right-skewed distribution suggests the presence of a few high-value observations corresponding to substantial increases in stock prices.

The analysis of dispersion reveals that absolute volatility, measured by the standard deviation, is higher for the KOSPI (283.71) than for the MSI20 (178.95). However, relative volatility—standard deviation relative to the mean—is greater for the MSI20 (16.8%) compared to the KOSPI (10.5%). This indicates that the Moroccan market is proportionally more unstable than its South Korean counterpart. Such heightened variability reflects a lower market depth and a greater sensitivity to economic or financial fluctuations.

Regarding the shape of the distributions, the kurtosis of the MSI20 (4.55) exceeds the threshold of 3, indicating a leptokurtic distribution characterized by frequent extreme values. In contrast, the KOSPI exhibits a platykurtic distribution (kurtosis = 2.19), closer to normality. This confirms that the Moroccan market is more exposed to intense volatility episodes and sudden price shocks.

Finally, the Jarque–Bera statistics are very high for both indices (469.88 for MSI20 and 92.46 for KOSPI), with p-values equal to zero, leading to the rejection of the null hypothesis of normality. These findings are consistent with the empirical properties of financial time series, which typically exhibit non-normality, skewness, and heavy tails.

Overall, these results highlight a clear contrast between a less stable, more volatile, and shock-sensitive Moroccan market and a more mature, better-regulated, and relatively more efficient South Korean market. This distinction justifies the relevance of a comparative approach when modeling and forecasting stock indices using linear and nonlinear methods.

4.2 ARIMA Model Results :

4.2.1 ARIMA Model Estimation and Validation

- **Analyse des autocorrelations (ACF & PACF) — *MSI20 & KOSPI***

For ARIMA, candidate specifications were systematically evaluated by varying p and q from 1 to 5. The final specification was selected by considering the Akaike Information Criterion (AIC), parameter significance, and residual diagnostics, including the absence of problematic autocorrelation and heteroscedasticity.

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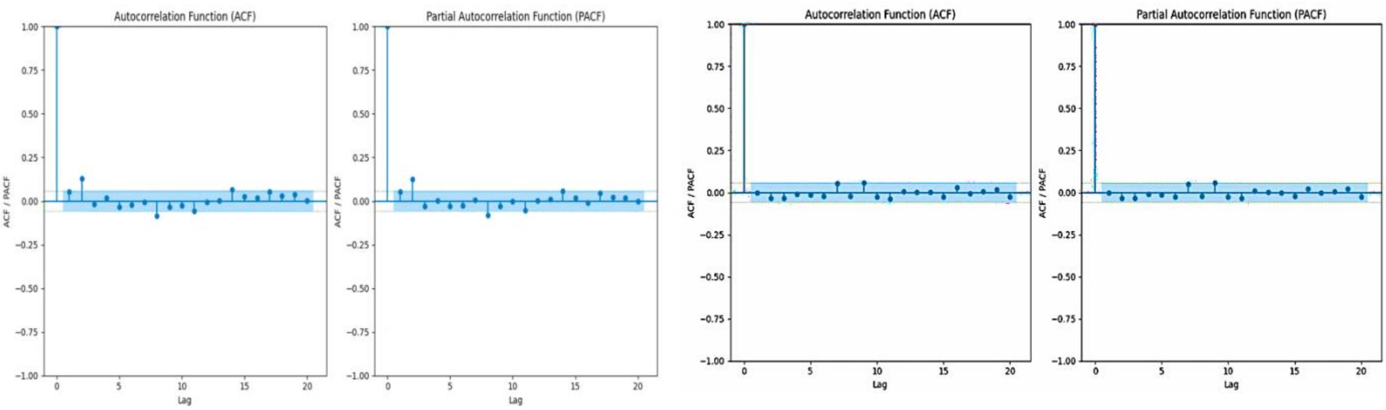
Figure 7:Autocorrélation Fonction ACF &PACF (MSI20 & KOSPI)



Source : calculations using Python (Google Colab).

For the KOSPI, the slowly decreasing ACF and the PACF with a peak only at the first lag indicate a non-stationary AR(1) process, characteristic of persistent financial series where the current value depends heavily on the previous value, typical of a random walk. For the MSI20, the ACF and PACF show different patterns: the ACF decreases more rapidly with several significant peaks, while the PACF shows a dominant peak at lag 1 followed by a few oscillations, suggesting a mixed stationary ARMA process, probably ARMA (1,1), where the series combines an autoregressive component with a moving average component, indicating a more complex but more stable temporal dynamic than the KOSPI.

- **Applying the ARIMA model**

The 70%, 30% chronological split was retained because the objective is to evaluate genuine out-of-sample forecasting performance. Using 70% of observations for training provides a sufficiently large historical window for model estimation, while reserving 30% for testing provides a substantial out-of-sample period for assessing predictive accuracy. Importantly, the split was applied consistently across the two markets to preserve comparability.

Next, we evaluate and compare the ARIMA and ARIMA-ANN models by calculating the MSE, MAPE, MAE, RMSE, and R2 for each, in order to determine which, one provides the most accurate predictions.

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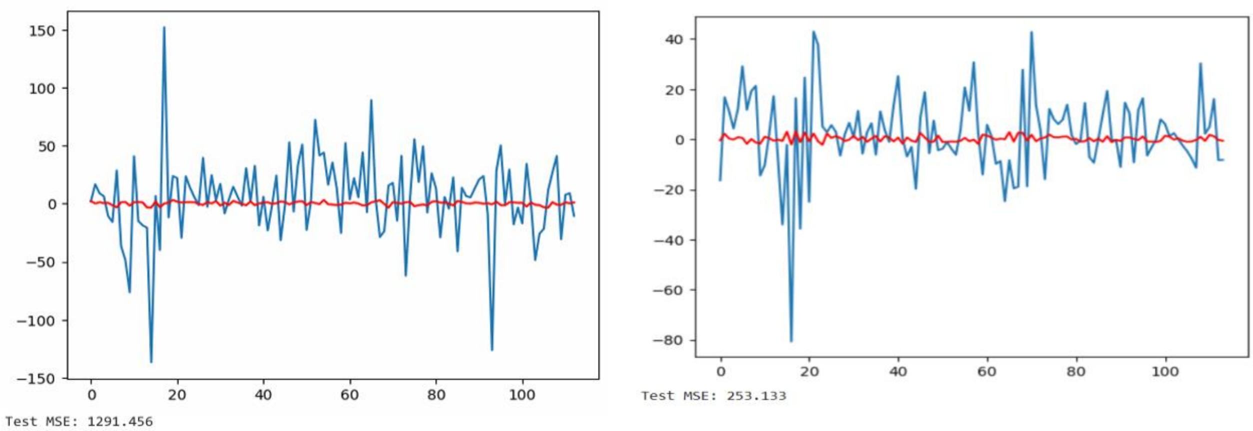
- **Forecasting with the ARIMA Model**

Figure 8:Prévision ARIMA MSI20 & KOSPI



Source : Calculations using Python (Google Colab).

	ARIMA				
SCORE	**RMSE**	**MSE**	**MAE**	**MAPE**	**R^2**
MSI20	15.91	253.133	11.307	192.346%	0.026
KOSPI	35.937	1291.456	25.171	116.908%	-0.014

Les résultats obtenus mettent également en évidence une différence de comportement prédictif entre les deux marchés étudiés. Bien que le MSI20 présente des erreurs de prévision inférieures à celles du KOSPI en termes de RMSE, MSE et MAE, son coefficient de détermination demeure très faible ($R^2 = 0,026$), indiquant que le modèle n'explique qu'une part marginale de la variabilité observée. Le KOSPI présente une situation encore plus défavorable, avec un R^2 négatifs (-0,014), traduisant une performance légèrement inférieure à une prévision fondée sur la moyenne historique. L'observation des trajectoires prédites confirme ces résultats : les prévisions ARIMA sont fortement lissées et restent proches du niveau moyen, alors que les valeurs réelles connaissent des fluctuations importantes et des mouvements de forte amplitude. Cette divergence suggère que les dépendances linéaires exploitées par ARIMA ne suffisent pas à représenter la dynamique complexe des deux marchés. Par ailleurs, les MAPE élevés observés pour le MSI20 (192,346%) et le KOSPI (116, 908%) doivent être interprétés avec prudence en raison de la sensibilité de cet indicateur aux observations proches de zéro. Dans l'ensemble, ces résultats soulignent les limites d'un modèle linéaire classique pour la prévision des indices boursiers et justifient l'exploration de méthodes capables de mieux prendre en compte les

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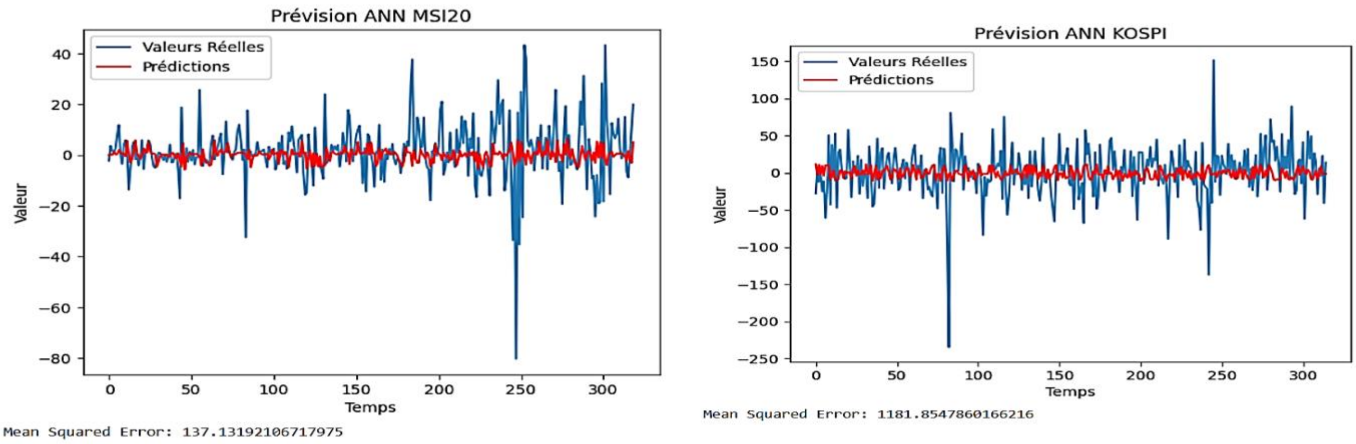
relations non linéaires, les changements de régime et les dynamiques complexes des séries financières, notamment les approches de Machine Learning et de Deep Learning.

4.3 ANN Model Results:

- **Forecasting with the ANN Model:**

Artificial neural networks (ANNs) are artificial intelligence tools that simulate the functioning of biological neural networks, such as the human brain. Unlike models such as ARIMA, which focus on linearity, ANNs are distinguished by their ability to model complex, nonlinear relationships. Their main feature is learning, allowing continuous adaptation to data and flexible function approximation. This flexibility makes them promising tools for predicting stock market returns, offering an approach capable of capturing complex patterns and adapting to dynamic changes in financial markets.

<u>Figure 9:Prévision ANN MSI20 & KOSPI</u>



Source : calculations using Python (Google Colab).

Based on the metrics provided, analysis of the ANN (Artificial Neural Network) model's performance reveals a significant improvement over the previous ARIMA model, but with contrasting results between the two indices:

<u>MSI20:</u>

- The MSE of 137.13 represents a substantial improvement over the MSE of 253.13 obtained with ARIMA.
- The reduction of approximately 46% in the root mean square error demonstrates the ANN model's ability to better capture the dynamics of the Moroccan market.
- Although significantly superior to ARIMA, performance remains moderate with a notable residual error.

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KOSPI:

- The MSE of 1181.85, although high, is a slight improvement over ARIMA's MSE of 1291.46.
- The reduction in error is less pronounced than for MSI20 (approximately 8.5%).
- The magnitude of the error suggests that the Korean market has an intrinsic complexity that is more difficult to model, even with nonlinear approaches

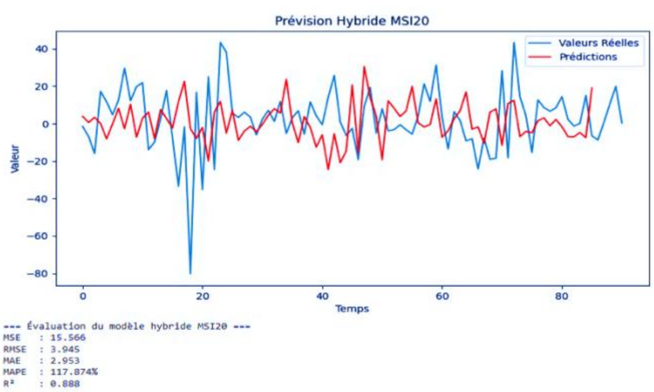
The ANN model confirms its advantage over linear approaches, particularly for the MSI20, where the improvement is substantial. However, the persistence of significant errors—especially for the KOSPI—indicates that:

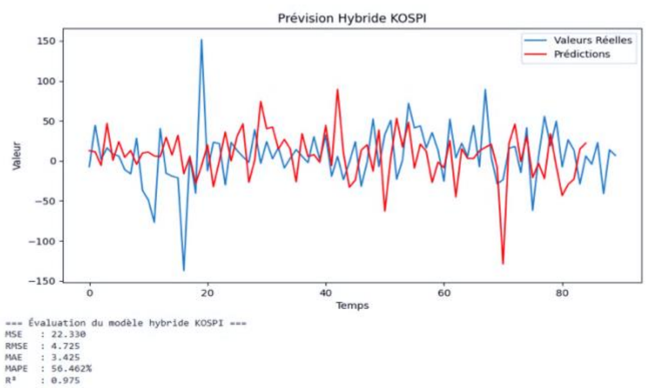
1. Financial markets retain a strong stochastic component.
2. The KOSPI exhibits more pronounced complexity and volatility.
3. More advanced approaches (hybrid models, inclusion of external variables) may be required to achieve satisfactory forecasting accuracy.

This analysis supports the hypothesis that nonlinear models are better suited for financial forecasting, while also highlighting the persistent limitations in modeling stock market time series.

4.4 Results of the ARIMA–ANN Hybrid Model

Figure 10:Prévision Hybride MSI20 & KOSPI





Source : calculations using Python (Google Colab).

Indicateur	MSI20	KOSPI	Analyse comparative
MSE	15.566	22.330	Both are weak; MSI20 is slightly better.

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RMSE	3.945	4.725	Very close; MSI20 is slightly more accurate in absolute terms.
MAE	2.953	3.425	Minor difference.
MAPE	117.874%	56.462%	KOSPI has much lower relative errors.
R^2	0.888	0.975	KOSPI has much better explanatory power.

The substantially stronger performance of the hybrid model on the KOSPI should be interpreted cautiously. The higher R^2 and lower MAPE suggest that the linear–nonlinear decomposition captures a larger proportion of the predictive structure present in the Korean sample. One possible explanation is that differences in market liquidity, trading activity, information availability, and market structure may affect the statistical properties of the series and consequently the ability of forecasting models to identify persistent patterns. However, because these factors are not directly incorporated into the present empirical model, they cannot be interpreted as causal determinants. Rather, they represent plausible mechanisms that should be explicitly tested in future research.

4.5 General discussion

The empirical results obtained for the two markets under study—the MSI20 representing the Moroccan stock market and the KOSPI representing the South Korean market—demonstrate the outstanding performance of the hybrid ARIMA–ANN model in forecasting stock indices. For the MSI20, the model yields an MSE of 15.566, an RMSE of 3.945, an MAE of 2.953, and an R^2 of 0.888, indicating a strong explanatory capacity. However, the MAPE of 117.874% reflects high volatility and difficulty in accurately capturing certain extreme fluctuations in the Moroccan market.

In contrast, the model applied to the KOSPI shows even more satisfactory performance, with an MSE of 22.330, an RMSE of 4.725, an MAE of 3.425, a MAPE of 56.462%, and—most notably—an R^2 of 0.975. This highlights an excellent forecasting ability and a strong correlation between actual and predicted values.

These results confirm that combining linear approaches (ARIMA) with nonlinear methods (ANN) significantly enhances forecasting accuracy compared to traditional models used independently. The stronger explanatory power observed in the South Korean market may be attributed to better data quality, greater market stability, and higher liquidity, all of which facilitate a more accurate capture of underlying dynamics.

Overall, the hybrid ARIMA–ANN model proves to be a robust and relevant approach for modeling and forecasting financial time series, particularly in markets characterized by complex and nonlinear behaviors.

5 Conclusion :

This study examined the predictive performance of three complementary forecasting approaches—ARIMA, Artificial Neural Networks (ANN), and a hybrid ARIMA–ANN model—using the MSI20 index in Morocco and the KOSPI index in South Korea. The comparative framework was designed to assess whether the relative effectiveness of linear, nonlinear, and hybrid forecasting approaches varies across financial markets with different structural characteristics.

The empirical results first reveal the limitations of the ARIMA model in forecasting the two stock market indices. The very high MAPE values, together with the low or negative R^2 values, indicate that the linear model has limited capacity to reproduce the complex dynamics observed in the financial series. Although ARIMA remains useful for capturing temporal dependence and linear patterns, its performance suggests that a purely linear representation is insufficient to adequately describe the irregular and nonlinear behavior of the markets considered.

The results obtained with the ANN model show a clear improvement compared with ARIMA. The reductions observed in MSE, RMSE, and MAE indicate that introducing nonlinear modeling capabilities allows the forecasting process to capture additional patterns that remain unexplained by the linear specification. However, the persistence of relatively high forecasting errors, particularly for the KOSPI, suggests that nonlinear modeling alone does not necessarily capture all the temporal structures embedded in financial market data. These findings support the relevance of combining linear and nonlinear modeling mechanisms rather than relying exclusively on one modeling paradigm.

The hybrid ARIMA–ANN model provides the strongest overall forecasting performance among the approaches examined. By first modeling the linear component through ARIMA and subsequently using ANN to capture nonlinear information remaining in the residuals, the hybrid framework benefits from the complementary characteristics of both approaches. For the MSI20, the hybrid model achieves an RMSE of 3.945 and an R^2 of 0.888, demonstrating a substantial improvement over the individual models. The results are even more pronounced for the KOSPI, where the hybrid model reaches an R^2 of 0.975 and records a substantially lower MAPE than the individual approaches. These findings indicate that the decomposition of financial time series into linear and nonlinear components can provide a more effective forecasting framework than the use of ARIMA or ANN independently.

The cross-market comparison also provides an important dimension to the analysis. The hybrid model performs considerably better on the South Korean market than on the Moroccan market. This difference may be related to structural characteristics such as market liquidity, trading activity, information availability, market depth, and investor composition, which may influence the statistical properties and predictability of financial time series. However, because these factors are not directly incorporated into the present empirical framework, they should be interpreted as plausible explanatory mechanisms rather than causal determinants of the observed differences. The results nevertheless suggest that the effectiveness of forecasting models may depend substantially on the specific characteristics of the market to which they are applied.

From a practical perspective, the findings suggest that the selection of forecasting models should be adapted to the characteristics of each financial market rather than based on the assumption that one model is universally optimal. For investors and portfolio managers, the superior performance of the hybrid ARIMA–ANN approach indicates that combining linear temporal dependence with nonlinear information may provide more informative forecasts and potentially support short-term market analysis, portfolio allocation, and risk-monitoring activities. Nevertheless, higher statistical forecasting accuracy should not be interpreted as a direct guarantee of investment profitability, since transaction costs, model uncertainty, structural breaks, unexpected shocks, and changing market conditions may affect actual investment outcomes.

The findings also have implications for financial regulators and market authorities. The differences observed between the MSI20 and KOSPI demonstrate that the effectiveness of artificial-intelligence-based forecasting systems may vary across market environments. Consequently, AI-based forecasting tools could be considered as complementary instruments for monitoring market dynamics and supporting quantitative analysis, while their outputs should be interpreted alongside conventional financial indicators, risk measures, and expert judgment.

Despite these contributions, several limitations should be acknowledged. First, financial markets are stochastic and continuously evolving systems that are exposed to unexpected shocks, structural changes, and changes in investor behavior. Therefore, the forecasting performance observed over the study period may not necessarily remain stable across different market regimes. Second, the present framework relies primarily on the historical information contained in the stock-index series and does not explicitly incorporate external economic or behavioral variables. Third, the comparative analysis does not directly test the extent to which market liquidity, trading volume, market depth, or investor composition explain the differences in model performance.

These limitations provide several directions for future research. Future studies could extend the hybrid ARIMA–ANN framework by incorporating exogenous macroeconomic variables, including interest rates, exchange rates, inflation, industrial activity, and international financial indicators. Investor sentiment could also be integrated through information extracted from financial news, social media, and other textual sources, potentially providing additional nonlinear information to the ANN component. Furthermore, future research could employ rolling-window or walk-forward forecasting procedures, alternative machine-learning and deep-learning architectures, and formal statistical tests of predictive accuracy to assess the robustness of the present findings across different market regimes and forecasting horizons.

Overall, the findings demonstrate that financial market forecasting benefits from approaches capable of jointly addressing linear temporal dependence and nonlinear dynamics. Among the three approaches examined, the hybrid ARIMA–ANN model provides the most consistent forecasting performance, particularly for the KOSPI. However, its effectiveness should be understood within the specific characteristics of each market and forecasting environment. The study therefore supports the use of hybrid statistical–artificial intelligence frameworks as a promising approach to financial forecasting while emphasizing the importance of market-specific modeling, robustness analysis, and the integration of broader economic and behavioral information.

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