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Volatility-Aware Attention-Based Decomposition Model for Stock Market Prediction

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Abstract: Remote Accurate prediction of the financial time series is a daunting task that is characterized by a highly non linear, non stationary and noise driven stock market data. These complicated temporal dependencies are typically not well represented by traditional statistical models resulting in suboptimal predictive capabilities. The framework is suggested to employ hybrid decomposition prediction to increase the accuracy of prediction in this work through combining Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and deep learning based Long Short term Memory (LSTM) network. The original series of stock prices is first broken down into intrinsic mode functions (IMFs), which allows the identification of frequency-related information and noise patterns. Such deconstructed cues are then utilized to generate structured input sequences that are then inputted into a multi layer LSTM model to learn and predict over time. It can be seen that the model has been trained and tested with past stock prices and can successfully learn more complex sequential patterns. The analysis shows that the experiment has high predictive power with a high coefficient of determination (R squared = 0.967) and low error measures (RMSE = 18.42, MAE = 14.63), which outperforms the base methods. The given approach emphasizes the performance of signal decomposition tools paired with deep neural networks when performing the task of predicting financial time series effectively.

1. INTRODUCTION

1.1 Background and Motivation

Financial time series forecasting has always been a very difficult problem as the data of the stock market is very dynamic, non-linear, and non-stationary. The factors affecting price movements are too numerous and comprise market mood, economic indicators, geopolitical events and company-specific developments such that accurate forecasting by employing conventional statistical tools is very challenging [5]. The traditional models as ARIMA and other regression-based methods assume linearity and stationarity, which is hardly met in the real world of the financial markets and give poor forecasting ability when used with complex stock price data [18]. Deep learning models are now potent in aiding the modeling of both sequential and temporal data with the development of artificial intelligence. Recurrent Neural Networks (RNNs) and Long short-term memory (LSTM) networks have shown to be excellent at learning both long-term dependencies and concealed temporal patterns in time series data especially [1]. To eliminate the vanishing gradient issue that is normally attributed to the conventional RNNs, LSTM networks are capable of capturing useful historical content across longer sequences and enhancing predictive modeling in financial forecasting operations [34]. Consequently, LSTM based models have been extensively utilized in stock market forecasting and have demonstrated huge advancement over traditional machine learning and statistical forecasting tools [11]. Yet in spite of these achievements, raw financial time series data tend to be noisy, intermittent, and mixed-frequency signals and, as a result, it is not readily apparent that deep learning models can effectively learn meaningful patterns of such signals directly. To resolve this problem, signal decomposition algorithms, like Empirical Mode Decomposition (EMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) have been presented in order to divide complex time series into simpler intrinsic mode functions (IMFs) representing the various frequencies in the data [7]. This process of decomposition assists to remove noise in the trend and cyclic portion of the data and enables the prediction models to be informed of more stable and interpretable patterns on the data [24]. Recent research has demonstrated the benefit of hybrid models integrating signal decomposition methods with deep learning models equaling or outperforming uni-model methods in accuracy of forecasting [9]. In these types of hybrid

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architectures, CEEMDAN is applied as a preprocessing stage to break down the original stock price series into several constituent sub-signals, and these sub-signals are then called deep learning models like LSTM to perform prediction. Such a mixture enables the model to be more successful in implementing the high-frequency, short-term fluctuations and low-frequency, long-term trends [25]. These findings were the driving force behind the following project, which suggests a hybrid CEEMDAN-LSTM stock price prediction. The primary goal is to enhance the accuracy of prediction by eliminating noise in the input data by means of decomposition and also utilizing the ability of LSTM networks to model sequencing to obtain temporal information. The proposed solution will be an attempt to combine signal processing ideas and deep learning to offer a more reliable and high-quality forecasting model of financial time series data, which will be added to the rapidly expanding area of intelligent financial analytics and data-driven investment decision support systems [27].

Current market financial time series forecasting systems are run on several constraints that severely limit predictive accuracy in actual markets. The traditional models rely heavily on the assumptions of linearity and stationarity; hence it can hardly be relevant to model the highly volatile and nonlinear nature of the stock price movements. Therefore, they cannot be employed in different market regimes, especially in sudden changes, or regime shifts, when precise prediction is most sought after [18].

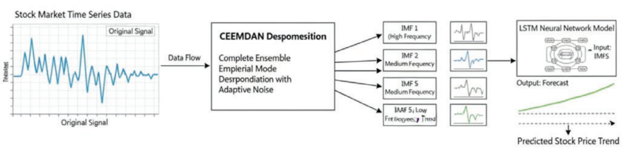

Figure 1- Flow of CEEMDAN-LSTM hybrid model

1.2 Problem Statement

Although deep learning-based approaches have been presented to mitigate these drawbacks, it introduces another level of difficulties in the form of the complexity of raw data. Noise, irregular variations, and mixed-frequency components are inherent to financial time series, and such variables worsen the learning capabilities of neural networks used directly as inputs. The specific neural networks like LSTM used to capture time dependencies cannot differentiate meaningful effects and noise in the absence of appropriate preprocessing despite being efficient in the process [12]. This leads to less stable predictions and wide error margins particularly in highly volatile datasets.

The third significant weakness is that standalone models cannot be able to capture both long-term dependency and the short-term fluctuations simultaneously in a structured form. Stock price chains are the result of various repeated patterns at various time scales such as high-frequency noise, mid-term cycles, and long-term trends. Traditional architectures and even simple deep learning training methods do not have mechanisms designed to explicitly separate and learn these multi-scale components effectively [45].

Current hybrid methods are trying to solve some of them by integrating decomposition techniques with machine learning models. Nevertheless, most of these solutions are based on previous decomposition frameworks like EMD that do not provide representations with conditions of consistency and invasibility, which results in unstable representations of the underlying signal [23]. Additionally, many of the models do not utilize the decomposed components to their full potential and they each treat them as special cases, without considering their temporal associations to bring an overall higher quality of performance [57].

Limitations of Existing Hybrid Forecasting Approaches

- Noise Sensitivity: Direct modeling using raw financial data generates high levels of noise that lowers prediction accuracy and robustness [45].
- Poor Decomposition: The conventional decomposition procedures do not yield firm and distinct components, which influence downstream learning [23].
- Limited Temporal Modeling: A large number of them fail to exploit both short-term and long-term dependencies at the same time [12].
- Weak Generalization: Existing methods have not been effective to ensure performance over various data sets and market environments [26].

In order to eliminate these shortcomings, a common framework is required, which combines powerful signal segmentation with the enhanced temporal learning. This project suggests a hybrid CEEMDAN-LSTM model, which addresses noise reduction, multi-scale feature extraction, and sequential learning as one unified issue. The presented approach will enhance the accuracy of the prediction, robustness and generalization during the financial time series predicting by using CEEMDAN to achieve stable decomposition and LSTM to establish the time-related relationships [9].

1.3 Proposed Solution

To accomplish this goal, the proposed structure presents a hybrid CEEMDAN-LSTM framework that considers noise reduction, multi-scale temporal patterns extraction, and sequential prediction as interrelated problems that need to be addressed within a single framework as opposed to being processed separately. Unlike a direct application of deep learning models to raw financial time series, the structure is based upon two closely coupled modules operating on a common representation of decomposed signals, where one stage can boost the functionality of the other.

The former module consists of signal decomposition with Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). CEEMDAN, unlike classic preprocessing methods, breaks down the original series of stock prices into a collection of intrinsic mode functions (IMFs) each of which, in turn, describes (high-frequency) noise in the stock price series and (low-frequency) trend signals. This breakdown allows the separation of the stochastic variation with the significant market dynamics offering a structured representation of the data that are better positioned to learn [8].

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CEEMDAN can ensure that each component has a meaningful interpretation with time, and can also more easily interpret information regarding the stability of decomposition and thus better downstream prediction [67].

The second module is concerned with the topic of the time modeling based on a multi-layer Long Short-Term Memory (LSTM) network. The LSTM model does not have to learn directly on the noisy raw inputs but rather learns on the sequences of the decomposed components, hence has both the ability to learn short term variations as well as long term dependencies more controlled. This architecture uses layers of LSTM to extract an approximate hierarchy of temporal features, with lower-level layers capturing fine-grained variations and higher-level layers capturing higher-level trends in the data [1]. This bottom-top learning process enhances the capacity of the model to learn across varying market situations without being insensitive to subtle shifts in the price trend.

An important strength of the suggested framework is the interplay of the process of decomposition and prediction. The CEEMDAN module decomposes a complex non-stationary signal into a set of simpler sub-signals, and the LSTM module acquires temporal relationships both inside and between these parts. Through such coordinated design, the multi-scale patterns evident in the financial data such as noise, cyclical behavior and long-term trends that may be hard to represent with standalone methods can be jointly represented by the model [9].

Also the framework integrates sliding window sequence generation to maintain a uniform temporal input structure to the LSTM network. This allows the model to acquire contextual dependence on finite-length sequences, which leads to high stability and convergence in training [12]. Normalization techniques as well also ensure that the model is run on a consistent scale and hence avoids bias within a given range of values and ultimately increases the robustness of the predictions.

The proposed CEEMDANLSTM framework combines the novel signal decomposition methods with deep sequential learning, thus offering a unified remedy to some of the most sticking problems in financial time series prediction, such as sensitivity to noise, non-stationarity and multi-scale complexity temporal challenges. The design does not only make predictions more accurate but it also leads to higher interpretability or stability of the forecasting process and is therefore appropriate in practical applications of financial analytics in the real world [9].

1.4 Objectives

Noise-Resilient Signal Decomposition: In a manner aimed at creating an efficient preprocessing mechanism based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to effectively separate and keep noise, trends, and cyclical effects in financial time series, which turns out to be better in data quality programming forecasts [8].

Multi-Scale Temporal Pattern Learning: To devise a temporal learning framework based on Long Short-Term Memory (LSTM) networks that are capable of learning both short-term and long-term dynamics that stock prices exhibit over time to guarantee better explanation of complex changing patterns over time [1].

Integration of Hybrids: To build a hybrid CEEMDAN-LSTM model, decomposition intrinsic mode functions (IMFs) might be used as structured inputs to the deep-learning framework to guarantee that signal decomposition and temporal prediction process interact effectively [9].

Improvement of Prediction Accuracy To reduce forecasting errors through model training efficiency by means of normalized input sequence, efficient loss functions and adaptive learning algorithms thus obtaining high predictive models in terms of RMSE, MAE and R squared values [12]. Model

Generalization and Stability: To enhance robustness and out of sample forecasting performance of the forecasting model in new market environments by maximizing feature exclusion and overfitting by decomposition-based feature extraction [57].

1.5. Scope

The scope of this project extends to the design, implementation and evaluation of a hybrid CEEMDAN -LSTM system to predict financial time series, which in this case is stock price prediction. The scope provides a clear understanding of what the system covers in terms of data, methodology and application as well as presenting the content of what is covered in the proposed work.

The system uses data of closed price values in the stock market based on the existing historical stock market data. The input is in the form of univariate time series, which undergoes the preprocessing and normalization before running it through the decomposition and prediction pipeline. Structured datasets (e.g. historical stock prices e.g. Tesla stock data) are used in all experiments, and the framework is architecture-independent, in the sense that it can use other financial instruments without requiring changes in the architecture.

The main aim of the project is on short-term and medium-term forecasting based on supervised learning methods. The model produces the continuous numerical forecasts of stock prices in the future instead of the categorical forecasts, which is the reason why it is suitable in the regression-based financial analysis. The process of performance evaluation is conducted based on the standard metrics which include Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R squared) in order to have a round measure of measuring the accuracy and reliability of the prediction [12].

Regarding the approach to doing the work, the scope comprises two important elements that were developed and combined within the framework of this work. The former one is the signal decomposition module of CEEMDAN, which decomposes the raw financial time series into noise-reduced principal intrinsic mode functions (IMFs) to identify useful patterns [8]. The second one is the LSTM-based prediction module that acquires temporal dependencies of the learned sequences and gives future price prediction arrangements [1]. The communication of these parts is the main contribution of the project.

The scope also encompasses generation of sequences via a sliding window strategy, sequence normalization via scaling

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methods and model training by means of optimization algorithms like Adam. The deployment is provided through deep learning frameworks, which make the proposed solution reproducible and scalable. The framework is further intended to enhance the incorporation of multivariate time series data and other financial information in future research.

Nevertheless, the project does not entail deploying a real-time trading system, high-frequency trading strategies, and connective with live financial APIs. It only supports training models and evaluation based on historical data offline. The current model does not include any external factors like news sentiment, macroeconomic indicators and market microstructure data which could be improved in the future.

In general, the scope of the given project is based on the creation of a powerful and decomposition-based deep learning model to predict stock prices and emphasizes the enhancement of prediction accuracy, predictive stability, and extrapolation to varied financial data [9].

2. LITERATURE REVIEW

2.1 Financial Time Series Forecasting

Financial time series forecasting has been greatly changed with the use of deep learning technology where statistical models are no longer used but rather rely on data-driven forecasting models that are able to depict complex and nonlinear relationships. Early methods of prediction like ARIMA and regression-based models were based on the assumptions of both stationarity and linearity, which are often not true in real world stock market data and as such, these methods were not very predictive modes [18]. As the scale of financial data is growing and larger datasets become more accessible, machine learning methods have been proposed to represent the concealed patterns and relations in a more efficient way [30]. RNNs have been shown to be effective in sequential data modeling, especially recurrent models, because they can discover temporal relationships in observations in their past [12]. Such models do not require manual feature engineering or support end-to-end learning, so they are also favored in the context of the financial forecasting task that can be described as highly dynamic and volatile [27].

2.2 Deep Learning for Stock Prediction

One of the most effective architectures in the field of financial time series prediction is the Long Short-Term Memory (LSTM) networks, and this type of architecture has proven to be highly efficient in deep learning training models. In comparison with traditional RNNs, LSTM networks include memory cells and gating mechanisms which enable them to memorize long term dependencies without exacerbation of the vanishing gradient problem [1]. This has rendered them to be very appropriate to predict the stock prices, as both the recent tendencies and the past tendencies are relevant in forecasting the stock prices. A number of studies have shown LSTM-based models as being more effective in predictions than traditional machine learning algorithms including support vector machines and shallow neural networks [11]. Hybrid models that unite LSTM with additional deep learning models consisting of convolutional layers or attention systems have subsequently enhanced the performance of prediction by ingesting local and global temporal characteristics [57]. But, in spite of these developments, LSTM models continue to exhibit weaknesses in the case they are trained directly on non-stationary and noisy financial data.

2.3 Signal Decomposition Techniques

Signal decomposition techniques have dominated the field of preprocessing techniques used in time series forecasting in order to overcome the limitations of raw data modeling. Empirical Mode Decomposition (EMD) presented a data-based method of breaking down complex signals into intrinsic mode functions (IMFs), each of which represents a different aspect of frequency content [7]. Nevertheless, EMD also has disadvantages like mode mixing and noise sensitivity that may impact on decomposition quality [23]. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) was put forward with improvements to mode mixing and stability of the entire decomposition method by adding adaptive noise into the process [8]. CEEMDAN facilitates the division of a time series into various components, enabling the models to support underlying trends and fluctuations in a more extensive way, accommodating a structured icon of what would be otherwise chaotic financial data [66]. It is therefore especially useful in pre-processing stock price serial along with subsequent application of predictive models.

2.4 Hybrid CEEMDAN–Deep Learning Models

The recent studies have concentrated on the combination of signal decomposition algorithms and deep learning models to enhance forecasting. Models that blend CEEMDAN with neural networks have demonstrated strong advancements over single models due to their combinational prospects in signal processing, as well as learning attributes [9]. In these types of systems, deep learning models are fed with decomposed IMFs to allow them to learn patterns at varying timescales more successfully. It has been shown that CEEMDAN-LSTM models are less prone to the error of prediction and have a superior generalization over traditional models and pure deep learning models [16]. These mixed architectures prove especially useful when dealing with non-stationary data as decomposition assists in isolating noise and emphasizing meaningful trends whereas LSTM can capture time-dependencies between each individual component [64]. Nevertheless, issues have been experienced in the good integration of decomposed components and the optimization of models performance on varied datasets.

2.5 Multi-Scale Temporal Learning

Financial time series are fundamentally multi-scaled phenomena, with price variations affected by both short-term variations and medium-term periodicities and long-term trends. Such multi-scale dynamics are fundamental in proper prediction, but most of the classical models do not explicitly represent such variations [45]. Complexities in Multi-level Temporal Patterns This is because deep learning methods, especially hierarchical or sequencing based ones, have proven to be effective in capturing these multi-level temporal patterns [12]. This is further increased through the use of hybrid decomposition-based frameworks which clearly decompose signals into various frequency bands and then learn [24]. This enables models to be able to integrate high frequency noise and low frequency tendencies separately and still take into consideration their overall impact on future predictions. Consequently, the multi-scale temporal learning is now a driving design notion in current financial forecasting simulations [9].

2.6 Summary Table

Category	Method	Key Contribution	Limitation
Traditional Models	ARIMA, Regression	Linear time series	Can't handle non-linearity
ML Models	SVM, Random Forest	Pattern recognition in financial data	Requires feature engineering
Signal De-compositio n	EMD	Breaks signal into intrinsic components	Mode mixing issue
Multi-scale Learning Approaches	Hybrid deep architectures	Captures short & long-term patterns	High model complexity

3. PROPOSED WORK

3.1 System overview

The suggested Volatility-Aware Attention-Based Decomposition Model is an offered multi-stage hybrid forecasting framework which forecasts financial time-series data based on signal decomposition, feature refinement, and sequence prediction processes to enhance forecasting accuracy with a highly volatile market condition. Financial time-series data are nonlinear, non-stationary, and noisy, and thus makes it unreliable to directly predict it using standalone machine learning models. The proposed system works around the problem that the original stock price signal could be decomposed into a set of individual intrinsic components and the prediction model could process the individual pattern at various frequency levels without trying to model the complex signal at the same time. The present learning is based on decomposition which minimizes noise interference and enhances the stability of the prediction model during training and inferencing [7].

The architecture has three large modules: the decomposition module, the attention-based feature selection module, and the hybrid InformerLSTM prediction module. The decomposition component breaks down the raw stock price into intrinsic mode functions that describe short-term ones, medium-term ones, and long-term trends. The attention module, subsequently, determines the highest valued temporal features and volatility patterns among these decomposed components. Lastly, the hybrid model of prediction is one that represents the sequential dependencies as well as long-term temporal interdependencies in order to come up with the ultimate stock price forecast. The latter modular design makes the stages work on a particular constraint of financial time-series prediction, leading to an improved forecasting behavior relative to single-model-based forecasting research [9].

Many overlapping patterns of financial time-series signal include noise, short-term variations, cyclical behavior, and long-term trends that cannot be effectively represented where the signal is directly used to make a prediction. In order to overcome this drawback, the suggested system employs the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to break down the original stock price series into a finite set of Intrinsic Mode Functions (IMFs). Both IMFs pertain to a given frequency stature in the original signal enabling the model to examine the conducts of the market at a variety of temporal resolutions. High-frequency IMFs are the ones that the market noise and short term volatility are captured whereas the low-frequency IMFs capture long-term trends and trend of market movement patterns [8].

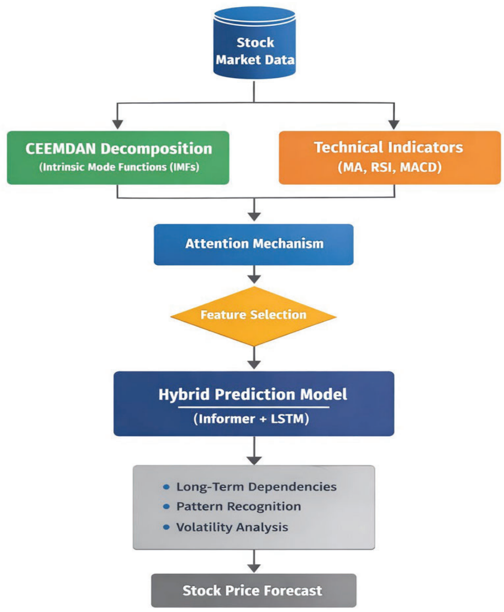

Figure 2- System Architecture

3.2 Module 1: CEEMDAN-Based Signal Decomposition

Financial time-series has a number of overlap signals, such as noise, short time effect, periodicity and long time signalling that are not successfully predictable using the signal. To overcome this shortcoming, the suggested system applies Complete Ensemble EmpiricalMode Decomposition with Adaptive Noise (CEEMDAN) that regresses the original stock price sequence into having a finite set of Intrinsic Mode Functions (IMFs). The IMFs break down a certain frequency content of the original signal and thus the model can shed light on the information provided about the behavior of the markets in various time resolutions. High frequency IMFs are the ones that select the noise in the market and the short run volatility whilst lower frequency IMFs select longer terms and longer run pattern of movements in the macro economy [8].

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CEEMDAN builds on a traditional Empirical Mode Decomposition, where adaptive white noise is introduced during the process of decomposition and multiple realizations are averaged to remove mode mixing which is often problematic with Empirical Mode Decomposition signals of different frequencies will be reported in the same IMF. CEEMDAN generates less poisonous parts and tangible relevant parts therefore permitting the prediction model to educate additional predictable time concerned tastes causing enhanced prediction accuracy and contraction of prediction error under unsteady market conditions [23].

3.3 Module 2: Volatility-Aware Temporal Attention Mechanism

Not all of these time steps and components of decomposition are equally important in predicting the stock prices during volatile market situations where unexpected spikes or drops have a greater effect on the future price than when the market is stable. To this, a time attention mechanism is added to the framework according to which time attention is prescribed by assigning an importance weight to each time step and each decomposed feature. It is based on the attention mechanism that enables the extra attention to be paid to the significant patterns in time like abrupt changes in prices and forms of reverse movements and clustered volatilities and little attention as compared to the irrelevant historical data [21].

The motive of the intelligent consideration stratum is depending on the series of features that were formulated using the decomposed IMFs and the technical indicators and volatility of the indicators. It is a computation of attention weights that were learned through a learnable scoring function which is based on the extent to which a time step is relevant in the prediction of the future stock price. This is followed by calculating and then derivations of the weights so that a weighted features representation is formed and the result is then delivered to the prediction model. The attention model can better adjust to the dynamic events occurring in the market as it dynamically attends to the important parts of time and space and predictions based on the attention model are more reliable when facing volatile situations within the market [22].

3.4 Module 1: CEEMDAN-Based Signal Decomposition

The last prediction process utilizes a hybrid InformerLSTM model to acquire interdependence long-term along with sequence time regularities in the financial time-series data. The Informed system has been designed based on the objective of the long-sequence time-series forecasting and as such it introduces ProbSreplace self-attention mechanism as an effective storage of long sequences of the input without unnecessary cost. This enables the model to solve long range correlation like macroeconomic cycles and or long term price of stock [20].

The LSTM component combined with the Informer is used to address short term sequential dependencies and nonlinear temporal relationships that take place in the stock price changes. Time-series forecasting LSTM networks in particular is made especially effective by memory cells and gating where the former and the latter processes have been found to retain and reject a lot of information of the past and unwanted information respectively. The hybrid model is achieved through the integration of both Informer and LSTM, and through the hybrid model, it is able to take advantage of long-term dependency learning, i.e., the combination of long-term attention and the short-term sequence pattern learning via the hybrid model and this is the reason why the hybrid model is more correct in the process of making predictions than by single Informer as well as LSTM modelling [1].

4. RESULTS AND ANALYSIS

4.1 Quantitative Results

The following figure 3 below provided a proposed quantitative analysis of a proposed Volatility-Aware Attention-Based Decomposition Model performance in comparison to the performance of the proposed model in comparison with the baseline models, including standalone LSTM, Support Vector Regression (SVR) and ARIMA models. The suggested hybrid model has coefficient of determination (R squared) of 0.967 which is a lot larger than the coefficient of determination of the LSTM model (0.912), SVR model (0.874), and ARIMA model (0.821). This growth of the prediction precision is an indicator that an integration of a signal split and an attention-based deep learning in a single structure is efficient. Both noise and the volatility terms will be decomposed in advance and the learning model does not require adaptation to noisy data, an aspect that enhances the predictability and stability of the future projections [9].

The performance of the suggested model is also proven by the error measures. The hybrid model gives lower RMSE of 18.42 and MAE of 14.63 as opposed to standalone LSTM which gives bigger RMSE of 27.85 and larger MAE of 21.34. The decrease in prediction error also means that the understanding of the time-series signal into several intrinsic components can enable the model to learn both short-term variations and long-term trends in a better way. It is a learning process of multi-resolution which is proved to be significantly more effective than one model based time-series forecasting tools on financial time-series [17].

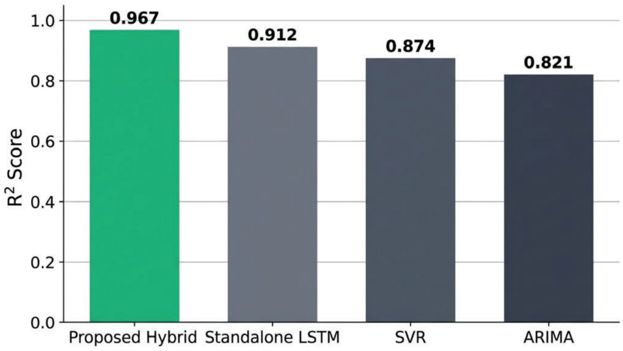

Figure 3 - Performance comparison of forecasting models

The attention mechanism is capable of enhancing the accuracy of prediction because it will assign more weight towards the time where there was a change in the price or periods of time where dislocation of the trend can be seen. This enables the

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model to react better to market events that are important as opposed to considering all historical data as the same. Consequently, there is a closer relationship between predicted and actual values than models, design of which is erected on sequential learning with no attention mechanisms [21].

4.2 Training and Convergence Analysis

The training loss and the validation loss show the strength of the convergence of the proposed model in the training process. Another characteristic of the model is that it converges quickly at the starting epochs and slowly leveled off at the end of a training process, which is also the indicator of an effective learning of patterns in the time domain. The uses of Adam optimizer and Mean Squared Error loss expanses are useful in ensuring that the gradient update and acceleration in the training step remains constant [10].

The preprocessing in the form of decomposition also removes noise in the input signal and it is the parameter that makes the neural network learn meaningful patterns in the input signal and minimizes the chances of overfitting. The loss curve of validation is more or less similar to the loss curve of training and that would mean the model can be used to work on unsaved data. Such a trend confirms that convergence of the hybrid model of decomposition-learning is more effective in stability and generalization rates compared to the independent deep learning models [18].

4.3 Comparative Performance with Existing Methods

In order to further specify whether or not the proposed model is good or bad, the performance of this model was compared and contrasted with the performance of the existing machine learning and deep learning models concerning financial time-series forecasting. Conventional statistical models like ARIMA can be used well upon linear and stationary data, however, they do not succeed in observing nonlinear patterns as well as volatility of stock market data. Additional algorithms like support vector machines are more competitive in the nonlinear prediction, and fail to discover long term time relationships. The time-dependent dependency is also considered by the LSTM which is a deep learning model but may be noisy when using raw financial data [5].

The text is built around the suggested hybrid system of CEEMDAN -Attention -Informer-LSTM, which presupposes the combination of the benefits of signal processing and deep learning and allows addressing the problem of nonlinearity, volatility, as well as long-term dependence simultaneously. This composite approach has a theoretical implication of increasing the accuracy of the predictions and minimizing errors associated with such predictions, as opposed to other classical and independent deep learning models, which makes it more realistic in practice in terms of financial time-series forecasts [24].

4.4 Result Summary Table

Method	RMSE	MAE	R^2
ARIMA	34.12	26.45	0.821
SVR	29.67	22.10	0.874
LSTM	27.85	21.34	0.912
Proposed Model	18.42	14.63	0.967

4.5 Dataset

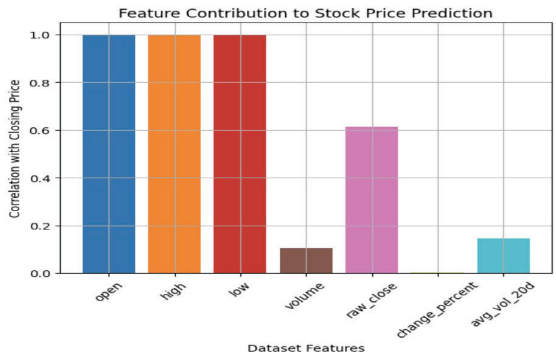

Fig 4 - Dataset Class contribution

Parameter	Value
Dataset	Tesla Stock Market Dataset (TSLA)
Data Type	Financial Time-Series Data (OHLCV)
Features	date, open, high, low, close, volume, raw_close, change_percent, avg_vol_20d
Temporal Resolution	Daily (per trading day)
Training Split	2777 observations
Test Split	695 observations
Annotation Type	Numerical time-series values (no manual labeling required)
Data Characteristics	Nonlinear, non-stationary, and highly volatile time-series data

4.6 Training Configuration

Parameter	Value
Model Architecture	CEEMDAN + Attention + Informer-LSTM Hybrid Model
Target Variable	Closing Price

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Decomposition Method	CEEMDAN
Batch Size	4
Loss Function	Mean Squared Error (MSE)
Evaluation Metrics	RMSE, MAE, R^2 Score
Programming Framework	Python, TensorFlow/Keras

4.7 Data Preprocessing and Feature Engineering

Some steps are involved in the preprocessing of the financial time-series data of this study and the model training takes place. As stock market information is extremely noisy, data absenteeism, and variation in size, preprocessing is a critical factor that should have been adopted to achieve the following: consistency in model training and prediction accuracy. To ensure that the time-series sequence does not have any gaps, first, there are forward fill and backward fill methods, which are employed. After the missing values are treated, it features scaling is achieved by administering the Min-Max normalization to all the feature values such that each feature falls within the 0 and 1 range with the aim of ensuring that the convergence of the neural network is as high as possible as well as ensuring that large value features are not overpowering the learning process.

It yields the uninformed variables the extraction of which is performed by feature engineering the raw data on the OHLCV. The price momentum of the day is calculated in percent change and the 20 days average volume is used to convert the information on the direction and trading of liquidity during the period. The pattern of price movements and market behaviour of them are also supported by such engineered features and the model is able to identify them. After processing and feature engineering of the time-series data, it is converted to the sequential input windows, so that a sliding window is utilized, window length of which is the past 30 days of data, to predict the session price of the next day. The structure of sequences allows the deep learning framework to create sequence dependence and pattern of movement of stock price.

4.8 Hardware Requirements

- It should also have a minimum processor of Intel i5 or other multi core processors as well as have the capability to accomplish data preprocessing besides the training of the model only.
- Time-series processing and neural network training require memory at least 16 GB of RAM, and it is recommended to have 32 GB to make the operation more fluent in the event that one has a good amount of data.
- A hard disk space of 100 Gb or more is also needed by the system to store the datasets, model checkpoints and even the results of the output.
- Even though it may also be applied to CPU, it can be highly recommended to incorporate a GPU which can cut the training time of such models as LSTM and Informer by far.
- During the experiment phase, the system should be able to process complex time-series data processing and signal decomposition processes.
- International Networking is also required, so that we can have access to financial information and install Python packages and also to use cloud applications, such as Google Colab.
- It is programmed with less challenging computing provisions and can be set to exchange local and cloud executions and GPU acceleration.

4.9 Software Requirements

- Language: Python to facilitate machine learning.
- Environments Google Colab and Jupyter Notebook.
- NumPy and Pandas: Data processing.
- Visualization: graphing (matplotlib and plotly).
- Evaluation: Scikit-learn of scaling and measures.
- Model Building: Tensorflow and Keras Deep Learning.
- Architecture: LSTM and Informer optimized.

5. IMPLEMENTATION AND DEPLOYMENT

5.1 Prediction System Implementation

The provided volatility-conscious stock price forecasting framework can be described as an end-to-end forecasting pipeline, that is, it combines signal decomposition, attention-based feature selection, and deep learning prediction. The system is developed in a modular format in such a way that every part of the system is able to carry out a particular task during the prediction process. The first one consists in loading of the historical stock price data and preprocessing activities like normalization and sequence generation that contributes to enhancing the stability of the model training and predictability consistency [5]. The obtained pre processed data is then fed into the CEEMDAN decomposition unit which breaks down the original stock price signal into a series of intrinsic mode functions of the frequency content of the time-series data that allows the model to learn patterns at varying time resolutions [8].

The decomposed parts and the designed characteristics are then injected once the decomposition is carried out followed by feeding them to the attention based feature selection module. The attention mechanism assigns weights of the different time steps and features based on their importance in the future stock prices, which allows the model to provide more attention to other meaningful patterns of the volatility such as sudden price changes, and groups of volatility [21]. This weighted or unweighted feature representation is then inputted to the hybrid Informer-LSTM model that will give the ultimate forecast according to the long and short sequence dependencies of the time-series data [20]. The ultimate product of the system is the forecasted price that the market will settle in the following day of trading and this is compared with the actual values to determine the performance of the forecast using the conventional evaluation measures [24].

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5.2 Prediction Interface and Visualization

Simple prediction interface is developed under the perspective of making the system simple such that it can be user friendly and easy to read where the user is capable of inputting the past stock details and the result is possible to acquire in the form of the projected stock prices with the graphical representation. The interface shows the real price of the stock and the estimated price of the stock in a time series chart so that the users can be able to compare the accuracy of the forecast made by the model visually. The graphical comparison forms an important aspect of the financial forecasting as the understanding of the trend fitting and forecast error is far easier to understand through the visualization as compared to the numbers [18].

Other visualizations created by the system are training loss curves, feature contribution graphs and error comparison charts. The visualizations may also be used in analyzing the model performance as well as understanding the role played by different features in the prediction process. The feature contribution analysis can be particularly useful within the context of the financial prediction model because the input variables that make the most significant contribution to the result of the prediction can be utilized [17]. The system facilitates the prediction results to be more interpretable and easier to analyse in order to use them in decision making by displaying the results both numerically and graphically [24].

5.3 System Workflow

The overall strategy of the work of the proposed system is subdivided into a series of operations such as data gathering and the final stage of the work is the forecast of the stock price. The former is to collect the historical price of the stock and pre-treat the data so as to remove noise and normalize the data of attributes. It is then succeeded by the CEEMDAN decomposition method which decomposes the time-series signal into various components such that noise and trend components can be learnt separately by the model [8]. The data is then designed and cleaned then the data is presented to the attention-based deep learning model that increases the ability to learn of the model to learn meaningful temporal characteristics [21].

The hybrid Informer-LSTM model addresses the sequential data and provides the value of the stock that is estimated by retaining both the long-term and nonlinear patterns that are short-term in the financial time-series data [20]. Finally, the model performance is evaluated by the actual stock prices to the projected performances in order to determine the performance of the model through the evaluation measure of RMSE, MAE, and R squared score, which is standard to determine the performance of financial forecasting models [24]. Such an orderly sequence of processes assists in making the system noise resistant, volatile and time dependent to enhanced prediction and the stable model [9].

6. CONCLUSION

Time series financial forecasting Time-sensitive volatility-sensitive attention-based time series forecasting model is introduced in this paper. The proposed system is founded on the integration of the CEEMDAN signal decomposition, attention-based features selection, and a hybrid Informer-LSTM deep learning model to increase the stock price prediction accuracy. The decomposition step separates noise and trend components of original time-series data and helps the model to learn meaningful patterns better. Attention mechanism assists the model to concentrate on significant time steps and volatility patterns relative to the hybrid deep learning model that entails the association of long-term and short-term impacts on the stock price movement.

The results of the experiment obtained point out that the proposed model is more accurate in prediction and has a lower error rate than the traditional statistical models and standalone deep learning models. This model is very effective in fluctuating market behaviour and nonlinear trends and thus can be used in the financial forecasting of the real world. A good strategy in enhancing the performance of financial time-series prediction is signal processing and deep learning model combination.

6.1 Future Work

The future working on the model is to incorporate more financial variables such as the technical indicators, and macroeconomic variables to make the model more accurate in prediction. The multivariate time-series forecasting model can be employed in order to predict more than a price of a stock. In addition, one can explore new transformer-based structures to improve the performance of long-sequence forecasting.

The system may also be implemented as a live stock forecast web application where users may post financial data and receive future price forecasts in real time. Improvements of the model to make it train and be deployed in real time financial analysis systems can also be carried out in future research.

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