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Estimating Future Stock Return for the pharmaceutical sector using Bayesian Vector Auto regression modeling and artificial Intelligence

Noor Sabah Hameed Al-Dahaan[1*] Mohammed Faez Hasan[2], Hussein Hadi Abdulameer[3], Haider Yonis Kadhem[4]

1 P.hD in Financial Management, Associate Professor of the Department of Finance and Banking Sciences. University of Kerbala, Kerbala, Iraq. ORCID: https://orcid.org/0000-0002-4492-610X
2 P.hD in Finance and Investments Sciences, Associate Professor of the Department of Finance and Banking Sciences. University of Kerbala, Kerbala, Iraq. ORCID: https://orcid.org/0000-0002-4579-3214
3 P.hD in Financial Management, Associate Professor of the Department of Finance and Banking Sciences. University of Kerbala, Kerbala, Iraq. ORCID: https://orcid.org/0000-0002-4579-3214
4 P.hD in Financial Markets, Assistant Professor of the Department of Finance and Banking Sciences. University of Kerbala, Kerbala, Iraq. ORCID: https://orcid.org/0009-0001-4735-7272

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ABSTRACT

The process of forecasting stock returns in the pharmaceutical industry is quite complex and risky because of such issues as the decision making process by regulatory authorities, the results of the research and development, and the variability in the macroeconomic conditions. The paper constructs a decision-support model by evaluating two modern forecasting models namely Bayesian Vector Auto regression (BVAR) model and Artificial Neural Network- Radial Basis Function (ANN-RBF) to predict stock returns of three stock exchange listed pharmaceutical companies based on Amman Stock Exchange. The given framework is based on the methodology where the two models are trained using time series data during the time frame 20192024 and the predictions are made during 20252030. The results show that BVAR, which includes the incorporation of time-dependences of macroeconomic variables, gives better forecasts of returns that possess the features of stability and linearity but ANN-RBF has better forecasts of returns that have volatility and nonlinearity. These findings prompt the need to consider such characteristics in the forecasting studies in order to produce meaningful results. In addition to methodological inputs, the research provides feasible guidelines to investors, corporate leaders, and other policy makers that seek to cope with the risk, make long-term investments, and guide financial decision-making in the pharmaceutical firms. Also, the research incorporates methods of applied mathematics, artificial intelligence, and finance, which supports the importance of forecasting models as evidence-based decision-making tools in conditions with high risks.

1. Introduction

Stock markets form a key component of a financial system of a country, just like derivatives,

* *Corresponding author.*
E-mail address: *noor.s@uokerbala.edu.iq*

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bonds, and commodities, and are basic drivers of economic growth. They represent sectoral supply and demand trends, and dividend payments can give returns to the investors which leads to wealth generation [7]. The performance in the stock market has in both the emerging and the developed economies been associated with high levels of change in the domestic output [36]. The performance in the stock market has in both the emerging and the developed economies been associated with high levels of change in the domestic output ([7]; Gollopeni et al., 2023), In spite of the fact that some studies have conflicting results (Bae et al., 2021; Rahman et al., 2024). The stock prices are vulnerable to various risks such as financial, economic and political risks, which can affect the performance of a country.

To avoid those risks, secure the interest of investors, guarantee that all regulations are adhered to, and secure the stability of the national economies, numerous methods have been created to predict returns of stocks in specific periods of time. These predictive mechanisms have transformed the old statistical techniques into modern machine learning models with the use of the big data analytics, artificial intelligence, and high-performance computing infrastructure [14; 24]. Nonetheless, traditional stock return prediction models have disadvantages like the use of stable, linear series of data, failure to respond to dynamic changes in the market and biases with unexpected impacts like political instability and market volatility [14]. Pharmaceutical industry has its own set of problems, which are the high costs of capital and research, the need to meet local and global regulatory requirements, concerns of employee welfare, threats on intellectual property, and the responsiveness to macro-economic trends [29]. Other risks are phase III clinical trials failure and inability to get marketing authorizations [1]. The existing product portfolios in the pharmaceutical companies and prospective future drugs are significant determinants of the market value of the company. Due to the visibility of such companies, publication of clinical trial results promptly is important, since, results have a significant impact on financial performance, and stock market behavior, in an already highly risky environment [5].

In financial markets, decision-making has become more complex and requires forecasting models to provide the ability to combine uncertainty, nonlinearity, and external shocks in order to create predictive frameworks that are robust [25]. In this context, stock markets are not only reflections of the supply and demand interactions within the industries, they also become the pillars of the national economic stability and planning of finances [9]. The pharmaceutical sector, especially, is very susceptible to regulatory ruling, research findings, the issue of intellectual property and macroeconomic shocks [10]. Even one regulatory hiccup or a clinical failure can create a high degree of volatility that creates uncertainty among the managers, investors, and policymakers [28]. This underscores a need to have decision-support models that allow predictive accuracy and interpretability to be balanced in order to plan investments, reduce risks, and sustain development.

Conventional econometric models, e.g., the autoregressive and the moving average models have helped in the understanding of market behavior but these models are limited in their ability to address nonlinear and volatile environments [17]. By contrast, the methods of artificial intelligence and machine learning, especially the neural networks have shown to be better at capturing the complex interaction between financial, economic, and firm-specific variables [33]. However, AI models can be faced with the problem of overfitting, lack of macroeconomic relationships, and interpretability [26]. In this regard, the current research paper will utilize a comparative and integrative approach, as both BVAR and ANN-RBF models are evaluated as stock returns predictors in pharmaceutical firms listed on the Amman Stock Exchange.

Machine learning has become a revolutionary method of trying to solve the nonlinearities of stock returns prediction. At a more specific level, the recent years have seen the emergence of more sophisticated ML and deep learning algorithms that are used to forecast stock market returns with a higher degree of accuracy, as opposed to the constraints of conventional statistical and econometric models. Of these, neural networks have achieved a consistent level of superiority over linear models by being able to effectively capture the complex interaction of firm-specific determinants, including profitability and investment with macroeconomic determinants, including interest rates and inflation [11]. Support vector machines, long short-term memory networks and artificial neural networks are other popular techniques that are used [18]. Nevertheless, there are still difficulties, including the insufficient attention to exogenous shocks and the lack of macroeconomic variables, which restrict the further application of ML-based stock forecasting techniques [30].

It is against this background that the present study is expected to forecast stock returns based on a mixture of the advantages of autoregressive models and neural network technologies to aid in making informed buying, selling, or holding decisions. Stocks returns have a great impact on the strategic decision of the investors and hence they have to be forecasted accurately. The paper aims at comparing and contrasting BVAR and ANN-RBF models in order to determine the best model of predicting stock returns in pharmaceutical companies listed at the Amman Stock Exchange, and these are linear and nonlinear data trends. The suggested framework represents a combination of probabilistic reasoning with predictive abilities of machine learning which presents a new contribution to the literature. Although, previously, stock market prediction in different industries has been studied in the Amman Stock Exchange, current work is the first attempt at directing the investigation specifically on the pharmaceutical industry in Jordan with combination of Bayesian auto regression and machine learning.

This study will boost the accuracy of stock returns prediction, and in the process, enable informed investment choice and good risk management in one of the industries that are vital to national health and financial stability. The results would help investors to reduce risks peculiar to the sector, because regulatory resolutions or research results may significantly change positions on the market and stability of firms. As a result, there is a great need to develop effective and efficient forecasting tools that can offer significant information to the academic world, policymakers, policy makers, and other stakeholders in the pharmaceutical industry.

2. Literature Review

This part will summarize the previous studies by authors that have been carried out in the pharmaceutical sector and on stock returns prediction, including the classical and state-of-the-art machine learning methods. It is divided into four sub-sections, summarizing the research related to the autoregressive techniques, implementation of machine learning and artificial intelligence techniques in stock market prediction, studies that look at the pharmaceutical industry specifically and those that look at the Amman Stock Exchange (ASE).

2.1 Application of Auto Regression Methods in Predicting Stock Market Returns

Zhao and Park [34] used the Panel Vector Auto regression tool to test the association amid Economic Policy Uncertainty (EPU) and stock market returns and the results revealed that domestic and foreign EPUs reacting to stock returns varied. It was found that growth in returns in the stock market has a positive impact on domestic output. Recent studies have proposed a high-dimensional BVAR model that can be used to evaluate the impacts of traditional monetary policy shocks. With the help of this sophisticated model, the effects of the US Federal Reserve on the consumer prices were discovered in significant ways in times of inflation. Zhao [35] We used an event-based data to predict the financial market returns applying a Bayesian framework and multiple regression algorithms; the results of our study have shown that both Bayesian Vector Autoregression (BVAR) and traditional frequentist models performed better as compared to non-Bayesian models (autoregressive and moving average models). Magris et al. [19] The extension and testing of a Bayesian bilinear neural network were done, thus showing its stability as compared to other traditional machine learning methods.

The Auto Regressive Exogenous (ARX) model which is a linear, regression based model has also been used by the researchers to predict the shares of a stock, with the least-squares optimization used as a model estimation technique. Based on the empirical evidence, it is concluded that the ARX model has a low level of suitability in terms of short-term forecasting. Tu et al. [30] Introduced a hybrid regression model, combining the autoregressive integrated moving average (ARIMA) model with Gaussian Process Regression (GPR), and a composite covariance model (GPRC), which were later confirmed to be effective in predicting stock returns. The hybrid framework was superior to the comparative models such as ARIMA, artificial neural network (ANN) and GPRC that were used individually. In addition to methodological innovation, stock returns forecasting has been used as a decision support instrument in order to maximize the managerial, investment and policy making performance. With accurate predictions, managers can maximize capital allocation, organize research and development activities, and simplify supply-chain operations, especially where there is a high degree of uncertainty, as is the case in areas like pharmaceuticals [26]. Investors use predictive models to diversify their portfolios, to control their risks in the market, and to determine the best time to either enter or exit the market, whereas policymakers can use the predictive models to predict systemic risks and to come up with regulatory measures to ensure market stability. Khare and Kapoor [17] This study highlights the value of equity forecasting to risk management in a portfolio, whereas [25] The current paper explains how deep learning models may be applied in the process of improving the pricing of assets and aiding investment planning.

2.2 Application of Machine Learning/Artificial Intelligence Techniques Upon Stock Market Prediction

Scholars have used a wide range of machine learning, deep learning, and artificial intelligence models to predict stock returns in diverse settings, and these models have used a wide range of financial and macroeconomic factors. These studies always support the soundness and accuracy of such methodologies. As an example, randomly forest and gradient-boosting decision tree algorithms have been applicable in predicting financial time series [34], Although the Long Short-Term Memory networks (LSTM) have proved to be effective in detecting time-related dependencies of stock returns [23]. Other frameworks, such as Multilayer Perceptron (MLP) and Recurrent Neural Networks (RNN) have also proven some significant predictive performance [8].

Oyewole et al. [22] The paper has performed a thorough review of the use of deep neural networks, artificial neural networks (ANNs), feedforward networks, radial basis function networks (RBF), recurrent neural networks (RNNs), convolutional neural networks (CNNs), long short-term memory networks (LSTMs), generative adversarial networks (GANs), multilayer perceptrons (MLPs), and gated recurrent networks (GRUs). Using cross-validation on the fourteen machine learning algorithms, the study concluded that the Gaussian process regression (GPR) has continuously performed better compared to the other models in terms of prediction accuracy. Khan et al. [16] Comparatively, nine machine-learning techniques were tested on stock-market returns prediction and it was found that the Random Forest model is the best since it has the highest accuracy of 91.27 followed by XGBoost, AdaBoost, and artificial neural networks with radial-basis functions. On the other hand, the traditional logistic regression achieved a lower accuracy of 85.51 0.00% thus highlighting the improved predictive power of sophisticated machine-learning methods. Also, the researchers used a Doc2Vec model in a deep-learning model by combining traditional market variables and textual data based on social media and it outperformed the forecasting accuracy of ARIMA, recurrent neural network, and long-short-term memory.

Dhar et al. [9] It has been noted that the modern equity forecasting approaches, including diffusion indices, forecast-combination methods, economically motivated model constraints, and regime-shift analysis, are all reliable in providing improvements in predicting returns over the historical averages. Wang [32] Neural network models were found to be similar in predicting performance based on different factor models, but the success was very dependent on the firm-specific variables. Sonkavde et al. [27] This paper has examined the use of various machine-learning and deep-learning models to predict stock returns and noted that Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures are especially useful when working with continuous or sequential market data, but traditional recurrent neural networks (RNN) can be used when operating on entirely historical data. Moreover, the paper highlighted the efficacy of ensemble techniques that integrates support-vector machine (SVM), diverse neural network structures, and decision tree based regressors. However, the authors warned that richer feature representations might be necessary to create robust model training, just in case price-variation information is not enough.

Phuoc et al. [23] To predict the price movement in the stock in the Vietnamese market, the LSTM algorithm was used to predict the stock price with an accuracy rate of 93 per cent and thus validating the applicability of the LSTM methodologies in analytical evaluation as well as predicting the changes in stock price. Altogether, these studies prove that machine learning and artificial intelligence frameworks present significant advantages in outlining nonlinear and complex relationships between firm-specific factors and macroeconomic variables, which justifies their affirmation as essential tools in modern stock returns prediction.

2.3 Stock Market Predictions for the Pharmaceutical Industry

Wang [32] Investigated the pharmaceutical industry reaction to abrupt and radical shocks, including the COVID-19 pandemic, with the help of a hybrid deep learning model incorporating Long Short-Term Memory (LSTM) and Transformer architectures. Compared to other models such as Support Vector Machine, Random Forest, and Naïve Bayes, the proposed hybrid algorithm managed to forecast the movements of stocks with multimodal datasets and was also able to derive causal relationships between the market sentiment and the stock trends, which is paramount to the pharmaceutical industry. Kaur and Chavali [15] Using the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH -M), the model generated smooth predictions of the stock price dynamics in pharmaceutical companies, and the results of the analysis showed that the stock volatility increased after the COVID-19 pandemic. The researchers concluded that GARCH -M is especially effective in the task of the prediction of returns of stocks of pharmaceutical companies, which provides information-grounded data regarding the dynamics of volatility and risk-return relationships.

Abramavičius et al. [1] The investigators used finite Gaussian mixture modeling in assessing the effect of drug development setbacks (DDS) on the stocks of pharmaceutical companies and found that drug development setbacks have a negative effect on the valuations of pharmaceutical companies. Meher et al. [20] The analysis utilized time-series information of the sampled Indian pharmaceutical companies based on the Auto-Regressive Integrated Moving Average (ARIMA) model. The results showed that the estimated values were very close to the actual ones and the authors suggested having both the autoregressive and moving average elements to guarantee the effective description of the stock price changes in the pharmaceutical sector. He et al. [13] Due to interest in companies creating COVID-19 vaccines, the study forecasted the stock price based on several contemporaneous aspects and exogenous events. The authors applied the Multilayer Perceptron (MLP) models with the help of the logistic regression and decision trees and proved that predictive performance improved significantly with the combination of feature engineering and data-mining methods. Omar et al. [21] The current analysis has found three high-performing models of predicting stock indices under the increased volatility due to the COVID-19 pandemic: two implementations of autoregressive deep neural networks and random forest (RF) models. The methods performed better than the traditional time-series forecasting methods, including the autoregressive moving average (ARMA) model, in forecasting the rapid changes in stock prices.

2.4 Stock Market Predictions in Amman Stock Exchange

Alswalmeh and Qaqish [3] This paper was an analysis of performance of the banking sector stocks listed in the Amman Stock Exchange (ASE) using a set of financial ratios. The analysis conducted with the help of ordinary least squares (OLS) regression revealed that the ratios have a significant predictive ability in terms of the fluctuations of the banking sector index. Al-Najjar [2] The researchers compared the ASE Index (ASEI), which is a growing stock exchange index, and international indexes like the S and P 500 and NASDAQ using artificial neural networks (ANN), correlation and stepwise regression. The results were used to conclude that the ANN was effective in capturing the relationships between the ASEI and the international indices with a significantly high degree of correlation between the ASEI and the S&P 500 being observed. Wadi et al. [31] ARIMA model was used to predict the ASE stocks and thus provided good short-term predictions to investors. Another study used regression extrapolation to analyze the impact of systematic and unsystematic risks on the stock returns of ASE-listed companies, which showed that the inflation and firm size have a negative impact on stock returns in Jordan. In addition, nonlinear artificial neural network (ANN) model predictive skills were compared with traditional regression models in forecasting ASE stock returns. The findings showed better accuracy by using the stationary ANN models making them the best choice in the prediction of stock returns in this case.

3. Methodology

This section will outline the methodological framework which will be used to accomplish the objectives of the study. The target population included companies that were in the pharmaceutical and medical industries and listed in the ASE, Jordan. Out of an initial sample of 27 companies listed in the market, three companies including Jordanian Drug House, Hayat Pharmaceutical Company and Philadelphia Company were selected based on the availability and completeness of their financial records over the given time frame. The paper has collected secondary data in form of closing share prices of the sampled companies over a five-year period of January 2019 to November 2024. The data on time-series of the individual companies have been coded as follows.

R1: Time-series data of Jordanian Drug House.
R2: Hayat Pharmaceuticals Time-series data.
R3: Philadelphia time-series data.

First, the time-series data was exposed to the Augmented Dickey Fuller (ADF) test to determine the stationarity of the three variables R1, R2 and R3. The stationarity is essential in the further use of autoregressive models like Bayesian VAR (BVAR) since non-stationary observations can cause spurious regressions and invalidity of predictions [12]. The precision of forecasting was evaluated using performance measures, which are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) while BVAR models were considered. To illustrate the time distribution of the returns, scatterplots were created. Having estimated BVAR model of each research variable, the models were used to create predictions of the period between January 2025 and December 2030. The Radial Basis Function (RBF) model which is a feedforward neural network paradigm was then used to make the research variables prognostic. The hypotheses were later formulated as follows in line with the objectives of the study.

H1: *In comparison with artificial neural networks (ANNs), Bayesian vector autoregression (VAR) models are found to exhibit high forecasting performance in stable time-series prediction of financial returns (i.e., R2 and R3).*

H2: *The forecasting accuracy of artificial neural networks is better than that of Bayesian vector autoregressive models in the case of volatile time series like R1.*

H3: *The predictive ability of forecasting depends on the inherent properties of the data; combined BAR and ANNs show better predictive ability when there is interaction of both linear and nonlinear predictors.*

4. Results

This part outlines the findings of the analysis of the data using two different methodological models of Bayesian Vector Auto regression (BVAR) model and artificial neural network (ANN) methods, and is aimed at answering the research questions. The first sub-section explores the stationarity properties of the time-series data whereas the second sub-section explores the autoregressive modelling process. The third sub- section displays the estimation of the BVAR model and its predictions between January 2025 and December 2030. The last sub -section focuses on the application of radial basis function (RBF) feed-forward neural network to estimate the values of the three variables under research, and a discussion of the RBF network and the ANN-RBF hybrid model outputs.

4.1 Time Series Data - Stationarity Analysis

The time-series data of the three pharmaceutical companies throughout the study period during the months between January 2019 and December 2024 are shown in Figure 1. The results of the Augmented Dickey Fuller (ADF) test reported in Table 1 reveal that the all three variables (R1, R2, and R3) are stationary with a statistically significant p -value of 0.000 in the various model specifications, such as no constant, constant, and constant with trend. The fact that the unit root hypothesis was rejected proves that the time series under analysis was stable in nature, meaning that it had a constant mean and constant variance throughout the time period under analysis. These findings are in line with the canonical theory of econometrics whereby, stationarity is a necessary requirement in order to be able to draw reliable inferences based on the time-series models. The results of the Augmented Dickey Fuller test, which are demonstrated in Figure 1 and Table 1, support the fact that pharmaceutical stock returns are stationary and are in line with standard methodological norms [12].

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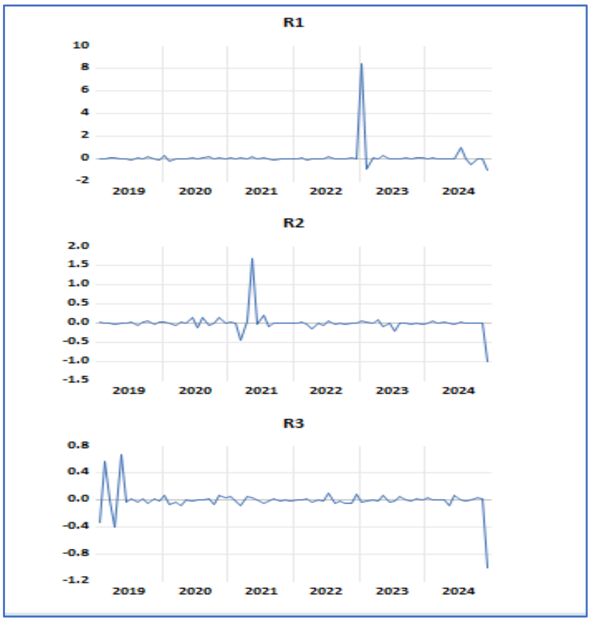

Fig.1: Augmented Dickey-Fuller (ADF) Results of the Variables
Source: Author's own analysis.

The analysis has shown that the R3 firm (Philadelphia Company) has the highest level of persistence, with the test statistic of -10.081 under trend specification, which means that the equity returns of the firm did not experience any significant structural perturbations or exogenous shocks. This finding is congruent with the results of Attílio [4], In a study that reported that stable stock returns often convey market efficiency, a Global Vector Autoregressive model was used to investigate the effect of exogenous shocks on equity returns. Although stationarity is extremely important in time-series analysis, it does not necessarily give predictive power, with the accuracy of any forecasts again depending on exogenous effects and on actually specifics of the model used.

Table 1
Unit Root Test Results (Augmented Dickey-Fuller)

Variable	Statistic	Without	With the Constant	The Presence of Constant and Direction
R1	T-test	-9.226	-9.270	-9.224
	Prob.	0.000	0.000	0.000
Decision		**Significant**	**Significant**	**Significant**
R2	T-test	-7.557	-7.489	-7.571
	Prob.	0.000	0.000	0.000
Decision		**Significant**	**Significant**	**Significant**
R3	T-test	-9.774	-9.692	-10.081
	Prob.	0.000	0.000	0.000
Decision		**Significant**	**Significant**	**Significant**

Source: Author's own analysis.

4.2 Autoregressive Model Estimation

After the evaluation of stationarity, Bayesian Vector Auto regression (BVAR) model was then performed and confirmed on each research variable. The findings of the analysis are tabulated in Table 2 and plotted in Figures 2 4; the findings also give the measures of forecasting performance, that is, mean absolute error (MAE) and root-mean-square error (RMSE), and the forecasting values of appreciation of all three variables. Table 2, therefore, highlights the effectiveness of the BVAR models in the short-term persistence of pharmaceutical stocks returns. The following points summarize the main findings based on these findings.

- R1 (Jordanian Drug House): The only dominant influence on the model is exerted by R1 (-1) =

0.552, SD = 0.078, hence, indicating high short-term persistence in returns. On the other hand, the secondary lag (R1 (-2) = 0.008) is small in importance meaning that there is a low ability to remember over the long term.

- R2 (Hayat Pharmaceuticals): the first lag (R 2 (- 1) = 0.647, SD = 0.081) has a considerably stronger persistence, and the second lag (R 2 (- 2) = -0.012) adds a relatively small mean-reverting this element.
- R3 The primary lag (R3 -1 = 0.57, SD = 0.082) prevails, similar to R1 and R2, but the model also gives the smallest forecast errors (MAE = 0.0771, RMSE = 0.163), which means increased predictive accuracy.

The root-mean-square error (RMSE) measures of 1.008, 0.246, and 0.163 of R1, R2, and R3, respectively, show that the forecast-error volatility is less systematic across the series with the largest stability of R3. In line with this, data on the mean absolute error (MAE) namely 0.255, 0.085 and 0.0771 in R1, R2, and R3 respectively show that the predicted returns are on average nearest to the observed results. The relatively small standard deviations, such as 0.078 that R1(−1) has, indicate that the estimates of the parameters are accurate, which is a necessary condition of strong Bayesian inference. The high percentage of first-lag coefficients supports the previous results and thus confirms the existence of short-term momentum in the stock returns. Moreover, the standard-deviation levels are low, which confirms the fact that the BVAR model reduces uncertainty in the estimation, particularly with the use of small samples. The accuracy of forecasts was measured on the basis of MAE and RMSE, whereby RMSE asymmetrically penalizes large deviations and hence explains the low RMSE of R3 of 0.163 despite having an equal MAE as R2. Interestingly, first-lag coefficients (e.g., R2 (-1) = 0.647) are significant to indicate that new return values have a big impact on future expectations, These findings are compatible with what literature exists. The negative second-lag value of R2 (R2 = -0.012) can either be a sign of the market correction or profit taking activity. The high performance of R3 (MAE = 0.0771) can be probably explained by the fact that it has stable fundamentals and it is less inclined to be affected by external shocks, which proves the hypothesis that firm-specific factors play a central role in predicting the accuracy.

Table 2
Bayesian Autoregressive Model Estimates

Series	**Variables**	**Appreciation**		**Forecast Quality Criteria**	
		Parameter	**Standard Deviation**	**MAE**	**RMSE**
Jordanian Drug	R1(-1)	0.552	0.078		
House	R1(-2)	0.008	0.046	0.255	1.008
	constant	0.038	0.124		
Pharmaceutical	R2(-1)	0.647	0.081		
Life	R2(-2)	-0.012	0.047	0.085	0.246
	constant	-0.008	0.03		
Philadelphia	R3(-1)	0.57	0.082		
	R3(-2)	0.006	0.047	0.0771	0.163
	constant	-0.018	0.018		

Source: Author’s own research.

Figure 2 compares the empirical and the projected returns of R1 (Jordanian Drug House) where the available data are drawn as discrete points on a scatter diagram and the model projections are represented by a functional curve or continuous line. When the BVAR model was applied to R1 a Mean Absolute Error (MAE) value was 0.255 and a root mean square error (RMSE) was equal to 1.008.

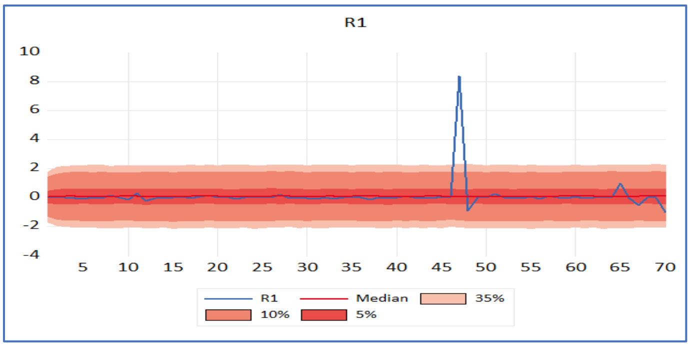

Fig.2: Spread of True and Predicted R1 Time Series Data

Figure 3 specifies the respective findings of R2 (Hayat Pharmaceuticals) with smaller error margins with a mean absolute error (MAE) of 0.085 and root mean squared error (RMSE) of 0.246. The smaller values of RMSE and MAE of R2 indicates a better predictive power, which is likely caused by a stronger short-run momentum (R2(-1) = 0.647 compared with R1(-1) = 0.552). The residual plot, based on the dispersion of error, has a very small system error, and hence, confirms the strength of the model.

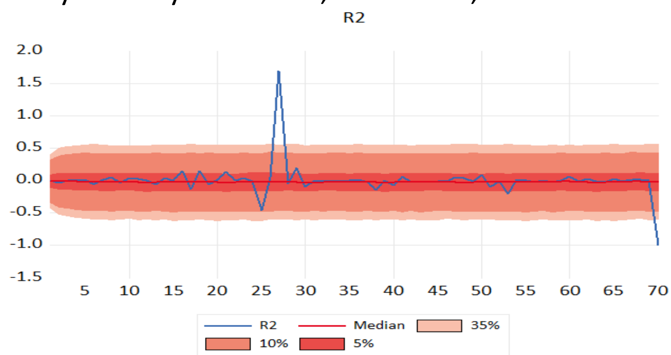

Fig.3: Spread of True and Predicted R2 Time Series Data

Figure 4 also shows that the observed and predicted R3 time-series data is in concordance thus supporting the thought that the forecasts generated by the Bayesian Vector Autoregression (BVAR) model are valid.

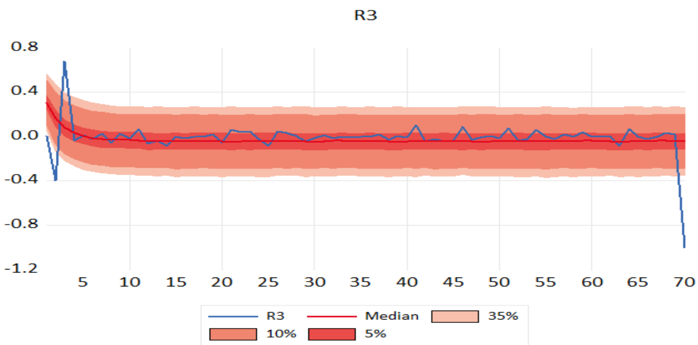

Fig. 4: Spread of True and Predicted R3 Time Series Data

4.3 Forecasting using BAR

The Bayesian Vector Auto regression (BVAR) model was used in this section to make stock returns predictions of the three firms (R1, R2, and R3) between January 2025 and December 2030. The monthly forecasts obtained with the help of the BVAR model are shown in Table 3. Among the key findings, there is a change of R1 to positive returns during the period of 2026-2030 (e.g., +0.511 in January 2025), although in the transition, R1 remains negative at the beginning of 2025 (as well as the Cp95). R2 and R3 on the other hand show consistent near-zero or even negative returns (e.g.,: -0.019 -0.030; -0.035-0.047), indicating relative stability or stagnation. These are projections that are relevant to these predictions in the BVAR model that rely on the short-term momentum as was indicated in Table 2 (e.g., R1(-1) = 0.552). The seasonal variations including the peak of R1 in mid-2026 are most likely to reflect the cyclical one-sector dynamics that include the approval schedule of pharmaceutical products. The ensuing recovery in returns R1 is seemingly caused through Bayesian updating of lagged returns series as well as exogenous variables especially breakthroughs in research and development. The performance of the artificial neural network (ANN) models in filtering noises revealed by the comparatively stable performance of R2 and R3 is not a recent finding, concluding the previous empirical outcomes. In this regard, Table 3 shows the effectiveness of Bayesian vector autoregression (BVAR) model in selected momentum-based trends in R1, as well as simultaneously highlighting the support value of ANN methodologies in stabilising predictions of both R2 and R3.

Table 3
Stock Returns Predictions for All the Three Firms (R1, R2 and R3) for January 2025–December 2030

Year	Month	Jordanian Drug House R1	Pharmaceutical Life R2	Philadelphia R3	Year	Month	Jordanian Drug House R1	Pharmaceutical Life R2	Philadelphia R3
2025	January	-0.511	-0.027	-0.045	**2026**	January	0.087	-0.019	-0.042
	February	-0.252	-0.023	-0.042		February	0.077	-0.025	-0.044
	March	-0.103	-0.025	-0.044		March	0.092	-0.023	-0.043
	April	-0.028	-0.019	-0.041		April	0.098	-0.022	-0.043
	May	0.038	-0.027	-0.045		May	0.106	-0.023	-0.043
	June	0.078	-0.018	-0.040		June	0.094	-0.021	-0.041
	July	0.100	-0.019	-0.041		July	0.112	-0.015	-0.038
	August	0.083	-0.015	-0.041		August	0.100	-0.023	-0.042
	September	0.064	-0.023	-0.044		September	0.110	-0.023	-0.044
	October	0.064	-0.026	-0.046		October	0.085	-0.020	-0.043
	November	0.103	-0.019	-0.042		November	0.084	-0.027	-0.047
	December	0.097	-0.027	-0.047		December	0.108	-0.022	-0.043
2027	January	0.108	-0.018	-0.039	2028	January	0.110	-0.025	-0.044
	February	0.076	-0.019	-0.042		February	0.086	-0.025	-0.044
	March	0.090	-0.010	-0.036		March	0.096	-0.028	-0.045
	April	0.063	-0.015	-0.040		April	0.063	-0.024	-0.045
	May	0.106	-0.021	-0.042		May	0.077	-0.028	-0.045
	June	0.088	-0.016	-0.041		June	0.090	-0.029	-0.047
	July	0.075	-0.015	-0.039		July	0.077	-0.025	-0.046
	August	0.087	-0.022	-0.043		August	0.083	-0.018	-0.041
	September	0.073	-0.022	-0.043		September	0.068	-0.029	-0.046
	October	0.058	-0.021	-0.043		October	0.057	-0.030	-0.047
	November	0.072	-0.022	-0.044		November	0.057	-0.030	-0.044
	December	0.092	-0.026	-0.044		December	0.082	-0.024	-0.044
2029	January	0.082	-0.030	-0.047	2030	January	0.100	-0.020	-0.042
	February	0.078	-0.026	-0.044		February	0.092	-0.019	-0.041
	March	0.095	-0.028	-0.045		March	0.098	-0.019	-0.042
	April	0.106	-0.027	-0.046		April	0.058	-0.025	-0.044
	May	0.111	-0.019	-0.041		May	0.061	-0.021	-0.044
	June	0.063	-0.019	-0.041		June	0.054	-0.017	-0.040
	July	0.057	-0.022	-0.043		July	0.060	-0.009	-0.035
	August	0.083	-0.022	-0.043		August	0.091	-0.013	-0.040
	September	0.102	-0.017	-0.041		September	0.086	-0.022	-0.041
	October	0.072	-0.023	-0.043		October	0.068	-0.024	-0.044
	November	0.101	-0.020	-0.044		November	0.086	-0.021	-0.042
	December	0.077	-0.023	-0.044		December	0.094	-0.019	-0.041

Source: Author's own research.

4.4 ANN-RBF Feed-Forward Neural Network Model

In this section, the use of an artificial neural network with radial basis function (ANN-RBF) to provide stock returns forecasts of the three pharmaceutical enterprises to be studied (R1, R2 and R3) is outlined. The used model is a radial basis function feed-forward neural network that was trained on the accessible times-series data to forecast the intended variables. The results of this analysis are summarized in Table 4. Table 4 shows that R3 achieved the most relative error (0.969) and training accuracy, which is 77.8 percent of the data, These results are evidence of strong pattern recognition and predictive behavior. On the contrary, R1 has the highest testing error (6.091) compared to its training error (0.991), which indicates that there exists overfitting, despite the fact that 73.6% of the data were used in the training set. The same overfitting problems have been reported in literature [6]. Altogether, Table 4 illustrates the effectiveness of the RBF network to produce consistent predictions on R3, but it also highlights the overfitting issue that became apparent in R1.

Table 4
ANN_RBF Neural Network Model Results for All the Three Pharma Firms (R1, R2 and R3)

Variables	N. of Hidden Layer	Sample	N	Percent	Relative Error
R1	1	Training	53	%73.6	0.991
		Testing	19	%26.4	6.091
R2	1	Training	55	%76.4	1.0006
		Testing	17	%23.6	1.494
R3	1	Training	56	%77.8	0.969
		Testing	16	%22.2	1.184

As shown in Table 5, asset R1 had to deteriorate when modest positive returns (0.150 in January 2025) were transformed into negative values (−0.130 in December 2030) by the time the model ended, as the hypothesis of overfitting or the effect of omitted exogenous variables, including regulatory changes. Conversely, assets R2 and R3 had significantly more stable near-zero returns (R2: 0.010 to -0.020; R3: -0.020 to -0.040), thus indicating the successful acquisition of sector-dependent stability, presumably due to the ability of the RBF model to reproduce low-volatility effects. Such a strong negative trend in the returns of R1 is inconsistent with the forecasts of the BVAR provided in Table 3, hence highlighting the exaggerated vulnerability of ANN-RBF model to stochastic shocks in the highly volatile series. These results affirm that, despite the strength of neural networks in stabilising returns of securities with relatively low levels of volatility, neural networks still fail to withstand over-fitting when faced with volatile and transient patterns of returns, a finding that is consistent with prior empirical studies.

Table 5
Forecasting of Research Variables for the Period January 2025 - December 2030

Year	**Month**	**Jordanian Drug House**	**Pharmaceutical Life**	**Philadelphia**	**Year**	**Month**	**Jordanian Drug House**	**Pharmaceutical Life**	**Philadelphia**
		R1	**R2**	**R3**			**R1**	**R2**	**R3**
2025	January	0.150	0.010	-0.020	**2026**	January	0.100	0.010	-0.020
	February	0.140	0.010	-0.020		February	0.090	0.000	-0.020
	March	0.140	0.010	-0.020		March	0.090	0.000	-0.020
	April	0.140	0.010	-0.020		April	0.080	0.000	-0.030
	May	0.130	0.010	-0.020		May	0.080	0.000	-0.030
	June	0.130	0.010	-0.020		June	0.070	0.000	-0.030
	July	0.120	0.010	-0.020		July	0.070	0.000	-0.030
	August	0.120	0.010	-0.020		August	0.060	0.000	-0.030
	September	0.110	0.010	-0.020		September	0.060	0.000	-0.030
	October	0.110	0.010	-0.020		October	0.050	0.000	-0.030
	November	0.100	0.010	-0.020		November	0.050	0.000	-0.030
	December	0.100	0.010	-0.020		December	0.040	0.000	-0.030
2027	January	0.040	0.000	-0.030	**2028**	January	-0.020	0.000	-0.030
	February	0.030	0.000	-0.030		February	-0.020	-0.010	-0.030
	March	0.030	0.000	-0.030		March	-0.020	-0.010	-0.030

Table 5
Forecasting of Research Variables for the Period January 2025 - December 2030 (Cont…)

Year	Month	Jordanian Drug House	Pharmaceutical Life	Philadelphia	Year	Month	Jordanian Drug House	Pharmaceutical Life	Philadelphia
		R1	R2	R3			R1	R2	R3
	April	0.020	0.000	-0.030		April	-0.030	-0.010	-0.030
	May	0.020	0.000	-0.030		May	-0.030	-0.010	-0.030
	June	0.020	0.000	-0.030		June	-0.040	-0.010	-0.030
	July	0.010	0.000	-0.030		July	-0.040	-0.010	-0.030
	August	0.010	0.000	-0.030		August	-0.040	-0.010	-0.030
	September	0.000	0.000	-0.030		September	-0.050	-0.010	-0.030
	October	0.000	0.000	-0.030		October	-0.050	-0.010	-0.030
	November	-0.010	0.000	-0.030		November	-0.060	-0.010	-0.040
	December	-0.010	0.000	-0.030		December	-0.060	-0.010	-0.040
2029	January	-0.060	-0.010	-0.040	**2030**	January	-0.100	-0.010	-0.040
	February	-0.070	-0.010	-0.040		February	-0.110	-0.010	-0.040
	March	-0.070	-0.010	-0.040		March	-0.110	-0.010	-0.040
	April	-0.070	-0.010	-0.040		April	-0.110	-0.020	-0.040
	May	-0.080	-0.010	-0.040		May	-0.120	-0.020	-0.040
	June	-0.080	-0.010	-0.040		June	-0.120	-0.020	-0.040
	July	-0.080	-0.010	-0.040		July	-0.120	-0.020	-0.040
	August	-0.090	-0.010	-0.040		August	-0.120	-0.020	-0.040
	September	-0.090	-0.010	-0.040		September	-0.130	-0.020	-0.040
	October	-0.090	-0.010	-0.040		October	-0.130	-0.020	-0.040
	November	-0.100	-0.010	-0.040		November	-0.130	-0.020	-0.040
	December	-0.100	-0.010	-0.040		December	-0.130	-0.020	-0.040

Source: Author's own research.

The IMSE values of forecasting performance of BVAR and ANN-RBF are summarized in table 6. The results comparison shows that ANN-RBF had the lowest IMSE value of R1 that was more accurate than BVAR, however, in the case of R2 and R3 BVAR gave better estimations and predictions.

Key observations from Table 6 include:

R1: ANN-RBF model performed better than the BVAR (IMSE = 0.352 relative to 1.008), which means that it is more flexible to nonlinear tendencies and stochastic variation patterns in R1 returns.

The smallest integrated mean-squared error statistics were obtained: R2 0.246 compared with 0.394 and R3 0.163 compared with 1.700, indicating the strength of the models in modeling the linear interdependencies that are stable.

These findings suggest that Bayesian vector auto regression (BVAR) model proves to be especially effective in the setting of stability and well-defined autoregressive networks. In comparison, the artificial neural network with radial-basis-function (ANN-RBF) scheme has a strong strength in handling complex, noisy data sets, but has a higher chance of overfitting as indicated by the higher integrated mean-squared error (IMSE) of R3.

Table 6

IMSE Values of Both BAR and ANN-RBF Models for the Three Study Firms (R1, R2 and R3)

Model	Variable	IMSE	Best Model
Bayesian Autoregressive Model	R1	1.008	ANN-RBF
ANN-RBF		0.352	
Bayesian Autoregressive Model	R2	0.246	Bayesian Autoregressive Model
ANN-RBF		0.394	
Bayesian Autoregressive Model	R3	0.163	Bayesian Autoregressive Model
ANN-RBF		1.700	

Source: Author's own research

5. Conclusion

The research compared the performance of the BVAR and ANN-RBF models in prediction of stock returns in pharmaceutical companies that are listed in ASE. Findings point to the level of efficacy being predicted based on the data characteristics. The BVAR was found to be more accurate with stable, linear series, by being able to integrate time dependencies and macroeconomic variables, compared to ANN-RBF, which was more accurate with volatile, nonlinear series, and could find the hidden regularities in noisy data. Nevertheless, ANN-RBF over fitted in stable series, which points to the importance of selecting models carefully. These results indicate that one model is not always the best. With its benefits of interpretability and strong predictive ability of Bayesian Vector Auto regression (BVAR) combined with the flexibility and nonlinear modelling properties of an Artificial Neural Network-Radial Basis Functions (ANN-RBF), this hybrid-forecasting framework provides increased resistance to financial uncertainty. Applied, such forecasts can guide the strategic capital investment, research and development priorities, and risk-management by the pharmaceutical managers, including choices made on the expansion of production capacity, investment in a new drug development or risk-hedging in the face of exogenous shocks.

To investors, the framework acts as decision-support tool that can be used to optimize the buy, hold or sell strategy in high volatility conditions. Representatives and regulators can use the structure to predict systemic risks and thus protect financial stability in an industry that is highly sensitive to regulatory licenses, research and development and macroeconomic shocks. In addition to pharmaceuticals, the application of applied mathematics and artificial intelligence facilitates the fact that the decision-making framework can be transferred to other industries of energy, defence, and supply-chain management that also demand strong forecasting in the face of uncertainty. The research also contributes to sustainable growth when it comes to the allocation of resources, planning investment, and proactive risk management, which are essential, in the long term, to resilience in high-risk industries. The limitation of the study is that three firms are only considered, which hampers the generalizability of the findings, and the use of historical data, which inhibits responsiveness in response to the sudden shock. Future studies ought to increase the sample size, use multimodal sources and seek to develop hybrid models that can offer the interpretability of econometrics and the flexibility of the more advanced artificial intelligence.

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