Exploring New Frontiers: XCEEMDAN, Bidirectional LSTM, Attention Mechanism, and Spline in Stock Price Forecasting

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ABSTRACT

The Attention Mechanism is acknowledged as a machine learning method proficient in managing relationships within sequential data, surpassing traditional models in this regard. However, the unique characteristics of stock data, including substantial volatility, multidimensionality, and non-linear patterns, present challenges in attaining accurate forecasts of stock prices. This research aims to tackle these hurdles by enhancing a prior model through the incorporation of an Attention Mechanism, resulting in an enhanced model. The forecasted data are standardized and prepared for analysis before undergoing signal decomposition into high and low-frequency components. Subsequently, the Attention Mechanism processes the high-frequency signals. Evaluation entails comparing the performance of the proposed model with that of the previous model using identical parameters. The findings indicate that the proposed model achieves a reduced RMSE value of 0.5708777053 compared to the previous model's average RMSE value of 0.5823726212, indicating enhanced accuracy in stock price prediction. This approach is anticipated to make a substantial contribution to the advancement of more dependable and effective stock price prediction models, addressing the limitations of prior methodologies.

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1. INTRODUCTION

Forecasting stock prices entails trying to predict the future worth of a company's shares or other securities traded in the stock market. Proficient forecasts in this domain can result in increased profits for investors [1]. Nonetheless, the stock market poses challenges owing to its data attributes, characterized by notable fluctuations, high dimensions, and non-linearities, rendering prediction arduous [2]. An array of factors, including political, economic, market trends, technological advancements, and investor sentiment, can influence fluctuations in stock prices [3].

Recent developments in stock price prediction involve combining signal processing methods, machine learning algorithms, and traditional stochastic models. Signal processing methods are used to address irregular data (noise), machine learning algorithms analyze complex time series patterns, and traditional stochastic models handle simpler time series patterns. This integration allows for the creation of a comprehensive model that takes into account both historical and future data [4].

Researchers [5] introduced the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) technique for signal processing. CEEMDAN offers expedited processing times compared to the Ensemble Empirical Mode Decomposition (EEMD) method and can analyze non-linear and non-stationary signals. M. Roondiwala, H. Patel, and S. Varma utilized the Long Short Term Memory

(LSTM) model for stock price forecasting. However, LSTM encounters challenges in efficiently utilizing historical data dependence, which Cao et al. addressed through the CEEMDAN-LSTM model, resulting in enhanced prediction accuracy.

A team of researchers [9] introduced the Empirical Mode Decomposition - Long Short Term Memory - Cubic Spline Interpolation (EMD-LSTM-CSI) model, which offers faster processing times and greater stability in stock price forecasting. This model surpasses other models such as Support Vector Machines, traditional LSTM models, Attention-based LSTM models, and various EMD-LSTM variants. Additionally, research by Lin et al. [20] demonstrated that incorporating CEEMDAN into financial data analysis produces excellent results, effectively deciphering complex data structures and accurately predicting market trends.

In their study, authors De Luca Avila and De Bona [4] introduced the XCEEMDAN-LSTM-Spline model, which enhances prediction accuracy compared to the CEEMDAN-LSTM model. Bidirectional LSTM models, as suggested by Jia et al., [2] and Siami-Namini et al. [10] offer improved predictive capabilities by comprehensively capturing data context through traversal in both forward and backward directions. Hence, this study advocates for a model utilizing XCEEMDAN-Bidirectional LSTM-Spline. Preprocessed data undergoes normalization and XCEEMDAN processing to manage chaotic data characteristics by mitigating noise. Subsequently, an additional Bidirectional LSTM layer captures supplementary information, complemented by a Spline model to mitigate overfitting issues and enhance stock price prediction accuracy.

Recent research shows the effectiveness of different methods in predicting stock prices. For example, Kelvin et al. [18] introduced a model that combines preprocessing with Bidirectional LSTM and Spline techniques to enhance prediction accuracy. Additionally, Zhang, J et al. proposed a model that incorporates the Attention Mechanism to improve prediction outcomes.

The inclusion of the Attention Mechanism in stock price prediction models provides several benefits. Attention mechanisms enable models to concentrate on relevant sections of the input data, thereby capturing more complex patterns and dependencies. By merging the Attention Mechanism with the XCEEMDAN-Bidirectional LSTM-Spline model, we aim to enhance predictive capabilities by allowing the model to selectively focus on significant features in the input data, thus improving its ability to identify complex relationships and fluctuations in stock prices. This integration justifies our approach of combining the XCEEMDAN-Bidirectional LSTM-Spline model with the Attention Mechanism.

Specifically, the Attention Mechanism is well-regarded for its effectiveness in capturing dependencies within sequential data, making it a valuable component for stock price prediction models. By incorporating attention mechanisms, the model can dynamically adjust its focus during predictions, enabling it to adaptively prioritize different input features. This adaptive capability enhances the model’s ability to capture pertinent information and improve prediction accuracy. Consequently, adding the Attention Mechanism to the XCEEMDAN-Bidirectional LSTM-Spline model offers a promising path for further improving stock price prediction performance.

Nonetheless, there are several gaps in current research that this study seeks to address. Existing models often face challenges in handling irregular data and effectively utilizing historical data dependencies. Moreover, there is a shortage of integrated approaches that combine signal processing, machine learning, and stochastic models. Our study contributes by proposing a new model that integrates XCEEMDAN for improved management of noisy, non-linear data, Bidirectional LSTM for capturing temporal dependencies in both directions, and the Attention Mechanism for focusing on the most relevant features. Additionally, we incorporate a Spline model to mitigate overfitting and enhance generalization. This integrated method aims to improve the accuracy and robustness of stock price predictions, addressing the identified gaps in the literature.

2. RESEARCH METHOD

2.1. Forecasting Stock Prices

Shares are bought, sold, and traded in the stock market.[3]. It has unique data features, like big changes, lots of data, and complexity, which make it hard to predict [2]. Changes in stock prices depend on supply and demand: if there are more sellers than buyers, prices generally go down; if there are more buyers than sellers, prices tend to rise [11].

Forecasting stock prices means trying to guess what a company's shares or other financial assets will be worth in the future. Predicting prices has been important for a long time because it can lead to big profits [1]. Looking at trends over many years can help understand the ups and downs of the stock market, which are often unpredictable and complicated. Traditionally, there have been two main ways to predict stock prices [12]:

1. Analyzing historical stock prices, including opening and closing prices as well as trading volume, aims to forecast future prices.

2. Qualitative analysis looks at external factors like a company's background, market conditions, and news from experts in finance.
3. Machine learning techniques are applied in stock market analysis, particularly when handling complex datasets that are not easily interpretable. These approaches excel at uncovering obscured patterns and connections within extensive datasets, frequently outperforming traditional methodologies.

Stock price prediction methodologies have undergone significant advancements over time. Initial strategies relied on probabilistic frameworks, whereas contemporary approaches harness the power of machine learning algorithms. Several probabilistic models have emerged to analyze data dynamics without presuming linear trends or temporal coherence. The new model integrates three fundamental elements: preprocessing methods, machine learning algorithms, and conventional probabilistic models. Preprocessing plays a crucial role in readying data for model deployment, with CEEMDAN standing out as one method capable of handling intricate and dynamic signals. Machine learning algorithms, such as Bidirectional LSTM, along with traditional stochastic models, are employed for stock price predictions [4]. Furthermore, this study incorporates an attention mechanism into the Bidirectional LSTM model.

2.1. XCEEMDAN

CEEMDAN, a signal decomposition technique extends the capabilities of Empirical Mode Decomposition (EMD) for analyzing nonlinear and non-stationary signals [8]. EMD breaks down such signals into Intrinsic Mode Functions (IMF) along with a residual signal [13]. Chaotic nonlinear data can introduce uncertainty and irregularity into observed data, where noise arises from accompanying processes or measurement inaccuracies [14]. The steps of EMD can be found in the previous research paper by Kelvin et al. [18].

EMD possesses the capability to manage non-stationary and nonlinear signals, yet it encounters an issue known as "Mixing mode". This phenomenon occurs when there are highly similar oscillations present in different modes or when modes exhibit vastly different amplitudes. To address this challenge, Ensemble Empirical Mode Decomposition (EEMD) was developed, aiming to substantially mitigate mode mixing within the EMD algorithm [15].

However, the EEMD algorithm fails to completely eliminate Gaussian white noise post-signal reconstruction, leading to reconstruction errors. In response to this issue, CEEMDAN has been introduced as an enhanced iteration of EEMD [5]. CEEMDAN demonstrates superior efficacy in eliminating mode mixing, resulting in nearly negligible reconstruction errors and low computational complexity [8].

CEEMDAN will be specifically applied to external variables, representing factors influencing the price series to be predicted. For example, in a dataset used for model training and testing comprising various stock market indicators such as the opening price, highest price, lowest price, closing price, and daily financial volume, where the closing price signifies the series to be predicted, the application of CEEMDAN to these external variables is referred to as XCEEMDAN. The algorithm for XCEEMDAN can be found in the prior research paper by Kelvin et al. [18].

2.2. Bidirectional Long Short Term Memory (Bidirectional LSTM)

Bidirectional LSTM represents a variation of the Recurrent Neural Network (RNN), designed to address the issue of long-term dependency encountered in standard RNNs and LSTM models. By incorporating LSTM units in both forward and backward directions, Bidirectional LSTM gathers information from the data in both temporal directions simultaneously, thereby ensuring that potentially overlooked data is captured more effectively. The process begins with data preprocessing, followed by passing the input through the Bidirectional LSTM neural network layers, ultimately culminating in the prediction output, as depicted in Figure 1. In the forward layer, computations are executed from the initial time step to the final one, with the hidden layer's output persistently collected and stored. Conversely, in the backward layer, computations are reversed from the final time step to the initial one, capturing and storing the hidden layer's output at each time step. As illustrated in Figure 2, the six unique weights (w1, w2, w3, w4, w5, w6) are utilized repeatedly throughout the process: connecting the forward and backward hidden layers (w1, w3), connecting the hidden layer to itself (w2, w5), and connecting the forward and backward hidden layers to the output layer (w4, w6). The output layer combines the outputs from both the forward and backward layers to generate the final prediction result [2]. The steps of the Bidirectional LSTM algorithm can be found in the previous research paper by Kelvin et al. [18].

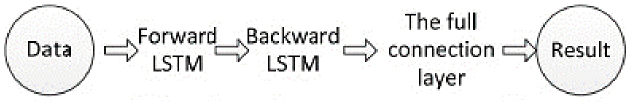

Figure 1. Structure Diagram Bidirectional LSTM [2]

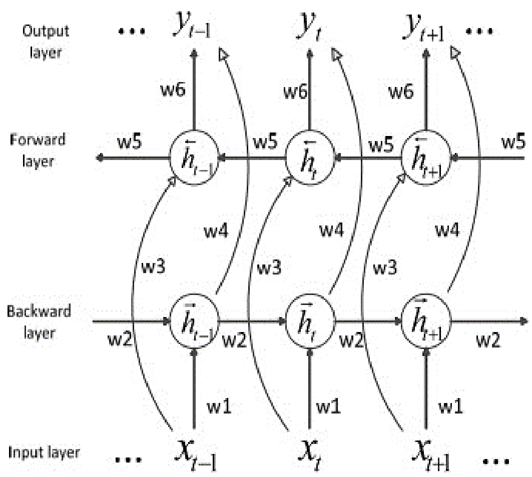

Figure 2. Bidirectional Neural Network LSTM [2]

2.3. Attention Mechanism

The concept of attention mechanism has its roots in the investigation of human visual perception. Conventional neural networks lack the ability to discern the significance of signals during information processing. Conversely, the attention mechanism enables the allocation of varying weights to different features, prioritizing crucial information with higher weights while disregarding less relevant data. This differentiated weight assignment enhances the efficiency of information processing, addressing the issue of information loss typically encountered with long sequences in LSTM models. Hence, integrating the attention mechanism could potentially enhance the accuracy of stock price predictions even further [19].

2.4. Cubic Spline Interpolation

Cubic spline interpolation is a method for creating smooth, connected curves through a set of points. It involves integrating cubic curves between each pair of adjacent points. This algorithm follows specific steps to achieve this interpolation [16]. Detailed steps can be found in the previous research paper by Kelvin et al. [18].

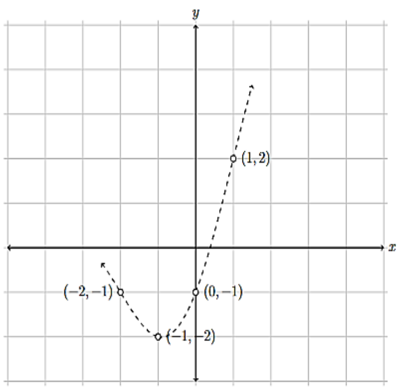

Figure 3. Interpolation using a cubic spline with four points [17]

This research methodology embarks on a journey through eight pivotal stages. Initially, it delves into dataset exploration, meticulously discerning target and exogenous features, and calibrating the IMF threshold. Progressing to the second phase, the dataset undergoes normalization, seamlessly aligning the data within a 0 to 1 spectrum. The third phase orchestrates data preprocessing using XCEEMDAN, orchestrating the generation of IMF signals. Subsequently, in the fourth phase, the IMF signal frequencies are meticulously categorized based on the predefined IMF threshold value. Transitioning to the fifth stage, the narrative unfolds as low-level IMF signals, resonating with high frequencies, are envisioned through the lens of the Bidirectional LSTM model, fortified by an attention mechanism. Meanwhile, the saga continues as high-level IMF signals, resonating with low frequencies, are prophesied using a spline model. These prophesied IMF signals harmonize, culminating in the extraction of the target feature's anticipated values. Ultimately, the storyline crescendos as rigorous testing unfolds, painting a vivid portrait of predictions for the target features, as elegantly depicted in the flowchart immortalized in Figure 4.

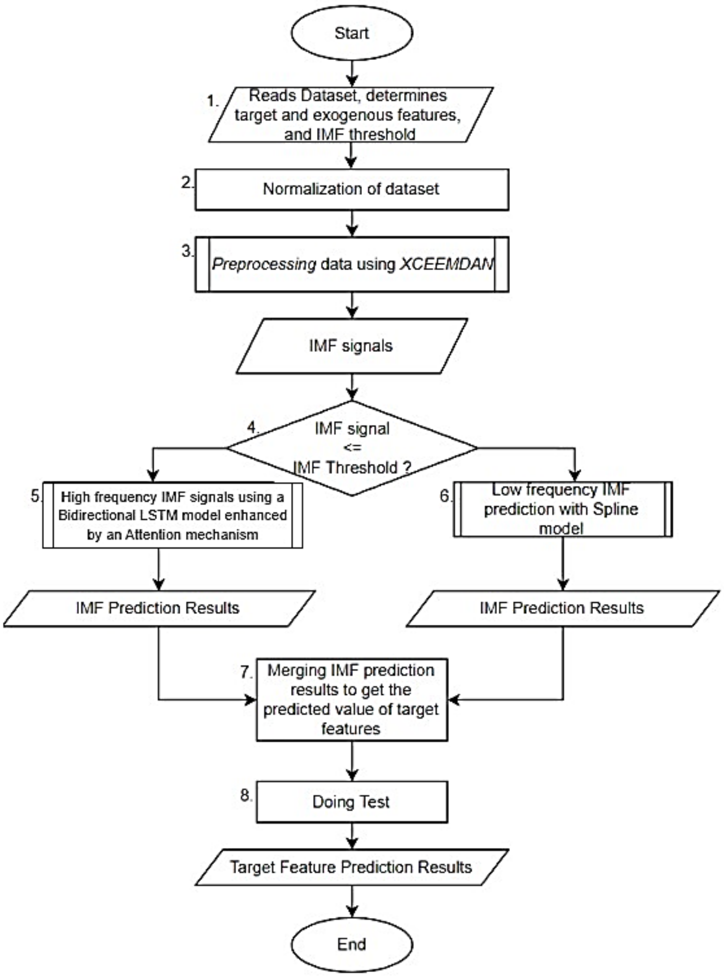

Figure 4. Methodology Visualization Flowchart

The forecasted adjusted closing stock price is derived through amalgamating the holistic IMF prediction outcomes using the Bidirectional LSTM - Spline model, augmented with the attention mechanism. This projected adjusted closing price undergoes scrutiny through comparison with the actual closing price, juxtaposing train_predicted with train_real, validation_predicted with validation_real, and test_predicted with test_real values. Visual representation of this comparison, illustrating the predicted adjusted close against PETR4 equity's real values at the IMF 2 threshold, is depicted in Figure 5. The y-axis delineates the forecasted adjusted close, while the x-axis denotes the timeframe.

The framework for problem resolution is depicted in Figure 6. The process initiates with data preprocessing utilizing a signal processing method called CEEMDAN on exogenous features for input data processing (referred to as XCEEMDAN). Subsequently, the output from XCEEMDAN is employed as input for the LSTM-Spline model to forecast stock prices. Compared to the CEEMDAN-LSTM model, XCEEMDAN-LSTM-SPLINE showcases a notable enhancement of 65.233% in average RMSE performance. Previous research on the Bidirectional LSTM model utilized for stock price prediction demonstrates an average accuracy increase of 37.78% compared to the LSTM model [4]. The XCEEMDAN-Bidirectional LSTM-Spline model effectively enhances accuracy in contrast to the XCEEMDAN-LSTM-Spline model, as evidenced by a lower Root Mean Square Error (RMSE) value of 0.7929055 at the IMF 2 threshold [18]. The integration of the Attention mechanism not only boosts information processing efficiency but also tackles information loss issues commonly encountered in long sequences within LSTM models, thereby making the model more robust and dependable in stock price prediction [19].

Figure 5. Comparison graph of the predicted value of adj close with the real value of PETR4 equity with the IMF threshold value of 2

Building upon these initial conditions, the intended research involves employing XCEEMDAN for data preprocessing. The resulting output from XCEEMDAN is then utilized as input for Bidirectional LSTM-Spline, incorporating the attention mechanism, to predict stock prices. This amalgamation of four methods has yet to be tested for its ability to retain both backward and forward data and capture additional information supporting prediction results. The data utilized in this study constitutes secondary data sourced from Yahoo Finance, encompassing historical records of Brazilian equities PETR4, VALE3, BOVA11, ITUB4, BBDC4, B3SA3, BBAS3, ABEV3, MGLU3 spanning from January 1, 2010, to December 31, 2023 [5]. This dataset is publicly accessible at the link https://finance.yahoo.com after rectifying gaps induced by weekends and holidays. The attributes employed in this study are open, high, low, adj close, and volume, given their high correlation with the output results of the adjusted close price. In this study, we compared the XCEEMDAN Bidirectional LSTM Spline model with the proposed XCEMDAN - Bidirectional LSTM - Attention Mechanism - Spline model (the proposed model) at the IMF 2 threshold value. We have demonstrated that the performance of the proposed model surpasses that of the other models examined. This comparison is illustrated in Figure 6.

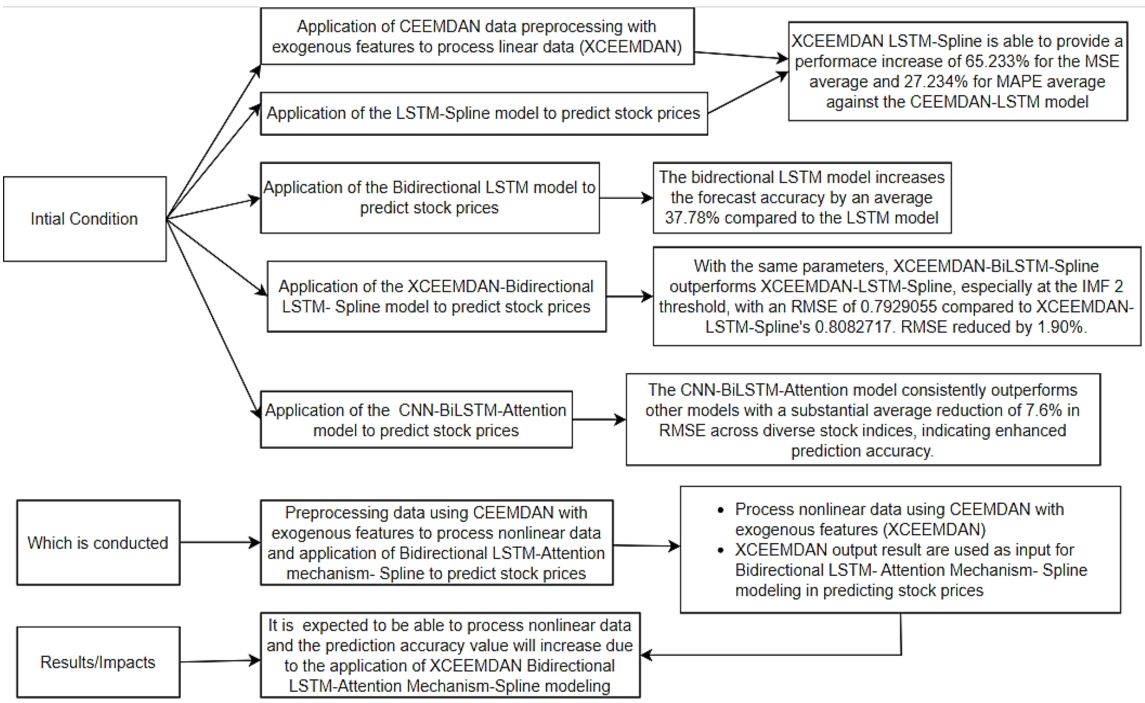

Figure 6. Framework for Problem Resolution

3. RESULTS AND ANALYSIS

In this experiment, we aimed to identify the model with the lowest RMSE across various datasets, employing identical parameters as detailed in Table 1. The results of this comparison are presented in Table 2. Notably, the XCEEMDAN-Bidirectional LSTM-Attention Mechanism-Spline model exhibited superior performance at the IMF 2 threshold, with an RMSE of 0.5708777053 compared to the XCEEMDAN-Bidirectional LSTM-Spline model's RMSE of 0.5823726212, indicating its enhanced predictive accuracy.

Table 1. Parameters used in model testing with Threshold at IMF 2

Model	XCEEMDAN- Bidirectional LSTM – Spline	XCEEMDAN- Bidirectional LSTM – Attention Mechanism- Spline
Desc.	Kelvin et al. (2022)	Proposed model
Neuron	128,64	128,64
Dense	16,4,1	16,4,1
Start date	1/1/2010	1/1/2010
End date	31/12/2023	31/12/2023
Noise scale	0.15	0.15
Noise seed	3877415934	3877415934

Table 2. Parameters used in model testing with Threshold at IMF 2

Model	XCEEMDAN- Bidirectional LSTM – Spline	XCEEMDAN- Bidirectional LSTM – Attention Mechanism- Spline
Desc.	Kelvin et al. (2022)	Proposed model
PETR4	0.5295243582	0.5187685475
VALE3	1.330331274	1.340392813
BOVA11	1.338174056	1.264265789
ITUB4	0.3848225672	0.3776617867
BBDC4	0.3180853057	0.3117363035
B3SA3	0.3137688701	0.2999769985
BBAS3	0.7205406243	0.7161180332
ABEV3	0.163315958	0.1624699187
MGLU3	0.1427905777	0.1465091581
AVERAGE	0.5823726212	0.5708777053

4. CONCLUSION

After analyzing the test results and discussions, it's clear that under identical parameters, the XCEEMDAN - Bidirectional LSTM - Attention Mechanism - Spline model outperforms at the IMF 2 threshold, boasting an RMSE of 0.5708777053 compared to 0.5823726212 without the attention mechanism. This demonstrates that incorporating the attention mechanism significantly boosts the model's stock price prediction accuracy.

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