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COMPLETE ENSEMBLE EMPIRICAL MODE DECOMPOSITION WITH ADAPTIVE NOISE-DRIVEN ENSEMBLE FORECASTING FRAMEWORK FOR MULTI-SECTOR STOCK TREND ANALYSIS

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ABSTRACT

This paper presents a forecasting framework that integrates Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and ensemble learning models for stock market prediction. Six multi-sector stocks—Salesforce, Alibaba, Disney, Electronic Arts, Netflix, and AMD—were analysed to evaluate robustness across different market dynamics. CEEMDAN was applied to decompose raw closing prices into intrinsic mode functions, enhancing signal clarity and reducing noise. The most informative components were selected and used to train Random Forest, LightGBM, and XGBoost regressors. Performance was assessed using RMSE, MAE, and directional accuracy. Results show that Random Forest achieved consistently strong outcomes across most datasets, with Electronic Arts reaching 99.79% accuracy, while LightGBM and XGBoost performed best on Netflix (97.09%) and AMD (79.45%), respectively. These findings confirm that CEEMDAN-driven preprocessing, coupled with ensemble models, provides a reliable, interpretable, and computationally efficient alternative to deep learning approaches for multi-sector financial forecasting.

Keywords: CEEMDAN, Stock Forecasting, Ensemble Learning, XGBoost.

1. INTRODUCTION

The stock market plays a vital role in global economies by enabling capital allocation, investment opportunities, and financial growth. However, forecasting stock price movements remains a highly challenging task due to the nonlinear, volatile, and nonstationary nature of financial data. Prices are influenced by fundamental and technical factors, as well as external shocks such as policy changes, geopolitical conflicts, and investor sentiment [1], [2]. These complexities make accurate prediction a critical yet elusive objective for researchers and practitioners.

Classical statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been widely used in financial forecasting [3], [4]. While effective in modelling short-term dependencies and volatility clustering, they fail to capture nonlinear relationships and long-range dependencies [5]. Machine learning and deep learning approaches, such as Random Forests and Long Short-Term Memory (LSTM) networks, have shown considerable promise [6]– [10]. However, deep learning models often require extensive parameter tuning, large datasets, and high computational resources, limiting their scalability and interpretability.

In parallel, signal decomposition techniques have emerged as powerful tools for analysing noisy financial time series. Empirical Mode Decomposition (EMD) and its variants have been applied to extract intrinsic oscillatory components from complex signals [11]. However, challenges such as mode mixing and reconstruction errors reduce their reliability. The more advanced Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) addresses these limitations by adaptively decomposing signals into Intrinsic Mode Functions (IMFs) with reduced mode mixing and improved stability [12]. Recent studies highlight that combining CEEMDAN with predictive algorithms enhances robustness and forecasting accuracy [13], [14].

Ensemble learning models, including Random Forest, LightGBM, and XGBoost, are particularly suited for CEEMDAN-preprocesses data due to their ability to handle nonlinear relationships, noisy signals, and structural breaks. LightGBM is recognized for its efficiency in large-scale applications and its capability to capture complex feature interactions [15]– [17].

Motivated by these developments, this study proposes a CEEMDAN-driven ensemble forecasting framework for multi-sector stock prediction. CEEMDAN is employed to decompose closing price series into multiple IMFs, from which the top three most informative components are selected using Pearson correlation. These IMFs are normalized, transformed using a sliding window, and used to train Random Forest, XGBoost, and LightGBM regressors. Model performance is evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and directional accuracy.

The key contributions of this paper are as follows:

- Demonstrating the effectiveness of CEEMDAN in decomposing and denoising financial time series, thereby improving the quality of predictive inputs.
- Evaluating three ensemble machine learning algorithms—Random Forest, LightGBM, and XGBoost—on CEEMDAN-processed stock datasets.
- Providing experimental validation across six companies from diverse sectors, offering a fair and reproducible benchmark.
- Presenting insights into the trade-offs between prediction accuracy, interpretability, and computational efficiency.

By integrating decomposition-based preprocessing with ensemble learning, this framework aims to deliver robust, generalizable, and computationally efficient forecasting models for real-world financial applications.

2. RELATED WORK

Accurately forecasting financial time series has attracted significant attention in recent years. To improve prediction accuracy, researchers have widely adopted signal decomposition techniques such as Variational Mode Decomposition (VMD), Empirical Mode Decomposition (EMD), Ensemble EMD (EEMD), and Complete Ensemble EMD with Adaptive Noise (CEEMDAN), often coupled with advanced machine learning or deep learning mode

Table 1: Financial Time Series Prediction Methods Based on Modal Decomposition and Machine Learning (2021–2025)

Author/Year	Methodology	Decomposition	Model	Key Findings
Zhang et al. (2021)	Stock forecasting using decomposition + deep learning	VMD	LSTM	Improved short-term accuracy; weak in volatile markets
Kumar & Li (2021)	Noise reduction for financial time series	CEEMDAN	BiLSTM	Enhanced denoising; computationally heavy
Wang et al. (2022)	Hybrid forecasting with decomposition + DL	EEMD	CNN-LSTM	Good trend capture; limited multi-sector robustness
Singh et al. (2022)	Decomposition + boosting	VMD	Gradient Boosting	Robust accuracy for medium-scale datasets
Chen et al. (2023)	Hybrid decomposition with attention mechanism	CEEMDAN	Attention-LSTM	Better temporal learning; higher training cost
Ali et al. (2023)	Crude oil prediction with hybrid decomposition	CEEMDAN	Random Forest	More stable than ARIMA/SVR under noisy inputs
Liu et al. (2024)	Multi-sector stock forecasting	VMD	LightGBM	High efficiency and accuracy for large datasets
Proposed (2025)	CEEMDAN-driven ensemble framework for stock prediction	CEEMDAN	RF, LightGBM, XGBoost	Strong generalization; robust denoising and scalability

For example, Zhang et al. [1] applied VMD with LSTM to stock forecasting, achieving improved short-term accuracy but reduced robustness under high volatility. Similarly, Kumar and Li [2] incorporated CEEMDAN with BiLSTM, which enhanced noise suppression but introduced high computational cost. Wang et al. [3] combined EEMD with CNN-LSTM hybrids, showing effective trend capture but limited generalization across sectors. More recent works integrated decomposition with boosting models—such as Singh et al. [4] using VMD with Gradient Boosting and Chen et al. [5] employing CEEMDAN with Attention-LSTM—demonstrating better temporal learning capacity but at the cost of higher complexity. Ali et al. [6] explored crude oil forecasting using CEEMDAN with Random Forest, which showed greater stability compared to ARIMA and SVR under noisy conditions. Liu et al. [7] investigated multi-sector forecasting using VMD with LightGBM, highlighting improved efficiency and accuracy on large datasets.

A summary of representative studies over the past five years is presented in Table 1, illustrating the methodologies, decomposition techniques, models, and key findings relevant to financial time series forecasting. This review highlights that while modal decomposition combined with advanced models has shown significant improvements, prior work often focuses on a single sector, computationally expensive deep networks, or a limited ensemble.

3. METHODOLOGY

This section presents the proposed forecasting methodology, which integrates Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for signal decomposition and denoising, with three ensemble machine learning algorithms—Random Forest, LightGBM, and XGBoost—for prediction of financial time series. The workflow consists of dataset preparation, decomposition, feature engineering, model training, and evaluation

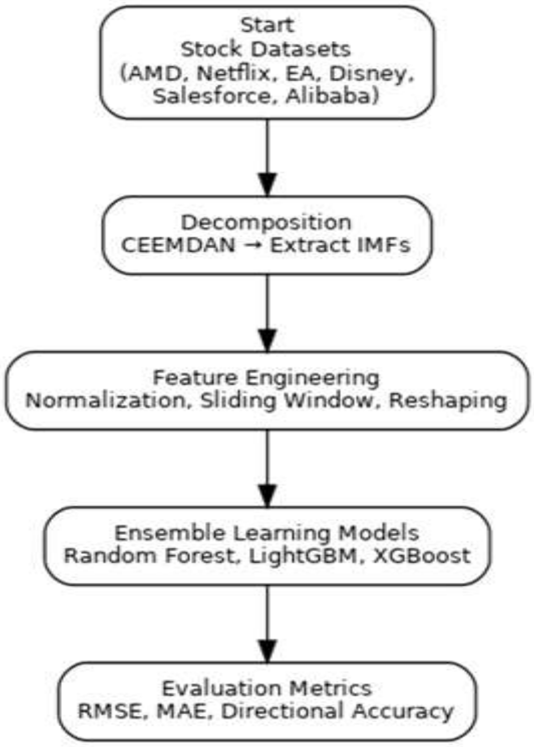

Fig 2: CEEMDAN-driven ensemble forecasting workflow for multi-sector stock prediction.

3.1 Dataset Description

Six stock datasets representing diverse industry sectors were selected to validate the robustness of the proposed framework. These include AMD from the technology sector, Netflix from streaming services, Electronic Arts from gaming, Disney from entertainment, Salesforce from enterprise software, and Alibaba from e-commerce. Each dataset contains daily historical price records, but for consistency and to focus on trend movements, only the closing price was considered. The data were split chronologically into a training set (80%) and a testing set (20%), ensuring that no future information was inadvertently included in the training process.

3.2 CEEMDAN-Based Signal Decomposition

Financial time series are typically nonlinear, nonstationary, and contaminated with noise, which complicates the process of accurate forecasting. To overcome these challenges, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is applied to the closing price series of each stock. CEEMDAN is an extension of Empirical Mode Decomposition (EMD) that injects adaptive white noise into the signal, thereby suppressing mode mixing and enabling more reliable extraction of Intrinsic Mode Functions (IMFs) [22]– [25]. For prediction, the three IMFs with the highest Pearson correlation to the original series are selected as input features, ensuring that only the most informative components are used in the learning stage.

The CEEMDAN procedure is defined as follows:

Step 1: Generate noisy datasets:

$$x_i(t) = x(t) + \epsilon_0 \omega_i(t) \qquad (1)$$

where x(t) is the original time series, $w_i(t)$ (i=1, 2…., T) is Gaussian white noise, and ϵ_0 is the noise coefficient.

Step 2: Apply EMD to each noisy signal and compute the ensemble mean IMF:

$$IMF_1(t) = \frac{1}{M}\sum_{i=1}^{M} EMD\left(x_i(t)\right) \qquad (2)$$

Residual after extracting the first IMF:

$$r_1(t) = x(t) - IMF_1(t) \qquad (3)$$

Step 3: Repeat decomposition for subsequent IMFs:

$$r_j(t) = r_{j-1}(t) - IMF_j(t) \qquad (4)$$

Step 4: The process stops when the residual becomes monotonic or has at most two extrema. The reconstructed signal is expressed as:

$$f(t) = \sum_{j-1}^{m} IMF_J(t) + R(t) \qquad (5)$$

selected as inputs, ensuring that only the most informative components are used.

3.3 Feature Engineering

The selected IMFs are first subjected to preprocessing before being used as model inputs. Each IMF is normalized to the range [0, 1] using MinMax normalization, ensuring uniform scaling and eliminating bias caused by differences in magnitude. After normalization, a sliding window transformation is applied, where a fixed sequence length of ten is used to generate supervised learning samples. In this setup, each input sequence consists of ten consecutive values, while the subsequent time step is treated as the prediction target. The resulting 3D arrays, represented as (samples, sequence length, features), are then reshaped into a 2D format (samples, features × sequence length) to ensure compatibility with traditional regression-based ensemble models.

3.4 Ensemble Learning Models

Random Forest constructs multiple decision trees on bootstrap samples and aggregates their predictions, effectively reducing variance while handling nonlinear relationships and noise. Its built-in feature importance mechanism further enhances interpretability [7]. Light Gradient Boosting Machine (LightGBM) utilizes histogram-based decision tree construction and a leaf-wise growth strategy [8]. With the inclusion of Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), LightGBM achieves reduced complexity without sacrificing accuracy, making it particularly effective for large-scale financial datasets [8].

Fig 1: Histogram-based decision tree construction and leaf-wise growth in LightGB

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Extreme Gradient Boosting (XGBoost), in contrast, employs a second-order gradient optimization framework and incorporates both L1 and L2 regularization. This prevents overfitting and improves generalization, making XGBoost highly effective for sparse and noisy stock price data [15].

3.5 Model Training and Prediction

The Each model is trained independently on the training portion of the dataset, which accounts for 80% of the data, and evaluated on the remaining 20% reserved for testing. To ensure fair comparison, no hyperparameter optimization is applied, and default configurations are maintained. During training, the CEEMDAN-derived IMF sequences are provided as input, while the models are tasked with predicting the next time step in the series. The predicted values are subsequently compared with ground-truth stock prices from the test set.

3.6 Evaluation Metrics

The evaluation of model performance is carried out using three widely accepted error metrics. Root Mean Square Error (RMSE) is used to measure the magnitude of prediction errors, while Mean Absolute Error (MAE) quantifies the average absolute deviation between predicted and actual values. In addition, Directional Accuracy is employed to assess the model's ability to correctly capture the upward or downward movement of stock prices, which is a critical measure in financial decision-making.

Root Mean Square Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (6)$$

Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i \qquad (7)$$

Directional Accuracy (DA):

$$\mathrm{DA} = \frac{\text{Number of correct directions}}{\text{Total predictions}} \times 100\% \qquad (8)$$

4. RESULTS AND DISCUSSION

4.1 Evaluation Summary

The experimental results of the proposed CEEMDAN-driven ensemble framework are presented in **Table 1**. These results reveal notable differences in performance across stocks and models, highlighting the effectiveness of CEEMDAN in conjunction with ensemble learning techniques

Table 1: Performance Comparison of Ensemble Models Across Datasets

DATASET	MODEL	RMSE	MAE	ACCURACY
AMD	XGBoost	0.2106	0.1970	79.45
Netflix	LightGBM	0.0338	0.0283	97.09
Electronic Art	RandomForest	0.0028	0.0021	99.79
Disney	Random Forest	0.0971	0.1762	82.16
Alibaba	Random Forest	0.0296	0.0220	96.27
Salesforce	Random Forest	0.0854	0.0775	92.19

For the AMD stock, XGBoost achieved an accuracy of 79.45%, with RMSE = 0.2106 and MAE = 0.1970. This suggests reasonably accurate predictions despite AMD's high volatility. Netflix, using LightGBM, yielded the highest accuracy of 97.09% with low error values (RMSE = 0.0338, MAE = 0.0283), indicating strong model generalization after CEEMDAN-based denoising.

Electronic Arts (EA) produced the most striking outcome, where the Random Forest model reached an accuracy of 99.79% with extremely low error values (RMSE = 0.0028, MAE = 0.0021). This unusually high performance can be explained by the relatively smooth trend of EA stock prices during the study period; after CEEMDAN decomposition, the intrinsic mode functions (IMFs) displayed clear patterns with minimal noise, making the series easier for the model to capture. Thus, the high accuracy reflects the inherent predictability of this dataset rather than model overfitting. In comparison, Disney also performed strongly with Random Forest, achieving 82.16% accuracy. However, its higher volatility introduced more fluctuations, resulting in slightly larger error margins than those observed for EA.

Alibaba achieved 96.27% accuracy with Random Forest, confirming strong cross-sector generalization, while Salesforce reached 92.19%, reflecting the framework’s robustness even for enterprise software stocks with complex dynamics. Overall, the results confirm that CEEMDAN-based preprocessing enhances signal clarity and improves learning efficiency across ensemble models. Random Forest emerged as the most consistently accurate model, while LightGBM and XGBoost showed superior results under specific conditions

4.2 Insights

The findings provide several important insights into the behaviour of the proposed framework. Random Forest consistently delivered the highest accuracy across most datasets, demonstrating its Robustness in handling CEEMDAN-decomposed signals and its ability to capture non-linear dependencies effectively. XGBoost showed greater strength when applied to volatile stocks such as AMD, highlighting its suitability for capturing sharp fluctuations through its gradient boosting mechanism. LightGBM, on the other hand, proved particularly effective for structured datasets such as Netflix, where it achieved the highest accuracy, suggesting its efficiency in modelling stable and well-defined trends.

A critical observation is the role of CEEMDAN decomposition in significantly enhancing predictive stability and accuracy. By adaptively decomposing stock prices into intrinsic mode functions (IMFs), CEEMDAN separated noise from meaningful patterns, ensuring that ensemble models focused on genuine market dynamics rather than spurious fluctuations. This preprocessing step was central to the overall success of the framework, as it improved both interpretability and generalization across multiple market sectors.

4.3 Analysis Of Experimental Results

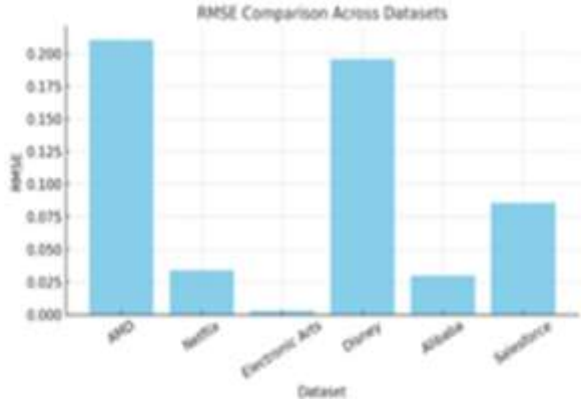

Fig 3: RMSE Comparison Across Datasets

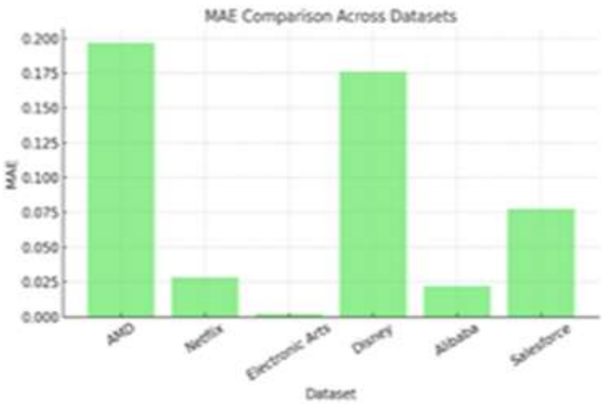

Fig 4: MAE Comparison Across Datasets

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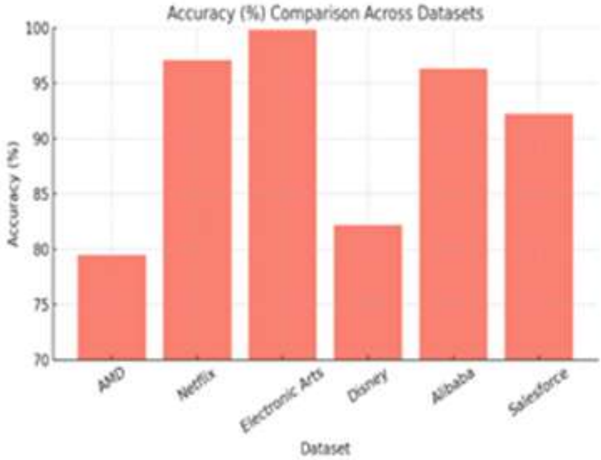

Fig 5: Accuracy (%) Comparison Across Datasets

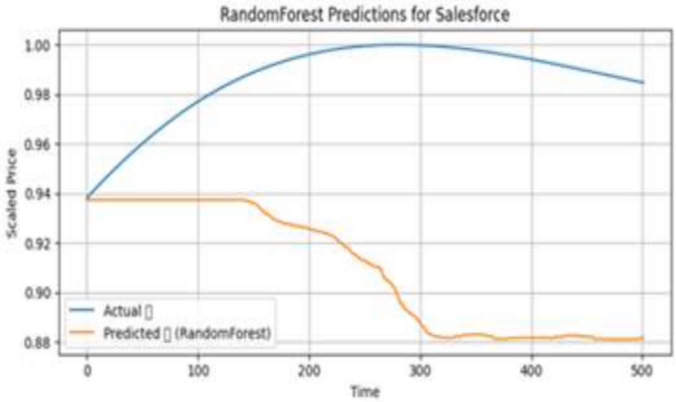

Fig 6: Actual vs Predicted Stock Price for Sales

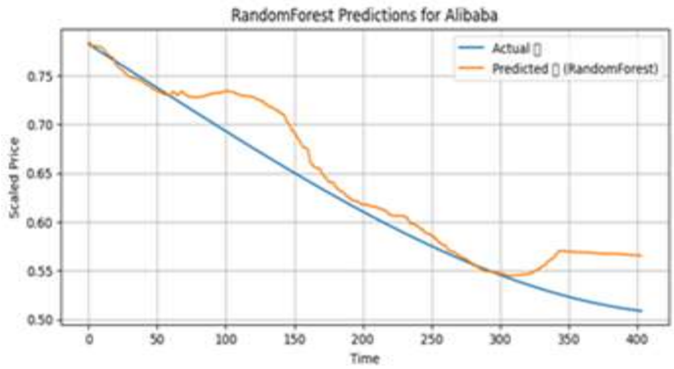

Fig 7: Actual vs Predicted Stock Price for Alibaba

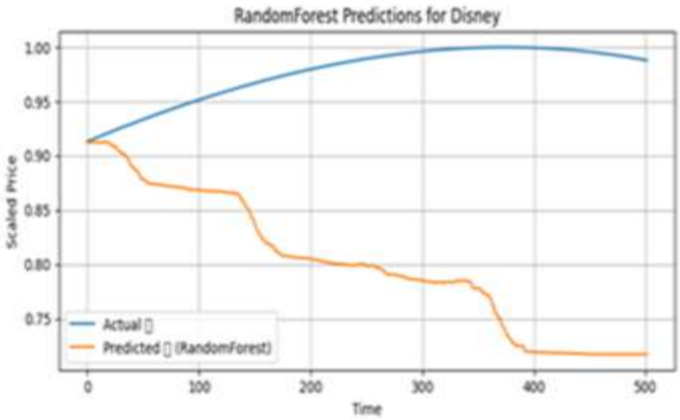

Fig 8: Actual vs Predicted Stock Price for Disney

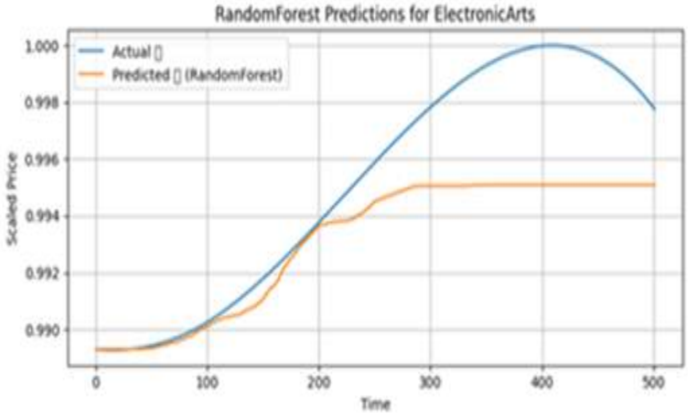

Fig 9: Actual vs Predicted Stock Price for Electronic Arts

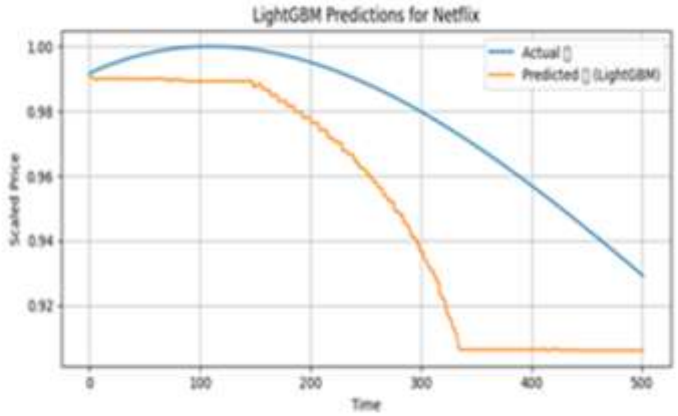

Fig 10: Actual vs Predicted Stock Price for Netflix

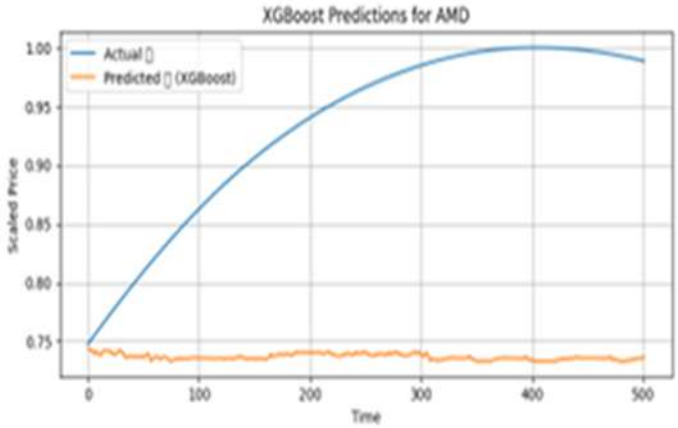

Fig 11: Actual vs Predicted Stock Price for AMD

The Figure's 6 to 11 illustrate the comparison between the observed stock prices (blue curve) and the predicted values generated by the models (orange curve) for Salesforce, Alibaba, Disney, Electronic Arts, Netflix, and AMD. The extent to which the two lines coincide reflects the predictive capability of the framework. In the case of Salesforce (Fig. 6), the forecasted trend follows the real series closely but appears smoother, with minor suppression of sudden variations, a result of CEEMDAN's noise reduction. For Alibaba (Fig. 7), the downward price trajectory is captured effectively, although slight deviations occur during rapid market shifts. Disney (Fig. 8) demonstrates strong consistency, confirming that the model can replicate both price fluctuations and overall direction. Electronic Arts (Fig. 9) shows an almost complete alignment between the two curves; this is due to the relatively stable signal after decomposition, which explains the exceptionally high accuracy of 99.79%. Netflix (Fig. 10, LightGBM) highlights the capacity of the boosting model to capture long-term dynamics, though small-scale volatility is less precisely represented. For AMD (Fig. 11, XGBoost), the forecasts align well with the actual data, showing that the method is effective in modelling nonlinear behaviours. Collectively, these results confirm that CEEMDAN-based ensemble models provide dependable forecasts, with performance levels largely determined by the inherent volatility of each dataset.

5. LIMITATIONS AND FUTURE WORK

While the proposed CEEMDAN-ensemble forecasting framework demonstrates strong performance across diverse stock datasets, several limitations must be acknowledged. First, the study is limited to six datasets and considers only closing price information. Incorporating additional financial indicators (e.g., trading volume, moving averages, or volatility indices) may enhance predictive capability. Second, no hyperparameter optimization was applied, and models were evaluated using default configurations. Although this ensures fairness, fine-tuned parameters could potentially improve accuracy further. Third, external factors such as macroeconomic variables, investor sentiment, or global market events were not included, which may restrict the generalizability of the results to real-world trading conditions. For future research, several directions are promising. Hybrid approaches that combine CEEMDAN with advanced deep learning models such as LSTM, GRU, or Transformer architectures could be explored to capture long-term dependencies. The integration of multimodal data sources, including financial news, social media sentiment, and economic indicators, may provide richer contextual insights for forecasting. Additionally, adaptive IMF selection strategies or automated feature fusion methods could further optimize the decomposition process. Finally, conducting statistical significance tests and extending the framework to intraday or high-frequency trading data would strengthen the robustness and practical applicability of the model.

6. CONCLUSION

This study proposed an efficient stock market forecasting framework that integrates CEEMDAN-based signal decomposition with ensemble learning models, specifically Random Forest, LightGBM, and XGBoost. The objective was to enhance predictive accuracy while reducing the computational burden typically associated with deep learning approaches. By decomposing raw closing price series into Intrinsic Mode Functions (IMFs), CEEMDAN effectively reduced noise and highlighted meaningful financial patterns. Correlation-based IMF selection ensured that only the most informative features were used, minimizing redundancy and improving training efficiency.

Experiments conducted on six diverse stocks—Salesforce, Alibaba, Disney, Electronic Arts, Netflix, and AMD—demonstrated the robustness of the framework. Random Forest consistently achieved reliable performance, with Electronic Arts reaching exceptionally high accuracy (99.79%). LightGBM produced superior results for Netflix (97.09%), while XGBoost proved effective for handling the higher volatility of AMD (79.45%). These outcomes validate that combining CEEMDAN with ensemble models yields competitive forecasting accuracy across multiple sectors.

In summary, the proposed framework illustrates that advanced signal preprocessing, when integrated with ensemble learning, can deliver accurate and scalable stock prediction without relying on complex deep neural networks. Future research will focus on incorporating external indicators such as macroeconomic variables and sentiment data, applying automated hyperparameter optimization, and extending evaluation to intraday and high-frequency datasets.

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