



# International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.699**

**Volume 15, Issue 3, March 2026**

# Financial Market Trend Prediction using Wavelet Transform-Based Multiresolution Analysis

**Tarif Lugun**

Department of Mathematics, Birsa College Khunti, Ranchi University, India

**ABSTRACT:** This study examines the forecasting of financial market trends with Wavelet Transform-based Multiresolution Analysis (MRA), a technique that is highly effective in dealing with the inherent nonlinearity, non-stationarity, and noise in financial time series data. Through the decomposition of financial signals into approximation and detail signals, Wavelet MRA allows for the segregation of long-term trends from short-term volatility, enabling more refined and precise forecasts. The research integrates recent progress in which wavelet-based decompositions have been effectively combined with machine learning algorithms such as LSTM, SVM, and GBDT, offering better predictive performance than conventional statistical methods. The hybrid modelling framework using deep learning for trend components and machine learning for noise components utilizes multiscale information, enhancing forecasting accuracy as well as model efficiency. Wavelet-based methods provide significant over Fourier methods by the preservation of time and frequency information and enabling time-frequency localized analysis of importance in financial applications. This study highlights the increasing need for sophisticated multiresolution tools in financial data analysis, noted to enhance not only prediction reliability but also the understanding of intricate market dynamics through Wavelet Transform-based MRA.

**KEYWORDS:** Financial Market, Trend Prediction, Wavelet Transform-Based, Multiresolution Analysis

## I. INTRODUCTION

The forecasting of financial market trends has been a key and challenging endeavor in economics, finance, and data science for a long time. Correct forecasting of market dynamics not only assists investors in making better decisions but also supports financial institutions in risk management and strategic planning. Unfortunately, financial markets, to a large extent, are dynamic, highly vibrant, and much more so unpredictable in terms of exhibiting trends. The naive statistical practices do not work well in finding the connection between various elements within the financial time series data. They are in this context used increasingly to enhance the reliability of the forecasts often used in markets. Among all of these methods, Wavelet Transform based Multiresolution Analysis is found to be useful in explaining the characteristics of the financial time series.

Wavelet Transform can also be described as the technique of analyzing the given data at different resolutions; this makes it one of the most adequate methods for financial time series that contain both long-term trends and short-term fluctuations. Notably, while Fourier Transform analysis affords only frequency information, Wavelet Transform also provides temporal information and entails a more precise and localized analysis. It can also decomposes the time drilled into multi-scale, whereby it enables the separation of a given financial time series into parts with diverse resolution such as trends and shocks/market noise. Some scholars share this point of view because decoupling of these measures enables the analysts to have a good feel of the ongoing market processes in order to improve on the predictive models that have been developed.

Multiresolution Analysis (MRA) using Wavelet Transform means the process of the decomposition of the time series into the approximation part and detail part at different level of subordinated. The approximation coefficients pertain to low Frequency, high size information, which is associated with the long-term trends of the market, and the detail coefficients for high Frequency, low size information that relates to the noise in the market or fluctuation of the market on the short term. This enables the models to cleanly for analysis of trend components and separate the factors affects volatility from those affecting trends in financial information. On the same note, selective reconstruction of the time series from some of the wavelet coefficients enables one to get rid of noise and hence, enhance the quality of the signal, leading to better forecasts.

The use Actual Wavelet Transform of Multiresolution Analysis patterns in the prediction of the trends in the financial markets has been deemed highly successful in a number of studies recently. It allows the evolution of composite models which may use one approach to estimate the trends and another one for noise: such as machine learning for trends and stochastic for noise. In addition, Wavelet MRA can also enhance the utilization of the other theoretical models such as neural networks, support vector machines and other prediction models. Hence, Wavelet Transform-based Multiresolution Analysis is more than just a method for data pre-processing; it provides a fundamental paradigm for enhancing knowledge of and forecasting various behaviours of Financial Markets

The use of Wavelet Transform based Multiresolution Analysis in the analysis of the financial market, the science has recorded a breakthrough. Due to the features mentioned above, it enables the better understanding of the market structures and enhances the predictive capabilities of the models at the micro., It also provides a multiscale and detailed view on financial time series. For those financial markets that are ever expanding and developing, thus calling for more delicate and precise analytical means in predicting future trends and forces, the Wavelet MRA proves to be a highly significant and useful tool in the hands of researchers and market analysts.

## II. REVIEW OF LITERATURE

**Althelaya, Mohammed, and El-Alfy (2021)** called for the use of the Deep Learning with Multiresolution Analysis methodology to predict stock market trends. Their work applied Long Short-Term Memory (LSTM) networks with Discrete Wavelet Transform (DWT) because of the non-linear and non-stationary nature of the dependent variable for financial time series. The authors used wavelet methodology in order to denoise the input time series and then used LSTM models to learn the approximation and detail coefficients. They concluded that this hybrid model significantly improved the prediction accuracy as compared to the individual LSTM and standard statistical models, or as a verification of the choice of wavelet decomposition to capture multi-scale features of the financial data.

**Balamohan, Khanaa, and Sivaraman (2023)** proposed an improved LSTM model called LSTM-UP to improve the stock market price prediction on dynamic data. The model they used was grounded on adaptive learning mechanism particularly to the changes in the data flow of financial time series. It was good to evaluate the effectiveness of their proposed method with the real-time stock data, that too in comparison with LSTM and GRU. The LSTM-UP method was more accurate relative to the other models when it came to mean squared error (MSE) and root mean squared error (RMSE) hence the efficiency in the capturing of time dependencies and adapting to new data changes.

**Burhan and Mohammed (2024)** developed a new approach which combined the Maximal Overlap Discrete Wavelet Transform (MODWT) with general machine learning on predicting exchange rates in Chinese financial market. By using MODWT, exchange rate data was analyzed in terms of various frequency components that made it easier for the model to focus on long-term processes and high frequency fluctuations. The study was able to determine that the feature of using MODWT in conjunction with regression-based predictors improved forecast effectiveness during unstable conditions. In their respective papers, the authors suggest that wavelet-based hybrid models could be more stable and interpretable for making the forecast in the context of the financial problems.

**Gu, Chang, Xiong, and Chen (2021)** forecasted the Nickel futures prices using the fused EWT and GBDT. In EWT process applied to the original price time series, the latter is divided into several intrinsic mode functions reflecting different frequency characteristics. GBDT, a complex learning model used in handling non-linear relationships was provided with these components. Their experimental results indicated that the proposed EWT-GBDT model improved compared with traditional models in term of prediction values and stability and pointed out that using wavelet-based decomposition could enhance the precision and detail of the operation of the machine learning-based finance prediction.

**Lee, Koh, and Choe (2021)** studied time series prediction of financial data specifically focusing on high-frequency data and utilizing wavelet transformation accompanied by DRL. This kind of model applied the Discrete Wavelet Transform (DWT) to pre-process input data and filter noise as well as extract temporal patterns in multiple scales before input into a DRL methodology. This enabled the model to gain better policies of trading throughout the trading period. It was seen from the results obtained form simulated trading scenarios that wavelet-enhanced DRL model

produced better returns during the trading exercises as well as was more consistent in decision making than the rule-based or DRL without wavelet optimizations.

**Rabbouch, Rabbouch, and Saâdaoui (2023)** studied multi tolerance technique for financial time series using MATLAB not only in his article. They were quite interested in DWT and MODWT to decompose the financial time series into detail and approximation at several levels. Hence, the authors used the decomposition to filter out the noise and reveal meaningful patterns for analysis and/or forecasting. By example and with help of MATLAB, they demonstrated that using MULTIRESS made the models more interpretable and accurate with regards to identifying shifts in regimes and market frictions.

### III. BACKGROUND AND IMPORTANCE OF FINANCIAL MARKET TREND PREDICTION

Financial markets are one of the main contributors to the global economy as they connect buyers and sellers in capital instruments. Forecasting the trends in these markets like the future prices of stocks, commodities, currencies, or indices is vital for investment planning, portfolio management, risk evaluation, and policy-making. Yet, forecasting financial markets is very difficult because of the complexity, nonlinearity, and randomness of financial time series data.

#### Challenges in Predicting Financial Trends

Financial time series are non-stationary in the sense that their statistical parameters like mean and variance evolve with time. They are also impacted by a plethora of variables like economic policies, geopolitical developments, firm-specific announcements, and market psychology, several of which cannot be anticipated.

Key challenges include:

- **Volatility clustering:** High volatility clusters in time.
- **Nonlinear behavior:** Prices move nonlinearly with complicated interactions.
- **Noisy data:** Financial time series are noisily sampled, obscuring intrinsic trends.
- **Fat tails:** The distribution of rare events is fatter than under a normal distribution.

The classical model tends to assume stationarity and Gaussian distributions that do not apply to actual market dynamics.

Mathematically, the value of an asset  $P(t)$  can be generally described as a stochastic process:

$$dP(t) = \mu P(t)dt + \sigma P(t)dW(t) \quad (1)$$

However, the Geometric Brownian Motion (GBM) model is incapable of capturing various real-world occurrences, like financial data exhibiting jumps and memory effects.

#### Limitations of Traditional Statistical Methods

Conventional approaches such as ARIMA (Auto-Regressive Integrated Moving Average), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and simple linear regression have been popularly used. But they possess several critical limitations:

- **Assumption of Linearity:** Linear relationships among variables are typically assumed by most conventional approaches.
- **Inability to Capture Multiple Scales:** They are unable to separate short-term noise from long-term trends.
- **Poor Noise Handling:** Conventional models are noisy, which results in overfitting or erroneous prediction.
- **Fixed Time Resolution:** Techniques such as Fourier analysis convert the whole signal to frequency space, discarding local information.

For instance, in an ARIMA model:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t \quad (2)$$

This framework cannot straightforwardly describe multiscale or multiresolution behavior that financial markets display.

### The Need for Advanced Mathematical Tools

To overcome these limitations, sophisticated mathematical methods like Wavelet Transform, Neural Networks, Support Vector Machines (SVM), and Deep Learning models are required.

Wavelet-based approaches have the following advantages:

- Multiresolution analysis: Capacity to analyze both global (long-term trends) and local (short-term fluctuations) features of the signal.
- Time-Frequency Localization: Wavelets enable us to know when and at what frequency some events take place.
- Noise Reduction: Wavelet thresholding methods can efficiently eliminate noise.

In Continuous Wavelet Transform (CWT), a time series  $f(t)$  is transformed as:

$$W(a, b) = \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right) dt \quad (3)$$

Therefore, Wavelet Transform both captures temporal and frequency information, as opposed to Fourier techniques, and so is very appropriate for financial usage.

The Discrete Wavelet Transform (DWT), more computationally effective, breaks the time series down into approximation and detail parts at multiple levels. These can be represented as:

$$f(t) = \sum_k C_{J, k} \phi_{J, k}(t) + \sum_{j=1}^J \sum_k d_{j, k} \psi_{j, k}(t) \quad (4)$$

These decompositions render Wavelet Transform-based Multiresolution Analysis (MRA) a powerful tool for the extraction of meaningful patterns in intricate financial data.

## IV. ROLE OF WAVELET TRANSFORM IN FINANCIAL DATA ANALYSIS

Wavelet Transform has turned out to be an effective instrument in the science of financial data analysis as a result of its capability to tackle the non-stationary, nonlinear, and noisy nature of financial time series. Unlike conventional signal processing tools like the Fourier Transform, the Wavelet Transform provides localized insights both in time and frequency domains and hence finds applications especially while analyzing financial signals comprising irregularities, abrupt changes, and multiscale behavior.

### Advantages of Wavelet Transform over Fourier Transform

The Fourier Transform (FT) breaks up a time-domain signal into frequency components, taking as an hypothesis that the signal is stationary (that its statistical characteristics are unchanging over time). This situation does not very often occur in financial data, which is instead non-stationary. FT is defined as:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t} dt \quad (5)$$

Although this change provides data on what frequencies are within the signal, it doesn't tell us when those frequencies are there. Hence, abrupt changes like market crashes or spikes aren't represented that well.

In comparison, the Wavelet Transform applies scaled and shifted forms of a function referred to as a mother wavelet to examine the signal. The Continuous Wavelet Transform (CWT) is given by:

$$W(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right) dt \quad (6)$$

This shift facilitates one to make both frequency content and the timing location of these frequencies more available making it especially suitable for time-varying and noisy financial time series.

### Time-Frequency Localization and Multiscale Analysis

One of the main advantages of wavelets is their time-frequency localization: they are able to have high frequency resolution for low frequencies (for long-term trends) and high time resolution for high frequencies (for short-term fluctuations or noise). This is referred to as Multiresolution Analysis (MRA).

The Discrete Wavelet Transform (DWT), applied in MRA, breaks down a signal into approximation and detail coefficients:

$$f(t) = A_J(t) + \sum_{j=1}^J D_j(t) \quad (7)$$

The wavelet function  $\psi(t)$  and the scaling function  $\phi(t)$  are employed to produce the multilevel decomposition:

$$\phi_{j,k}(t) = 2^{j/2} \phi(2^j t - k), \quad \psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \quad (8)$$

Here, the level  $j$  represents a particular frequency range, and the parameter  $k$  localizes the analysis in time. This decomposition is able to present the time series in a hierarchical manner at multiple scales, isolating long-term market dynamics and short-term abnormalities apart.

### Application to Financial Time Series Data

Financial time series data like stock prices, exchange rates, and market indices typically have long-run trends, cyclic behavior, and short-run aberrations. Utilizing wavelet-based multiresolution analysis makes it possible for analysts to identify and analyze each of these constituents separately.

For instance:

- Approximation coefficients indicate long-term market direction or investor sentiment.
- Coefficient details pinpoint high-frequency market shocks, news events, or trading anomalies.

Let's take a real financial time series  $P(t)$ . Its wavelet decomposition can be expressed as:

$$P(t) = \sum_k c_{j,k} \phi_{j,k}(t) + \sum_{j=1}^J \sum_k d_{j,k} \psi_{j,k}(t) \quad (9)$$

This decomposition is useful in:

- Denoising financial time series by application of thresholding methods (i.e., soft/hard thresholding of  $d_{j,k}$ ),
- Forecasting by approximating the approximation term with machine learning algorithms (i.e., LSTM, ARIMA),
- Estimating volatility through processing of high-frequency detail components,
- Anomaly detection by locating spikes or sudden spikes in certain scales.

In general, wavelet transforms like Haar, Daubechies, and Symlets are implemented, based on the smoothness and compactness needed for data under examination.

## V. CONCEPT OF MULTIREOLUTION ANALYSIS (MRA)

Multiresolution Analysis (MRA) is a core concept within wavelet theory that permits complex time series signals to be decomposed into components of different resolutions or frequency bands. This enables financial analysts to analyze the structure of the signal at multiple levels of detail, thus separating long-term trends from short-term noise (or volatility). MRA finds special relevance in predicting financial market trends, where macroeconomic trends and micro-level volatility must be examined and modelled separately.

### Decomposition into Approximation and Detail Coefficients

In MRA, a signal is examined at several scales through two main collections of functions: the scaling function  $\phi(t)$  and the wavelet function  $\psi(t)$ . The signal  $f(t)$  is divided into an approximation component that represents the low-frequency (coarse-scale) behavior, and detail components reflecting the high-frequency (fine-scale) fluctuations.

The level  $J$  decomposition is mathematically represented as:

$$f(t) = A_J(t) + \sum_{j=1}^J D_j(t) \quad (10)$$

Alternatively, using coefficients and basis functions:

$$f(t) = \sum_k c_{j,k} \phi_{j,k}(t) + \sum_{j=1}^J \sum_k d_{j,k} \psi_{j,k}(t) \quad (11)$$

This hierarchical breakdown is the essence of MRA, wherein every subsequent level gives a progressively smoothed or coarse approximation of the original signal.

### Understanding Trends and Noise Separately

One of the strongest features of MRA is its capability to isolate trends from noise. In financial information:

- Approximation coefficients  $A_J(t)$  pick up underlying market trends, macroeconomic trends, and long-term investor patterns.
- Detail coefficients  $D_j(t)$ , particularly at lower scales (i.e., higher frequencies), tend to include noise, short-term fluctuations, and unpredictable variability.

This isolation allows analysts to model each separately. For example:

- Trends can be predicted using models like ARIMA, LSTM, or regression.
- Noise components may be analyzed for intraday trading models or removed to improve data quality.

For instance, a stock price time series  $P(t)$  can be reconstructed from:

$$P(t) = \text{Trend}(t) + \text{Noise}(t) = A_J(t) + \sum_{j=1}^J D_j(t) \quad (12)$$

To analyze the components independently is to gain a better insight into market behavior.

### Noise Filtering and Signal Enhancement for Better Prediction

Wavelet-based MRA also facilitates denoising, which plays a crucial role in enhancing prediction performance. Financial signals tend to be noisy due to micro-transactions, outside shocks, and measurement errors. Denoising may be achieved by thresholding the detail coefficients, suppressing noise effectively.

The denoising procedure generally entails:

#### 1. Decomposition of the signal using DWT

#### 2. Thresholding of detail coefficients:

- **Hard thresholding:**

$$d'_{j,k} = \begin{cases} d_{j,k}, & \text{if } |d_{j,k}| > \lambda \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

- **Soft thresholding:**

$$d'_{j,k} = \text{sign}(d_{j,k}) \cdot \max(|d_{j,k}| - \lambda, 0) \quad (14)$$

Where  $\lambda$  is a threshold value, often based on statistical properties (e.g., universal threshold  $\lambda = \sigma\sqrt{2\log n}$ ).

### Reconstruction of the signal using the filtered coefficients

It changes the signal becomes less noisy and makes it adequate for use in predictive modelling. It improves:

- Machine learning algorithms by eliminating irrelevant noise,
- Trend prediction by isolating clean long-term patterns,
- Volatility analysis based on residuals or preserved high-frequency components.

## VI. INTEGRATION OF WAVELET MRA WITH PREDICTIVE MODELS

Wavelet MRA combined with the predictive models is used as an efficient tool for forecast and tendencies in the financial markets. Applying the proposed hybrid system based on the primary properties and characteristics of wavelet decomposition with machine learning (ML) and deep learning (DL) guarantees more accurate and comprehensive prediction and better control of noisy and non-stationary data.

### Hybrid Modelling Approach (Trends vs. Noise)

In the functional area of finance especially when handling time series data, separation of the trends from the noises or fluctuations is very important to gain better accuracy in the results of the forecast. According to wavelet MRA, the signal is divided into the approximate part (trend) and the detailed part (noise). Essentially, the hybrid strategy incorporates different models for each part thus enhancing the prediction as a result of the division.

**1. Trend Modelling:** The approximation term  $AJ(t)$ , the long-term trend, can also be modelled using one of the statistical models such as the Autoregressive Integrated Moving Average (ARIMA) or Long Short-Term Memory (LSTM) networks when it comes to the analysis of sequential, time series data.

o **ARIMA Model:** The ARIMA model can be used in the approximation  $AJ(t)$  as:

$$Y_t = \alpha + \sum_{i=1}^p \phi_i Y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t \quad (15)$$

o **LSTM Model:** This approximation can also be fed into LSTM network for time series learning and is most capable of learning long-term dependencies in data. The LSTM updates its internal state by using the following equations:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \quad (16)$$

$$\begin{aligned} C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\ o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh(C_t) \end{aligned}$$

**Noise Modelling:** These are the detail parts  $D_j(t)$  which are normally seen as variations at higher frequencies originated due to market shocks, news, or noise. Many components of such tapes can be fit by using machine learning algorithms, such as Support Vector Machines (SVM) or Random Forests in order to model short-run irregularity and predict fluctuations.

• **Support Vector Machine (SVM):** There is an equation that shows the ability of the SVM to forecast the prices provided the detail coefficients  $D_j(t)$  which is given below:

$$f(x) = W^T \phi(x) + b \quad (17)$$

SVM has the ability to exploit the volatility and nonlinearities underlying high-frequency financial data.

• **Hybrid Model Output:** When both the noise and trend has been individually estimated, the final forecast is arrived at from the compounded of their individual model.

$$\hat{P}(t) = \hat{A}_j(t) + \hat{D}_j(t) \quad (18)$$

The hybrid strategy enables successful modelling of the systematic pattern and the randomness, yielding a better overall prediction.

**Use with Machine Learning and Deep Learning Techniques**

Wavelet MRA, when utilized in conjunction with machine learning and deep learning methodologies, allows highly efficient and effective predictive models to be developed. Decomposition into approximation and detail coefficients facilitates feature extraction, which is crucial for these methods to work well. This is how the integration process works:

**➤ Machine Learning Models:**

- Once the time series is decomposed with wavelet MRA, the approximation coefficients may be utilized as features for standard machine learning algorithms like Random Forests, Gradient Boosting Machines (GBM), or Support Vector Machines (SVM).
- The detail coefficients can be used as high-frequency features for identifying market volatility or short-term occurrences.
- The models are usually trained on the features that are extracted from the decomposition, as well as other external data (e.g., news sentiment, economic indicators).

**➤ Deep Learning Models:**

- **Convolutional Neural Networks (CNNs):** CNNs can be used on the coefficients of wavelet decomposition since the multiresolution aspect of wavelet analysis renders data appropriate for CNNs to extract spatial features within the time-frequency domain.
- **Long Short-Term Memory (LSTM) Networks:** LSTM networks are designed for modelling long-term dependencies and trends in the approximation components  $AJ(t)$  following wavelet decomposition, yet at the same time they are capable of coping with high-frequency noise with the capability of modelling time dependencies over long sequences.
- **Deep Reinforcement Learning (DRL):** DRL can be utilized to maximize trading strategies using wavelet-processed time series data. The agent is trained to learn optimal trading actions from long-term market trends and short-term noise components.

**Benefits in Predictive Accuracy and Model Efficiency**

- ❖ **Improved Accuracy:** Isolating the trends and noise, the predictive models concentrate on the most important information required for forecasting. For instance, the forecasting models used on the approximation coefficients identify the underlying market trend, whereas models used on the detail coefficients identify short-term activity and volatility. This set of signals yields overall higher accuracy than in conventional methods.
- ❖ **Enhanced Model Efficiency:** Wavelet decomposition serves to decrease the dimensionality of data by emphasizing the most important frequency bands. This reduces the amount of noise, which does not help the input of the machine learning or deep learning models in any way. Additionally, by disaggregating the long-term up and down trends, the model can reach the solution and the convergence to the final solution is faster.
- ❖ **Noise Reduction:** Therefore, noise that goes through wavelet based denoising gives better and stable data for the predictive modelling. This increases the signal-to-noise ratio, allowing models to focus on the centres of prominent patterns and not the noise which, in most cases, adversely affects predictive power to a larger degree.

**VII. CONCLUSION**

This research shows that using Wavelet Transform based MRA can improve the predictive capability of financial markets due to the effectiveness of handling issues of non-stationarity, non-linearity, and noisiness of financial time series data. Using MRA based on wavelets, complex signals of the financial series can be segregated into the trend part and the noise part; this way, it is possible to apply accurate models for long-term trends through LSTM and other deep learning and for short-term volatility with the help of the machine learning methods like SVM. Unlike traditional statistic analysis approaches which do not capture complex market behaviours, the wavelet-based approach preserves time and frequency information hence gives a larger and more localized (region of interest) details of the market. Through Wavelet MRA integration and coupling it with a more detailed model, it is possible to improve the container's predictive ability, manipulate noise, and increase the model's working efficiency. With financial markets becoming increasingly complex, Wavelet Transform-based approaches present an effective and adaptive platform for future prediction work, again affirming their pivotal role in financial data analysis and strategic financial decision-making.

**REFERENCES**

1. Abdeltawab, A., Xi, Z., & Longjia, Z. (2024). Enhanced tool condition monitoring using wavelet transform-based hybrid deep learning based on sensor signal and vision system. *The International Journal of Advanced Manufacturing Technology*, 132(9), 5111-5140.
2. Acuna-García, J. A., Luz Canchola-Magdaleno, S., & Olmos Trejo, C. A. (2022). Stock Market Forecasting Using Continuous Wavelet Transform and Long Short-Term Memory Neural Networks. *International Journal of Advanced Research in Computer Science*, 13(6).
3. Althelaya, K. A., Mohammed, S. A., & El-Alfy, E. S. M. (2021). Combining deep learning and multiresolution analysis for stock market forecasting. *IEEE Access*, 9, 13099-13111.
4. Balamohan, S., Khanaa, V., & Sivaraman, K. (2023). Effective Stock Market Pricing Prediction Using Long Short-Term Memory-Upgraded Model (LSTM-UP) on Evolving Data Sets. *SN Computer Science*, 4(5), 658.
5. Burhan, B., & Mohammed, F. A. (2024). A Hybrid Model for Financial Forecasting Based on Maximal Overlap Discrete Wavelet Transform; Evidence from Chinese Exchange Rates. *Journal of Economics and Administrative Sciences*, 30(142), 476-491.
6. Gu, Q., Chang, Y., Xiong, N., & Chen, L. (2021). Forecasting Nickel futures price based on the empirical wavelet transform and gradient boosting decision trees. *Applied Soft Computing*, 109, 107472.
7. Lee, J., Koh, H., & Choe, H. J. (2021). Learning to trade in financial time series using high-frequency through wavelet transformation and deep reinforcement learning. *Applied Intelligence*, 51(8), 6202-6223.
8. Rabbouch, H., Rabbouch, B., & Saâdaoui, F. (2023). Multiresolution Data Analytics for Financial Time Series Using MATLAB. In *Data Analytics for Management, Banking and Finance: Theories and Application* (pp. 113-134). Cham: Springer Nature Switzerland.
9. Rubio, L., Palacio Pinedo, A., MejíaCastaño, A., & Ramos, F. (2023). Forecasting volatility by using wavelet transform, ARIMA and GARCH models. *Eurasian Economic Review*, 13(3), 803-830.
10. Safa, K., Belatreche, A., Ouadfel, S., & Jiang, R. (2024). WALDATA: wavelet transform based adversarial learning for the detection of anomalous trading activities. *Expert Systems with Applications*, 255, 124729.
11. Singh, P., Singh, N. K., & Singh, A. K. (2025). Wavelet Transform Based Gated-Recurrent Unit Deep Learning Approach for Power Output of Solar Photovoltaic System Forecasting. *SN Computer Science*, 6(3), 243.
12. Verma, S., Sahu, S. P., & Sahu, T. P. (2023). Discrete wavelet transform-based feature engineering for stock market prediction. *International Journal of Information Technology*, 15(2), 1179-1188.
13. Volpatti, G. (2024). Multi-scale periodic analysis of financial indexes for quantitative financial forecasts.
14. Wang, J. (2021). Application of wavelet transform image processing technology in financial stock analysis. *Journal of Intelligent & Fuzzy Systems*, 40(2), 2017-2027.
15. Zhang, Y., Qin, J., Lin, B., Su, Y., & Yang, X. (2025). Wavelet denoising and double-layer feature selection for stock trend prediction. *Computational Economics*, 1-29.



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  [ijirset@gmail.com](mailto:ijirset@gmail.com)



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details