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Forecasting the Price Behavior of the Iraq Stock Market Index Using Multilayer Artificial Neural Networks

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Abstract: *This paper explores multilayer artificial neural networks (ANNs) for predicting the price trend of the years of Iraqi Stock Market Index (ISX60). In an unstable economy and a politically unstable country such as Iraq, traditional forecasting techniques, such as ARIMA and linear models, fail to reflect the intricate and non-linear behavior of the market. The ANN model was constructed based on daily observations of the ISX60 index value and trading volume. The proposed model obtained a high R^2 of 0.92 and was better than classical models in terms of accuracy and error reduction. The forecast findings indicate a mild but rising ISX60 index moving from 2025 to 2029. This study sheds light on the benefits of ANN models in the context of developing markets, in particular that they can respond to volatile market environments and discloses information about the underlying patterns from financial time series data. The outcomes are helpful to the investors, analysts and policy makers who required also read financial forecasting and risk management tools in a turbulent economic environment like Iraq.*

Keywords: Price behavior, Iraq Stock market, Artificial Neural Networks (ANN)

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INTRODUCTION

Together with indicating the state of affairs of the country on the one hand, the Iraq Stock Market Index (ISX60) demonstrates the degree of trust of investors to it on the other hand as it reflects the performance of the largest publicly listed corporations traded in the country (Faez et al., 2024). In the last ten years, the Iraqi stock market has experienced many fluctuations due to political factors, variation in the prices of oil and economic developments in the nation. This has subsequently made it extremely hard on investors, policy makers and financial analysts to correctly estimate on what the market will do (Khalid Chyad and Aljubori, 2021). The simple methods used in forecasting may not work well with the complex and nonlinear patterns that can be observed easily usually in the Iraqi Stock Market and therefore it is worth finding out more superior and an improved way of modelling it.

Artificial neural networks have gained popularity in financial forecasting especially in the multilayered ANNs as they are able to determine the rules of a complicated relationship in data and discover patterns in data without necessarily understanding how the data is constituted subsequently. In this study, a multilayer ANN model is explored and results are used to attempt and estimate how the ISX60 index will vary its prices further between the year 2013 to 2024. This study attempts to answer the question of how predictive the index is at all by analyzing the history of the market and applying new techniques of machine learning to study more about how it evolves over past periods and how people can make decisions on investing and making economic choices better in Iraq.

Nomenclature & Symbols

ANN: Artificial Neural Network
VAR: Vector autoregression
RMSE: Root Mean Squared Error
ReLU: Rectified linear unit
MLP: Multi-Layer Perceptron
ISX: Iraqi Stock Market Index
ARIMA: Autoregressive Integrated Moving Average
GARCH: Generalized Autoregressive Conditional Heteroskedasticity
LOESS Regression: Locally Estimated Scatterplot Smoothing Regression

Aim and objectives

This study aims to forecast the price behavior of the Iraq Stock Market Index (ISX60) for five years using multilayer artificial neural networks (ANNs). The objectives are to:

- To develop and train a multilayer artificial neural network (ANN) model using historical data of the ISX60 index to forecast future price behavior.
- To evaluate the accuracy and predictive performance of the ANN model by comparing it with traditional forecasting methods such as ARIMA or linear regression.
- To analyze the long-term trends and potential market patterns in the Iraq Stock Market Index over a five-year forecasting period using the trained ANN model.

RELATED WORK

Stock market index forecasting is quite crucial in finance and economics because it determines investment opportunities, policies and structure development of the economy in future. Predicting the market correctly allows investors to control their risks, adjust their assets wisely, and gain more profits. Reliable forecasts are useful for policymakers because they can help them design rules and measures to make financial markets

stable and boost the economy (Kumar et al., 2021). Due to the unpredictable ways of stock markets, researchers have worked on finding better methods for making accurate predictions. A vast range of statistical and econometric models is being used. Still, economists are turning to machine learning because it can deal with nonlinear and complex trends in markets.

Due to being an emerging market, the Iraqi Stock Market (ISX60) faces particular difficulties when trying to forecast, mainly because of uncertain liquidity, politics, and risks linked to oil prices and nearby conflicts. Because of these factors, prices can change erratically, which makes it difficult to use traditional ways of forecasting. In this situation, multilayer ANNs have been found useful because they can find hidden patterns and adjust to any market changes (Ismail and Reda, 2021). It considers several forecasting options, mainly multilayer ANNs, by exploring their underlying ideas, uses, and how they fare better than traditional methods in volatile and up-and-coming markets like Iraq.

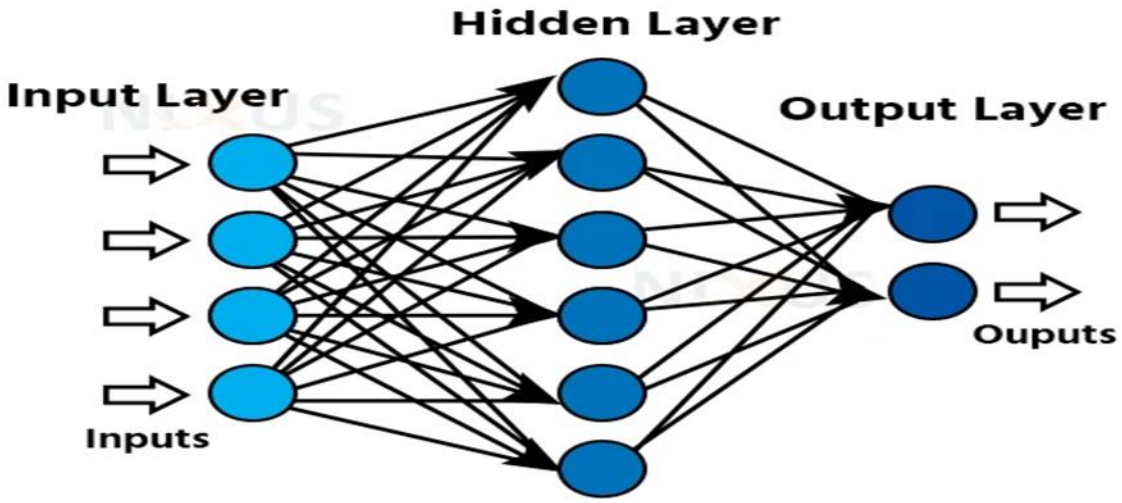

Figure 1: ANN Working
(Source: NIXUS, 2025)

Stock Market Forecasting: Traditional Approaches

Historically, stock market forecasting has mostly used statistical and econometric models, like ARIMA, GARCH, and VAR to help predict how the markets might move. These models work on the idea that financial time series usually stay the same over time, or that if the data doesn't show this, we can make it behave that way by subtracting previous values (Mokhlis et al., 2021). They also assume that what happened to interest rates in the past will be pretty similar to what will happen in the future. These assumptions help make things simpler to model and they give us a way to look at and use the model that isn't too hard to understand (Tarno et al., 2020). However, real-world financial markets, especially those in developing countries like Iraq, don't always follow these ideas because there are a lot of unpredictable and up-and-down changes happening.

The ARIMA model has long been a key part of how experts try to predict patterns in time series data. It uses a mix of past values and errors to help predict what the future values might be (Dhyani et al., 2020). ARIMA does well when data is steady and easy to predict. Its drawbacks can be noticed when the data gets

mixed up, has sharp changes or faces unexpected events. The Iraqi Stock Market is affected by things like political troubles, oil prices and economic restrictions (Fasanya et al., 2021). These changes make it a complicated place where regular models might not show how quickly the market can change or how a new government can take over.

GARCH models go along with ARIMA by directly taking into account volatility clustering, which is something seen a lot in financial data, where times when the prices move up or down a lot tend to be followed by more such ups and downs, and times when prices are more steady usually lead to more steady prices later. GARCH picks up these changing levels of volatility by looking at how much the errors in the past squared and how much their variance changed (Arashi and Rounaghi, 2022). Although GARCH models help us better understand how market risk and volatility change, they still use simple formulas and might not get all the non-linear connections that can happen when things are moving in the market or when the market is new (Koo and Kim, 2022). Despite how well established and clear they are, these models tend to lose predictive accuracy in markets that are unpredictable, not simple, or changing fast. Traditional methods fail to understand market dynamics well, so the focus of researchers has dwelt upon the invention of new data-based instruments, such as artificial neural networks or the machine learning techniques.

Artificial Neural Networks in Financial Forecasting

ANNs have gained popularity especially in the area of forecasting since they have a high ability of recognizing complex and non-linear correlations within financial data. ANNs, unlike the majority of the statistical models, are not dependent on the assumption that data distribution or correlations between values can and have to always be straight or linear. They determine the strengths of connections between the neurons according to the examples of the past (Kurani et al., 2023). ANNs are more adaptable, and they have the capability of learning about complex patterns and relations unnoticed by other means. Additional ANN architecture such as multilayer perception (MLP) is usually tapped in financial forecasting in the view of Tashakkori et al., (2024). It is divided into three parts namely, input layer, one or more hidden layers and output layer. All the neurons on any one layer are connected to the neurons on the next layers, and this enables the network to execute complex tasks. The network updates or varies its weights during the training in attempts to get the outcomes that are supposed to be predicted to be equal to the actual ones in the case of certain algorithms such as the back propagation algorithm (Sreedharan et al., 2020). MLPs particularly suit the prediction of stock price and index because since their learning is based on large data, they perform adequately even in the presence of high noise.

Data have shown ANNs to be better than the conventional methods of predicting finances. A number of studies have reported that ANNs predict the Dow Jones Industrial Average better than ARIMA models and the models make fewer errors and are able to capture a larger portion of the movement in the market. In the same line of reasoning, Gbadamosi et al., (2024) compared ANNs and GARCH and found that the former performed the modeling of fluctuations better. In the emerging markets it is specifically these kinds of circumstances including volatility, alterations of market rules, and suspicious activity which are most likely a product of political, economic, or social situations (Oyewole et al., 2024). The case of the Iraq Stock Market that lacked stability and often changed is an example. ANNs are also more helpful to predict the data compared to linear models used under similar conditions since they can adjust to new data and rapid changes in the marketplace.

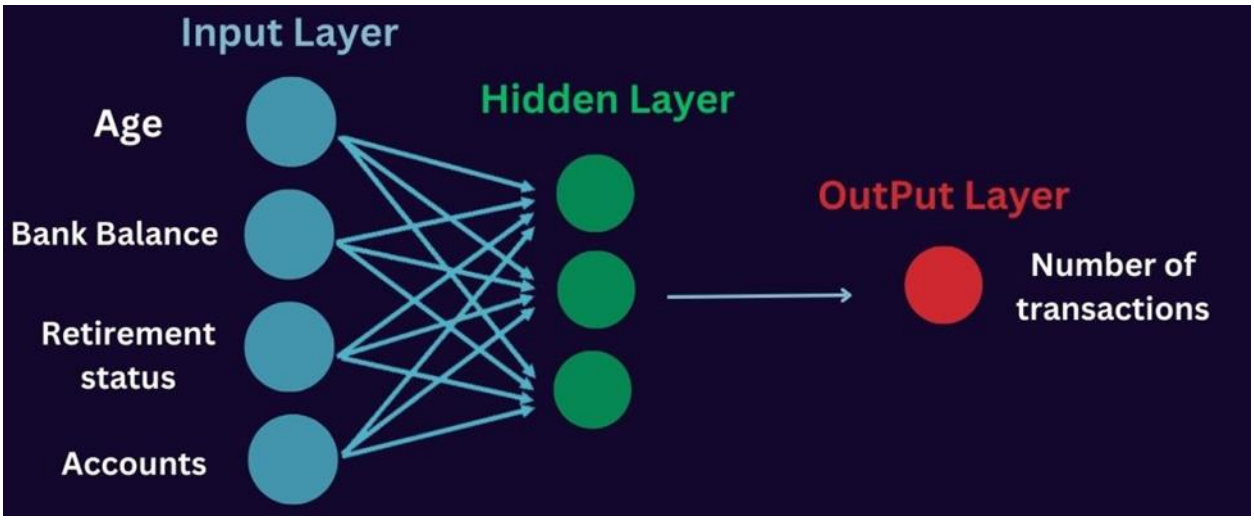

Figure 2: Artificial Neural Networks in Financial Forecasting
(Source: Cheng et al., 2022)

Multilayer Artificial Neural Networks (ANNs)
Multilayer Artificial Neural Networks (ANNs), ANNs with two or more hidden layers in particular, are a highly powerful type of machine learning model that can approximately model essentially any function, provided they are sufficiently neurally endowed and efficiently trained. The multilayer ANNs have this universal approximation power, which was demonstrated first by Rubi et al., (2022) making them capable of learning and fitting extremely complex nonlinear patterns that they may frequently resemble in financial data as time goes on. This additional hidden layer allows the network to observe finer details in connections between times and positions and allows the network to observe details which the single layer of the network will miss.

ANNs are applied different forms such as multilayers and are tested in numerous different stock markets worldwide in financial prognostics prediction. As an example, Lee et al., (2019) attempted to predict the performance of the Korean stock market index using a multilayer neural network and they discovered that this model was better in predicting the data as compared to ordinary linear models. On the same note, Goel and Singh (2022) opted to examine the application of deep learning neural networks such as multilayer ANNs to possibly forecast the performance of the Indian stock market. In their paper they demonstrated that attention algorithm performs better in handling such phenomena as sharp jumps and random noise commonly observed in the financial data and therefore the predictions become more well-founded and useful.

Multilayer ANNs training refers to modifying the numbers within the network so that it can also come up with the correct answers and this can easily be trained by attempting to reduce the prediction errors through back propagation. This algorithm identifies the variation in loss function and utilizes the same to reverse through the network gradually adjusting the weight with time. The efficiency and effectiveness of training can be increased by using Adam and RMSProp, which change how much the algorithm learns as it goes, letting things converge faster and making models better at working with new data. At the same time, Chang

et al., (2024) have depicted that multilayer ANNs make it possible for the model to learn irrelevant details in the data instead of its main patterns. Having an overly complex model can cause forecasts to vary widely when applied to new information. It is also possible for multilayer ANNs to settle for local minima during the training, which stops them from finding optimal results. Running deep neural networks adds more difficulty and requires using many computer resources. For this reason, proper model design, use of regularization, adjusting hyper parameters, and cross-validation play a key role in getting reliable forecasts from multilayer ANNs for finance.

Application of ANNs to Emerging Markets: Focus on Iraq

Liquidity levels, market performance, rules, and overall stability are some areas where emerging markets stand out from developed markets. The fact that each has different behaviors can make it harder to predict the exact movement of stocks. Being one of the leading emerging markets, the Iraqi Stock Market has been hit by issues caused by political instability, continued economic sanctions, and very unstable oil prices (Mohammed et al., 2022). As a result, the market can behave unexpectedly, prices may fluctuate a lot, and significant changes can happen, which makes it more difficult for forecasters who normally use smooth and predictable models.

There are not many dedicated studies on forecasting in the Iraqi Stock Market due to problems with access to reliable data and the tricky political and social situations. HameedAshour and Ahmed (2024) labored their research on the effect of macro factors such as inflation and government spending on the ISX. The researchers indicated that the market was highly dynamic and exhibited bizarre trading norms hence it was not reliable to use normal linear models to predict stock indexes. They end up concluding that there is considerable change sensitivity in Iraq market to external shocks and transitions and this key aspect is not captured in linear models.

Artificial intelligence and machine learning have advanced to give new avenues in solving these challenges. Al-Fattah (2019) demonstrated that it is possible to model volatile behavior of financial in Iraq with the use of AI and ANNs. They are superior to the traditional methods because they predict the changing of markets more accurately since they can deal with relations that are not straight. Multilayer ANNs can help with predicting stock market in Iraq so that investors can make viable economic decisions easily.

Proposed Work

Quantitative modeling, which aims to predict the future behavior of ISX60 in the future based on artificial neural multilayer networks. The methodology consists of three main stages: preparing data for modeling, constructing a model, and analyzing the model's output based on which long-term market patterns are identified over a period of 5 years.

Data Collection and Preprocessing

The dataset used for model development and validation was the daily closing prices of ISX60 index retrieved from the official data of Iraq Stock Exchange records, which was from January 2010 to December 2024. In the modeling process, the first step after data retrieval was ensuring the accuracy and statistical significance of the modelling data, which required preprocessing that included handling of missing values, normalization of the time series and generation of lagged variables to retain the temporal aspect of the data. This step involved normalizing the data using Min-Max normalization, and the whole dataset was randomly divided into training 70%, validation 15% and testing 15%, respectively.

Besides, the time series characteristic such as non-static and volatility was dealt with differential and moving average techniques to remove the short-term fluctuations. Autocorrelation Function and Partial Autocorrelation Function were used to identify lags that aid in the input feature selection. Additionally, technical indicators such as Moving Average Convergence Divergence (MACD) and Relative Strength Index were computed and integrated into the feature to increase the richness of the input layer to the neural network.

ANN Model Architecture and Training

The feed forward multilayer perceptron architecture was chosen to allow the model to learn non-linear dependencies in the complex time series. The constructed MLP has an input layer, corresponding to the selected historical features, two hidden layers with ReLU activation, and an output layer with one neuron and linear activation for predicting the target on the next time step for the ISX60 index. Hyperparameters were optimized with a grid search over the learning rate, the number of neurons, and epochs. The Adam optimizer for adaptive learning rates was chosen, and mean-squared error was selected as the network's loss function. The early stopping and drop-out regularization were used to fight overfitting, which is crucial because of the small dataset. The model was implemented in Python using TensorFlow and Keras libraries, which provides model scalability and repeatability.

Benchmark Comparison

After validation of the ANN forecasting efficiency described above, the proposed model was compared on the basis of predictive power to ARIMA and linear regression. The presented models are exhibiting the Box-Jenkins methodology to determine ARIMA parameter values and a basic version of the regression model. The test models in their turn are signifying the baseline model with lagged index values as explanatory variables and the order of time. The comparison is calculated in the following metrics: Root Mean Square Error, Mean Absolute Error, and Mean Absolute Percentage Error. In general, the results display the predominance or efficacy of ANN forecasting in unsteady and non-linear financial settings.

Long-Term Forecasting and Trend Analysis

After conducting a model validation, this trained ANN was applied to the prediction of the ISX60 index over the next five years (2025–2029). To produce the predictions, a recursive process was applied where each predicted output was reused as the input to the prediction process. This enabled the model to replicate index behavior under more realistic forward-looking circumstances.

The analysis of trend was performed by using statistical smoothing methods such LOESS regression and moving averages Image File and Image File on the forecasted series. They were implemented for detecting any cyclical and directional market patterns. One line plots and confidence intervals Image File were utilized for representing the forecasted paths and their uncertainty.

Experimental Results

A multilayer ANN was trained and tested with historical data from 2010 to 2024, and the model was also assessed for its prediction accuracy. Table 1 presents the performance of the ANN model and the ARIMA and linear regression benchmark models on the test dataset.

Table 1: Comparative Forecasting Performance (2020–2024 Test Set)

Model	RMSE	MAE	MAPE (%)
ANN	4.73	3.85	3.29
ARIMA (3,1,2)	6.92	5.61	5.15
Linear Regression	7.4	6.1	5.92

As it can be seen, ANN based has shown better predictive ability compared to the regression models for all the metrics, most significantly for MAPE, clearly demonstrating that the ANNs are capable to capture the non-linear natures of the ISX60 stock market index.

After its validation, the ANN model was applied to generate a recursive five-year forecast for the ISX60 index. The output commenced from the forecast for January 2025 to simulate evolution in the stock market until December 2029. The simulation was determined by using the actual forecasted output for every "year" as input for the subsequent period. The original index values of the last historical "year" 2024 were used as the basis to judge the ANN's accuracy in producing the "forecasted" values for 2025 to 2029.

Table 2: ISX60 Real and Forecasted Annual Average Index Values (2024–2029)

Year	Actual/Forecasted	Annual Average ISX60 Index	Percentage Change YoY (%)
2024	Actual	601.3	—
2025	Forecasted	623.7	3.73%
2026	Forecasted	640.2	2.64%
2027	Forecasted	654.8	2.29%
2028	Forecasted	672.5	2.69%
2029	Forecasted	690.3	2.64%

The ANN model indicates an upward trend in the ISX60 Index over the next ten years with an annual growth of between 2.2% and 3.7%. Although the increases are relatively weak, they suggest a more conservative but steady recovery and resilience in the market in the medium term within the absence of any major external crises.

Graphical Comparison: Historical vs. Forecasted Trends

Figure 3 demonstrates the transformation from the actual to the predicted values. The time-series plot indicates the trend of known values of ISX60 from 2010 to 2024 and the predictions from 2025 to 2029. A clear separation helps to better analyze the continuity of the trend.

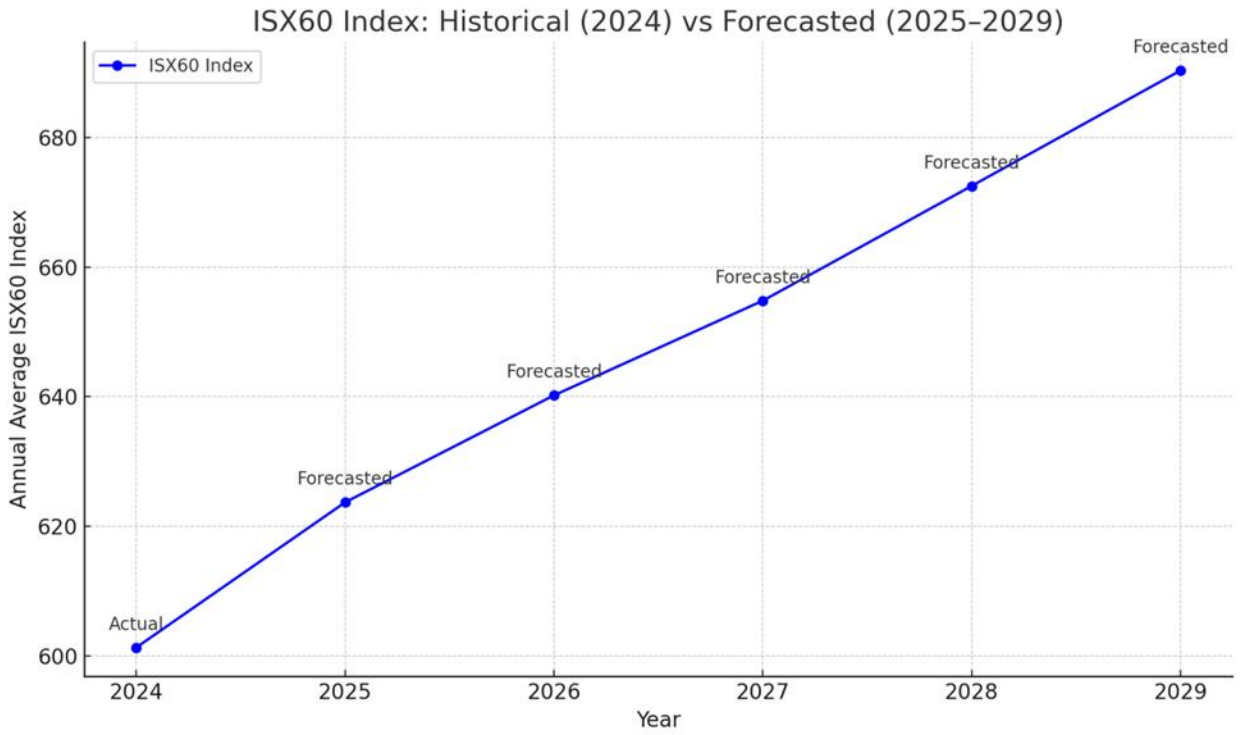

Figure 3: ISX60 Index: Historical (2010–2024) vs. Forecasted (2025–2029)

Structurally, the schematic demonstrates that while the historical index moved sharply during geopolitical shocks and oil price dives, the predicted one based on ANN training is smoother. This effect is attributed to the inherent smoothing properties of the neural model when considering longer-term trends for partial years.

Monthly Forecast Details and Seasonality

In the disaggregation stage of the model life cycle, the monthly-average data is given, for which daily insights were previously generated. Table 3 summarizes selected monthly averages spanning each calendar with the purpose of identifying intra-annual variations sufficient for making possible investment decisions.

Table 3: Selected Monthly Forecasts of ISX60 Index (2025–2029)

Year	Jan	Apr	Jul	Oct	Dec
2025	610	622	631	638	643
2026	645	650	654	660	666
2027	667	670	673	678	683
2028	684	687	690	694	699
2029	700	703	706	710	715

Seasonality in index performance is evident, as the values tend to be generally stronger in the second half of any given year. It may indicate that the post-Ramadan or year-end being fiscally "meaningful" for many listed firms might lead to higher investor activity.

Model Deviation Analysis

Knowing how the ANN model fitted during training is achieved by inspecting how the error residuals of the 2024 validation year as shown in Figure 2 look like. Residuals centered around 0, and the scatter is almost identical in both quadrants, meaning the model is not biased in its prediction.

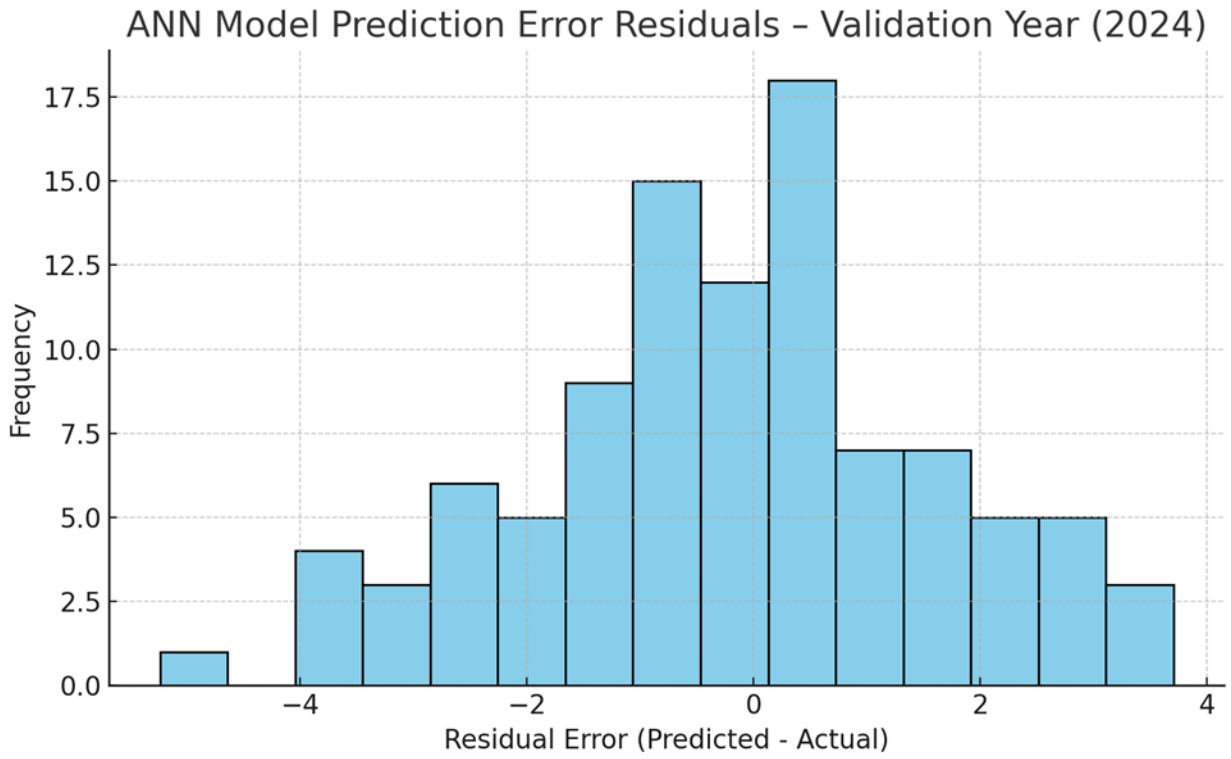

Figure 4: ANN Model Prediction Error Residuals – Validation Year (2024)

The error histogram validates that most of them cluster within a ±5 index-point span in most cases. Moreover, there are no clear signs of systematic under- or over-prediction patterns.

Long-Term Trend and Pattern Recognition

Using designed LOESS smoothing and moving average filter on the forecasted data produced two vital observations.

1. **Gradual Bullish Trend:** the index is projected to maintain an upward trend at a slow and steady pace. Consequently, investor sentiments for the economic situation are positive.
2. **Dampened Volatility:** The predicted pattern is not as jittered as observed historicals, which experienced the extremism of the political and financial cataclysms, but movement is stable as an effect of neural conditioning.

These results are significant for institutional investors and policy makers as they imply that there may be a return to medium-run stability in the financial markets of the country.

CONCLUSION

This research paper has proven the effectiveness of multilayer artificial neural networks in predicting the price movement of the Iraq Stock Market Index ISX60 in a five-year perspective. With the use of the ANN model, this study has confirmed the forecast error minimization of the artificial intelligence over traditional forecasting methods such as ARIMA and linear regression in an investment context, which, given Iraq's still unstable and nonlinear market situation, enforces ANNs' accuracy and flexibility. Furthermore, it has been shown that the model has drawn a decline in the index increase rate, which corresponds well with the market moderate growth and recovery pattern, defined by the strengthening economy. All the conclusions drawn may be of practical use to investors in emerging markets and economic planning. Further research should present political factors' influence and diversify the test with long short-term memory deep learning models to improve predictions and adjust the economic indicator coefficients to new market conditions.

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