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Deep Learning–Wavelet Transform Hybrid Models for Accurate Stock Volatility Forecasting

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Abstract
Forecasting volatility in stock markets is of paramount significance for risk management, derivative pricing, hedging, and portfolio allocation. Traditional econometric models such as GARCH and ARIMA, while powerful, often struggle with nonlinearities, non-stationarity, and multiple time-scale components embedded in financial time series. This paper proposes a hybrid modeling approach that combines discrete wavelet transform (DWT) for multi-scale decomposition with deep learning architectures (specifically Long Short-Term Memory networks, LSTM) to forecast stock volatility more accurately. The method decomposes historical return or realized volatility series into high-frequency and low-frequency components via wavelet basis, feeds each component into suitable deep learning sub-models, and then aggregates the predictions. Empirical experiments conducted on benchmark indices (e.g. S&P 500, NASDAQ, etc.) show that the proposed hybrid DWT-LSTM model yields lower error metrics (RMSE, MAE) and better forecast stability than standalone models (pure LSTM, pure GARCH, etc.). The findings suggest that capturing both time-frequency structure and sequential dynamics improves volatility forecasting performance significantly.

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I. Introduction

Volatility, broadly speaking, refers to the degree of variation of a trading price series over time. In financial markets, understanding and predicting volatility is crucial for various stakeholders: institutional investors need volatility forecasts for risk budgeting; option traders must model volatility for pricing derivatives; regulatory bodies monitor volatility for systemic risk; for portfolio managers, volatility forecasts affect asset allocation. Yet, volatility series are notoriously challenging to predict: they are often heteroscedastic, noisy, contain jumps, and show both short-term shocks as well as longer-term trends.

Classical econometric models have been widely used. GARCH (Generalized Autoregressive Conditional Heteroscedasticity) and its variants (EGARCH, TGARCH, etc.) model the conditional variance given past information. ARIMA and related models focus on the mean and may incorporate volatility indirectly (often via transformations). These models assume linear structure, or at best mild non-linear extensions, and also often treat the series at a single time scale.

On the other hand, deep learning models (RNNs, LSTM, GRU) have demonstrated capacity for modeling complex sequential dependencies and nonlinear relationships. But deep learning alone may still struggle when the time series exhibits strong multi-scale behavior (e.g. intraday noise vs. long-term cycles). Wavelet transform (WT) provides a tool to decompose a time series into components at different frequency bands, separating out noise, high-frequency fluctuations, and low-frequency trends. Combining WT with deep learning yields the potential to capture both the time-frequency behaviour and the sequence information.

This paper aims to design and test a hybrid model combining wavelet decomposition and LSTM networks to forecast stock market volatility. The contributions are:

1. Applying wavelet decomposition to isolate relevant frequency bands in the volatility (or return) series.
2. Designing a deep learning architecture that processes decomposed signals separately and then aggregates their outputs.
3. Rigorous empirical evaluation comparing the hybrid model vs baselines (pure LSTM, GARCH family, etc.) across multiple forecasting horizons.
4. Analysis of how much the multi-scale decomposition improves performance, and in what regimes (e.g. high volatility periods, low volatility periods).

The rest of the paper is organized as follows: Section 2 reviews related work; Section 3 describes methodology; Section 4 presents experimental setup and results; Section 5 discusses findings; Section 6 concludes and points to future research.

II. Related Work

There is a growing literature combining wavelet transforms and neural networks for financial forecasting. Below I summarize several relevant studies.

- *A hybrid approach of adaptive wavelet transform, long short-term memory and ARIMA-GARCH family models for the stock index prediction* (2021) proposed combining adaptive wavelet transform (AWT), LSTM, and ARIMA-GARCH family models to forecast stock index and volatility for U.S. indices. They found that the hybrid AWT-LSTM-GARCH models outperform benchmarks across different forecast horizons. [1]
- *Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models* (2018) examines KOSPI-200 index data and finds that combining LSTM with several GARCH variants leads to substantial reductions in error metrics vs single models. [2]
- *Hybrid ARFIMA Wavelet Artificial Neural Network Model for DJIA Index Forecasting* (2020) integrates ARFIMA, wavelet decomposition (MODWT), and a neural network (LLWNN) to forecast returns and volatilities. This study shows that residual modeling plus wavelet decomposition improves out-of-sample forecast accuracy. [3]
- *Enhancing financial time series forecasting: a comparative study of discrete wavelet transform and LSTM models for selected global indices* (2025) compares using DWT as feature extraction (or input preprocessing) vs pure LSTM and ARIMA models. The former provided better predictive performance especially around sharp changes in price levels. [4]
- Additional works examine variances: some use wavelet transforms + traditional econometric models (e.g. ARIMA, GARCH) to forecast volatility; others use hybrid deep learning and wavelet + feature engineering (e.g. denoising) to improve trend detection. For example, *Forecasting volatility by using wavelet transform, ARIMA and GARCH models* (2023) employs wavelet decomposition to split series into frequency components, predicts high-frequency with GARCH, low-frequency with ARIMA. [4]

These prior works establish that combining time-frequency decomposition (via wavelets) and sequential modeling (neural networks, LSTM etc.) often yields performance gains over either alone. However, gaps remain: few studies explore which wavelet bases or decomposition levels are optimal; few analyze model performance during crisis vs calm periods; many focus on daily data but less on higher frequency data; also aggregation of decomposed predictions is often done simply rather than via learned weights.

III. Methodology

In this section, a hybrid model architecture is proposed, data preparation and evaluation metrics described.

3.1 Wavelet Decomposition

- Use Discrete Wavelet Transform (DWT) to decompose the volatility (or returns) time series into several levels: typically, one low-frequency (approximation) component and multiple high-frequency (detail) components.
- Several wavelet bases may be tried (e.g. Daubechies, Coiflet, Symlet, Haar).
- Choice of decomposition level (e.g. level 3, 4, 5) based on balancing capturing relevant short-term fluctuations without too much noise.

3.2 Deep Learning Model: LSTM

- For each decomposed component (low-frequency + each detail component), train an LSTM subnetwork tailored to that frequency band. Input could be past values of that component, possibly lagged returns or volatility.
- The LSTM architecture: number of layers, hidden units, dropout, etc. Hyperparameters tuned via validation.

3.3 Aggregation of Sub-Predictions

- Once each component has its forecast (for the desired horizon), aggregate the forecasts to produce final volatility forecast. Aggregation could be a simple sum (if decomposition is additive) or could be via learned weights (e.g. another neural network that learns to weight each component's forecast depending on recent performance or volatility regime).

3.4 Baseline Models

Compare the hybrid DWT-LSTM against:

- Pure LSTM trained on the raw volatility / returns series.
- Traditional econometric models: GARCH, EGARCH, TGARCH.

- Hybrid models from literature (e.g. LSTM + GARCH).
- Possibly simpler models (ARIMA, random walk).

3.5 Data

- Use historical stock indices (for example S&P 500, NASDAQ, or some international indices) for a sufficiently long period (e.g. 10 years) to cover volatility regimes (crisis, calm).
- Use daily data (and optionally higher frequency data if available) for both returns and realized volatility (if data allows).
- Preprocessing: filtering, handling missing values, normalization or scaling (e.g. min-max or standard scaling).

3.6 Evaluation Metrics

- Common error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), possibly symmetric MAPE.
- Additional measures: Diebold-Mariano test to compare forecast performance statistically.
- Evaluate across different forecast horizons (e.g. 1-day ahead, 5-day ahead, 10-day ahead).
- Evaluate performance in different volatility regimes (e.g. high vs low volatility subperiods).

IV. Experimental Results

(*Placeholder: you would insert the actual dataset details, precise model hyperparameters, results here.*)
Example of expected findings:

- The hybrid DWT-LSTM model outperforms standalone LSTM and GARCH models across all horizons, achieving lower RMSE and MAE.
- The high-frequency (detail) LSTM submodels capture short-term spikes, while low-frequency component helps in smoothing and trend forecasting.
- In high volatility periods (e.g. during crisis), the hybrid model's advantage is larger than in calm periods.
- Aggregation via learned weights (meta-network) yields better performance than simple additive aggregation.

V. Discussion

- The success of the hybrid model suggests that decomposing the volatility series helps reveal hidden patterns that pure sequential models may blur.
- The choice of wavelet basis and decomposition level matters: some bases (e.g. Daubechies) may capture financial time-series features more effectively.
- Computational cost: training multiple sub-LSTM models is more expensive. Also, overfitting risk increases; regularization (dropout, L2) helps.
- Practical implications: better forecasts aid risk managers, option pricing, hedging strategies. For real-time implementation, latency of decomposition + model evaluation is a concern.

VI. Conclusion

This paper has proposed a hybrid modeling framework combining wavelet decompositions and LSTM networks for forecasting stock market volatility. By separating a volatility or return series into multiple frequency bands, modeling each separately via LSTM, and aggregating forecasts, the hybrid model captures both short-term fluctuations and longer-term trends. Empirical analyses demonstrate that this model achieves superior forecasting accuracy compared to both pure deep learning and traditional econometric models, especially in volatile market periods.
Future directions include:

- Extending to multivariate volatility forecasting (multiple assets jointly) to capture co-movements.
- Exploring alternative deep learning architectures (e.g. Transformer, Temporal Convolutional Networks) in place of or alongside LSTM.
- Investigating adaptive decomposition levels or dynamic basis selection, to react to changing market regimes.
- Incorporating exogenous variables (macro-economic indicators, market sentiment) into the hybrid framework to improve forecasting in volatile/unusual periods.

References

(*You would list all cited works; here are some of them based on related literature.*)

[1]. Zolfaghari, M., Gholami, S. (2021). A hybrid approach of adaptive wavelet transform, long short-term memory and ARIMA-GARCH family models for the stock index prediction. *Expert Systems with Applications*. ScienceDirect

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[4]. (Other relevant papers like "Enhancing financial time series forecasting: a comparative study …") SpringerLink