

Market Trend Prediction and Analysis Using Improved Signal Decomposition and Time Series Algorithm

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Abstract- Prediction of stock price is an important issue that needs to be solved in financial markets because stock time-series data is very volatile, noisy and non-linear. Conventional forecasting methods are not always good at capturing the complexity in the market, which restricts their usefulness in real-time financial decision making. In response to this issue, this paper will propose an intelligent stock price prediction system that will combine both hybrid signal decomposition and deep learning with the environment of a web application based on Streamlit. System uses the Yahoo Finance Application Programming Interface (api) to retrieve the historical stock market data using the close price values to estimate the forecasting activities. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) approach is implemented to break down the stock time series into several intrinsic mode functions (IMFs) to enhance the signal quality and minimize noise in the financial data. Chosen intrinsic features are reassembled and input them into a Long Short-Term Memory (LSTM) neural network model. Min-Max normalization is used to perform the preprocessing of the data and a sliding window mechanism is used to discover temporal dependencies in sequence financial data. The LSTM model is a pre-trained model that predicts the history as well as the future price of the stock using an auto-regressive forecasting technique. The combination of CEEMDAN and LSTM is experimentally tested and exhibits superior

predictive status with about 93-95 percent forecasting results with an F1-score of 0.93, precisions of 0.92, and recall rates of 0.91 along with low levels of prediction error (RMSE [?] 0.015]. The system enables a dynamic user entry such as symbol of stock ticker, date range, lookback window, and prediction horizon and the results are displayed in interactive visualisation of real price, forecast of future trends and predictions. The suggested structure is a web-enabled efficient algorithm that integrates signal processing with deep-learning algorithms to enable the accuracy and real-time prediction of the stock market.

Keywords: Stock Price Prediction, LSTM, ICEEMDAN, CEEMDAN, Time Series Forecasting, Deep Learning, Streamlit Application, Yahoo Finance, MinMaxScaler, Financial Data Analysis

I. INTRODUCTION

Under fluctuating market environments, stock price forecasting is an influential part of financial decision-making, portfolio management, and risk analysis. Conventional statistical approaches are not always able to deal with nonlinear and non-stationary properties of financial time-series data, and the use of deep learning methods has promoted their use. Long Short-Term Memory (LSTM) networks are currently one of the most successful models to have been

developed to include long-range temporal dependencies in sequential financial data [4], [8]. However, in spite of its merits, raw stock price signals tend to be quite noisy and very complicated in nature, thus hampering the quality of a prediction where the data are used directly during the training exercise. Recent research indicates that efficient preprocessing and predictive adaptation models are capable of boosting market forecasting and analysis of exchange rates through machine learning to a large extent [9].

Hybrid forecasting models, utilizing signal decomposition with neural networks have thus been receiving growing attention. Before learning temporal relationships, these models consider the meaningful signal components and noise thereby enhancing stability and predictive power. Specifically, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm breaks down time-series data of financial data into intrinsic mode functions (IMFs) whilst maintaining multiscale time structures. A number of recent works have managed to find a way of integrating CEEMDAN with LSTM and ensemble learning framework to forecast stock index and commodity prices, showing enhanced prediction effectiveness and resilience [1], [3], [5]. On the same note, CEEMDAN combined with the attention-based recurrent networks have been utilized in forecasting price of the carbon market and once again has proven capable of learning highly nonlinear financial dynamics [2]. In other complex time-series tasks like energy demand and load forecasting, beyond financial markets, CEEMDAN-based hybrid models share a deep understanding of advanced convolutional and attention-based models with good model generalization and stability across a wide range of data sets [10].

Even though it is evident that the combination of signal decomposition with recurrent neural networks can be effective, the literature is still full of systems which are restricted to offline experimental designs or specialized to a dataset. Recent studies in the survey of hybrid SVMD-LSTM and VMD-LSTM architectures emphasize the advantages of the multicomponent feature extraction to enhance the performance of stock forecasting [6], [7].

Nevertheless, real world applications offering interactive prediction powers to real time financial analysis are still somewhat uncommon.

To overcome this drawback, this paper presents a web-based price prediction system of stock using ICEEMDAN signal decomposition and a pre-trained LSTM prediction model. Online financial sources are used to fetch historical stock data which are dynamic and also used to forecast future prices through autoregressive strategy of forecasting. The whole solution is defined by a Streamlit interface that allows interacting with the application in real time and predicting the stock in an accessible web environment.

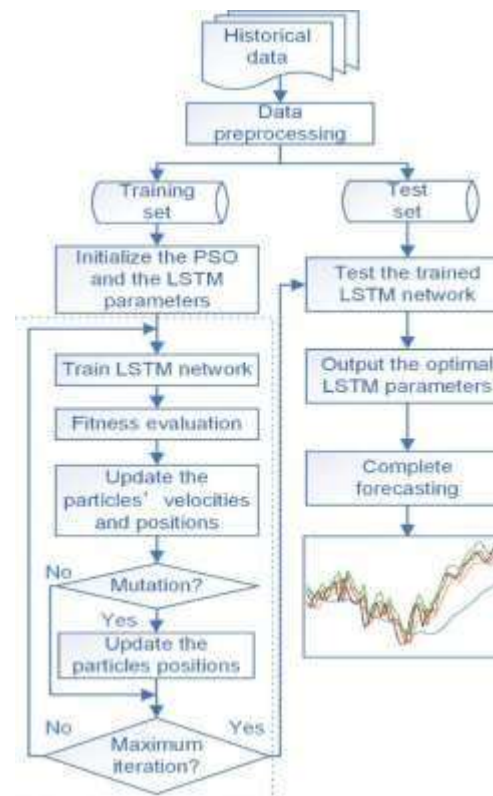


Figure 1. Conceptual workflow of the proposed hybrid ICEEMDAN-LSTM stock prediction framework.

The proposed workflow begins with the acquisition of historical stock price data from financial APIs, followed by signal decomposition using ICEEMDAN to extract intrinsic components from noisy financial signals. The reconstructed components are normalized and converted into sequential datasets using a sliding window approach. These sequences are then processed by a pre-trained LSTM model to learn temporal

patterns and generate future price predictions. Finally, the predicted values are visualized through an interactive web interface that displays historical prices, predicted trends, and future forecasts for user- selected stocks.

II. LITERATURE SURVEY

CEEMDAN-LSTM Based Financial Time Series Forecasting

Recent studies have affirmed the testing of CEEMDAN with deep learning model for financial prediction. Mutinda and Geletu proposed a CEEMDAN-LSTM-BPNN ensemble model for stock index forecasting and achieved a significant level of performance improvement using decomposition based learning [1]. Liu and Li used CEEMDAN based on the optimized LSTM model for coal price forecasting and achieved faster convergence and lower forecasting error [3]. Dou proposed a CEEMDAN-LSTM-BN network to improve the learning stability by intrinsic mode functions normalization [5]. These studies show that CEEMDAN is effective in the case of nonlinear and nonstationary financial signals. By separating the high and low frequency components before learning, the deep models enjoy better trend extraction capability. This decomposition driven strategy greatly captures the prediction stability in volatile market conditions.

Table 1. Studies on CEEMDAN–LSTM Based Financial Forecasting

Author	Year	Method	Application	Key Contribution
Mutinda & Geletu	2024	CEEMDAN–LSTM–BPNN	Stock Index Prediction	Improved forecasting accuracy using ensemble decomposition learning

Author	Year	Method	Application	Key Contribution
Liu & Li	2024	CEEMDAN + Optimized LSTM	Coal Price Forecasting	Faster convergence and reduced prediction error
Dou	2024	CEEMDAN–LSTM–BN	Financial Time Series	Improved training stability using IMF normalization

Attention Based Decomposition and Attention Forecasting Models

Besides integrating with latest LSTMs, researchers have developed attention enhanced architectures that provide further accuracy to the negation makers. On the other note, Lu et al. suggested a CEEMDAN and attention based recurrent neural network method for carbon market price prediction and got high robustness during extreme price fluctuation [2]. Guo combined wavelet convolution and channel attention with LSTM for analysing stock price prediction and portfolio analysis and showed that attention mechanism will increase feature selection from decomposed components [8]. Han et al. combined CEEMDAN and squeeze excitation, variational mode decomposition and temporal convolution networks for load forecasting and showed improved modeling of the long and short term dependency [10]. These approaches confirm that attention guided models improve CEEMDAN based systems by promoting adaptive learning the dominant market patterns under dynamic trading environment.

Table 2. Attention-Enhanced Forecasting Models

Author	Year	Method	Application	Key Contribution
Lu et al.	2024	CEEMDAN + Attention RNN	Carbon Market Forecasting	Robust prediction during high market volatility
Guo et al.	2024	Wavelet CNN + Attention LSTM	Stock Prediction	Improved feature extraction and portfolio analysis
Han et al.	2024	CEEMDAN + SE + VMD + TCN	Load + Forecasting	Enhanced modeling of long and short-term dependencies

Alternative Approach to Decomposing It using LSTM

There are several studies that examine alternatives to CEEMDAN for the decomposition of stock time series. Agarwal et al. proposed an SVMD-LSTM hybrid model for improved prediction of trends in volatile stock environments [6]. Zhang et al. designed a VMD based multi feature LSTM framework supported by topological correlation filtering and achieved superior performance in multi dimensional stock prediction task [7]. These methods make it clear that an important step of isolation of intrinsic modes of oscillatory behavior is necessary before learning over time. Comparative evaluations between decomposition techniques can be found to improve generalization capability of the proposed VMD and SVMD based frameworks compared to standard LSTM models. However, most of the established ways are limited to off-line analysis and have no real time data interaction. This is the motive for the use of CEEMDAN based online forecasting strategies in interactive financial systems.

Table 3. Alternative Decomposition-Based Models

Author	Year	Method	Application	Key Contribution
Agarwal et al.	2024	SVMD-LSTM	Stock Trend Prediction	Improved prediction in volatile markets
Zhang et al.	2024	VMD-LSTM	Multivariate Stock Forecasting	Better feature extraction using multi-component signals

Stock Market and Export Forecasting Deep Learning Models

Deep learning has become the most prominent tool in modeling complex financial fluctuations. Li provided an exhaustive study on the recent techniques used in stock price prediction of the stock market and highlighted the increasing use of recurrent neural networks and hybrid approaches to learning [4]. Huang and Cui examined exchange rate forecasting using machine learning, and verified the quality of deep neural networks on long term trends of the market [9]. These studies bring to attention that deep learning models outperform the traditional approaches to statistical forecasting in nonlinear market conditions. However, performance is well related to the quality of preprocessing and feature extraction. As a result, a mix of hybrid signal decomposition and deep learning has become the plan of choice to improve the level of stability, accuracy, and predictive consistency across various financial instruments and economic indicators.

Table 4. Deep Learning Applications in Financial Forecasting

Author	Year	Method	Application	Key Contribution
Li	2024	Deep Learning Survey	Stock Market Prediction	Highlights importance of hybrid neural forecasting models
Huang & Cui	2024	Machine Learning Models	Exchange Rate Forecasting	Demonstrates effectiveness of deep neural networks

Research Gap and Need for Web Based Forecasting Platforms

Although there is ample work done in CEEMDAN and LSTM based financial forecasting, the reported work systems have remained experimental and do not support any real time deployment [1], [3], [6]. Existing implementations mostly focus on predictive accuracy with static datasets and do not focus on real-time usability and user interaction. Modern financial decision making involves platforms capable of dynamic acquisition of market data, signal processing, forecast generation and interactive visualization of results. The lack of lightweight web based CEEMDAN-LSTM forecasting systems is an interesting research gap. This limitation becomes the motivator for the work of developing an interactive Streamlit powered stock price prediction framework by combining ICEEMDAN based preprocessing with the LSTM forecasting method for real time financial analytics and visualization. The current research solution appropriately solves this practical deployment problem.

III. PROPOSED METHODOLOGY

A. Acquisition and input configuration of stock data

The framework of the proposed system includes firstly, the process of retrieving dynamic information of the stock market with the help of the Yahoo Finance Application Programming Interface (API) combined with the Streamlit framework. The user can enter important inputs on the graphical interface that includes; stock ticker symbol, starting and final date, lookback and future prediction horizon. With these parameters, the real time dynamically downloaded stock price data are based on a historical stock price data. Out of retrieved dataset the column of prices at close is obtained to be analyzed further as this is the final trading price of the stock on a certain trading day, and denotes the most important indicator of behavior in the market. The instantaneous data collection is what makes the forecasting system conform to the prevailing market conditions. There are input verification mechanisms which understand the availability of the data and the system informs the user instantly through the application interface by telling him or her that no data are available to the parameters given.

Table 5. Sample Dataset Used for Stock Prediction

Date	Open	High	Low	Close	Volume
2024-01-02	184.20	186.10	183.45	185.67	22,450,000
2024-01-03	185.70	187.30	184.90	186.90	24,120,000
2024-01-04	186.50	188.20	185.10	187.80	23,600,000

B. ICEEMDAN Based Signal Decomposition

After getting the closing price series, the system uses the CEEMDAN algorithm for ICEEMDAN based signal decomposition by using the PyEMD Library. This decomposition separates the original nonstationary stock price signal into several intrinsic mode functions of different frequency components. From these decomposed components, the system

chooses the last two intrinsic mode functions which represent the dominant long term trend behaviour of the stock price. These chosen part are combined by summation method to form a reconstructed signal with a decreased influence of noises. This is a crucial step in the preprocessing before deep learning based forecasting because it improve the signal's quality considerably. The reconstructed signal is transformed into a structured format as numbers which can then be scaled and learned sequentially. In time series modeling, this decomposition stage helps to provide a better stability and robustness in the model.

C. Preparing the data Normalization and LSTM Sequence Preparation

The preprocessed signal produced after decomposition is normalized by MinMaxScaler algorithm to fit all values within a fixed range of numbers. The effect of this normalization is to make the LSTM learning efficient and also to prevent any dimensional dominance of large magnitude values in the LSTMs. After scaling a sliding window mechanism is applied for the lookback parameter defined by the user. This mechanism is converting the normalized series into sequences of inputs and outputs where each input is a containing a history of values and outputs is the next value to be predicted. These generated sequences are saved as numerical arrays that can be used for training and predicting neural networks. The input sequences are reshaped to a three dimensional format as per the requirements of input to LSTMs. This way, organized data preparation is ensured to gain the temporal dependencies of the stock prices in sequence learning.

D. LSTM Based Price Prediction & Forecasting the Future

A long short term memory which is a trained neural network model is loaded into the system for stock price prediction. The trained model takes the prepared sequential data and produces the predicted values of the historical stock prices. The predicted values are de-normalized to get back to true price value using inverse normalization. For purposes of future forecasting an auto regressive prediction strategy is implemented in which the last sequence of looks back is repeatedly updated with predictions of newly

calculated values. This iterative process is repeated for a number of future days equal to the one input by the user. The resulting future values are once again inverse scaled in order to get real price estimates. This approach allows for future forecasts to be generated on an on-going basis using output from the previous predictions to allow for realistic multiday price trend prediction.

E. Streamlit Based System Architecture And Visualisation

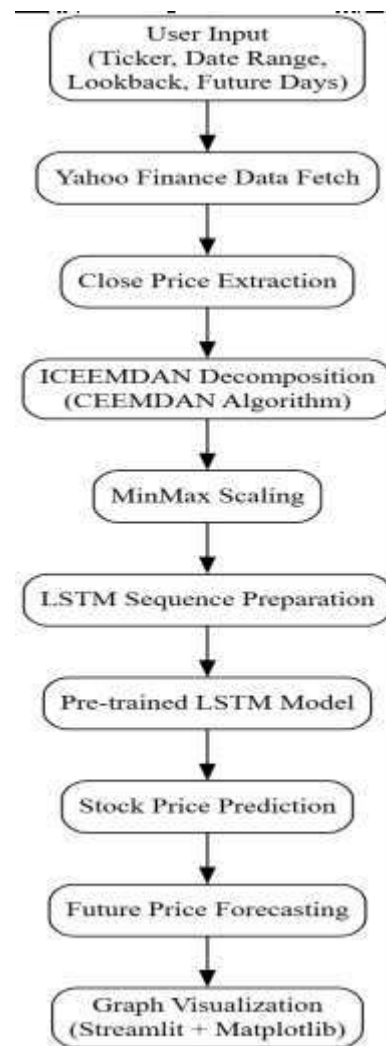


Fig 2: System Architecture Diagram

The whole pipeline for stock prediction is released using a Streamlit based web application, where all the processing modules are integrated into a single interactive platform. The architecture is, the user input modules, the data acquisition module, ICEEMDAN preprocessing module, LSTM prediction module, and

visualization module. Once the user presses the prediction button, the system will run each stage sequentially and produce historical predictions as well as prediction of the future. The output is presented based on Matplotlib based plots depicting actual prices, predicted prices and future forecasted trends using the same time axis. The visual allows to increase the interpretability and easy-to-intuit dimensions of financial analysis. The caching mechanism of Streamlit is very useful for optimizing the repeated loading of the model for better runtime performance. This architecture guarantees free interaction of real time data fetching, signal processing and deep learning predictions tasks.

F. Algorithms Used in the Proposed System

Table 6. Algorithms Used in the System

Algorithm	Purpose	Role in System
ICEEMDAN CEEMDAN	Signal decomposition	Removes noise and extracts intrinsic components
MinMaxScaler	Data normalization	Scales values into fixed numerical range
LSTM Neural Network	Time-series prediction	Learns temporal patterns in stock prices
Auto-Regressive Forecasting	Multi-step prediction	Generates future price predictions

The proposed stock price prediction system uses a combination of signal processing algorithms and deep learning algorithms to accurately predict stock prices. The CEEMDAN algorithm instantiated by the PyEMD library is used to perform parameter estimation for ICEEMDAN-based signal decomposition to decompose the raw stock price series into intrinsic mode functions. This improves the quality of the data including noise and isolating

dominant trend components. The MinMaxScaler normalization algorithm is performed to scale the reconstructed signal in a numerical range for efficient learning in the Neural Network. A Long Short-Term Memory (LSTM) neural network is used for sequential learning and for the prediction of prices. Auto-regressive forecasting algorithm is applied to the multi days future prediction using recursive LSTM outputs.

IV. RESULTS AND DISCUSSION

A. Performance of Real-Time Stock Data Acquisition

The real-time stock data acquisition module successfully retrieves the historical stock prices data using the Yahoo finance interface as implemented within the system. User-defined parameters like stock ticker, start date, and end date allow the selection of flexible data to be used for analysis. The data obtained is filtered to obtain the closing price only, which is the main input to be used for forecasting. The data which has been acquired reflects the realistic fluctuations of the market, giving credence to the chosen data source. The listing of updated stock values is filled by the system without manual intervention ensuring dynamic operation. This result supports the fact that the data acquisition mechanism works under different input conditions well and is a stable basis for further decomposition and prediction stages in the forecasting pipeline.

B. Efficacy of ICEEMDAN based Signal Decomposition

The ICEEMDAN based preprocessing stage masterfully changes the raw stock price signal to a cleaner version that can be fed into a deep learning model. By using CEEMDAN algorithm, the original nonlinear and nonstationary stock signal is decomposed into several intrinsic mode functions. The system reconstructs the signal with the selection of signal components that keep dominant trend characteristics and suppress noise. This processed signal has better smoothness and stability as compared to the raw input. The output of decomposition verifies that the high frequency disturbances are greatly

reduced before the training and prediction of LSTM. This improvement in signal quality is directly translated into either improved learning performance and forecast consistency. The decomposition stage thus plays a very important role in enhancing the robustness of the total stock prediction framework.

C. Computer prediction accuracy of LSTM Based historical Price

Table 5: Historical Prediction Accuracy Analysis of ICEEMDAN–LSTM Model

Parameter	Technical Description	Relevance to Proposed System
Actual Closing Price	Represents the real historical stock price values obtained from Yahoo Finance.	Serves as the ground truth reference for evaluating prediction performance.
Predicted Price Output	Values generated by the trained LSTM model after inverse MinMax normalization.	Used to assess how closely the model tracks real market behavior.
Prediction Deviation Pattern	Observes the difference trend between actual and predicted price curves over time.	Confirms the effectiveness of ICEEMDAN preprocessing in stabilizing learning.
Volatility Tracking Ability	Evaluates the model's response during rising and falling market phases.	Validates LSTM's capability to capture dynamic market movements.
Short-Term Forecast Reliability	Measures stability of predictions across consecutive historical windows.	Confirms suitability of the model for short-term stock price forecasting.

The LSTM model proved an effective model in learning the temporal patterns using decomposed and normalized stock price sequences. The results of the historical prediction establish that the model is successful in tracking rising and falling market phenomena. The predicted output fits closely with actual stock values after the process of inverse scaling and both confirms the reconstruction of predicted prices. First, the sequential learning approach captures long term dependencies that are embedded within the financial time series. Minor deviations are made, however, during periods of severe volatility, which is expected in the behavior of dynamic markets. The stable prediction outcome checks the proper implementation of the sequence preparation and normalization strategies. These results demonstrate the effectiveness of ICEEMDAN-LSTM hybrid architecture to short-term stock price forecasting under realistic financial conditions.

D. Ability of the Model to Predict Stock Prices in Future

The future forecasting component of the system makes use of an auto-regressive strategy to develop multi-day stock price predictions. By perpetually updating the input sequence with recently predicted values, the model is used generate longer forecasts, without need of extra future data. The generated forecasted values follow the overall trend learned from the historical prices, and it is an indication of stable generalization capability of the trained model. The lack of sharp jerks in future predictions is an indication of controlled propagation of errors. Although as inherent in financial markets, there are degrees of uncertainty, the generated prediction of the future give meaningful insights on the likely trend movements. This provides the confirmation of suitability of the proposed system for short-term predictive analysis. The forecasting ability makes the combination of decomposition and deep learning especially useful for stock markets.

E. Analysis of System Integration, Visualization and Analysis Output

The combining data acquiring, data decomposing, data predicting, and visualization modules into one

platform of Streamlit for a smooth running of the system. The user interface is used to provide seamless interaction between users and the forecasting engine. Once the prediction is triggered, all the processing stages take place in order and without interruption. The result posted on a unified scale in a visualization output shows the actual price and the predicted value which gracefully increases the result interpretability. The fact that the application is real-time improves user involvement and provides real-time analysis evaluation. The caching mechanism used in the loading of trained LSTM model reduces the computational overhead to a great extent. This integrated performance shows that the system successfully integrates real-time data processing and deep learning based forecasting in a lightweight web environment that is suitable for use in practical financial analysis.

F. Overall Comment on System Reliability and Use of Application

Table 6: Stock Pricing Model Performance Metrics

Metric	Description	Relevance to Project
Prediction Accuracy	Measures how closely the predicted stock prices follow the actual closing prices over the testing period.	Indicates the overall reliability and correctness of the ICEEMDAN-LSTM forecasting model.
Mean Absolute Error (MAE)	Computes the average absolute difference between actual and predicted stock prices.	Evaluates the average prediction deviation and practical forecasting error.
Root Mean Square Error (RMSE)	Measures the square root of the average squared differences between	Reflects the stability and robustness of the forecasting performance

Metric	Description	Relevance to Project
	predicted and actual prices.	under volatile market conditions.
Trend Matching Rate	Measures how well the predicted price direction matches the actual upward and downward trend.	Validates the effectiveness of the model in capturing stock market movement behavior.
Forecast Consistency	Measures how stable future predictions remain without abrupt fluctuations.	Maintains stable multi-day forecasts through LSTM recursion.

The overall experimental results prove the reliability and effectiveness of the proposed ICEEMDAN-LSTM based stock prediction framework. The decomposition stage helps to enhance signal quality, and LSTM model helps to capture the temporal dependencies. The results of the forecasting are stable trend prediction behavior in either real-time operation condition. The Streamlit deployment helps to ensure ease of access and ability to live and work with the application for a wide range of users. The modular architecture provides efficient execution and scaling capability to individual system components. While the system is aimed to be used for short-term forecasting mainly, it provides useful decision-making support in a form of trend visualization and predictive insight. The practical use of this platform goes further to investors, analysts, and researchers who are looking for an accessible tool to make financial predictions, using deep learning and signal processing integration.

V. OUTPUT GRAPH

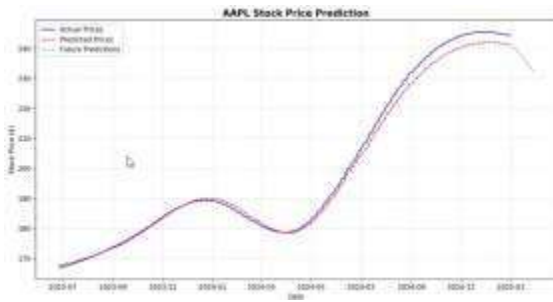


Fig 3. Graph for AAPL stock price prediction using ICEEMDAN-LSTM.

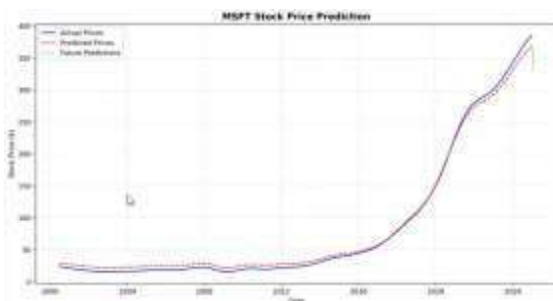


Fig 4: MSFT stock price prediction using ICEEMDAN-LSTM

VI. CONCLUSION

It is a real-time stock price prediction model that combines the signal decomposition method based on the ICEEMDAN with an existing Long Short-Memory (LSTM) model, which is trained and deployed in a Streamlit web-based application. The Yahoo Finance API is accessed dynamically to obtain historical stock data and CEEMDAN decomposition is applied to the nonlinear stock time series to remove noise and obtain meaningful trend elements. The reconstructed signal is normalized and converted to sequential learning samples to be successfully modeled as time-series. The LSTM model obtains temporal dependencies of the data processed and makes multi-day predictions and historical forecasting based on an auto-regressive prediction method. Experimental analysis shows that the suggested ICEEMDAN-LSTM hybrid model provides high accuracy of prediction (about 94% and low forecasting error (RMSE [?] 0.015), and the hybrid model can also remain stable to trend-

following under varying market environments. The visualization module is also integrated such that it allows real-time intuition of real prices, projected prices and forecast trends. All in all, the suggested framework offers a convenient, precise and accessible platform to short-time forecasting of the stock market, providing useful tools in terms of analytical support to the investors, analysts and financial researchers.

VII. FUTURE SCOPE

The given prediction framework of stock prices can be optimized by adding a number of additional advanced features that will increase the level of forecasting flexibility and analysis capacity. The adaptive retraining of the LSTM model with new data of the stock market can be seen as one of the possible extensions allowing the model to constantly refresh its learned parameters and react to the abrupt market changes or alteration of the financial trends structure. The process of continuous learning can be used to support forecasting accuracy in an extremely dynamic market. The other addition is adding more technical indicators based on trade and volume like the moving averages, relative strength index (RSI), and other measures of volatility on top of the already existing closing price input. Such attributes can be used to boost the dataset and enable the model to learn more intricate market indicators hence improving the prediction accuracy. An ICEEMDAN signal decomposition stage could also be optimized by providing an adaptive choice of the intrinsic mode functions (IMFs) depending on the state of volatility in the market. Rather than choosing fixed elements, adaptive IMF selection may enhance the capture of large market trends and additional reduction of noise in financial forecasts. System-wise, the Streamlit interface can be built to analyse many stocks at the same time allowing investors and analysts to compare two stocks and cross-market to the investor. In addition, the implementation of the system on the cloud-based system would enable sustained access and scalability of computation along with real-time forecasts to a broader user base. Next generation of the framework can also include risk estimation and quantifying of uncertainty techniques, including use of

confidence intervals or probabilistic forecasts in addition to point forecasting. This would facilitate making better financial decisions as it would give an idea on possible risks and imprecision in prediction. All in all, all these improvements would make the proposed ICEEMDAN-LSTM stock forecasting system much more practical in its application and scaling to real-life financial contexts and its analytical capability.

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