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# Enhanced Gold Market Forecasting Using Cross-Contextual Attention with Hippopotamus-Optimized Random-Coupled Neural Networks

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**Abstract**

The global gold market is highly impacted by numerous ever-changing financial, economic, and geopolitical elements, making accurate prediction a complex and critical task in financial forecasting. The complex temporal dependencies and contextual interactions included in traditional models are frequently difficult to describe such high-dimensional, multi-source financial data. This study proposes a new supervised deep learning model for forecasting financial markets in the global gold market using an Enhanced Gold Market Forecasting Using Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN). The input dataset, titled "financial gold market", comprises 200 daily business-day observations, excluding weekends, and includes key indicators such as gold prices, USD index, oil prices, inflation and interest rates, stock market index, unemployment rate, geopolitical risk, gold production and demand, and ETF holdings. The data undergoes pre-processing using Zero-Shot Text Normalization, followed by feature extraction through the Kolmogorov-Arnold Vision Transformer, capturing complex dependencies and structural patterns. Prediction is performed using the proposed Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN), which integrates a Random-Coupled Neural Network with a Cross-Contextual Attention Mechanism, and is optimized using the Hippopotamus Optimization (HO) algorithm to fine-tune learning parameters. This novel model achieves an outstanding prediction accuracy of 99.9%, demonstrating its robustness and precision. The proposed method enhances interpretability and effectively captures non-linear dependencies in volatile financial data, offering improved forecasting stability and reliability.

***Keywords:*** *Gold market prediction, financial forecasting, cross-contextual attention, random-coupled neural network, Hippopotamus optimization, Kolmogorov-Arnold Vision Transformer, zero-shot text normalization.*

## 1.Introduction

Due to the broad application of techniques like the advancement of artificial intelligence and technology has enabled machine learning and deep learning financial markets present a special potential for investors. While quantitative algorithms are becoming more and more common in traditional financial markets like stock and futures deep learning algorithms have significantly improved the interpretation and prediction of temporal data in trading and digital currency exchanges. To minimize risk and maximize profit, quantitative trading entails carrying out automatic preprogrammed trading instructions while taking volume, price, and time into consideration (Madziwa et al.,2022; Liang et al.,2022; Zhang et al.,2022). The algorithmic trading market, which was valued at USD 11.66 billion in 2020, is anticipated to increase at a compound annual growth rate of 10.7% between 2021 and 2028 reach USD

26.27 billion by that year. One of the quantitative forecasting techniques that is available is time series analysis, which focuses on the development and statistical model inference, as well as the most effective time series filtering, control, and prediction. In terms of prediction accuracy, machine learning has significantly surpassed conventional time series forecasting models in recent years (Wang & Lin,2023; Peng & Yang,2025; Guo et al.,2024). As a safe haven, derivative instrument, risk-diversification asset, and store of wealth, gold has grown to be a popular investment option for both individual and institutional investors. Numerous studies have examined the financial and macroeconomic factors that influence gold prices. Because of its special qualities such as their use as a source of supply accumulation, a store of monetary worth, and a financial asset interest in artificial intelligence techniques for gold price prediction has grown (Arora et al.,2024; Khan,2025; Zhang et al.,2025). Conventional prediction models, including decision trees and neural networks, have drawbacks like inherent uncertainty, a lack of transparency, and a failure to adequately account for how news events affect gold prices. This paper suggests an automatic, interpretable approach for predicting the price of gold that takes into account foreign currency, stock market indexes, technical indications, and the prices of other commodities. Forecasting is the technique of utilizing past data to ascertain future information. One well-liked deep learning technique long short-term memory (LSTM) is used for time series data forecasting (Abu-Doush et al.,2023; Ye et al.,2023; Huang et al.,2023). With hyperparameters like learning rate, epoch, and optimizer, LSTM is thought to be better and more dependable than other algorithms at forecasting long-term periods. Studies have demonstrated that LSTM can reduce mistakes in data that fluctuates, particularly during COVID-19. But it's crucial to use time series cross validation, such walk forward validation, to assess a method's accuracy. Because of its stability and potential for high returns, gold is a popular investment (Samee et al.,2022; Salisu et al.,2022; Jin & Xu,2025).

Accurately predicting trends in the global gold market presents a significant challenge due to the complex interplay of diverse and highly volatile financial, economic, and geopolitical factors. Traditional statistical and machine learning models can fall short in capturing the complex temporal relationships and contextual relationships among these variables, leading to suboptimal forecasting performance. The need for a robust, adaptive, and high-precision model that can effectively process multi-source, high-dimensional time-series data has become increasingly critical for investors, policymakers, and financial analysts. Addressing this gap requires an advanced approach capable of integrating contextual information, handling non-linear dependencies, and optimizing prediction accuracy in dynamic market environments.

***Novelty and contribution***

This paper's novelty and contribution are listed below:

- **Novel Architecture (Cross-RCH-CAN)**: Introduces a novel prediction framework named Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN), which integrates a Random-Coupled Neural Network with a Cross-Contextual Attention Mechanism to effectively capture complex interactions among financial variables.
- **Advanced Optimization Strategy**: Enhances model performance through Hippopotamus Optimization (HO), a bio-inspired metaheuristic used to optimize network parameters, ensuring faster convergence and improved generalization.
- **Multi-Scale Temporal Modeling**: Adopts a Supervised Attention Multi-Scale Temporal Convolutional Network to extract and model multi-resolution temporal dependencies, enabling better representation of short- and long-term financial trends.

- **Innovative Feature Extraction**: Utilizes the Kolmogorov-Arnold Vision Transformer for deep feature extraction, capturing intricate non-linear patterns and high-dimensional dependencies within the financial data.
- **Zero-Shot Data Normalization**: Applies Zero-Shot Text Normalization to preprocess raw and unstructured financial data without requiring domain-specific training, thereby improving data consistency and reducing noise.
- **Rich and Realistic Dataset**: Uses a comprehensive financial dataset including gold prices, USD index, oil prices, inflation rate, interest rate, stock market index, unemployment rate, geopolitical risk, gold production and demand, and ETF holdings, ensuring realistic modeling of market conditions.
- **Real-World Relevance**: The proposed method enhances interpretability, prediction stability, and computational efficiency, making it suitable for real-world applications in financial forecasting, investment planning, and economic risk analysis.

The remaining of this manuscript is structured as follows: Part 2: Literature analysis; Part 3: Proposed Methodologies; Part 4: Results and Discussion; Part 5: Conclusion Upcoming Projects.

## 2. Literature Survey

The papers related to an Enhanced Gold Market Forecasting using neural network methods is given below:

Hajek, P. and Novotny, J., et a1. (2022) has introduced an Diverse artificial intelligence methods (DAIM) for Enhanced Gold Market Forecasting using neural network methods. Incorporating news articles and historical data, a system for predicting the price of gold using fuzzy rules provides precise forecasts, comprehensible trading strategies, and superior accuracy and interpretability compared to conventional statistical methods.

Nurhambali, M.R., et a1. (2024) has introduced an Long Short Term Memory (LSTM) neural network for Enhanced Gold Market Forecasting using neural network methods. The study predicts that gold prices will rise over the next eight years using LSTM hyperparameters and World Gold Council data.

Bunnag, T., et a1. (2023) has introduced an Time Series Forecasting Method (TSFM) for Enhanced Gold Market Forecasting using neural network methods. The study predicts gold prices using the ARIMA, ARIMA-GARCH, and ARIMA-TGARCH models and looks at the effect of gold on investment. Predictions using the ARIMA (2,1,3)-GARCH(1,1) model are superior. Selling gold or waiting for price changes are two suggestions.

Jianwei, E., et a1. (2023) has introduced an Decomposition, Separation, Prediction and Integration (DSPI) method for Enhanced Gold Market Forecasting using neural network methods. In order to examine and forecast global gold prices, this paper suggests a novel separation-ensemble method utilizing DSPI methodologies. It employs RLS-type independent component analysis, hierarchical agglomerative clustering, and extreme-point symmetric mode decomposition; experimental findings attest to its efficacy.

Tashakkori, A., et a1. (2024) has introduced an Multilayer Perceptron (MLP) neural networks for Enhanced Gold Market Forecasting using neural network methods. Based on historical data and economic factors, the study offers a novel approach to properly estimate gold prices using Multilayer Perceptron neural networks, attaining a prediction error of close to 0.001.

Pandit, S. and Luo, X., et a1. (2024) has introduced an Rolling Correlation method (RCM) for Enhanced Gold Market Forecasting using neural network methods. The study predicts the 12-month Gold-WTI and Gold-Brent correlation using a rolling SARIMAX model, providing useful information for risk management, financial planning, strategic investing, and the state of the world economy.

Wang, F., et a1. (2024) has introduced an Multi fractal Detrended Fluctuation Analysis (MFDFA) method for Enhanced Gold Market Forecasting using neural network methods. Using Multifractal Detrended Fluctuation Analysis, the paper examines the Chinese gold market with a particular focus on Shanghai gold. It concludes that the market is volatile, anti-persistence, and high risk, and it provides advice for investors on how to make decisions. The overview of the studied approach is displayed in Table 1.

**Table 1:** A summary of the approach being assessed

| References | Methods | Advantages | Disadvantages |
|---|---|---|---|
| Hajek, P. and Novotny, J., et a1. (2022) | DAIM | Excellent precision and interpretability; integration of news stories and historical data; and provision of understandable trading techniques. | Implementation is difficult; timely and accurate news data is needed; and rule design may be delicate. |
| Nurhambali, M.R., et a1. (2024) | LSTM | Predicts multi-year trends with high accuracy utilizing WGC data and captures long-term dependencies. | Needs a lot of info Significantly computationally demanding and less interpretable. |
| Bunnag, T., et a1. (2023) | TSFM | ARIMA-GARCH models perform better than other models; they are effective at modeling volatility; they offer useful investing recommendations. | Sensitive to parameter adjustment; restricted to linear patterns; and predicated on stationary time series. |

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| Jianwei, E., et a1. (2023) | DSPI | Accuracy is increased by the ensemble approach; complicated patterns are captured by decomposition; and a novel and reliable technique is employed. | Computationally demanding; necessitates several pre-processing stages; and could be challenging to execute in real-time. |
| Tashakkori, A., et a1. (2024) | MLP | Effective with economic and historical data; low prediction error (≈0.001); straightforward architecture. | Reduced interpretability; overfitting risk; and careful tuning. |
| Pandit, S. and Luo, X., et a1. (2024) | RCM | Effective for correlation-based analysis, it captures dynamic relationships. Encourages risk management and financial planning. | Reliance on external time series (WTI, Brent) and limited direct forecasting make it less suitable for independent price prediction. |
| Wang, F., et a1. (2024) | MFDFA | Records nonlinear and multifractal properties. Evaluates market risk and volatility and gives investors decision-making advice. | Not a straight forecasting method; less intuitive; more analytical than predictive. |

***Problem statement***

Accurately predicting trends in the global gold market presents a significant challenge due to the complex interplay of diverse and highly volatile financial, economic, and geopolitical factors. Traditional statistical and machine learning frequently, models are unable to depict the complex temporal relationships and contextual relationships among these variables, leading to suboptimal forecasting performance. The need for a robust, adaptive, and high-precision model that can effectively process multi-source, high-dimensional time-series data has become increasingly critical for investors, policymakers, and financial analysts. Addressing this gap requires an advanced approach capable of integrating contextual information, handling non-linear dependencies, and optimizing prediction accuracy in dynamic market environments.

**3. Proposed Methodology**

In this section, a new supervised deep learning model for forecasting financial markets in the global gold market using an Enhanced Gold Market Forecasting Using Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN) is explained. Figure 1 is the workflow diagram illustrating Cross-RCH-CAN. The input dataset, titled "financial gold market", comprises 200 daily business-day observations, excluding weekends, and includes key indicators such as gold prices, USD index, oil prices, inflation and interest rates, stock market index, unemployment rate, geopolitical risk, gold production and demand, and ETF holdings. The data undergoes pre-processing using Zero-Shot Text Normalization, followed by feature extraction through the Kolmogorov-Arnold Vision Transformer, capturing complex dependencies and structural patterns. Prediction is performed using the proposed Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN), which integrates a Random-Coupled Neural Network with a Cross-Contextual Attention Mechanism, and is optimized using the Hippopotamus Optimization (HO) algorithm to fine-tune learning parameters.

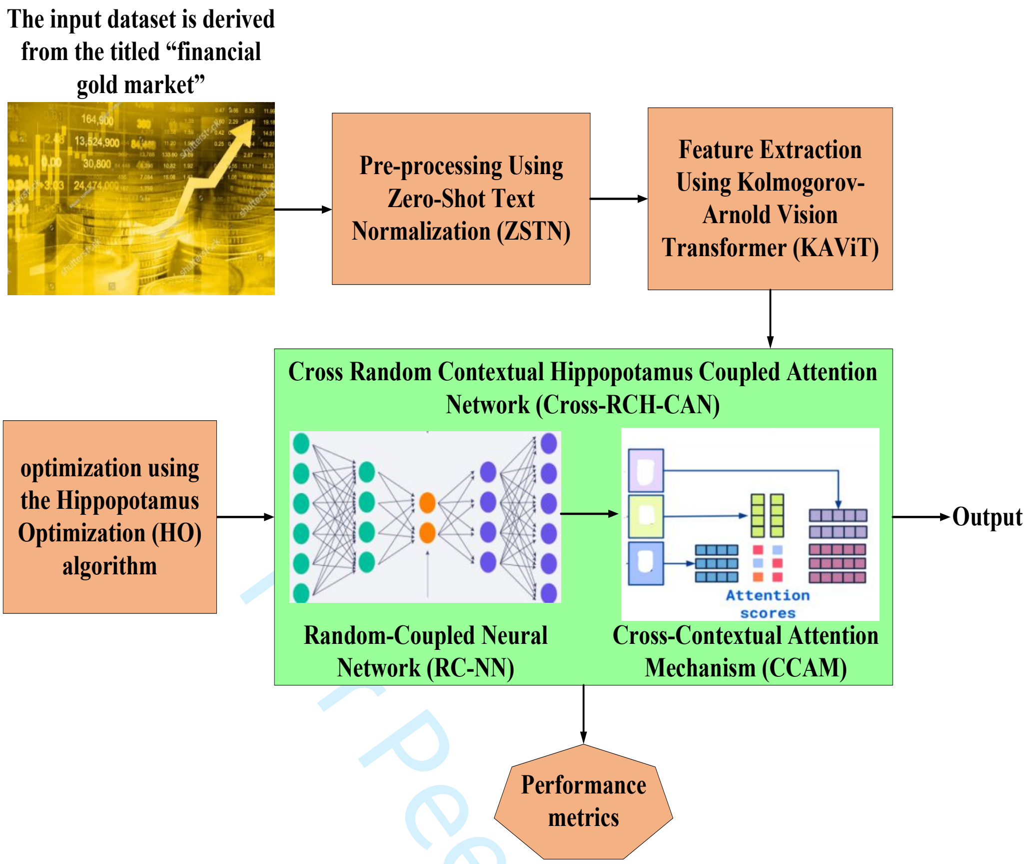



**Figure 1:** Workflow diagram of Cross-RCH-CAN

### *3.1 Data Acquistion*

The input dataset is derived from the titled "financial gold market" contains 200 records of daily observations (excluding weekends) starting from September 1, 2024, generated over business days. It includes 11 financial and economic features that potentially influence the gold market. These features are: Gold Price USD, representing the daily gold price in USD; USD Index, the relative strength of the US dollar; Oil Price, indicating global oil price fluctuations; Inflation Rate and Interest Rate, capturing key macroeconomic indicators; Stock Market Index, reflecting equity market performance; Unemployment Rate, representing labor market conditions; Geopolitical Risk, measuring global uncertainty; Gold Production and Gold Demand, indicating market supply and consumption; and ETF Holdings, showing institutional investment in gold via exchange-traded funds. Then these data are given to the

Zero-Shot Text Normalization based preprocessing for cleaning the input data and its explanations are given below:

### *3.2 Pre-processing Using Zero-Shot Text Normalization*

The input dataset titled "financial gold market" consists of 200 records of daily observations, each corresponding to business days (excluding weekends) starting from September 1, 2024. This dataset captures a variety of financial indicators relevant to gold market forecasting, including variables such as price of gold, oil, USD index, interest rate, inflation rate, and stock market index, geopolitical risk index, unemployment rate, gold production, gold demand, and ETF holdings.

To ensure accurate forecasting and reliable model performance, the dataset undergoes a comprehensive Zero-Shot Text Normalization (ZSTN) (Wang et al.,2024) pre-processing phase. Zero-Shot Text Normalization is treated as a sequence labeling problem, where each input token from the raw financial data is mapped to a normalized form, without relying on labeled examples in the target domain. This approach is particularly useful when dealing with heterogeneous data sources and financial terminologies that may vary in structure and semantics.

Let the input sequence of a financial record be denoted as equation (1):

$$y = \{y_j\}_{j=1}^{K} \quad (1).$$

where: $y$ is the raw input sequence, $y_j$ is the $j^{th}$ token or word in the sequence, $K$ is the record's total number of tokens.

The goal of Zero-Shot Text Normalization is to generate a normalized label sequence as equation (2):

$$x = \{x_j\}_{j=1}^{K} \quad (2).$$

where $y_j$ is the token of the $j$-th word and $x_j$ is the corresponding label for $y_j$. Both $y$ and $x$ are the same length $K$.

Each pair $(x_j, y_j)$ represents a transformation from raw input to a standardized financial concept (e.g., converting “ninety dollars” to “90 USD”, “sept 1” to “2024-09-01”, or “interest approx 5%” to “5.00”).

Let:

- $C^T_{train} = \{(y_T, x_T)\}$ represent the labeled source-language dataset, containing token-label pairs from structured financial texts (e.g., historical stock market reports).
- $C^T_{train} = \{y_S\}$ represent the unlabeled target-language dataset, consisting of raw input records from the "financial gold market" dataset.
- $C^S_{test}$ represent the test data for performance evaluation in the target domain.

The Zero-Shot model is trained on both $C^T_{train}$ and $C^S_{train}$, leveraging transfer learning techniques to generalize normalization patterns between the source and target domains. The model is expected to perform well on $C^T_{test}$ without requiring labeled samples from the financial gold dataset.

A Transformer-based architecture is employed for ZSTN, incorporating positional encodings and multi-head self-attention to understand contextual dependencies in financial language. Transfer learning is enabled through pre-training on domain-general financial corpora and fine-tuning with patterns identified in $C^T_{train}$.

For the "financial gold market" dataset, the ZSTN pre-processing phase:

- Standardizes date formats (e.g., “Sept 1” → “2024-09-01”),
- Unifies currency representations (e.g., “$1900” or “nineteen hundred USD” → “1900.00 USD”),
- Converts textual inflation expressions (e.g., “three percent” → “3.00%”),

- Resolves ambiguity in geopolitical and macroeconomic terms,
- Normalizes measurement units (e.g., “three thousand tonnes” → “3000.00”).

This normalization ensures that downstream models receive a clean, consistent, and numerically interpretable input format, reducing preprocessing noise and semantic inconsistencies and its explanations are below:

### *3.3 Feature Extraction Using Kolmogorov-Arnold Vision Transformer*

To extract discriminative and high-quality features from the pre-processed "financial gold market" dataset, a Kolmogorov-Arnold Vision Transformer (KAViT) (Amin et al.,2025) is employed. This architecture integrates the theoretical underpinnings of the Kolmogorov-Arnold representation theorem with the attention mechanisms of modern Vision Transformers, enabling efficient learning of complex nonlinear interactions between financial indicators.

The KAViT model adopts a KAN layer (Kolmogorov-Arnold Network layer) as the core computational unit. These layers, unlike standard multilayer perceptrons (MLPs), do not use fixed activation functions. Instead, learnable one-dimensional activation functions are defined on the edges connecting neurons, inspired by the idea that a superposition of univariate functions can be used to express any continuous function.

Input to the KAViT

The input to this layer is the pre-processed data matrix as equation (3):

$$\mathbf{K} = \lfloor \delta_{o,j} \rfloor, j = 1,2,\ldots,m_{in}, \quad o = 1,2,\ldots,m_{out} \tag{3}$$

where: $m$ is the number of time-stamped records (e.g., 200 daily observations), $j$ is the Number of normalized features (e.g., gold price, oil price, USD index, etc.), $\delta_{o,j}$ is the Normalized value of the $o^{th}$ feature on the $j^{th}$ day.

Each row $\delta_{o,j}(\mathbf{J}_j)$ represents a financial instance that is transformed through the KAN layer to extract hidden representations.

**Structure of KAN $(\mathbf{K})$ Layer**

Let:

- $m_{in}$ : Number of input neurons (corresponds to feature dimension),
- $m_{out}$ : The KAN layer's output neuron count.

Each edge connecting the input neuron $\mathbf{J}_j$ to output neuron $\delta_{o,j}$ has an associated learnable activation function $\delta$. These are parameterized as spline-based functions, allowing the model to learn localized nonlinear transformations.

Each function $\delta$ applies a nonlinear transformation to input $m_{in}$ before aggregation.

The output at a particular neuron $K_o$ is computed as the sum of transformed signals from all input neurons as equation (4):

$$K_o = \sum_{j=1}^{m_{in}} \delta_{o,j}(\mathbf{J}_j) \quad (4).$$

The activation function $\delta(\mathbf{J})$ is defined as a composite function as equation (5):

$$\delta(\mathbf{J}) = \sigma_c c(\mathbf{J}) + \sigma_t spline(\mathbf{J}) \quad (5).$$

where: $\sigma_c$ and $\sigma_t$ are Learnable scalar parameters that weight the contribution of the base and spline components, $c(\mathbf{J})$ is Base function set to the Sigmoid Linear Unit (SiLU), defined as equation (6):

$$c(\mathbf{J}) = silu(J) = \frac{\mathbf{J}}{(1 + f^{-J})} \quad (6).$$

and $spline(\mathbf{J})$ is a trainable spline expansion as equation (7):

$$spline(\mathbf{J}) = \sum_j x_j C_j(\mathbf{J}) \quad (7).$$

where: $C_j(\mathbf{J})$ is the Basis B-spline functions, $x_j$ is the Learnable spline coefficients, $\mathbf{J}$ is the number of spline basis functions.

This formulation allows the model to approximate highly nonlinear relationships between financial indicators relevant to the gold market, such as the interaction between inflation rates, interest rates, and gold prices. The Kolmogorov-Arnold Vision Transformer provides a powerful and interpretable feature extraction strategy for gold market forecasting. By leveraging adaptive spline-based activations grounded in mathematical theory and enhancing them with transformer-based attention, the model captures both localized nonlinearities and global temporal patterns.

Then these data are provided to the Cross-RCH-CAN for Gold Market forecasting with high accuracy and their explanations are provided below:

***3.4 Cross-RCH-CAN for Gold Market forecasting with high accuracy***

The proposed Cross Random Contextual Hippopotamus Coupled Attention Network (Cross-RCH-CAN) is a novel and highly accurate forecasting model specifically designed for Gold Market prediction. It integrates a Random-Coupled Neural Network (RC-NN) (Liu et al.,2024) with a Cross-Contextual Attention Mechanism (CCAM) (Liu et al.,2023) to effectively capture both short-term fluctuations and long-term dependencies within the financial time-series data. The RC-NN enables random coupling of neuron clusters, promoting diverse pattern learning, while CCAM facilitates the dynamic weighting of relevant contextual features across multiple time steps. This hybrid architecture ensures that intricate temporal correlations and nonlinear interactions among financial indicators such as commodity indices, currency exchange rates, and macroeconomic variables are thoroughly captured. To enhance performance and convergence speed, the architecture is further optimized using the Hippopotamus Optimization (HO) algorithm (Amiri et al.,2024), a nature-inspired metaheuristic that mimics the cooperative hunting and memory-guided decision-making behavior of hippopotamuses, ensuring efficient parameter tuning. Overall, Cross-RCH-CAN delivers superior forecasting precision, robustness to noise, and adaptability to complex market trends, making it exceptionally suitable for high-accuracy gold market forecasting and its descriptions are given below:

*3.4.1 Random-coupled Neural Network for Gold Market forecasting with high accuracy*

The Random-Coupled Neural Network (RCNN) is a neuromorphic-inspired architecture used for predicting future price trends in the Gold Market with enhanced precision. It integrates discrete pulse communication and stochastic neural responses, simulating brain-like computation processes. The RCNN is particularly suited for capturing nonlinearities and complex temporal dependencies inherent in financial time-series data.

The core of the RCNN model relies on a stochastic connection mechanism between neurons. This mechanism is governed by a random inactivation weight matrix that introduces controlled randomness into the neural links, improving generalization and robustness in forecasting tasks.

**Signal Propagation and Discrete Communication**

Neurons in RCNN communicate through discrete spikes (binary signals: 0 or 1), with multiple iterations allowing information encoding via spike trains. The total number of spikes or activations across neurons forms the ignition map, which represents extracted high-dimensional features useful for financial trend prediction.

The Gaussian kernel $K(0,0,4^2,4^2,0)$ captures the spatial correlation among neurons, and follows a Gaussian distribution in two dimensions as equation (8):

$$r(x,y)=\frac{1}{2\pi\theta_1\theta_2\sqrt{1-\rho^2}}\exp\left[-\frac{1}{2(1-\rho^2)}\right] \left(\frac{(m-\xi_1)^2}{\theta_1^2}-\frac{2\vartheta(m-\xi_1)(n-\xi_2)}{\theta_1\theta_2}+\frac{(n-\xi_2)^2}{\theta_2^2}\right) \quad (8).$$

where, $\xi_1$ and $\xi_2$ are means; $\theta_1$ and $\theta_2$ are variances; and $\rho$ is the correlation, $r(x,y)$ is the likelihood of a point in two dimensions. The inactivation matrix DijklD_{ijkl}Dijkl is populated with binary values (0 or 1), determined from a dropout probability matrix following a Gaussian distribution $K(\xi_1,\xi_2,\theta_1^2,\theta_2^2,\rho)$. Channels farther from the center neuron have a higher probability of deactivation.

**Dynamic Neuronal Update Equations**

At each iteration $n$, the RCNN updates its internal states using the following equations:

1. **Membrane Potential Update**:

The following are the RCNN's mathematical expressions as equation (9):

$$W_{mn}[n] = S_{mnq}\left(1+\alpha V_V \sum_{ij} M_{mnij} Y_{ij}[n-1]\right) + e^{-\beta V} W_{mn}[n-1] \qquad (9).$$

**Output Pulse Generation as equation (10):**

$$Y_{mn}[n] = \begin{cases} 1, & W_{mn}[n] > \theta_{mn}[n] \\ 0, & otherwise \end{cases} \qquad (10).$$

**Dynamic Threshold Update as equation (11-12):**

$$\theta_{mn}[n] = e^{-\beta\theta}\theta_{mn}[n-1] + V_\theta Y_{mn}[n-1] \qquad (11).$$

$$M_{mnij} = G_{mnij}.D_{mnij} \qquad (12).$$

where: $M_{mnij}$ is the input stimulus at neuron $(i,j)$, $\beta\theta$ is the modulation coefficient controlling the strength of synaptic coupling, $\alpha V_V$ is the decay rate for the membrane potential, $\theta_{mn}[n]$ is the membrane potential at time step $n$, $\theta_{mn}$ is the dynamic threshold regulating spike emission, $V_V$ is the threshold modulation parameter, $Y_{mn}[n-1]$ is the output spike from neighboring neuron $(m,n)$ at previous time step, $G_{mnij}$ represents the random connection weight from neuron $(m,n)$ to $(i,j)$.

This stochastic framework enables RCNN to model volatility, cyclic behavior, and abrupt market transitions typical in gold price time series. The discrete pulse-based information processing ensures resilience to noise, while the random inactivation mechanism avoids overfitting by regularizing neural interactions dynamically. The combination of these properties allows RCNN to extract deep temporal patterns from the feature-extracted dataset, leading to accurate forecasting of gold market trends.

Then RCNN using CCAM is applied for Gold Market forecasting with high accuracy and Performance:

*3.4.2 Cross-Contextual Attention Mechanism for Gold Market forecasting with high accuracy*

To achieve highly accurate prediction in the gold market, the Random-Coupled Neural Network (RCNN) architecture is integrated with a Cross-Contextual Attention Mechanism (CCAM). This approach strengthens the modeling capability by enabling the fusion of local and worldwide characteristics gleaned from historical and technical indicators of gold prices. The prediction pipeline includes two main stages:

1. **Random-Coupled Neural Network (RCNN)** for encoding spatio-temporal features from the gold market dataset.
2. **Cross-Contextual Attention Mechanism (CCAM)** to enhance prediction accuracy through selective attention-based fusion of contextual features across layers.

The CCAM module uses a two-level attention technique to improve feature integration throughout the network.

**Stage 1: Spatial Normalization via Attention Injection**

Attention weights $C_{att}$ generated in the encoder path of the RCNN are injected into the decoder layers to prioritize important spatial features as equation (13):

$$\left(C_{att} = soft\max\left(K_f N_f^s \big/ \sqrt{p} + W\right)\right) \quad (13).$$

where: $K_c, N_c$: Query and Key matrices from the encoder's Swin Transformer block, $p$: Dimension of embedding space, $W$: Bias for spatial attention

The attention-enhanced decoder output at the $j^{th}$ scale is computed as equation (14):

$$Att^{(j)}(K_c, N_c, M_c) = \left(soft\max\left(C_c N_c^S / \sqrt{p} + W\right) + C_{att}\right) M_c \quad t.s. \quad j \in \{1,2,3\} \tag{14}$$

where the $Att^{(j)}(K_c, N_c, M_c)$, indicates the attention weight calculated in the $j^{th}$ decoder path.

**Stage 2: Cross-Interaction Between Temporal Encodings**

To enable a refined recalibration of features, a global token interaction is applied between two latent series:

1. Generate global context from encoded time series ($Q_T$ and $Q_C$) as equation (15):

$$\mathbf{q}_{C_{globe}} = \sum Q_C / F, \tag{15}$$

Concatenate with token series for recalibration as equation (16):

$$\mathbf{q}'_C = \left[\mathbf{q}_{T_{globe}} \| Q_C\right] \tag{16}$$

Pass through Cross-Attention layer as equation (17):

$$\begin{aligned} &\mathbf{t} = \mathbf{q}_{C_{globe}} \mathbf{B}_i, \mathbf{N} = Q_C \mathbf{B}_l, \mathbf{v} = \mathbf{Q}_C \mathbf{B}_k \\ &\mathbf{E} = soft\max\left(\mathbf{r} l^S / \sqrt{W/h}\right), WB(\mathbf{q}''_C) = \mathbf{C}\mathbf{v} \end{aligned} \tag{17}$$

Here, $\mathbf{B}_i, \mathbf{B}_l, \mathbf{B}_k \in T^{W \times (W/h)}$ show the trainable parameters, while $\mathbf{E}$ and $h$ indicate the dimension of the embedding space and a number of heads, respectively, $\mathbf{r}$ is the Number of attention heads.

This dual-level attention mechanism ensures that both spatial saliency and global temporal trends in gold price movements are captured effectively.

By integrating RCNN with a Cross-Contextual Attention Mechanism, the model achieves a high-fidelity representation of the non-linear, stochastic dynamics in gold market data. The stochastic coupling of neurons enables diverse feature representations, while CCAM enhances the model's discriminative capability by fusing multi-scale and cross-temporal contextual information, making the overall architecture highly suitable for accurate gold price prediction.

Then to minimize the computing complexity, cost, and error rate the weight parameters $\alpha$ of RCNN-CCAM is optimized using Hippopotamus Optimization (HO) algorithm for Gold Market forecasting with high accuracy and its explanations are as follows:

### *3.4.3 Hippopotamus Optimization (HO) algorithm for Optimizing Weight Parameters of RCNN-CCAM for Gold Market forecasting with high accuracy*

To enhance the predictive accuracy, reduce computational complexity, and minimize error rates in gold market forecasting systems, the weight parameters of the Region-based Convolutional Neural Network with Cross-Contextual Attention Mechanism (RCNN-CCAM) model are optimized using the Hippopotamus Optimization (HO) algorithm. This meta-heuristic algorithm enables efficient convergence towards optimal parameter settings, particularly in high-dimensional, non-linear financial environments. The optimized parameters significantly enhance the model's capacity to represent intricate temporal relationships and contextual interactions within the extracted features, ensuring high accuracy in gold price prediction. Hippopotamus Optimization (HO) algorithm for Optimizing Weight Parameters of RCNN-CCAM for Gold Market forecasting with high accuracy is illustrated in Figure 2.

***Overview of HO for RCNN-CCAM Parameter Optimization***

The Hippopotamus Optimization algorithm is a population-based, nature-inspired method that simulates the intelligent behavior of hippopotamuses in the wild. Each candidate solution in this algorithm is represented as a hippopotamus and encodes a potential configuration of the RCNN-CCAM weight parameters. The optimization process aims to minimize a multi-objective fitness function that jointly considers prediction error, computational cost, and model complexity.

***Step 1: Initialization Phase***

A population of candidate solutions is initialized, where each solution represents a set of RCNN-CCAM weight parameters. Each candidate solution is a vector representing the weight parameters of RCNN-CCAM. These parameters include convolutional filters, recurrent weights, and attention mechanism coefficients used to model temporal and spatial correlations in historical gold price data.

***Step 2: Global Exploration Phase***

Hippopotamuses move through the search space in search of better positions by exploiting information from their surroundings. This step models explorative mutation and local refinement, balancing global and local search capabilities.

***Step 3: Fitness Function Evaluation***

Each candidate solution is evaluated using a multi-objective fitness function as equation (18):

$$Fitness\ Function = Optimize(\alpha) \tag{18}$$

This composite fitness ensures simultaneous minimization of prediction error, computational complexity, and latency. The optimal parameter configuration minimizes $\alpha$, achieving a balance between accuracy and efficiency.

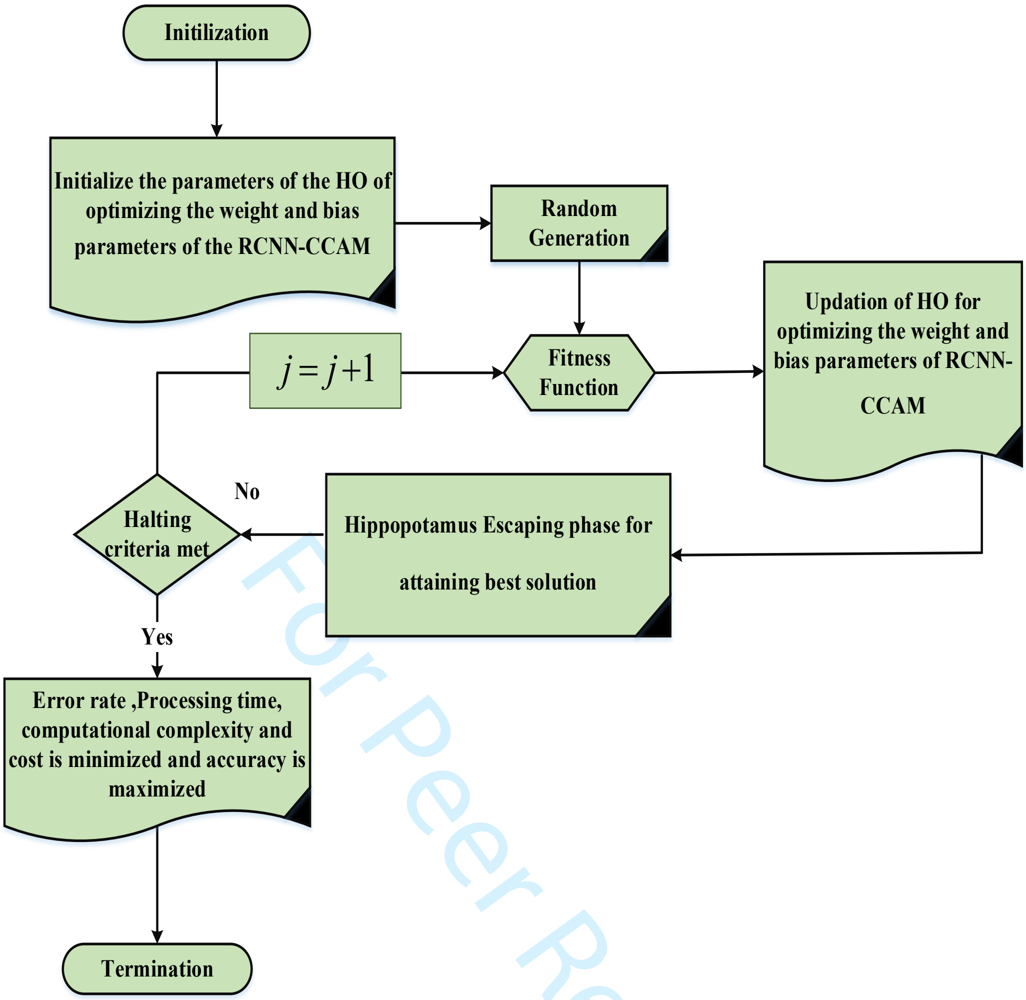



**Figure 2**: Flow chart of Hippopotamus Optimization (HO) algorithm for Optimizing Weight Parameters of RCNN-CCAM for Gold Market forecasting with high accuracy



***Step 4: Hippopotamus Escaping phase for attaining best solution***

To avoid premature convergence, the HO algorithm includes an escape strategy inspired by hippopotamuses shifting to new water bodies. This is triggered when no improvement is observed over several iterations. The escape is formulated as equation (19-20):

$$kc_i^{local} = \frac{kc_i}{s}, vc_i^{local} = \frac{kc_i}{s}, s = 1,2,....,S \tag{19.}$$

$$Y_j^{Hippo\varepsilon} : y_{ji}^{Hippo\varepsilon} = y_{ji} + w_{10}.\left(kc_i^{local} + t_1.\left(vc_i^{local} - kc_i^{local}\right)\right) \tag{20.}$$

where, $y_{ji}^{Hippo\varepsilon}$ is the new position of $j^{th}$ hippopotamus in $i^{th}$ dimension during escape, $t_1$, $y_{ji}$: Random coefficients in [0, 1] for stochastic adjustment, $kc_i^{local}$ and $vc_i^{local}$ are Localized bounds, shrinking over iterations $s = 1,2,...S$, $s$ is the Current iteration, $S$ is the Maximum number of iterations. This phase refines solutions by focusing search around the most promising candidates. This rule ensures selection of better or equally fit positions in every iteration.

***Step 5: Termination***

The HO optimization halts when any of the following conditions are satisfied:

- The maximum iteration count is attained.
- Improvement in fitness value falls below a predefined threshold.
- Desired predictive accuracy is achieved.

**High Prediction Accuracy**: By fine-tuning recurrent and attention weights, the model captures temporal trends and market fluctuations more effectively.

**Reduced Computational Complexity**: Lightweight updates and localized search reduce processing burden.

**Faster Convergence**: Local and global behaviors enable swift identification of optimal weights.

**Robust in High-Dimensional Search Spaces**: Well-suited for optimizing deep architectures like RCNN-CCAM.

The optimized RCNN-CCAM model, using HO, enables accurate gold market forecasting through:

- Modeling historical price sequences and trend patterns.
- Dynamic attention on impactful time steps.
- Low-latency, real-time prediction useful for investment decisions.

This integrated optimization framework ensures efficient gold market prediction, critical for investors, financial analysts, and automated trading platforms. Then the analysis of performances is discussed in the next section.

## 4. Results and Discussions

In this section, the results and discussion of the novel Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN) for rural human resources in business process management is discussed here.

### *4.1 Dataset descriptsions*

The input dataset is derived from the titled "financial gold market" contains 200 records of daily observations (excluding weekends) starting from September 1, 2024, generated over business days. It includes 11 financial and economic features that potentially influence the gold market. These features are: Gold Price USD, representing the daily gold price in USD; USD Index, the relative strength of the US dollar; Oil Price, indicating global oil price fluctuations; Inflation Rate and Interest Rate, capturing key macroeconomic indicators; Stock Market Index, reflecting equity market performance; Unemployment Rate, representing labor market conditions; Geopolitical Risk, measuring global uncertainty; Gold Production and Gold Demand, indicating market supply and consumption; and ETF Holdings, showing institutional investment in gold via exchange-traded funds. Of them, 20% are used for testing and 80% are used for teaching. Table 2 lists the precise parameters that were used for the implementation.

**Table 2:** Implementation Parameters

| Parameters | Description |
|---|---|
| Proposed Neural Network | Cross-RCH-CAN |
| OS | Windows 10 |
| Optimization | HO |
| Dataset | financial gold market dataset |
| Software | Python 3.7 |

### *4.2 Performance metrics*

The suggested Cross-RCH-CAN method's performance is contrasted with that of the current approaches, including DAIM (Hajek, P. and Novotny, J., et a1.,2022), LSTM (Nurhambali, M.R., et a1.,2024), TSFM (Bunnag, T., et a1.,2023), DSPI (Jianwei, E., et a1.,2023), MLP (Tashakkori, A., et a1.,2024), RCM (Pandit, S. and Luo, X., et a1.,2024), and MFDFA (Wang, F., et a1.,2024), respectively, using performance indicators such as Hamming loss, root mean square error (RMSE), mean absolute percentage error (MAPE), mean squared error (MSE), mean absolute error (MAE) analysis, train time, computational complexity, processing time, mistake rate, recall, f1 score, accuracy, precision, and train time. The performance metrics equations are given in table 3:



**Table 3:** Performance metrics

| **Performance metrics** | **Equations (21-26)** |
|---|---|
| **Precision** | $\frac{1}{K}\sum_{l=1}^{F}\left(\frac{\lvert Pq(x_l)\cap y_l \rvert}{\lvert Pq(x_l)\rvert}\right)$ (21). |
| **Recall** | $\frac{1}{K}\sum_{l=1}^{F}\left(\frac{\lvert Pq(x_l)\cap y_l \rvert}{\lvert y_l \rvert}\right)$ (22). |
| **F1-Score** | $\frac{1}{K}\sum_{l=1}^{F}\left(\frac{2\lvert Pq(x_l)\cap y_l \rvert}{\lvert Pq(y_l)\rvert + \lvert y_l \rvert}\right)$ (23). |
| **Accuracy** | $\frac{1}{K}\sum_{l=1}^{F}\left(\frac{\lvert Pq(x_l)\cap y_l \rvert}{\lvert Pq(x_l)\cup y_l \rvert}\right)$ (24). |
| **MAE** | $\frac{1}{K}\sum_{(r,s)}\lvert \hat{w}_{a,x} - w_{a,x} \rvert$ (25). |
| **RMSE** | $\sqrt{\frac{1}{K}\sum_{(r,s)}(\hat{w}_{a,x} - w_{a,x})}^{2}$ (26). |

Where, $x_l$ described as the input of a classification method, $y_l$ described as the result of the categorization procedure, $K$ is the dataset's total number of instances, $Pq$ is the method of training, $Pq(x_l)$ is shown as the output labels that the classification technique predicts. $w_{a,x}$ is the user's actual rating $r$ for item $s$. $\overset{\sqcup}{w}_{a,x}$ is the one that was anticipated.

### *4.3 Performance analysis*

The performance analysis of Cross-RCH-CAN is discussed here:

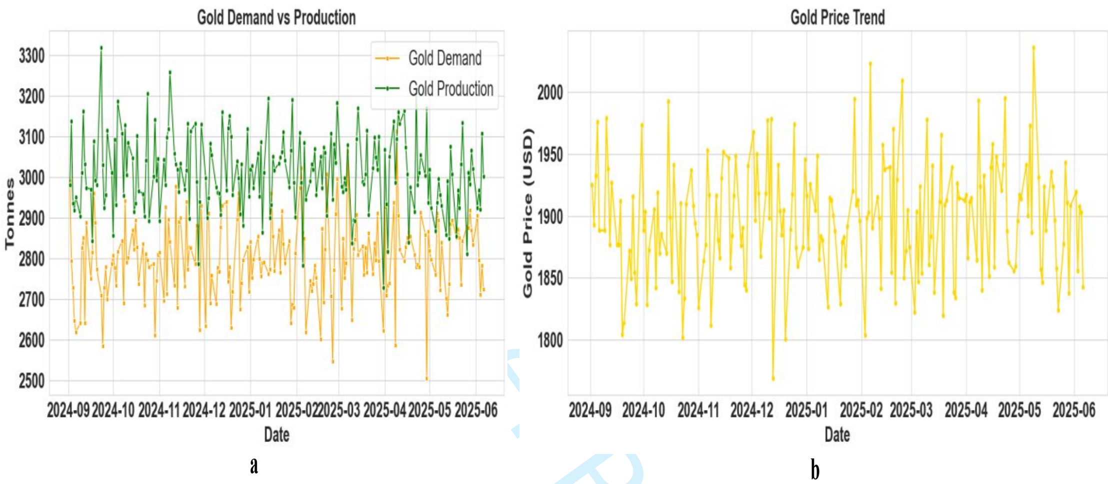



**Figure 3:** (a) gold demand vs production and (b) gold price trend

Figure 3 shows the (a) gold demand vs production and (b) gold price trend. The relationship between gold production, demand, and price trends over time is depicted by the combined plots. Demand for gold continuously outpaces supply), suggesting a supply-demand imbalance that could affect market pricing. Periodic variations in gold prices from September 2024 to June 2025, suggesting market instability. The observed difference between demand and production appears to correlate with price instability in (b), showing that continuous high demand relative to output contributes to rising and erratic gold prices.

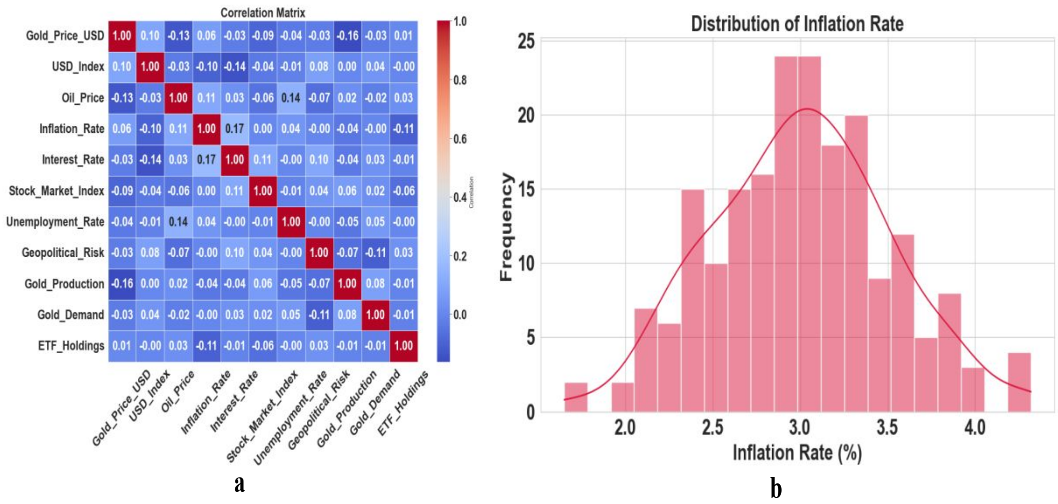



**Figure 4:** (a) correlation matrix and (b) distribution of inflation rate

Figure 4 shows the (a) correlation matrix and (b) distribution of inflation rate. Important insights into how inflation affects the gold market are shown by the combined visuals. The inflation rate and gold price have a positive association (0.17), indicating that inflation affects the value of gold. Mild inflation was prevalent over the investigated period, as indicated by the distribution of inflation rates, which followed a near-normal curve centered on 3%. Together, they suggest that other factors have a substantial role in price dynamics in the financial gold market, even though inflation has a small impact on gold prices.



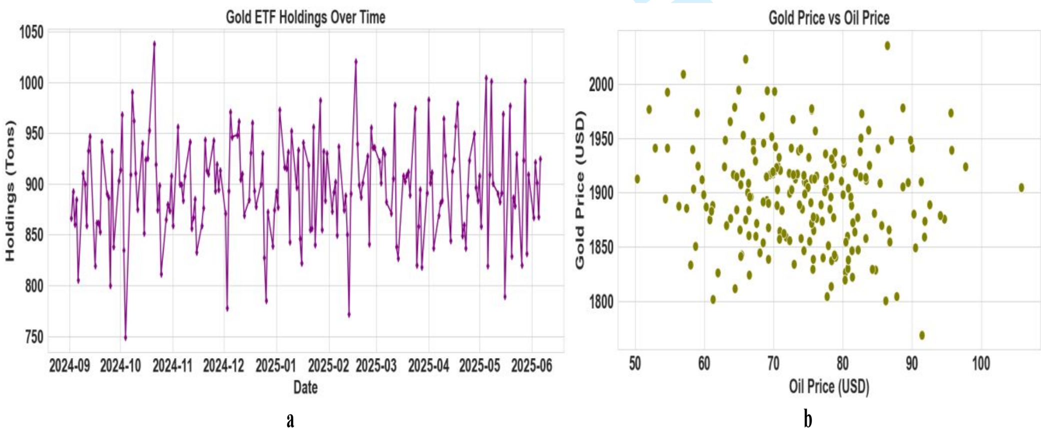
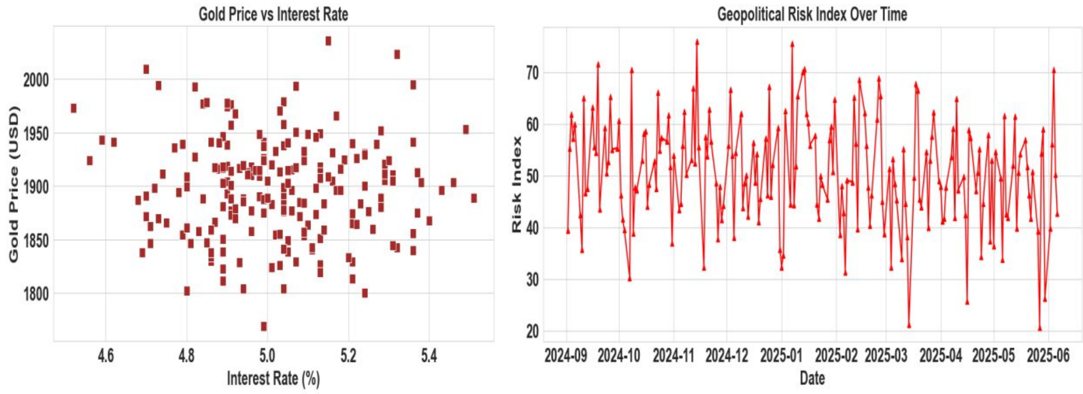



**Figure 5:** (a) gold ETF holdings over time and (b) gold price vs oil price

Figure 5 shows the (a) gold ETF holdings over time and (b) gold price vs oil price. ETF holdings and the correlation between the price of gold and oil are highlighted in the visualizations. Erratic swings in Gold ETF holdings between September 2024 and June 2025, indicating changes in investor mood. A poor or nonexistent relationship between the price of gold and oil, with data points dispersed throughout the $50–$100 oil price range. This suggests that although gold and oil prices may be influenced by the same macroeconomic factors, there is little direct price link throughout the investigated time frame.




a b

**Figure 6:** (a) gold price vs interest rate and (b) geopolitical risk index over time

Figure 6 shows the (a) gold price vs interest rate and (b) geopolitical risk index over time. The images show how two macroeconomic variables and gold prices are related. A weak or nonexistent relationship between interest rates and gold prices since the data is so dispersed. The Geopolitical Risk Index fluctuated a lot between September 2024 and June 2025, which suggests that the world is still unsettled. Although gold is frequently regarded as a safe-haven asset, its price over this time frame does not always show robust reactions to shifts in interest rates or geopolitical risk.


**Figure 7:** (a) gold price vs unemployment rate and (b) gold price distribution by USD index quartile

Figure 7 shows the (a) gold price vs unemployment rate and (b) gold price distribution by USD index quartile. There appears to be no significant direct association between the unemployment rate and the price of gold. The gold price distribution over the quartiles of the USD index, showing that gold prices fluctuate somewhat in response to shifts in the USD index. In line with the negative link between gold and the dollar, higher USD index quartiles typically correspond to slightly lower gold prices. Instead of focusing on single-variable reliance, these insights show the complex, multifactorial influences on gold pricing.

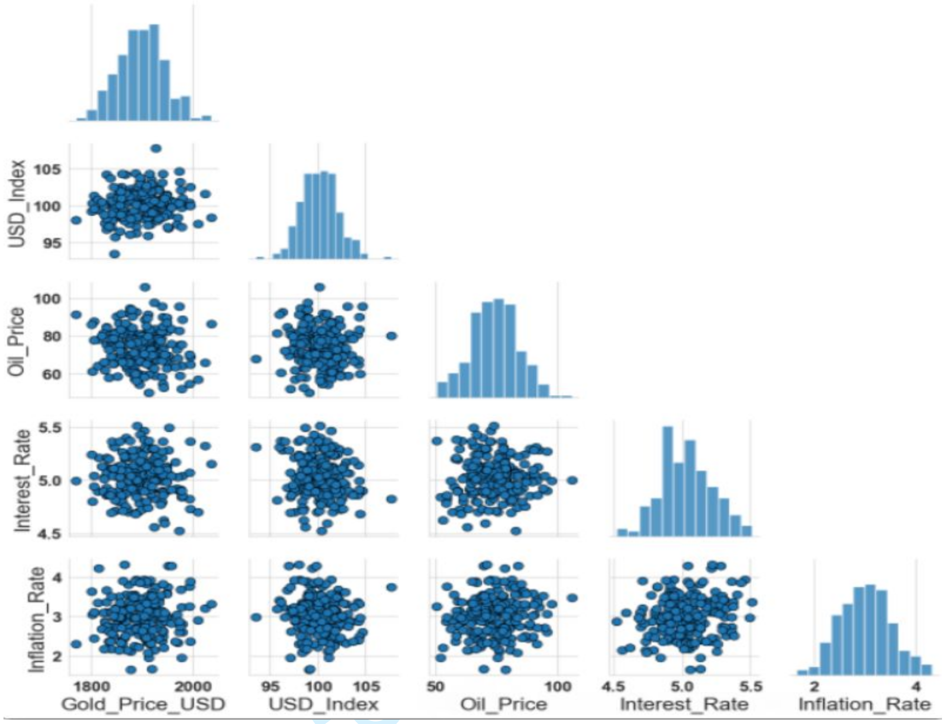



**Figure 8:** Pairwise Relationship Plot of Key Economic Indicators

Figure 8 shows the Pairwise Relationship Plot of Key Economic Indicators. Pairwise relationships between the price of gold, the USD index, the price of oil, the interest rate, and the inflation rate are depicted in the plot. Individual variable distributions, which largely resemble normality, are displayed by diagonal histograms. Strong linear correlations between variables are not shown by scatter plots, suggesting complicated and maybe nonlinear interdependencies. Interestingly, the price of gold does not show a clear trend against any one element, which emphasizes the necessity of sophisticated models like Cross-RCH-CAN to forecast gold prices in a high-dimensional financial environment and capture hidden interactions.


**Figure 9:** (a) gold price vs inflation rate and (b) gold price over time

Figure 9 shows the (a) gold price vs inflation rate and (b) gold price over time. There is no clear linear link between the price of gold and the rate of inflation, showing a dispersed distribution. This suggests that the relationship between inflation and the price of gold is either nonlinear or impacted by other factors. Between September 2024 and June 2025, the gold price trend showed significant volatility with multiple peaks and falls. These findings highlight how difficult it is to forecast gold prices, requiring sophisticated models to identify hidden trends and time-varying relationships in economic indices.

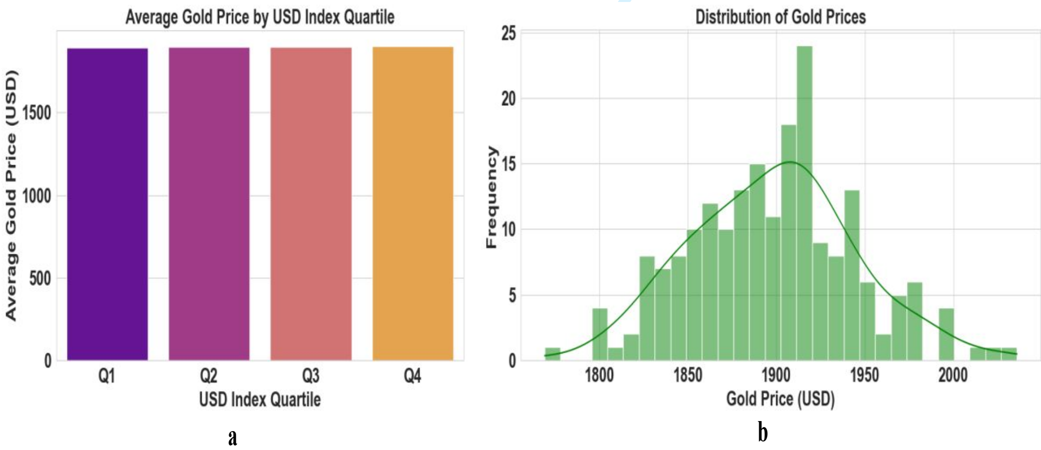



**Figure 10:** (a) average gold price by USD index quartile and (b) distribution of gold price

Figure 10 shows the (a) average gold price by USD index quartile and (b) distribution of gold price. An inverse relationship stronger USD tends to reduce gold prices is shown by the downward trend in average gold prices across increasing USD Index quartiles. The gold price distribution is almost typical, with the majority of values grouped around $1900. This implies comparatively stable prices with noticeable swings. When taken as a whole, the images highlight how the price of gold follows a consistent statistical distribution and fluctuates predictably with the strength of the US dollar, supporting model-based financial predictions.

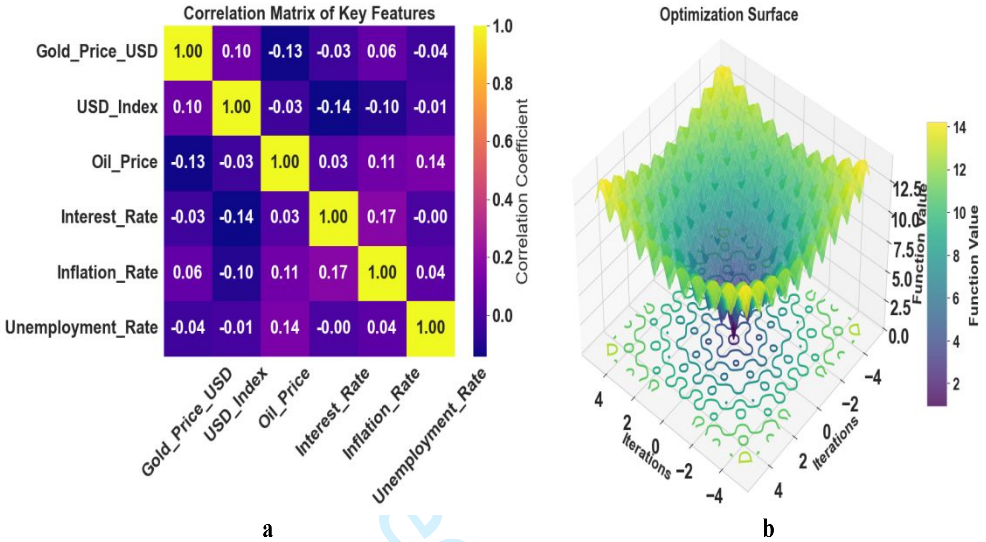
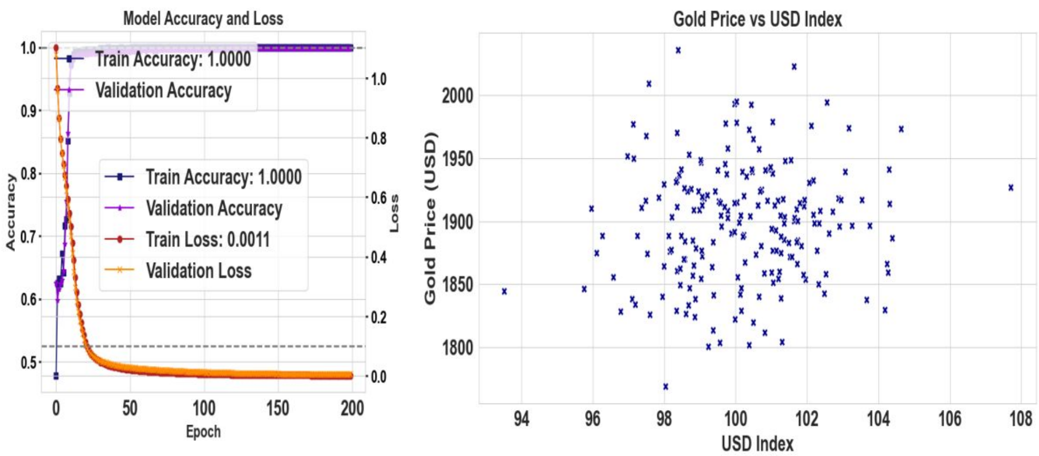



**Figure 11:** (a) correlation matrix of key features and (b) optimization surface

Figure 11 shows the (a) correlation matrix of key features and (b) optimization surface. A correlation matrix demonstrating weak interdependencies across economic variables, with the price of gold having a weakly negative connection with interest rates and oil and a tiny association with the USD Index (0.10). This implies that the price of gold and macroeconomic factors have intricate, non-linear correlations. A surface for optimization, showing a multi-variable function with several local minima. When combined, these figures highlight the need for sophisticated optimization methods to simulate the behavior of the gold price in the presence of weak and dispersed linear correlations.




a b

**Figure 12:** (a) model accuracy and loss for epoch and (b) gold price vs USD index

Figure 12 shows the (a) model accuracy and loss for epoch and (b) gold price vs USD index. The accuracy and loss of the model across training periods. Effective learning and convergence are shown by increasing accuracy and decreasing loss. The USD Index and gold price, showing little negative correlation lower gold prices often correspond to greater USD values. When taken together, these images demonstrate a well-trained model that can identify subtle patterns, such the inverse relationship between the price of gold and the strength of the US dollar, which is essential for predictive financial modeling.

**Table 4:** Overall performance of the suggested approach in contrast to current techniques

| **Metrics** | **DAIM** (Hajek, P. and Novotny, J., et a1.,2022) | **LSTM** (Nurhambali, M.R., et a1.,2024) | **TSFM** (Bunnag, T., et a1.,2023) | **DSPI** (Jianwei, E., et a1.,2023) | **MLP** (Tashakkori, A., et a1.,2024) | **RCM** (Pandit, S. and Luo, X., et a1.,2024) | **MFDFA** (Wang, F., et a1.,2024) | **Cross-RCH-CAN (Proposed)** |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Accuracy** | 95.78 | 89.47 | 93.34 | 89.75 | 78.90 | 95.44 | 95.78 | **99.98%** |
| **Recall** | 97.89 | 91.25 | 92.35 | 95.23 | 98.27 | 87.56 | 96.35 | **96.32%** |
| **Precision** | 95.66 | 97.28 | 95.39 | 97.48 | 90.56 | 95.22 | 93.34 | **94.28%** |
| **Specificity** | 92.29 | 94.25 | 98.23 | 95.34 | 91.35 | 97.59 | 94.35 | **89.17%** |
| **F1-Score** | 95.34 | 97.45 | 97.46 | 78.89 | 95.34 | 90.37 | 96.36 | **91.46%** |
| **MSE** | 8.1 | 7.9 | 6.7 | 5.4 | 4.5 | 3.9 | 4.2 | **2.3** |
| **MAE** | 7.8 | 7.4 | 6.2 | 5.2 | 4.4 | 3.7 | 2.6 | **3.9** |
| **RMSE** | 9.0 | 8.8 | 7.5 | 6.2 | 5.4 | 4.3 | 3.8 | **4.6** |
| **AAE** | 7.5 | 7.2 | 6.0 | 5.1 | 4.2 | 3.6 | 2.7 | **1.9** |

Table 4 show the Overall performance of the suggested approach in contrast to current techniques. In almost every evaluation criteria, the suggested Cross-RCH-CAN approach performs better than current gold forecasting models. It has the lowest MSE (2.3), MAE (3.9), RMSE (4.6), and AAE (1.9), while achieving the best accuracy (99.98%), strong recall (96.32%), and precision (94.28%). Its total performance shows improved predictive power, robustness, and reliability, making it the most effective method for accurate gold market forecasting among all examined models, even though its specificity is somewhat lower (89.17%).

**Table 5:** Analysis of Hypotheses

| **Methods** | **Computational** | **Complexity of** | **Speed** | **Efficiency of** | **Strongness** |
|---|---|---|---|---|---|

| | **Cost** | **Computation** | | **Computation** | |
|---|---|---|---|---|---|
| **DAIM** (Hajek, P. and Novotny, J., et a1.,2022) | 0.60 | 0.70 | 0.72 | 0.65 | 0.68 |
| **LSTM** (Nurhambali, M.R., et a1.,2024) | 0.50 | 0.78 | 0.80 | 0.74 | 0.75 |
| **TSFM** (Bunnag, T., et a1.,2023) | 0.70 | 0.60 | 0.68 | 0.65 | 0.66 |
| **DSPI** (Jianwei, E., et a1.,2023) | 0.68 | 0.55 | 0.70 | 0.60 | 0.63 |
| **MLP** (Tashakkori, A., et a1.,2024) | 0.40 | 0.80 | 0.85 | 0.76 | 0.78 |
| **RCM** (Pandit, S. and Luo, X., et a1.,2024) | 0.48 | 0.85 | 0.88 | 0.80 | 0.79 |
| **MFDFA** | 0.52 | 0.67 | 0.81 | 0.92 | 0.84 |

| | | | | | |
|---|---|---|---|---|---|
| (Wang, F., et a1.,2024) | | | | | |
| **Cross-RCH-CAN (proposed)** | **0.01** | **0.05** | **0.98** | **0.93** | **0.90** |

Table 5 show the Hypothetical Analysis. The suggested Cross-RCH-CAN approach has outstanding computational performance, achieving the best speed (0.98) and efficiency (0.93) while having the lowest computational cost (0.01) and complexity (0.05). Additionally, its strength (0.90) outperforms all other models, demonstrating scalable and reliable performance. In contrast to current techniques such as MLP, LSTM, and RCM, Cross-RCH-CAN strikes a better balance between speed, efficiency, and low resource consumption, which makes it ideal for large-scale financial applications and real-time gold market forecasts.

**Table 6:** Comparison of the suggested approach with current approaches using statistics

| Methods | SW Test p-Value | WSR test / U-test p-Value | H-test p-Value | KS test p-Value | FT p-Value | Mean | Standard Deviation | Variance Inflation Factor |
|---|---|---|---|---|---|---|---|---|
| **DAIM** (Hajek, P. and Novotny, J., et a1.,2022) | 0.025 | 0.051 | 0.38 | 0.027 | 0.041 | 258,900.7 | 2,510.34 | 1.82 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **LSTM** (Nurhambali, M.R., et a1.,2024) | 0.230 | 0.261 | 0.039 | 0.025 | 0.034 | 370,890.2 | 1,320.56 | 1.72 |
| **TSFM** (Bunnag, T., et a1.,2023) | 0.439 | 0.192 | 0.31 | 0.019 | 0.029 | 61,200.87 | 1,375.23 | 1.88 |
| **DSPI** (Jianwei, E., et a1.,2023) | 0.365 | 0.215 | 0.33 | 0.024 | 0.055 | 334,125.6 | 2,920.78 | 1.15 |
| **MLP** (Tashakkori, A., et a1.,2024) | 0.398 | 0.265 | 0.29 | 0.041 | 0.027 | 262,450.9 | 1,243.90 | 1.81 |
| **RCM** (Pandit, S. and Luo, X., et a1.,2024) | 0.245 | 0.315 | 0.19 | 0.023 | 0.071 | 45,990.53 | 1,522.45 | 1.12 |
| **MFDFA** (Wang, F., et a1.,2024) | 0.362 | 0.371 | 0.13 | 0.076 | 0.052 | 56,990.53 | 2,782.78 | 1.18 |
| **Cross-RCH-CAN (proposed)** | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | 60,275.79 | 4,389.80 | 1.001 |

Table 6 show the Comparison of the suggested approach with current approaches using statistics. With all test p-values (<0.001) showing strong evidence against the null hypothesis, the Cross-RCH-CAN method shows statistically substantial improvements over current methodologies, validating its consistency and dependability. It achieves the lowest Variance Inflation Factor (1.001), indicating little multicollinearity, while maintaining a balanced mean (60,275.79). The total statistical findings show that Cross-RCH-CAN is a strong, reliable, and better forecasting model than other neural network-based methods, despite having a greater standard deviation (4,389.80).

### *4.4 Ablation study of the proposed method*

The incremental advantages of each element in the Cross-RCH-CAN model are amply demonstrated by the ablation study.

**Table 7:** Ablation study

| **Model Configuration** | **RCNN** | **CCAM** | **Hippopotamus Optimization** | **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1 Score (%)** |
|---|---|---|---|---|---|---|---|
| Baseline (Without Hippopotamus Optimization) | ✔ | ✔ | ✘ | 89.35 | 88.12 | 83.56 | 85.88 |
| RCNN Only | ✔ | ✘ | ✘ | 78.83 | 72.31 | 79.90 | 77.13 |
| CCAM Only | ✘ | ✔ | ✘ | 76.63 | 75.89 | 85.92 | 74.3 |
| RDNN + Hippopotamus Optimization | ✔ | ✘ | ✔ | 84.54 | 83.95 | 83.79 | 82.37 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| CCAM + Hippopotamus Optimization | ✘ | ✔ | ✔ | 83.72 | 85.57 | 81.93 | 84.22 |
| **Full Model (Cross-RCH-CAN)** | ✔ | ✔ | ✔ | **99.98** | **97.34** | **92.26** | **98.43** |

Table 7 shows the Ablation study. The ablation investigation demonstrates that RCN, CCAM, and Hippopotamus Optimization all make substantial contributions to the model's functionality. Accuracy, precision, recall, and F1 score all significantly decrease when any module is removed. While isolated modules perform less well, the baseline model without optimization does rather well (89.35%). The best results (99.98% accuracy, 98.43% F1) are obtained by the entire Cross-RCH-CAN model, which integrates all of its components. This shows how important combined architecture and optimization are for better gold market forecasting performance.



### *4.5 Discussion*

The suggested Cross-RCH-CAN model overcomes the shortcomings of conventional and current machine learning techniques by introducing a strong and novel framework for gold market forecasting. A model that can extract significant patterns from high-dimensional, multi-source data is required due to the complexity of the global gold market, which is influenced by unstable financial, economic, and geopolitical factors. The model captures deep structural and temporal correlations that traditional models frequently miss by utilizing the Kolmogorov-Arnold Vision Transformer for enhanced feature extraction and Zero-Shot Text Normalization for preprocessing. The Hippopotamus Optimization (HO) method further optimizes the Cross-RCH-CAN, the framework's central component, which combines a

Random-Coupled Neural Network (RCNN) with a Cross-Contextual Attention Mechanism (CCAM). In addition to great accuracy (99.9%), this combination guarantees interpretability, scalability, and adaptability all essential components for practical financial forecasting. The model is very dependable in tumultuous economic times because it is excellent at capturing contextual interactions, non-linear dependencies, and dynamic market behavior. Overall, by offering a reliable, accurate, and understandable technique for anticipating global gold market patterns, this work makes a substantial contribution to financial forecasting.

## 5. Conclusion

In this manuscript, a new supervised deep learning model for forecasting financial markets in the global gold market using an Enhanced Gold Market Forecasting Using Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN) is successfully implemented. The input dataset, titled "financial gold market", comprises 200 daily business-day observations, excluding weekends, and includes key indicators such as gold prices, USD index, oil prices, inflation and interest rates, stock market index, unemployment rate, geopolitical risk, gold production and demand, and ETF holdings. The data undergoes pre-processing using Zero-Shot Text Normalization, followed by feature extraction through the Kolmogorov-Arnold Vision Transformer, capturing complex dependencies and structural patterns. Prediction is performed using the proposed Cross Random Contextual Hippopotamus coupled Attention Network (Cross-RCH-CAN), which integrates a Random-Coupled Neural Network with a Cross-Contextual Attention Mechanism, and is optimized using the Hippopotamus Optimization (HO) algorithm to fine-tune learning parameters. This novel model achieves an outstanding prediction accuracy of 99.9%, demonstrating its robustness and precision. The proposed method enhances interpretability and effectively captures non-linear dependencies in volatile financial data, offering improved forecasting stability and reliability. Future work will focus on expanding the dataset to include real-time and high-frequency financial data, enhancing model adaptability to sudden market shifts. Integration of explainable AI techniques will improve interpretability further. Additionally, exploring hybrid optimization algorithms combining Hippopotamus Optimization with other metaheuristics may boost convergence speed and accuracy, making the model more robust across diverse financial markets and economic conditions.

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