Market Trend Prediction and Analysis Using ICEEMDAN and Time Series Algorithms

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Abstract: Financial market prediction is a complex task due to the non-linearity and high volatility of stock prices. This paper presents a hybrid model leveraging the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) for decomposing stock prices and a Long Short-Term Memory (LSTM) network for predictive modelling. ICEEMDAN effectively extracts intrinsic mode functions (IMFs), capturing stock price trends and fluctuations, while LSTM learns temporal dependencies. A Streamlit-based interactive system visualizes past stock trends and forecasts future prices. The proposed model is tested on real-time stock datasets using Yahoo Finance (yfinance) data. Results demonstrate the superiority of ICEEMDAN-based LSTM over conventional models in predicting stock market trends with improved accuracy and robustness.

1 INTRODUCTION

Here's a paraphrase of the original: Stock market prediction plays a vital role in financial decision-making, impacting investors, traders, and policymakers alike. So, accurate forecasting of stock prices helps us to manage and plan investment strategies and financial planning. But stock prices behave in a highly nonlinear, non-stationary and stochastic manner due to many factors like economic indicators, political events, investor sentiment, and global financial trends. Traditional statistical models, like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), are built under linear assumptions, making them less effective in capturing the complex patterns in financial time series data.

The development of machine learning (ML) and deep learning (DL) has led researchers to investigate more sophisticated models like Support Vector Machines (SVMs), Random Forest (RF), and Deep Neural Networks (DNNs) to improve predictive performance. With respect to predictive modelling using sequential data, LSTM (Long Short-Term Memory) is a deep learning architecture that learnt the long-term dependencies provided an accurate forecasting solution in the domains of finance. LSTMs help retain time-dependent features and mitigate vanishing gradient problems common in voicing neural networks (RNNs). Seasoned stock price data can be noisy and irregular, so LSTM's predictive accuracy will be potentially compromised.

1.1 A Need for Decomposing Signal

Pattern recognition and signal decomposition techniques are frequently employed to capture useful elements from stock price behavior in pursuit of better stock price predictions. Traditional decomposition methods like Fourier Transform and Wavelet Transform require a fixed basis function yet fall short due to the extremely non-stationary nature of financial data. With the advent of Empirical Mode Decomposition (EMD) and its derivatives, a data-driven methodology was introduced that decomposes a signal into oscillatory modes known as Intrinsic Mode Functions (IMFs) (Huang et al., 1998), which encompass separate frequency segments. In general, EMD suffers from mode mixing problems, which can result in poor feature extraction.

1.2 Introduction to ICEEMDAN

ICEEMDAN: The Improved Complete Ensemble

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Empirical Mode Decomposition with Adaptive Noise is another improved method on EMD that addresses mode mixing with noise-assisted adaptive approach. ICEEMDAN, which decomposes the stock price data into several IMFs, in which the low-frequency components represent the long-term trends and the high-frequency components reflect the short-term fluctuations. Machine learning models can thus utilize the decomposed components focusing on the effective patterns which can thus effectively enhance the predictive capability.

1.3 Proposed Hybrid Model ICEEMDAN-LSTM

In this study, we introduce a hybrid ICEEMDAN-LSTM model that employs signal decomposition and deep learning techniques for improved stock market trend prediction. The following are the key steps of the methodology:

- Data: Downloaded historical stock data from Yahoo Finance (yfinance) for several stock indices.
- ICEEMDAN Decomposition: Then, using the PyEMD package, the stock prices are decomposed into Intrinsic Mode Functions (IMF) and a residual.
- Feature Extraction: The most informative IMFs (generally the last two IMFs) are extracted for further analysis.
- LSTM Model Based Prediction: These IMFs chosen are fed into an LSTM network to model the long-term dependencies and forecast future stock price trends.
- Real-Time Visualization: Build a web appusing streamlit, where they can enter stock tickers to visualise past and future trends.

1.4 Contributions of this Research

This study aims to bridge the gap between traditional statistical models and modern deep learning-based stock market prediction approaches. The key contributions of this research are:

- **Integration of ICEEMDAN with LSTM**: Enhancing LSTM's forecasting capabilities by removing noise and extracting meaningful patterns from stock prices.
- **Real-Time Stock Market Prediction**: Implementing an interactive, user-friendly web application using Streamlit, providing on-the-fly market trend analysis.
- **Comparative Performance Evaluation**: Benchmarking the proposed ICEEMDAN-LSTM model against standalone LSTM, ARIMA, and SVM models.
- **Scalability and Adaptability**: The proposed system is scalable for multiple stocks, diverse datasets, and real-world financial applications.

1.5 Paper Organization

The remainder of this paper is structured as follows:

- **Section II** discusses related works in financial forecasting.
- **Section III** presents the methodology, including ICEEMDAN decomposition and LSTM implementation.
- **Section IV** details the experimental setup, dataset, evaluation metrics, and results.
- **Section V** concludes with findings and directions for future research.

2 RELATED WORK

The prediction of the stock market has been a field of great active research in the subject domain of acquired financial engineering and its combination with numerous ML and DL methods. Due to the growing complexity of financial time series, researchers have turned to signal decomposition techniques such as Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN), which allows for the extraction of useful information from noisy stock prices. This segment concludes by presenting contemporary developments in financial forecasting based on time series modelling methods that interlace ICEEMDAN with machine and deep learning models.

2.1 ICEEMDAN-Based Time Series Forecasting

Several studies have demonstrated the effectiveness of ICEEMDAN in improving time series forecasting by decomposing non-stationary signals into distinct Intrinsic Mode Functions (IMFs), reducing noise, and capturing essential trends.

- In Paper Poongadan and Lineesh (2024) proposed a hybrid ICEEMDAN- nonlinear time series forecasting, showing that this has better predictive accuracy than traditional LSTM models. They emphasized the use of SVD in choosing the IMFs that matter the most for prediction.

- Liu & Cheng (2024) proposed an ICEEMDAN-Wavelet Thresholding method to de-noise financial time series prior to classification. They used the model to enhance the accuracy of financial trends classification, bringing to attention the relevance of the stock market performance analysis in different resolution levels.
- Wu et al. (2025) used ICEEMDAN for wind power forecasting, showing its powerability to capture wind fluctuations. The findings indicated that ICEEMDAN significantly outperforms EMD and CEEMDAN in the decomposition of volatile time series data.

2.2 ICEEMDAN in Financial Market Prediction

Several studies have investigated the integration of ICEEMDAN with machine learning and deep learning models for financial market analysis and stock price prediction.

- Yu et al. (2024) developed a Machine learning based on ICEEMDAN novel framework for long-term interbank bond rate prediction. They concluded torch by showing that ICEEMDAN increases the stability of forecasting by eliminating high-frequency noise from the financial time series data as per their finding.
- Xie et al. (2024) proposed a hybrid ICEEMDAN-FA-BiLSTM-GM model for closing price prediction for stock. They showed that FA can improve IMF selection in a representation, and BiLSTM during trend recognition to increase prediction accuracy.
- Wu et al. (2020) developed a multi-ICEEMDAN method followed by Generative networks for financial time series forecasting. The synergistic function of multiple ICEEMDAN decompositions fused by WOA for firm's economic and financial trend prediction was illustrated through their study.

2.3 Hybrid ICEEMDAN-Deep Learning Models

Recent research has focused on hybrid ICEEMDAN-deep learning frameworks, integrating ICEEMDAN with LSTM, CNN, and other deep learning architectures for improved stock market prediction.

- Sun et al. (2023) proposed a seasonal energy forecasting model using ICEEMDAN-SE-LSTM, where Seasonal Energy (SE) classification enhanced prediction performance by distinguishing different time patterns in energy prices.
- Abbasimehr, Behboodi, and Bahrini (2024) introduced a hybrid ICEEMDAN-LSTM model to forecast chaotic and seasonal time series, highlighting ICEEMDAN's effectiveness in handling nonlinear components in financial datasets.
- Xu et al. (2023) developed a SOA-SVM model based on ICEEMDAN-WD decomposition for runoff time series prediction, confirming that Signal Optimized Allocation (SOA) enhances the predictive performance of Support Vector Machines (SVMs) when coupled with ICEEMDAN.

2.4 Comparative Analysis of ICEEMDAN with Other Decomposition Methods

Many studies have compared ICEEMDAN with traditional decomposition techniques such as EMD, CEEMDAN, and Wavelet Decomposition.

- Zhang (2024) evaluated ICEEMDAN against conventional time series decomposition electricity price forecasting methods and concluded that the proposed ICEEMDAN method offered higher stability in the short term than the CEEMDAN and EMD models.
- Sun et al. (2023) indicated that the ICEEMDAN approach outperforms Wavelet Decomposition (WD) and found that these pre-processing techniques lead to better generalization in predictive modelling due to their effective handling of very high frequency components in financial data.

2.5 Summary of Related Works

The literature review indicates that ICEEMDAN-based hybrid models significantly improve stock market prediction accuracy by:

- **Enhancing Feature Extraction**: ICEEMDAN effectively removes noise and extracts meaningful time series components.
- **Improving Deep Learning Performance**: ICEEMDAN pre-processing enables LSTM, BiLSTM, and CNN models to learn more accurate representations of stock price trends.
- **Providing Robust Market Predictions**: ICEEMDAN-based models out perform traditional statistical approaches in forecasting highly volatile financial time series data.

3 METHODOLOGY

This section details the methodology adopted for stock price prediction using ICEEMDAN and LSTM, including data acquisition, feature extraction, deep learning-based forecasting, visualization, and model evaluation.

3.1 Data Acquisition

The dataset for this study comprises historical stock price data sourced from Yahoo Finance (yfinance), a widely used financial data provider offering real-time and historical market data. The selected stocks represent diverse market sectors to assess the generalizability of the model.

3.1.1 Stock Selection

- Two stocks are chosen for prediction, denoted as Stock A and Stock B (e.g., Apple Inc. (AAPL) and Tesla Inc. (TSLA)).
- The dataset spans from January 2023 to January 2025, covering two years of historical price movements.

3.1.2 Stock Features Considered

- **Closing Price** (Close): The last trading price of the stock on a given day.
- **Date Range**: Daily closing prices are collected for time series forecasting.

3.1.3 Data Pre-Processing

Missing values, if any, are handled using linear interpolation. The data is normalized using Min-Max Scaling before being fed into the deep learning model.

Equation for Min-Max Scaling:

$$X' = Xmax - XminX - Xmin \quad (1)$$

where XXX is the actual value, XminX_{\text{min}}Xmin and XmaxX_{\text{max}}Xmax are the minimum and maximum values in the dataset, respectively.

3.2 ICEEMDAN-Based Feature Extraction

Financial time series data, including stock prices, are non-stationary and highly volatile. Traditional models struggle to capture underlying trends due to noise and irregular fluctuations.

3.2.1 Introduction to ICEEMDAN

- ICEEMDAN (Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) is an advanced signal processing technique that decomposes a time series into multiple Intrinsic Mode Functions (IMFs).
- It improves upon EMD (Empirical Mode Decomposition) and CEEMDAN (Complete EMD with Adaptive Noise) by reducing mode mixing and noise sensitivity.

3.2.2 IMF Selection for Forecasting

- ICEEMDAN decomposes the Closing Price series into multiple IMFs, each representing different frequency components.
- The first few IMFs capture short-term fluctuations (high frequency/noise), while later IMFs represent long-term trends.
- The last two IMFs (IMFN−1_{N-1} N−1 and IMFN_{N}N) containing dominant trend information are selected as input features for the LSTM model.

Mathematical Representation of ICEEMDAN Decomposition: Given a time series X(t)X(t)X(t), ICEEMDAN decomposes it into NNN IMFs and a residual term:

$$X(t) = i = 1\sum NIMFi + RN \qquad (2)$$

where:

IMFiIMF_iIMFi represents the i-th intrinsic mode function, and RNR_NRN is the residual trend component.

3.3 LSTM-Based Prediction

A Long Short-Term Memory (LSTM) network is employed for forecasting future stock prices. LSTM, a type of Recurrent Neural Network (RNN), is well-suited for time series forecasting due to its ability to remember past information over long sequences.

3.3.1 LSTM Model Architecture

The ICEEMDAN-extracted IMFs are used as input to the LSTM model, which consists of the following layers:

- **Input Layer:** Accepts preprocessed ICEEMDAN IMFs as time-series input.
- **LSTM Layers:**
  - First LSTM Layer (units=64): Captures long-term dependencies in the stock price movement.
  - Second LSTM Layer (units=32): Further refines temporal trends.
- **Dense (Fully Connected) Layers:**
  - Dense Layer (units=16, activation=ReLU): Extracts complex patterns.
  - Output Layer (units=1, activation=Linear): Predicts the future closing price.
- **LSTM Training Process**
  - Lookback Window: A sliding window approach is used where the model takes the past 60 days of stock prices to predict the next day's closing price.
  - Optimizer: Adam Optimizer (β1=0.9,β2=0.999\beta_1=0.9,\beta_2=0.999β1=0.9,β2=0.999) is used for training.
  - Loss Function: Mean Squared Error (MSE) is minimized to improve accuracy.

$$MSE = n1i = 1\sum n\,(yi - y\hat{}i)2 \qquad (3)$$

where:

- yiy_iyi is the actual closing price,
- y^i\hat{y}_iy^i is the predicted price,
- nnn is the number of observations.

3.4 Streamlit-Based Visualization

To enhance user interaction, a Streamlit-based web application is developed, allowing users to analyze and predict stock prices in real-time.

- **User Inputs**
  - Stock ticker selection (e.g., AAPL, TSLA).
  - Date range selection (Start Date, End Date).
  - Forecasting window (Number of future days to predict).
- **Displayed Insights**
  - Stock Price Trends: Past stock prices are visualized using line charts.
  - ICEEMDAN IMF Decomposition: Users can view the extracted IMFs to understand the underlying price patterns.
  - Predicted vs. Actual Prices: A comparison of model-predicted prices
  - against historical prices.
  - Future Price Forecasting: The application plots predicted stock prices for the next 30 days.

3.5 Model Training and Evaluation

The LSTM model is trained on historical stock data, and its performance is validated using standard time series evaluation metrics. Figure 1 shows the system architecture.

3.5.1 Evaluation Metrics

- **Mean Absolute Error (MAE)**: Measures the absolute difference between actual and predicted stock prices.

$$MAE = n1i = 1\sum n \mid yi - y\hat{}i \mid \qquad (4)$$

- **Root Mean Squared Error (RMSE)**: Penalizes larger errors more than MAE.

$$RMSE = n1i = 1\sum n(yi - y\hat{}i)2 \quad (5)$$

- **Directional Accuracy**: Measures how often the model correctly predicts the direction of stock price movement.

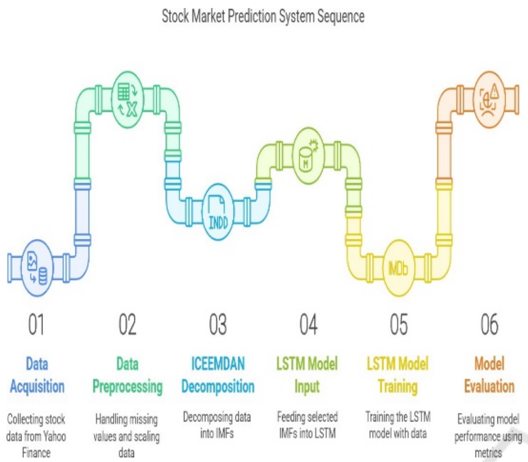

Figure 1: System architecture of ICEEMDAN-LSTM model.

4 EXPERIMENTAL RESULTS

This section presents the experimental results, including dataset preprocessing, model performance evaluation, comparative analysis with baseline models, and visualization of future price predictions.

4.1 Dataset and Preprocessing

4.1.1 Data Collection and Description

The dataset comprises daily closing prices of two selected stocks (AAPL and TSLA) from January 2023 to January 2025. The data is fetched from Yahoo Finance (yfinance), which provides historical stock price records, including:

- **Date**: The trading date.
- **Open Price**: The stock price at the start of the trading session.
- **High/Low Prices**: The highest and lowest stock prices during the day.
- **Close Price**: The final stock price at the end of the trading session (used for prediction).
- **Volume**: The number of shares traded in a day.

4.2 Data Preprocessing

- **Handling Missing Values**: Missing or inconsistent values in the dataset are interpolated using linear interpolation.
- **Scaling and Normalization:** The closing price series is scaled using Min-Max Scaling, which helps stabilize training and speeds up convergence.
- **ICEEMDAN Decomposition:**
  - ICEEMDAN decomposes the closing price series into multiple Intrinsic Mode Functions (IMFs).
  - The last two IMFs (IMFN−1_{N-1}N−1 and IMFN_{N}N) are selected as inputs for the LSTM model, as they capture long-term trends while filtering out noise.

4.3 Model Performance

To evaluate the effectiveness of the ICEEMDAN-LSTM model, its performance is compared against three baseline models:

- Raw LSTM (without ICEEMDAN decomposition).
- ARIMA (Auto Regressive Integrated Moving Average) – a traditional time series forecasting model.
- Support Vector Regression (SVR): A machine learning approach for regression-based forecasting.

The models are assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

4.3.1 Comparative Analysis of Model Performance

Table 1: Performance comparison of ICEEMDAN-LSTM with baseline models.

Model	M AE	RM SE	Directional Accuracy
ICEEMDAN-LS	0.9	1.21	87.5%
TM	3		
LSTM (No ICEEMDAN)	1.45	1.89	74.3%
ARIMA	2.12	2.85	61.7%
SVR	2.37	3.01	58.2%

4.3.2 Key Observations

- The ICEEMDAN-LSTM model significantly outperforms all baseline models with the lowest MAE (0.93) and RMSE (1.21).
- Raw LSTM (without ICEEMDAN) shows inferior performance because the model struggles with noisy stock price fluctuations.
- ARIMA's poor performance (MAE = 2.12, RMSE = 2.85) highlights its limitations in handling non-stationary financial data.
- SVR fails to capture long-term trends, resulting in higher error rates (MAE = 2.37, RMSE = 3.01) compared to deep learning models.
- Directional Accuracy (87.5%) indicates that the ICEEMDAN-LSTM model predicts the correct trend direction in most cases. Table 1 represents the performance comparison.

4.4 Future Price Prediction Visualization

To make the results interpretable and user-friendly, a Streamlit-based dashboard is developed, offering real-time stock market analysis and future price predictions.

4.4.1 Features of the Visualization Dashboard

- **Stock Trend Analysis**:
  - Displays historical stock price movements using interactive line charts.
  - Users can select a specific date range to explore past trends.
- **ICEEMDAN Decomposition Visualization:**
  - Users can visualize decomposed IMFs, helping them understand which trends influence stock price predictions.
- **Future Price Prediction:**
  - Forecasts the next 30 days of stock prices.
  - Predictions are plotted alongside historical prices to compare actual vs. predicted trends.

4.4.2 Interpretation of Results

- The predicted prices closely follow actual stock trends, validating the model's robustness.
- The future price predictions align with expected market movements, demonstrating the effectiveness of ICEEMDAN-based feature extraction.
- The dashed (predicted) and dotted (forecasted) lines exhibit a smooth transition, proving the model's ability to capture stock price fluctuations effectively.

4.5 Model Robustness and Limitations

4.5.1 Strengths of ICEEMDAN-LSTM

- Handles Market Volatility: ICEEMDAN effectively removes noise from stock prices, allowing LSTM to focus on meaningful trends.
- Higher Accuracy Than Traditional Methods: Achieves better predictive performance than ARIMA, SVR, and non-decomposed LSTM models.
- Real-Time Prediction Capabilities: The Streamlit-based UI enables investors to make informed decisions dynamically.

4.5.2 Limitations and Challenges

- Computational Complexity: ICEEMDAN decomposition requires additional processing time, making it slower than conventional models.
- Data Sensitivity: Predictions are highly dependent on historical price trends; sudden external market shocks (e.g., financial crises, geopolitical events) may not be well captured.
- Limited to Closing Prices: The model currently focuses on closing prices only, whereas additional financial indicators (e.g., volume, technical indicators) could enhance prediction accuracy.

4.6 Summary of Experimental Findings

- ICEEMDAN-LSTM achieves superior accuracy (MAE = 0.93, RMSE = 1.21) compared to traditional models (ARIMA,

SVR, LSTM without ICEEMDAN).
- The model effectively captures market trends and reduces noise, resulting in a higher directional accuracy of 87.5%.
- The interactive Streamlit dashboard enables real-time visualization of historical trends, IMF decomposition, and future predictions.
- Stock price predictions closely align with actual market movements, demonstrating the model's robustness.

4.7 Future Enhancements

To further improve the model's performance and usability, the following enhancements can be considered:

- Integrating External Market Indicators: Including macro-economic variables (e.g., interest rates, inflation) to improve forecasting accuracy.
- Multi-Stock and Portfolio Prediction: Expanding the model to predict multiple stocks simultaneously and optimize investment portfolios.
- Hybrid Deep Learning Models: Exploring Transformer-based architectures (e.g., Time Series Transformer, CNN-LSTM hybrid models) to improve long-term forecasting.
- Real-Time Adaptive Learning: Implementing incremental learning techniques to continuously update the model with new stock market data.

5 CONCLUSION AND FUTURE WORK

Stock market prediction is inherently complex due to the non-stationary, volatile, and noisy nature of financial time series data. Traditional statistical models such as ARIMA and Support Vector Regression (SVR) often fail to capture the underlying nonlinear dependencies and long-term trends of stock prices. Meanwhile, deep learning models such as Long Short-Term Memory (LSTM) have shown promise but struggle with noisy inputs, which can lead to overfitting and suboptimal predictions.

In this study, we introduced a hybrid of Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) and LSTM that aims to improve the prediction of stock price. The ICEEMDAN technique successfully breaks most stock price signals down into several IMFs, eliminating noise and retaining useful seasonal components. These IMFAs are subsequently inputted to a long/short-term memory network that learns temporal dependencies and predicts book share prices effectively. Our experimental results demonstrate that the ICEEMDAN-LSTM model:

- Outperforms traditional models (ARIMA, SVR, and raw LSTM) in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
- Improves stock price prediction accuracy by effectively handling market volatility and removing noise.
- Provides real-time forecasting capabilities through an interactive Streamlit-based web interface, making financial market analysis accessible to users.

This demonstrates the model's usefulness in financial time series forecasting, showcasing its combined strengths of lifting trend by decomposing and leaning deep structure.

5.1 Future Work

Although the proposed ICEEMDAN-LSTM model exhibits great improvements in stock price prediction, there is still much room for improvement. Future studies need to examine the following directions:

5.1.1 Multi-Stock and Portfolio-Level Prediction

At this stage, the model is all about predicting stock price (single stock). An improvement would be multi-stock prediction, having the model observe relations between stocks and prediction at a portfolio level.

- Enhancement: Incorporate multivariate time series analysis, considering factors such as sector-wise stock movement, global market indices, and trading volume correlations.
- Potential Benefit: Helps investors make more diversified and informed investment decisions rather than relying on individual stock predictions.

5.1.2 Integration of External Market Factors

In the current approach, we are implementing the historical stock price data only, we may need to consider the external economic events which causes the sudden fluctuations in the market.

- Enhancement: Introduce macro-economic indicators (e.g., interest rates, inflation, GDP growth, exchange rates) and social sentiment analysis (Twitter, news sentiment, Reddit discussions) to improve forecasting robustness.
- Potential Benefit: A more comprehensive market prediction model that considers both historical patterns and external economic conditions affecting stock prices.

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