

ADVANCES IN TIME SERIES FORECASTING MODELS

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Abstract: *This paper evaluates the performance of Artificial Neural Networks (ANNs), Nonlinear Autoregressive (NAR) networks, wavelet transforms, and hybrid models in forecasting, focusing on global gold demand from 2010 to 2023. Each method's ability to handle complex predictive tasks is assessed: ANNs demonstrate strong potential due to their deep learning capabilities but encounter challenges such as overfitting and high computational demands. NAR networks, utilizing LSTM and GRU units, effectively capture temporal dependencies but are sensitive to data quality. Proper wavelet selection is essential for successful wavelet transforms, as they enable detailed analysis of nonstationary data at multiple resolutions. To overcome the limitations of each individual model, hybrid models were explored to leverage their combined strengths while mitigating their weaknesses. The performance evaluation used metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Results indicate that the hybrid model integrating ANNs and wavelet transforms outperformed the standalone models, with a 54.74% reduction in MAPE and a 13.13% decrease in RMSE, highlighting improved forecasting accuracy and reliability, particularly in the context of predicting global gold demand. This study emphasizes the importance of methodological innovation in forecasting, providing valuable insights into optimizing model integration to enhance accuracy. These findings are anticipated to benefit sectors like finance and trade, where accurate gold demand forecasts are vital for strategic decision-making and sustainable economic policy development, especially in regions such as East Asia.*

Keywords: *Artificial Neural Networks (Anns), Nonlinear Autoregressive (NAR) Networks, Wavelet Transforms, Hybrid Forecasting Models, Time Series Analysis*

Introduction

Forecasting is pivotal across numerous sectors, such as finance, healthcare, supply chain management, and environmental monitoring, providing crucial insights for strategic decision-making. The creation of computer models like artificial neural networks (ANNs), nonlinear autoregressive (NAR) networks, wavelet transforms, and hybrid models has made forecasting tools much more accurate and useful. This study evaluates these methodologies to understand their individual and combined effectiveness in various forecasting applications, with a particular focus on the global demand for gold from 2010 to 2023 as a practical application. Gold is a strategic economic resource that directly impacts economic stability and sustainable development, particularly in regions like East Asia that heavily rely on international trade and investment in precious metals. Accurate forecasting of global gold demand plays a critical role in informing sustainable economic policies and trade strategies. These models can support sustainable economic growth and help mitigate the environmental risks associated with excessive resource exploitation.

Artificial neural networks (ANNs) emulate the structure and learning capabilities of the human brain, making them adept at recognizing complex patterns in large datasets. They have found significant applications in fields such as financial forecasting, medical diagnostics, and natural language processing. Despite their widespread use, challenges like overfitting and computational intensity can limit their applicability in resource-constrained environments.

Nonlinear autoregressive (NAR) networks use memory parts like long short-term memory (LSTM) (Abdul et al., 2023; Ferdiansyah et al., 2023a) units and gated recurrent units (GRU) to deal with the difficulties of time series forecasting. These models excel in capturing long-term dependencies, making them valuable for applications in meteorological forecasting and stock market predictions. However, the accuracy of NAR networks is heavily reliant on the quality and comprehensiveness of training data.

Wavelet transforms provide multiresolution analysis by decomposing signals into wavelets, making them particularly valuable for analyzing non-stationary time series data. Economic data analysis and seismic activity monitoring have effectively applied this technique. The success of wavelet transformations in practical applications depends on the accurate selection of wavelet types and parameters, which requires deep domain expertise (Jamal et al., 2021; Minu et al., 2010).

Hybrid models represent a pivotal advancement in the field of global demand forecasting, offering innovative solutions to the limitations of traditional models. These models amalgamate various techniques and methodologies such as Artificial Neural Networks (ANNs), Nonlinear Autoregressive (NAR) networks, and wavelet transforms, enabling a multi-level analysis and a more comprehensive assimilation of data. This integration significantly enhances the accuracy of predictive models, transforming them into powerful tools for supporting strategic decision-making across numerous vital sectors. Moreover, hybrid models address the deficiencies inherent in each separate technology, providing more stable and reliable predictive outcomes, especially when tackling complex challenges like forecasting global demand for strategic resources like gold. Hybrid models combine the strengths of different forecasting methodologies to mitigate individual limitations and enhance overall accuracy. Studies have demonstrated that integrating ANNs with wavelet transforms can result in superior forecasting

performance in complex scenarios, such as financial markets and climate predictions (Abdul et al., 2023; Ferdiansyah et al., 2023b, 2023a).

This study aims to conduct a rigorous evaluation of these models, focusing on their integration with hybrid systems to improve predictive accuracy. By comparing the effectiveness of ANNs, NAR networks, wavelet transforms, and hybrid models, this research seeks to identify best practices for achieving high precision in forecasting under varying conditions, specifically global gold demand. We expect the findings to enhance forecasting models and support decision-making processes in key industries, thereby promoting sustainable development in East Asia and bolstering global economic stability.

Method

Artificial Neural Networks

Artificial Neural Networks (ANNs) are systems inspired by the biological neural networks in the human brain used for processing data and learning patterns to provide predictions or make decisions. They consist of three main layers: an input layer that receives data, hidden layers that process the data with varying complexities, and an output layer that presents the results. The process bears a close resemblance to the brain's neural signal processing, which involves passing data through various neurons for modification and analysis (Ashour, 2023; Ferdiansyah et al., 2023b; Hameed Ashour & Abbas, 2023a, 2023b).

As a computational node, each neuron in the network receives signals from its predecessors and, upon reaching a specific threshold, triggers the activation function, which determines if the signal advances to the subsequent neuron. We use activation functions to introduce non-linear properties into the modeling, allowing the network to learn complex and dynamic patterns. A mechanism known as backpropagation continuously adjusts the network's weights during training to improve the accuracy of predictions and results. Figure 1 illustrates the architecture of artificial neural networks (Alayham et al., 2018; Ashour et al., 2022; Ferdiansyah et al., 2023b; Hossain et al., 2023; Lazcano et al., 2023; Semenoglou et al., 2023).

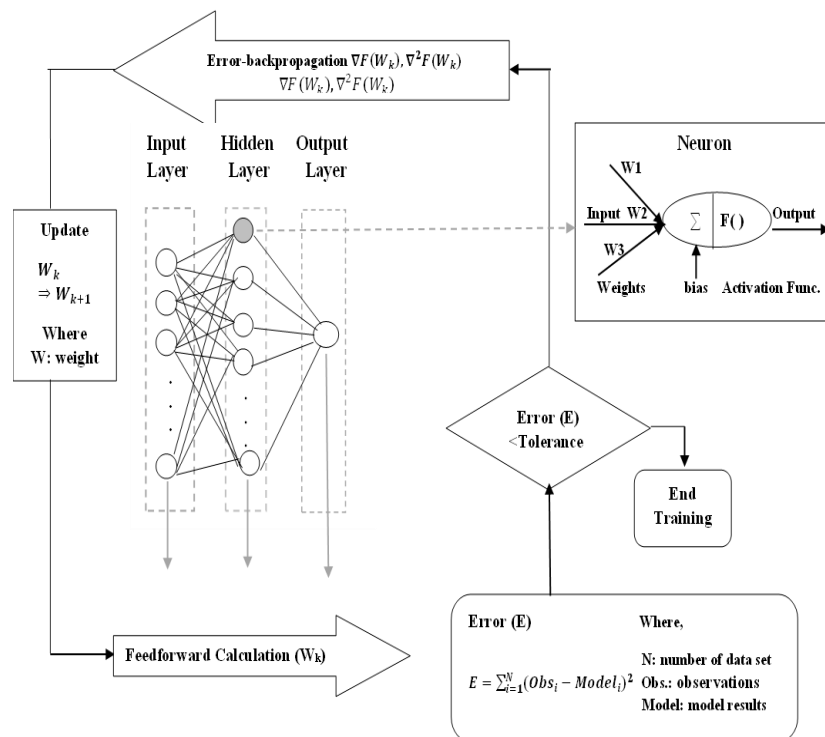


Figure 1: ANN Methodology

Nonlinear Autoregressive (NAR) networks represent an advanced approach to time series data processing through deep learning. These networks utilize units such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU) to explore long-range dependencies within data and predict future values based on past information. Characterized by their ability to capture complex and nonlinear relationships between time points, these networks serve as highly valuable tools for precise forecasting across various complex scenarios. Mathematically, such a network can be expressed as follows (Abdul et al., 2023; Ashour, 2022; Ferdiansyah et al., 2023a; Lazcano et al., 2023).

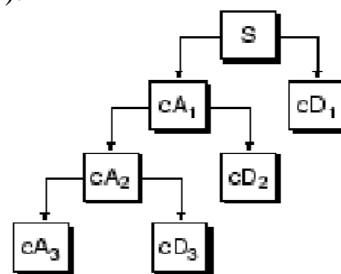
$$x_t = f(x_{t-1}, \dots, x_{t-p}) + \epsilon_t \quad (1)$$

NAR networks are extensively applied in fields such as meteorology, financial markets, and industrial control where accuracy plays a crucial role in planning and forecasting. In meteorology, these networks enable weather predictions based on detailed historical data, while in financial markets, they assist in analyzing trends and predicting price movements. This capability to interpret time series data makes NAR networks an indispensable tool in domains requiring reliable and intricate temporal forecasts (Ashour & Alashari, 2022; Ashour & Al-Dahhan, 2021).

Wavelet transforms

Wavelet transforms are a mathematical technique used for signal and image analysis. They decompose a signal into a set of wavelets. The method under study is based on signal analysis and has proven effective in various fields, including but not limited to image processing, data compression, disaster prediction, and other application areas. The fundamental principle behind wavelet analysis is the selection of an appropriate mother wave or wavelength, followed

by analysis conducted using its translations and dilations. Several different types of wavelets can serve as a mother wave, each with unique properties. Examples include the Haar wavelet, Meyer wavelet, Coiflet wavelet, Daubechies wavelet, and Morlet wavelet, among others. There are two different classifications of wavelet transforms: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) (Ashour & Al-Dahhan, 2021; Jamal et al., 2021; Minu et al., 2010). The inclusion of a normalization factor ensures the preservation of energy parity across all values of a and b . The analysis is conducted using incremental levels corresponding to the different stages of the analytical process. The first stage of the analysis involves dividing the original series 'S' into two distinct components, the approximate part 'A1' and the detail part 'D1'. Subsequently, the second level of analysis focuses on examining the 'approximate' part. In the Discrete Wavelet Transform (DWT), the "smooth time series" signal is separated into multiple analytical levels, extracting components that represent approximations and details for each level. Figure 2 illustrates the methodology of the wavelet transform (Ashour, 2022; Jamal et al., 2021; Minu et al., 2010).



$$f(t) = \sum_{i=1}^{i=j} D_i(t) + A_j(t)$$

where $D_i(t)$ denotes the wavelet detail and $A_j(t)$

Figure 2: Wavelet Transform Approach

Hybrid model

Hybrid modeling in forecasting refers to the integration of multiple analytical prediction techniques to enhance the accuracy and reliability of future forecasts. The hybrid model aims to improve overall forecast accuracy by combining the beneficial aspects of different models while minimizing the inherent limitations of each, providing a comprehensive, accurate, and optimized prediction. Hybrid techniques are frequently used in financial markets, weather forecasts, and demand predictions. These methods benefit from the combined capabilities of statistical models, machine learning, and sometimes domain-specific models to accommodate complex patterns in data that might be overlooked by a single modeling approach. This research employs a hybrid model that integrates Artificial Neural Networks (ANN) and Wavelet Transform (WT) as the chosen forecasting techniques, given their status as some of the best current technologies. Figure 3 illustrates the methodology of the modified hybrid model (Abdul et al., 2023; Ferdiansyah et al., 2023b, 2023a; Hameed Ashour & Abbas, 2023b).

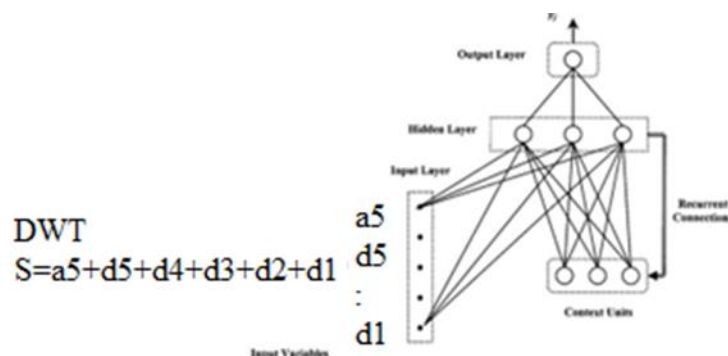


Figure 3: The Approach of The Improved Hybrid Model

Error accuracy measurement

To measure key error rates, the most important of which are the root mean square error (RMSE) and the mean absolute percentage error (MAPE), to evaluate the accuracy of time series forecasts and ensure the effectiveness of statistical models. We measure RMSE by calculating the square root of the mean squared differences between the predicted and actual values, allowing us to evaluate the magnitude of prediction errors in units consistent with the original data. This metric is particularly effective in penalizing large errors. On the other hand, MAPE provides an estimate of the mean absolute percentage error between the expected and actual values, making it easier to interpret and compare across different metrics. It is also considered useful in business contexts where accuracy in estimating relative errors is important. These metrics enable a comprehensive evaluation of forecasting models, helping to guide necessary improvements and ensure accurate and reliable predictions for various applications, including the financial sector, healthcare, and supply chain management (Alayham et al., 2018; Ashour et al., 2022; Hossain et al., 2023; Semenoglou et al., 2023). We can express it mathematically the following way: The most important error metrics for evaluating the accuracy of time series forecasts and ensuring the effectiveness of statistical models are the root mean square error (RMSE) and the mean absolute percentage error (MAPE). We measure RMSE by calculating the square root of the mean squared differences between the predicted and actual values, allowing us to evaluate the magnitude of prediction errors in units consistent with the original data. This metric is particularly effective in penalizing large errors (Abdul Hameed Ashour et al., 2022; Ahmed et al., 2020; Ashour, 2022; Lazcano et al., 2023). On the other hand, MAPE provides an estimate of the mean absolute percentage error between the expected and actual values, making it easier to interpret and compare across different metrics. It is also considered useful in business contexts where accuracy in estimating relative errors is important. These metrics enable a comprehensive evaluation of forecasting models, helping to guide necessary improvements and ensure accurate and reliable predictions for various applications, including the financial sector, healthcare, and supply chain management. We can express it mathematically through the following means (Abbas et al., 2020; Anbalagan et al., 2020; Ashour et al., 2020; Ashour & Alashari, 2022; Ashour & Al-Dahhan, 2020; Derbentsev et al., 2019; Munim et al., 2019).

$$MAPE = \frac{\sum \left| \frac{et}{yt} \right|}{n} * 100 \quad (2)$$

$$RMSE = \sqrt{\frac{\sum e_t^2}{n}} \quad (3)$$

Where:

y_t : time series data

e_t = error

Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are among the most prevalent and utilized metrics for assessing the accuracy of error in predictive modeling. These metrics provide critical insights into the performance of forecasting models, quantifying the deviation between predicted values and actual outcomes. RMSE finds the average size of the errors in a set of predictions without looking at their direction. It does this by squaring the residuals to get rid of negative values before averaging them. This makes the measure sensitive to bigger errors. Conversely, MAPE expresses accuracy as a percentage, offering an intuitive understanding of error magnitude relative to true values, making it particularly useful for comparing the performance of models across different scales or units. Together, these metrics are instrumental in refining predictive accuracy and are standard benchmarks in the evaluation of forecasting models.

Result

Figure 4 shows the global demand for gold from 2010 to 2023. The graph reflects the development of global demand for gold between 2010 and 2023. Global economic crises, such as the European debt crisis and financial turmoil, may have led to a clear peak in gold demand in 2012. Following that, we observe a gradual decline until 2016, followed by relative stability in the following years. The COVID-19 pandemic's effects on global markets and the economy largely contributed to the sharp decline in demand during 2020. In contrast, the partial recovery in demand in 2021 and 2022 indicates a return to gold investments with improved economic conditions and restored confidence in global markets.

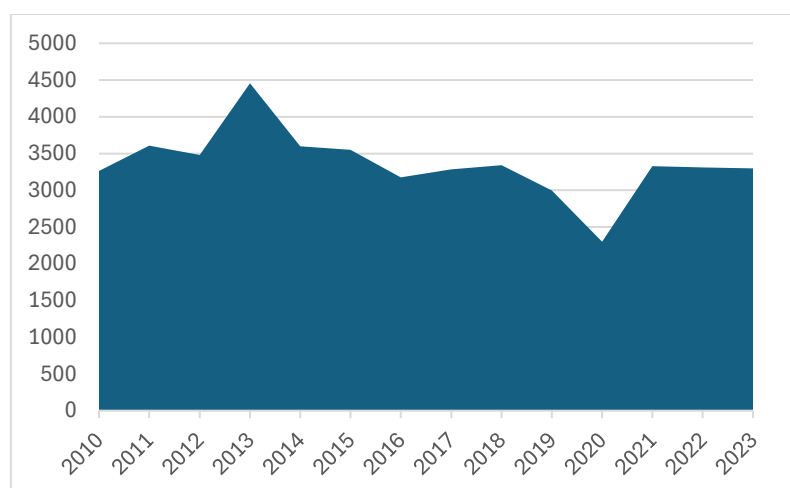


Figure 4: Time Series of Global Gold ((Source: World Gold Council)

NAR training efficiency is shown in Figure 5.

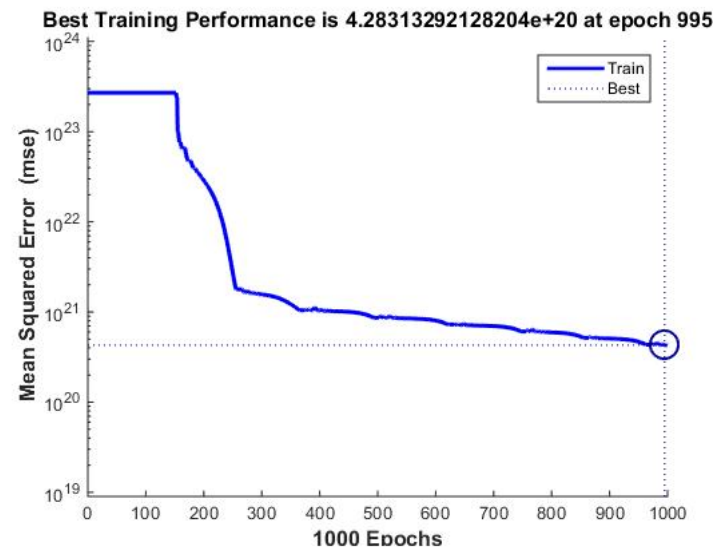


Figure 5: Tanning Performance of Nar

In Figure 5, the attached figure demonstrates the performance progression of a Modified Neural Response (NAR) model over 1,000 epochs. It exhibits a rapid improvement in performance within the initial 100 epochs, followed by a steady and gradual decrease in mean squared error until the end of the period. The graph stabilizes, with the best training performance achieved near the end, at a value of 4.28313292128204e+20 at epoch 995, reflecting the model's effectiveness in learning and continuously improving performance throughout the training cycle.

The output components from the wave analysis of the time series under consideration in Figure 6, These components provide input to an artificial neural network.

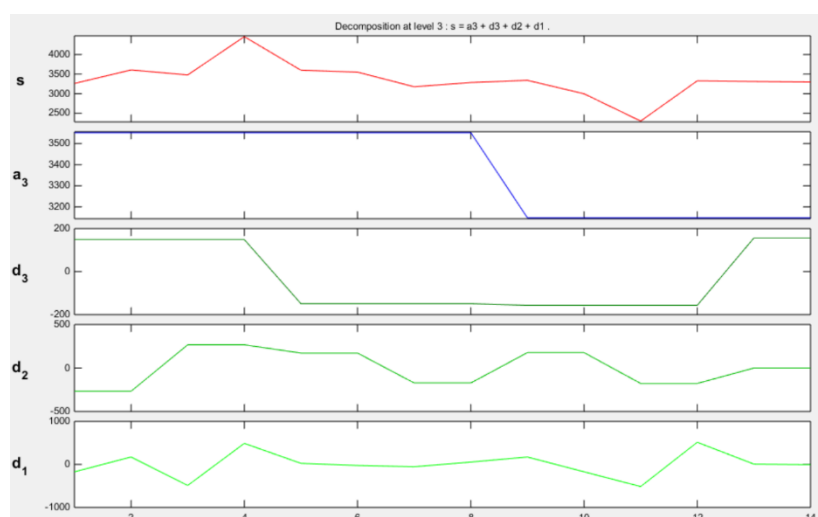


Figure 6: Time Series Decomposition

Figure 6 shows that the machine learning model is highly efficient, with the best validation performance achieved at a very low mean squared error of 426.8996 in just the second epoch. This indicates the model's ability to adapt and learn quickly from the data. The stable performance after this point, along with the narrow gap between the training, validation, and test lines, suggests that the model does not suffer from overfitting and exhibits good generalization, making it suitable for practical use in various applications requiring accurate and reliable predictions.

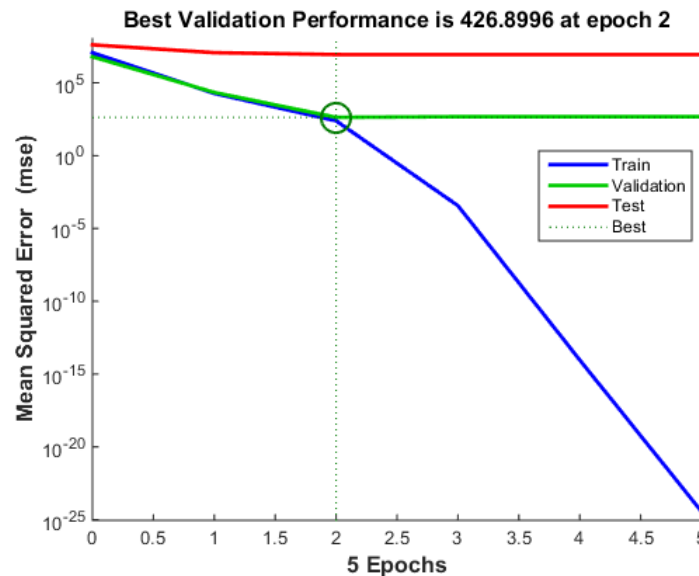


Figure 7: Tanning Performance of Wann

Table 1 highlights the differences between ANN and WANN. The results presented in Table 1 indicate a significant improvement in the performance of the hybrid model compared to the artificial neural network (ANN) model, as evidenced by the metrics MAPE and RMSE. For the MAPE, the hybrid model shows an improvement of 54.74%, demonstrating a substantial reduction in the mean absolute percentage error. In terms of RMSE, the improvement stands at 13.13%, indicating that the hybrid model yields more accurate predictions with a lower mean squared error.

The hybrid model's integration of advanced techniques, which combine elements from statistical modeling and machine learning methodologies, accounts for this notable enhancement. This allows for a deeper analysis of the data and more effective handling of its complexities. Such improvements underscore the importance of selecting appropriate methods in predictive model development to ensure the reliability and quality of the outcomes.

Table 1: Measurement Criteria

Technique	RMSE	MAPE
ANN	590.3	13.7
Hybrid model	512.8	6.2

The results in Table 1 clearly show that the hybrid model is much better at making predictions than the artificial neural network (ANN). This is true based on two main metrics: mean absolute percentage error (MAPE) and root mean square error (RMSE). The hybrid model achieved a MAPE of 6.2%, reflecting higher prediction accuracy compared to the 13.7% exhibited by the ANN model. Additionally, the hybrid model also excelled in the RMSE criterion with a score of 512.8, in contrast to 590.3 for the ANN, indicating that the predictions made using the hybrid model were on average less erroneous. This analysis underscores the potential benefits of using hybrid models, which may enhance performance more effectively than traditional single-method models, making them a promising option for complex economic forecasting applications.

Conclusion

The research on forecasting methods using artificial neural networks (ANNs), nonlinear autoregressive (NAR) networks, wavelet transforms, and a hybrid model has given us a lot of new information about how these technologies can be used in more complex ways. ANNs, with their architecture reflecting the neural processing of the human brain, prove effective in recognizing complex patterns and dependencies in data. The structure of these networks, which includes input, hidden, and output layers, shows how flexible and good at learning they are. This structure allows for dynamic data processing that mimics brain activity, which improves the accuracy of predictions and decision-making in a wide range of situations.

NAR networks, utilizing deep learning constructs like LSTM or GRU, excel at managing time series data by capturing intricate and nonlinear relationships within temporal sequences. Their application in domains demanding high precision in forecasts, such as meteorology and financial markets, underscores their robustness and reliability. Meanwhile, wavelet transforms offer a sophisticated mathematical approach to signal and image analysis, proving indispensable in a variety of fields ranging from image processing to disaster prediction. The methodology's ability to decompose signals into wavelets enables nuanced analysis that is pivotal for detailed and context-sensitive interpretations.

The hybrid model, integrating ANNs and wavelet transforms, demonstrates a formidable improvement in forecasting accuracy. The comparison test shows that this model is much better than the standalone ANN in terms of MAPE and RMSE, showing a 54.74% and 13.13% drop in prediction errors, respectively. We attribute this enhancement to the synergistic combination of statistical modeling and machine learning techniques, which optimize the handling of data complexities and enhance the overall reliability of predictions.

Such findings not only validate the efficacy of combining various predictive techniques but also highlight the critical role of methodological innovation in advancing the accuracy and applicability of forecasting models. The evolution of these methods promises further potential to refine predictive analytics, thereby contributing profoundly to sectors like finance, healthcare, and supply chain management, where strategic forecasting informs crucial decisions.

Authors' Contribution

Ashour, M. A. H. and Abbas, R. A. conceived and planned the Application. Ashour, M. A. H. planned and carried out the Application. Ashour, M. A. H. contributed to the interpretation of

the results. Abbas, R. A. took the lead in writing the manuscript. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

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