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# Self-Optimizing Algorithms For Continuous Learning In Financial Time-Series Forecasting

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**Abstract**
Self-optimizing algorithms are increasingly essential for continuous learning systems, especially in financial time-series forecasting, where data distributions are highly dynamic and non-stationary. Traditional machine learning and deep learning models rely on static training procedures, limiting their adaptability to rapid market fluctuations and leading to model drift and degraded predictive performance. The research proposes a self-optimizing continuous learning based on a Modified Osprey Attention-Gated Recurrent Unit (ModO-Att-GRU) model. The objective is to enable autonomous adaptation to evolving financial patterns through the integration of online learning, reinforcement-based optimization, and meta-learning strategies. Financial data is collected from a publicly available Kaggle stock market dataset. Min-Max normalization is employed as a preprocessing technique to stabilize training and improve convergence. For feature extraction, the Relative Strength Index (RSI) is utilized to capture momentum and trend-related information embedded in the time-series data.The proposed ModO-Att-GRU model incorporates an osprey-inspired optimization mechanism for dynamic weight adjustment, along with an attention gating mechanism to selectively focus on relevant temporal features. The proposed ModO-Att-GRU model was implemented and evaluated using Python. Experimental evaluation is conducted on financial datasets using metrics such as prediction accuracy (93.85%), and test Receiver Operating Characteristic Area under the Curve (ROC-AUC) (95.08%). Results demonstrate that the proposed method improves adaptability, reduces model drift, and enhances long-term forecasting performance compared to conventional methods.

**Keywords:** Time-Series, Continuous Learning, Modified Osprey Attention-Gated Recurrent Unit (ModO-Att-GRU), Stock Market Analytics.

## 1. Introduction

The financial sector is the most vibrant sector with a huge impact on the development of the economy of any nation. Changes in the exchange rate of currencies as well as changes in the stock index become the major factors reflecting the state of the nation's finances and assisting investors in making wise decisions [1]. Thus, the importance of predicting financial time series cannot be overemphasized since it is a necessary component of effective analysis of markets and the development of proper investment strategies.

The stock market, which is arguably the oldest financial institution, features prominently in the economy as a means of making stock index predictions vital for investments [2]. However, newer theories on the subject show that prices, usually given by OHLCV (open-high-low-close-volume) data not behave randomly but can be considerably affected by their previous behavior. Nonetheless, it is still quite hard to make predictions due to the high level of uncertainty and volatility associated with the financial market [3, 4]. Such difficulties are behind the advent of sophisticated tools for analyzing and predicting time series data. Commodity price forecasting, in particular, is known to be highly volatile, uncertain, and complex, which calls for accurate prediction methods [5]. In this regard, models based on transformers have become an important breakthrough in terms of showing impressive results in Computer Vision (CV), and their application to time series forecasting is growing because of their ability to model long-range dependencies [6]. Moreover, investments in stocks through the stock markets become an indispensable part of economic growth because the stock market helps in forming capital and achieving structural efficiency in the financial system. Thus, the stock market becomes a major indicator for measuring the economic and financial condition of any country or region [7, 8].

**Research Aim:** The designed model uses a Modified Osprey Attention-Gated GRU (ModO-Att-GRU) algorithm that leverages online learning, drift detection, and reinforcement learning for optimization to continuously adapt to changing market dynamics. Min-Max normalization, with RSI-based feature extraction techniques, is included to make learning more efficient and prediction more accurate.

**Research Organization:** The research work is structured into five sections. In Section 1, the introduction and background of financial time-series forecasting are provided. Section 2 deals with a review of previous literature on stock market analytics with time-series forecasting. Section 3 discusses the methodology of ModO-Att-GRU, preprocessing, and feature extraction. Section 4 includes experimental results and performance analysis. The conclusion of the research work is discussed in Section 5.

## 2. Related Work

Implementation Domains and Significant Influence of Financial Time Series Prediction for Stock Analysis was developed in [9], using the Analysis of Convolutional Neural Networks (CNNs) to predict stock analysis. The performance is evaluated with high prediction using different methods like error criterion, regression analysis, and visual representation, but there is a limitation in terms of insufficient financial data.The movement prediction of financial time series on stock market prediction was explored [10] with the help of an adaptive LSTM network with Batch Normalization (LSTM-BN). The performance of the modified adaptive LSTM for forecasting long-term financial data is better than before, with an improvement of 5-15% and other added benefits; the predictive ability of the LSTM network declines with the passage of time.Stock market prediction using an image-based time-series forecasting method was examined [11]. A Deep Convolutional Neural Network (DCNN) is used to forecast future events in financial markets, and the results show that an image-based time series forecasting model can outperform traditional or current models. The data generation mechanism for this series shows limited learning ability. The financial time series data is forecasted and classified using Generative Adversarial Networks (GANs) for stock market analysis in [12]. By implementing the GANs for stock market time series forecasting, the result obtains a probabilistic forecasting with GANs that surpasses LSTMs by providing higher accuracy and better estimations, complicated by the problem of optimization. Time series forecasting using an artificial electric field algorithm based on an elitist opposition algorithm for predicting stock market analysis was analyzed in [13], where Higher Order Neural Networks (HONNs) are used to predict stock levels. The accuracy achieved is 87.85% for closing stock prediction, but it suffers from limited data for stock prices. Improving the financial time-series forecasting ensemble by predicting the financial stock price was considered in [14] using the Adaptive Financial Reservoir Network with Hypernetwork Flow (AFRN-HyperFlow). The result shows an accuracy of 95% in detecting time-series forecasting, but fails when it comes to making decisions about stocks.The utilization of single multiplicative neuron models in the forecasting of time series for stock market analytics was discussed in [15]. The application of CNNs is stock market analytics and time series forecasting produced highly accurate and valuable information that helps to make decisions on the stock market. The issues encountered while using the CNN method and applying single multiplicative neuron models in forecasting time series.Application of trend forecasting and time series analysis of stocks for candlestick patterns, as well as sequence similarity for stock analysis, was conducted in [16]. By applying the LSTM algorithm for the accurate prediction of stocks, the model gets a result that achieves 50.71% accuracy for a stable stock market. Predicting using a pattern mining method in stock is limited.The comparative evaluation of the advanced AI models in Stock Price Analysis and Prediction to predict market price movements is presented in [17]. FinBERT, Generative Pre-trained Transformer (GPT-4), and Logistic

Regression (LR) were utilized to analyze stock prices based on financial time series data. It determined that LR performed better with 81.83% accuracy, FinBERT performed with 63.33% accuracy, and predefined GPT-4 performed with 54.19%. Although the main limitation of this methodology is the non-linear nature of the data, the successful application of these methodologies is likely due to effective feature engineering and regularization.

## 3. Methodology

Develop continuous learning that provides for more accurate predictions by making use of the Financial Time-Series Forecasting dataset within stock market analytics. Figure 1 shows the data acquisition to be carried out based on the Kaggle dataset of data and variables related to stock market analytics of Financial Data. The data preprocessing stage involves Min-Max normalization to scale the input data effectively. Feature extraction is performed using the Relative Strength Index (RSI) to capture stock market trends and reduce the impact of stock drift. The proposed model implements the ModO-Att-GRU model to enhance prediction performance and adaptability.

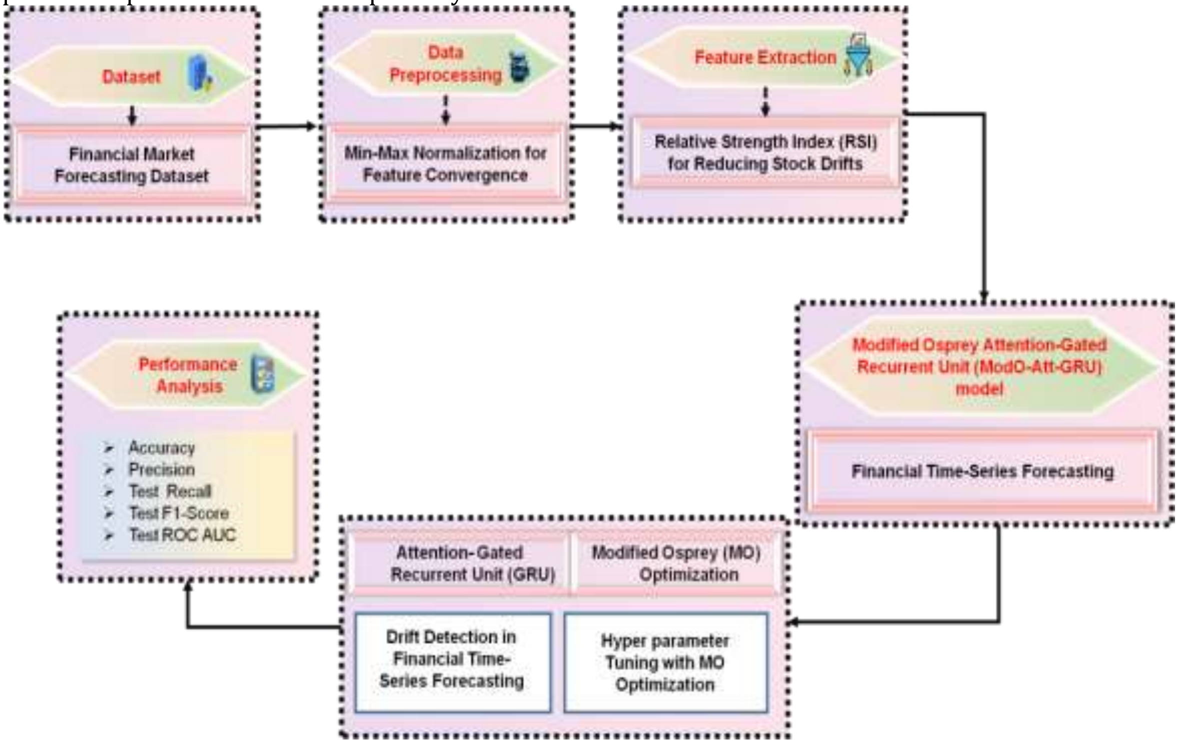


**Figure 1:** Methodology Workflow for Stock Market Analytics in Financial Time-Series Forecasting

### 3.1 Data Collection

The database utilized in this research is extracted from the Kaggle dataset repository (https://www.kaggle.com/datasets/zara2099/financial-time-series-forecasting-dataset/data). This database comprises structured financial time series data for stock market analysis based on OHLCV. A total of 4,000 records and 25 features comprising raw market prices, normalized features, technical indicators, and drift-based features for continuous learning analysis. The model is developed by splitting the data into 80% training data and 20% testing data. The design of this data helps in detecting drift and performing self-optimizing forecasts for a non-stationary market environment, which suits the proposed continuous learning-based method for robust stock market prediction.

### 3.2 Data Pre-processing using Min-Max Normalization

Min-Max Normalization is an important pre-processing technique required to deal with financial time-series data used in stock market analysis on the basis of highand low inputs. It comprises the collection of unprocessed historical financial data, which is highly volatile, non-stationary, and tends to change distributions due to strong drift in the financial time-series forecast. For the process phase, normalization techniques based on Min-Max are used for the normalization of each characteristic between [0, 1] to ensure uniformity and improve the feature convergence, as expressed in Equation (1).

$$Y_{new} = \frac{(Y-Y_{min})}{(Y_{max}-Y_{min})} \quad (1)$$

Where Y represents the values of financial features, $Y_{min}$ and $Y_{max}$ refer to the minimum and maximum stock prices in the dataset. $Y_{new}$ denotes the output obtained from this procedure is balanced and normalized data, which helps maintain time series pattern information while minimizing any potential scaling bias with fast feature convergence.

**3.3 Relative Strength Index (RSI) for Reducing Stock Drifts Trend Information in Time-Series Data**

The RSI is employed as the main technique for feature extraction to increase the efficiency of the trend representation and minimize the impact of drift. The input data for this algorithm includesraw price data obtained from the financial markets that are very volatile and non-stationary, causing significant changes in distribution, as expressed in Equations (2 and 3).

$$\mathrm{RSI} = 100 - \frac{100}{1+\mathrm{ST}} \qquad (2)$$

$$\mathrm{ST} = \frac{\mathrm{AverageGainOverpast\ 14\ days}}{\mathrm{AverageLossOverpast\ 14\ days}} \qquad (3)$$

Where RSI refers to the Relative Strength Index for technical characteristics that exist from 0 to 100, for more accurate determination of overbought and oversold states, making the RSI technique adaptive and minimizing the chances of mistakes while making forecasts under variable circumstances. ST refers to the moment when the technical indicator translates raw price movements into momentum factors, increasing the efficiency of technical features that are sensitive to the drift phenomenon. In Equation (3), $\frac{\mathrm{AverageGainOverpast\ 14\ days}}{\mathrm{AverageLossOverpast\ 14\ days}}$ denotes the processing phase, the value of the RSI is calculated within 14 days to measure momentum.

**3.4 Financial Time-Series Forecasting using Continuous Learning with Modified Osprey Attention-Gated Recurrent Unit (ModO-Att-GRU) model**

The proposed framework employs a Modified Osprey Attention-Gated Recurrent Unit (ModO-Att-GRU) model for continuous learning in financial time-series forecasting using OHLCV (Open, High, Low, Close, and Volume) stock market data. The ModO-Att-GRU method uses adaptive parameter optimization for efficient learning and accurate predictions. The GRU model discovers long-term temporal dependencies in the past financial data. Both models together help increase adaptability and accuracy, prevent model drift, and ensure that forecasts are accurate.

**Attention-based Gated Recurrent Unit (Att-GRU):** The developed hybrid architecture consists of an attention gating process that incorporates gated recurrent units to enhance the prediction analysis of time series data associated with financial applications in stock markets. This hybrid system enables the extraction of appropriate dependencies based on OHLCV indicators and RSI. The use of this hybrid model improves feature learning, is less prone to noise, and provides adaptability for accurate predictions.

**Attention Mechanism for Stock market temporal dependencies:** An attention mechanism is employed to enhance the accuracy of financial time-series forecasting by identifying and emphasizing the most relevant temporal dependencies within stock market data. This mechanism assigns greater importance to critical features, including OHLCV indicators and RSI values, thereby improving predictive performance. This helps the model to detect market volatility and to improve its prediction performance, as expressed in Equation (4).

$$\mathrm{d_s} = \alpha_s \mathrm{g} \qquad (4)$$

Where $\mathrm{d_s}$ indicates the context-augmented stock hidden state, with $\alpha_s$ being the attention coefficient at the time step s, and g as the input feature vector based on OHLCV and RSI stock market inputs that conform to the goal of accounting for important time dependencies in financial time-series prediction, as expressed in Equation (5).

$$\mathrm{b_s} = \mathrm{softmax}(\mathrm{score}(\mathrm{t_{s-1}}, \mathrm{g})) \qquad (5)$$

$\mathrm{b_s}$ refers to the scaled attention value through softmax on the compatibility function stock $\mathrm{softmax}(\mathrm{score}(\mathrm{t_{s-1}}, \mathrm{g}))$, with $\mathrm{t_{s-1}}$representing the last maximum hidden stock state and g being the input feature stock vector.

**Gated Recurrent Unit (GRU) for Drift Detection in Financial Time-Series Forecasting**

The proposed research includes the utilization of GRU as an essential sequential learning component in the detection of drift in financial time series forecasting using OHLCV data from stock markets. The input here is non-stationary financial data that exhibits dependence on past trends, thus indicating the temporal stock nature of the problem. During the process phase, GRU uses two forms of gating techniques,update gate and reset gate, to capture short and long-term dependencies without any loss of information, as expressed in Equations (6 and 7).

$$\mathrm{r_t} = \sigma(\mathrm{W_r}.[\mathrm{h_{t-1}}, \mathrm{X_t}]) \qquad (6)$$

$$\mathrm{z_t} = \sigma(\mathrm{W_z}.[\mathrm{h_{t-1}}, \mathrm{X_t}]) \qquad (7)$$

Where $\mathrm{r_t}$ represents the reset gate stock value, $\mathrm{W_r}$ stands for the reset stock weight matrix, $\mathrm{h_{t-1}}$ is the hidden state from the past with stock market OHLCV trend values, $\mathrm{X_t}$ denotes the stock input value at time t, and σ refers to the sigmoid function, in Equation (5) $z_t$ is the update gate stock value, $W_z$ is the update gate stock weight matrix, and its main purpose is to control the amount of past stock information compared to OHLCV information, as expressed in Equations (8 and 9).

$$\widehat{h_t} = \tanh(w_{\hat{h}}.[r_t * h_{t-1}, X_t]) \quad (8)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \widehat{h_t} \quad (9)$$

Where $\widehat{h_t}$ refers to the candidate hidden state, tanh denotes the tangent of a candidate state stock weight matrix $w_{\hat{h}}$, and the combination of reset-modulated past stock memory along with current financial input. $r_t$ represents the reset gate stock value, and $h_{t-1}$ is the hidden state from the past with stock market OHLCV trend values. $X_t$ denotes the stock input value at time t. In Equation (9), the $h_t$ is the final hidden stock state that represents updated memory of stock markets that integrate past OHLCV behavior with new stock information according to the update gate stock control. $z_t$ is the update gate stock value, as expressed in Equation (10).

$$\widehat{y_t} = \sigma(W_o.h_t) \quad (10)$$

$\widehat{y_t}$ is the predicted stock output for the financial trend or drift state, whereas $W_o$ is the output stock weight matrix from the hidden representation to the predicted output with the σ sigmoid function. $h_t$ is the final hidden stock state that represents updated memory of stock markets that integrate past OHLCV behavior with new stock information according to the update gate stock control.

**Hyperparameter Tuning with Modified Osprey (MO) Optimization:**This research work utilizes MO Optimization in the hyperparameter tuning process of self-optimizing financial time series forecasting through OHLCV datasets. In this regard, the data input comprises drift-laden and non-stationary financial datasets, whereby the proper setting of the model parameters is crucial for predictive stability under ever-changing market conditions. As part of the process stage, the MO optimization technique improves upon the traditional Osprey optimizer by introducing chaos-based search behavior and Gaussian mutation into the optimization scheme, as expressed in Equation (11).

$$r_k = a p_j^2 \sin(\pi p_j) \quad (11)$$

Where $r_k$ indicates the chaotic search component that helps in diversifying the hyperparameter search space based on the changes in the OHLCV market dynamics. a is the parameter responsible for controlling the chaos that affects the level of exploration during optimization. $p_j$is the stands for the present chaotic variable state that leads to the generation of non-linear searches. $\sin(\pi p_j)$ adds randomness into the system, as expressed in Equation (12).

$$p_0 \in [0,1], a \in (0,4] \quad (12)$$

Where, $p_0 \in [0,1]$ refers to the initial chaotic value used between 0 and 1 to begin the stock price search process. $a \in (0,4]$ denotes the chaos parameter that varies between 0 and 4, which controls the dynamics of the chaotic stock sequence, as expressed in Equation (13).

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (13)$$

g(x) is a Gaussian Probability Density Function that is utilized for generating financial mutations while performing optimizations. x stands for the finance mutation value used on the hyper-parameter solution. μ indicates the average value of the Gaussian distribution, representing the central tendency of generating financial mutations. σ stands for the standard deviation of mutations. exp(·) calculates the probability for generating finance mutations about the mean value, as expressed in Equation (14).

$$Y_{i,j}^{MOP} = Y_{i,j} \times (1 + k \times g(0,1)) \quad (14)$$

Where, $Y_{i,j}^{MOP}$ refers to the finance mutated value of the hyperparameter as produced using the MO optimization method.$Y_{i,j}$is the value of the hyperparameter before the finance mutation takes place. $k$ is the mutation constant used to determine the strength of parameter modification. $g(0,1)$ is a Gaussian value taken from the standard distribution of values. Multiplying $k$ and $g(0,1)$ to produce a mutated value of the hyperparameter. The output of the optimization procedure provides dynamic tuning of the hyperparameters to provide better convergence and greater adaptability towards drifts for improvement of overall ModO-Att-GRU performance in continuous finance prediction scenarios.

**Hyperparameter of proposed (ModO-Att-GRU):** The proposed ModO-Att-GRU model for stock market time series forecasting employs an optimized hyperparameter configuration, which guarantees a stable learning process, faster convergence, and improved drift learning capabilities for OHLCV-based stock market analytics. For optimizing learning, the proposed model exploits the Adam optimization technique with a learning rate equal to 0.001, a batch size of 64, and 100 training epochs to achieve fast convergence and stability. Moreover, in the case of the optimization method for modified Osprey, there are 30 members and 50 iterations of evolutionary optimization that provide adaptability to drift awareness.

## 4. Results

The proposed ModO-Att-GRU-based continuous learning method exhibits well performance for financial time series prediction when using OHLCV data from the stock markets in terms of detecting drifts in non-stationary conditions. Table 1 depicts the Hardware and software configuration used for implementing and evaluating the proposed ModO-Att-GRU-based financial time-series forecasting system.

**Table 1: Experimental Setup**

| Component | Specification |
|---|---|
| CPU | Intel Core i7 |
| RAM | 16 GB |
| GPU | NVIDIA GeForce RTX 3060 |
| Operating System | Windows 11 (64-bit) |
| Programming Language | Python 3.11 |
| Development Environment | Jupyter Notebook |
| Framework | TensorFlow 2.x |
| Libraries | Scikit-learn, Pandas, NumPy, Matplotlib |

**4.1 Exploratory Data Analysis:** The relationship between variables in the stock feature space is presented in Figure 2, which shows the multivariate for stock market time-series prediction. The distribution of the stock price, scaled volume, and prediction confidence level on the diagonals of the time series, and their linear correlation and multimodal distributions are highlighted using the off-diagonals.

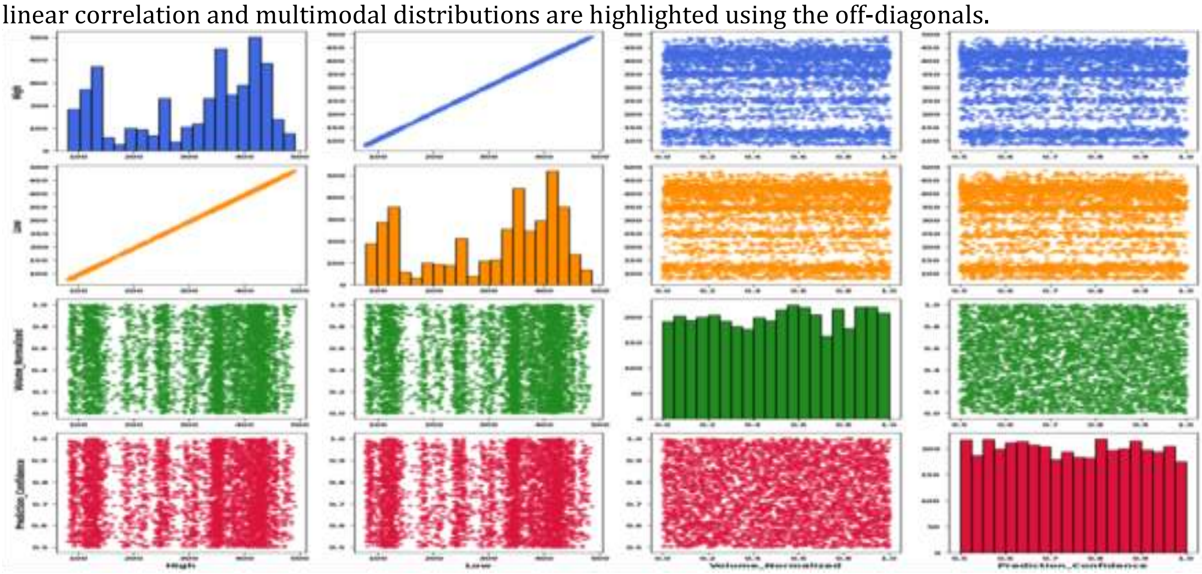

**Figure 2:**Self-Supervised Financial Drift Identification and Multi-Modality Feature Analysis

Figure 3(a) presents the dynamic evolution and variance distribution of standardized price series (Open Norm, High Norm, LowNorm, CloseNorm) in an ongoing series of 300 consecutive observations. Changes in the size of the bands reflect volatility regimes at the macro level, which are critical in terms of market spread restrictions for adaptive forecasting. Figure 3(b) shows the optimization control parameters such as RSI, Drift Score, Adaptive Learning Rate, Meta Learning Score, Convergence Rate, and Prediction Confidence influence. The near-zero values of off-diagonal coefficients confirm that the model is free from multicollinearity because of the orthogonality. Figure 3(c) depicts a trajectory of the stock's discrete returns for the cumulative gains of a portfolio. It is also useful in distinguishing the difference between short-term movements and long-term trends in stock finance, creating separate boundaries for risk predictions in extreme conditions. Figure 3(d) demonstrates a high-frequency time series analysis of the historical evolution of market structure drift on a multiyear macroeconomic scale. The volatility peaks and stochasticity in a big change in the distribution over time, and act as a trigger for automatic model training and adaptive hyperparameters.

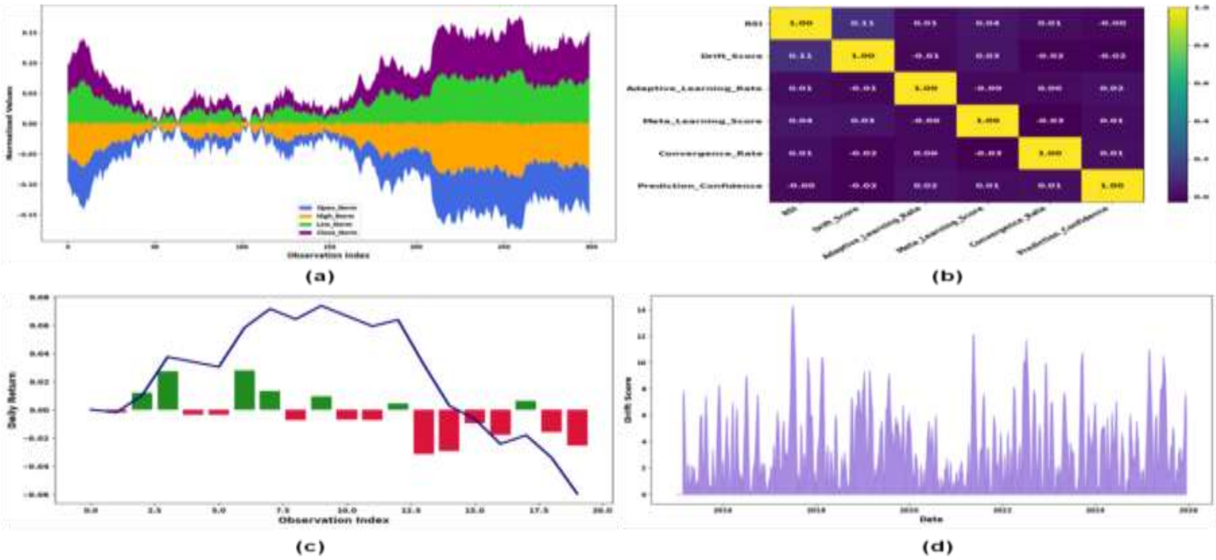


**Figure 3:**Data Visualization of (a) Standardized Price Series Evolution, (b) Correlation Analysis of Drift Prediction Features, (c) Financial Trend Dynamics, and (d) Historical Market Structure Evolution

**4.2 Performance Evaluation:** The ModO-Att-GRU-based continuous learning model is tested based on the OHLCV stock market dataset with an emphasis on detecting drift in a non-stationary financial dataset. The accuracy shows the overall stock market analytic prediction accuracy of the models, while precision is used to evaluate the model's prediction power of positive market movements. The test recall indicates the sensitivity of the model to detect real changes in markets, while the test F1-score helps balance the precision of positive market movements and the recall of real changes in markets for robust testing. The test ROC-AUC indicates the discriminative power of the stock market models.

Table 2 and Figure 4 present the comparison analysis of existing and the proposed methods, and the existing methods of the GPT Predefined Approach [17] achieve a low accuracy for the time-series forecasting. The FinBERT [17] method shows a high accuracy of stock prediction compared to the GPT Predefined Approach. The LR [17] method achieves a high accuracy of the stock drift prediction, with its prediction stability higher than the previous existing methods. The proposed ModO-Att-GRU model shows a better performance with a high accuracy of 93.85%, a precision of 93.42%, a test Recall of 94.10%, a test F1-Score of 91.79%, and a test ROC-AUC of 95.08%.

**Table 2:** Comparison Analysis of Existing and Proposed Methods

| Metrics | Accuracy (%) | Precision (%) | Test Recall (%) | Test F1 Score (%) | Test ROC-AUC (%) |
|---|---|---|---|---|---|
| GPT Predefined Approach [17] | 54.19 | 72.66 | 45.09 | 32.69 | 65.37 |
| FinBERT [17] | 63.33 | 63.76 | 63.33 | 63.30 | 65.59 |
| LR [17] | 81.83 | 82.57 | 81.15 | 81.85 | 89.76 |
| ModO-Att-GRU [Proposed] | 93.85 | 93.42 | 94.10 | 91.79 | 95.08 |

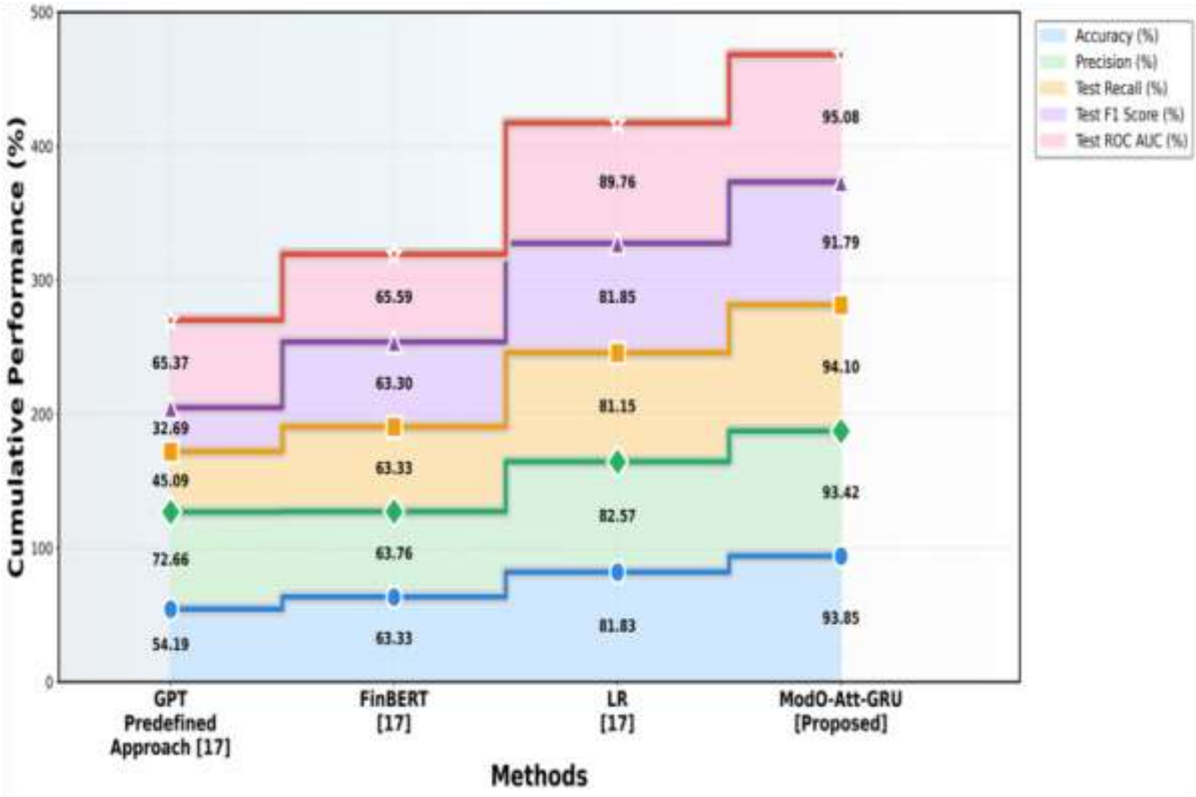


**Figure 4:**Performance Comparison of Existing Methods and Proposed ModO-Att-GRU Model

**4.3 Discussion:** Propose a model for developing a continuous learning method for predicting financial time series based on OHLCV stock market data that incorporates drift detection capabilities in current methods, such as GPT, FinBERT, and LR. The GPT Predefined Approach [17], with flaws like overly conservative probability distribution, high requirements in terms of computation resources, and low relevance to the finance area, is also unable to deal with the problem of the nonlinear nature and non-stationarity in financial data. The FinBERT [17] method lacks the high requirements for computing resources, and the LR [17] model is not very effective when it comes to financial predictions. To tackle the identified problems, the proposed ModO-Att-GRU model integrates online learning, attention, and MO optimization for drift detection. The RSI-based feature extraction helps to detect changes in the market environment, leading to improved efficiency and accuracy in forecasting.

## 5. Conclusion

This research accomplished the goal of developing the self-optimizing learning model with the proposed ModO-Att-GRU model for the purpose of financial time series forecasting. The data collection from the stock market to be done to facilitate preprocessing and minimize drift through RSI.It includes enabling the adaptive and continual learning of stock market is dynamics while preventing drift through the use of attention-based feature selection and optimization techniques that utilize reinforcement. The proposed ModO-Att-GRU Model detects the drifts for the stock market analytics in time series forecasting. The experimental results obtained an accuracy of 93.85%, a precision of 93.42%, a test recall of 94.10%, a test F1-score of 91.79%, and a test ROC-AUC score of 95.08%. Limitations include reliance on data quality and computational complexity when making online updates. The model varies performance levels during extreme drifts in the stock market. Future research focuses on incorporating multi-source financial data and transformer-based architectures.

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