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RESEARCH ARTICLE

A Two-Stage Deep Fusion Integration Framework Based on Feature Fusion and Residual Correction for Gold Price Forecasting

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ABSTRACT Given the far-reaching impact of the gold price on global financial markets, accurately predicting the gold price has become essential, with machine learning methods emerging as a prominent tool to tackle this challenge. Nonetheless, traditional single prediction models usually suffer from limited predictive performance and fail to capture complex variability of market behavior. Aiming to solve these limitations, an innovative two-stage hybrid deep integration framework that combines feature extraction and residual correction techniques is proposed with a view to predicting the gold price more accurately. The prediction effectiveness is enhanced by employing a variational modal decomposition to cluster time series data into three classes. The first stage employs variational mode decomposition to categorize time series data, improving computational efficiency and initial prediction accuracy. The second stage refines these predictions through a novel residual correction process, leveraging back propagation, long and short-term memory, and convolutional neural networks. In addition, through the in-depth analysis and processing of residuals, it is demonstrated that starvation of our method further improves the credibility of the prediction results, and effectively predicts the price movements of the four major gold markets. This approach not only provides a remarkably valuable perspective for policy makers, investors, and trading firms in the gold market, but also deals with the shortcomings of a single model in the face of complex market dynamics, and lays the foundation for the development of even more powerful forecasting models in the future.

INDEX TERMS Feature fusion, integration model, price forecast, residual correction.

I. INTRODUCTION

Gold, a precious metal, has played multiple significant roles in the history of mankind. It serves as a medium of exchange, and a means of storing value, as well as a globally recognized symbol of wealth. In the financial markets, gold's status as a safe-haven asset and an inflation hedge provides investors with degree of security in times of economic turmoil [1], [2], [3]. Therefore, the value of gold is derived not only from its physical properties, such as scarcity and durability, but also from its historical and cultural significance, as well as its widely recognized financial status.

The price of gold represents an important indicator of the state of the banking and stock markets, and has a significant predictive effect on the economic and financial spheres. As a result, accurately predicting the movement of the gold price has become a focus of both industry and academic attention. It is essential for strategic decision-making not

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only for company management and government departments, but also for commercial investors [2], [3], [4]. Additionally, the volatility of the gold market increases investment risks, and fluctuations are influenced by a combination of many complex factors. Historically, gold has been favored by financial experts due to high liquidity and solid performance during financial crises [5]. After the collapse which marked the end of the fixed exchange rate between gold and the US dollar, the price of gold rose significantly, reaching new highs in the 1970s and early 1980s. During the global financial crisis of 2008, in the face of widespread economic uncertainty and market turmoil, gold once again became the asset of choice for investors looking for a safe-haven, with the price reaching a peak of approximately US$1,900 per ounce in 2011. It is also typical that the profitability of gold mining companies is particularly affected by price fluctuations. A decrease in the price of gold can render mining projects unprofitable [3]. Consequently, predicting gold movements is essential for financial investors and policymakers in making informed investment decisions and mitigating potential risks [4]. An in-depth analysis of the factors that drive gold price volatility can offer valuable insights to global investors, governments, and economic players, enabling them to make more rational and informed decisions in the complex and volatile financial markets.

According to existing literature, a lot of efforts and contributions have been made in gold price forecasting. These methods of gold price forecasting through gold price time series can be classified into three categories: traditional statistical method, machine learning method and hybrid model. Firstly, traditional econometric methods emerged early and were widely used, including autoregressive integrated moving average model (ARIMA), generalized autoregressive conditional heteroskedasticity model (GARCH), error correction model (ECM), vector autoregression (VAR), etc. Traditional statistical models often assume that the underlying relationships of the time series data is linear. However, the price of gold is governed by a variety of non-linear factors such as macroeconomic indicators, geopolitical events and market sentiment [6], [7], [8], [9]. While traditional statistical models require the input time series data to be static, i.e. to exhibit a constant mean and variance over time, gold prices tend to exhibit non-stationary behaviour due to trends, seasonality and structural breaks [10]. Transformations such as differencing or detrending might be may be required to make the data stationary, but these processes result in the loss of valuable information [2].

Given these limitations, researchers are increasingly turning to alternative methods, such as machine learning and hybrid models, which can more effectively capture the nonlinearities, non-stationarities, and complex interactions inherent in gold price time series data [11]. It has been shown that single machine learning models are an improvement over traditional statistical models in forecasting gold prices [9], [12]. However, they still face certain limitations, especially when trained on limited data or with a high number of features, and have the problem of overfitting [13], [14]. Overfitting models may perform well on the training data but fail to generalize to unseen data, resulting in poor forecasting performance [15]. Hence, researchers have adopted various fusion models to address the deficiencies of single machine learning models in predicting gold prices [15], [16], [17]. Typically, these fusion models blend the strengths of different techniques to improve prediction accuracy and compensate for the limitations of individual models, such as stacked generalization, weighted averaging etc. [11], [16], [18], [19]. These methods train multiple base models on the same dataset and then combine their predictions using meta-models. To produce the final prediction, the meta-model is trained on the output of the base models. After assembling, it can fully utilize the strengths of different models. These methods also combine the predictions of multiple models by assigning weights to their outputs. These methods can also combine the predictions of multiple models by assigning weights to the outputs, where the weights can be defined based on the performance of individual models, enabling the higher performing models to contribute more to the final prediction. In turn, averaging reduces the impact of errors in a single model and improves overall accuracy [19].

Nevertheless, careful selection of the appropriate base models, fusion techniques, and hyperparameters plays a crucial role in improving the performance of fusion models. On the other hand, finding the optimal combination often requires extensive experimentation, which is not only time-consuming but also consumes computational resources. Despite these limitations, fusion models have already exhibited potential benefits in addressing the challenges associated with gold price forecasting and other complex prediction tasks [18], [20]. When properly implemented, these models can enhance performance by integrating the strengths and compensating for the weaknesses of different models.

To overcome these critical issues, an innovative two-stage deep fusion integration framework, which is based on feature extraction and residual correction, is proposed in this study with the aim of improving the prediction accuracy of gold prices. By fine-tuning the residuals of the prediction model, we are able to further enhance the accuracy of the prediction results. The framework carefully considers the shortcomings of decomposed ensemble models and employs feature reconstruction techniques to identify the optimal feature subsequence. Within this subsequence, a feature fusion model is employed to cope with the challenges of complex data as well as high noise levels. Furthermore, in-depth processing of residuals helps to improve the accuracy of prediction.

Our proposed framework integrates variational mode decomposition [21], Gaussian mixture modeling [22], back propagation, long short-term memory, and convolutional neural networks. By decomposing the gold price series into a number of subsequences, we reduce the complexity of the data and make the series smoother. These subsequences are clustered into three major sequences using Gaussian mixture modeling, improving computational efficiency. Next, we developed a BP-CNN-LSTM fusion model and trained the subsequences with a combination of backpropagation, long and short-term memory, and convolutional neural networks. By splicing the obtained tensors, we obtained preliminary fitted values and further corrected the residuals using the proposed BP-CNN-LSTM fusion model to achieve effective prediction of gold price. This paper is structured as follows: Section II provides an overview of related work in gold price forecasting. Section III details the proposed two-stage deep integration framework, including the methodologies employed. Section IV presents the experimental setup and results, along with a discussion of the findings. Finally, Section V concludes the study and outlines potential directions for future research.

II. METHODOLOGY

This section will introduce the specific principles of the methods and technical models involved in gold price forecasting research.

A. VARIATIONAL MODE DECOMPOSITION (VMD)

Variational Mode Decomposition (VMD), proposed by Dragomiretskiy and Zosso [21] in 2014 as an extended version of the EMD algorithm, is a non-recursive and adaptive method for decomposing non-smooth and non-linear signals. VMD is well-suited to financial time series forecasting, including gold price prediction, and has been widely used in various fields, such as fault diagnosis, time series prediction, and image processing. Li et al. [23] successfully predicted short-term wind speed by using VMD to eliminate the instability of wind speed data. Yan and Mu [24] also employed VMD and CEEMDAN to reduce noise in financial time series data, thus enhancing prediction accuracy. VMD can decompose complex signals into a set of intrinsic mode functions (IMFs), each of which can be regarded as the fluctuation of a single frequency mode. The problem to be solved is the constrained variational optimisation problem. This can be stated as follows:

$$\begin{aligned} &\min_{\{u_m\}_k, \{w\}_k} \sum\nolimits_k \mid \frac{\partial}{\partial t}((\delta(t) + j\pi t) * u_k(t)e^{-jw_k t}) \mid_2^2 \\ &s.t. \ \sum\nolimits_k u_k(t) = f(t) \end{aligned} \tag{1}$$

In the formula, u_k refers to the k mode function after the input signal decomposition, w_k represents the central frequency, and K is the number of modes to be decomposed. The δ (t) is the unit impulse function, and f (t) is the original signal. To solve the optimization problem, we introduce the Lagrange multiplier λ and the second-order penalty factor α, and then transform the constrained variational problem into an unconstrained variational problem, obtaining the augmented Lagrange expression:

$$\begin{aligned} L(\{u\}_k, w\}_k, \lambda_t) = \alpha \sum\nolimits_k &\mid \frac{\partial}{\partial t}((\delta(t) + j\pi t) * u_k(t)e^{-jw_k t}) \mid_2^2 \\ &+ \mid f(t) - \sum\nolimits_k u_k(t) \mid_2^2 \backslash + \lambda(t)(f(t) \\ &- \sum\nolimits_k u_k(t)) \end{aligned} \tag{2}$$

Equation (2) is solved as a saddle point. The parameters u_1, w_2, λ_1, and n are initialized. The initial value of n is set to 0, and a cyclic process is initiated such that $n = n + 1$. The values of u_k, w_t, and λ_t are updated using the following formula. When the components satisfy equation (6), the solution is completed.

B. GAUSSIAN MIXTURE MODEL (GMM)

Gaussian Mixture Models (GMMs) function as an amalgamation of 'K' Gaussian models [22], characterized by a unique probability distribution of the form:

$$P(x \mid \theta) = \sum\nolimits_{k=1}^{K} \alpha_k \phi(x \mid \theta_k) \tag{3}$$

Here, each is a coefficient satisfying $\alpha_k \geq 0$, with $\sum_{k=1}^{K} \alpha_k = 1$. The term $\varphi(x \mid \theta_k)$ represents a Gaussian distribution, with $\theta_k = (\mu_k, \sigma_k^2)$ referred to as the k-th sub-model. The Gaussian distribution $\varphi(x \mid \theta_k)$ can be defined as:

$$\phi(x \mid \theta_k) = \frac{1}{(2\pi)^{\frac{D}{2}} \mid \Sigma_k \mid^{\frac{1}{2}}} \exp\left(-\frac{(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)}{2}\right) \tag{4}$$

GMM provides a generative modelling methodology that models the process of generating data as a combination of multiple Gaussian probability distributions [25]. For instance, envisage two one-dimensional standard Gaussian distributions N(0,1) and N(2,1) which are assigned weights of 0.7 and 0.3, respectively. The generation of a new data points first involves randomly selecting a distribution according to these weights, and then sampling from the selected distribution to obtain a point. It is assumed that is that each point is generated independently, and the process is iteratively continued until the desired data count is reached. The flexibility of this model allows it to represent complex data distributions. In practice, the parameters of GMM are derived from observed data through maximum likelihood estimation, a process that often utilizes the expectation-maximization (EM) algorithm. This algorithm iteratively optimizes the model parameters with respect to observed data, making it applicable in various fields like image processing, signal processing, and machine learning. In the case of gold price prediction, the ability of GMM to perform cluster analysis on subseries derived from variational modal decomposition (VMD) significantly reduces model complexity and improves computational efficiency, making GMM a key component of a comprehensive approach to gold price prediction.

C. BACK PROPAGATION NEURAL NETWORK (BP)

The BP neural network is an artificial neural network learning process that combines an error back-propagation algorithm as a learning mechanism, which is a multi-layer forward network with weights non-linear differentiable functions and consists of two processes: forward propagation of information and backward propagation of errors. The input layer tasked with gathering information from the external environment and conveying it to the neurons in the intermediate layer. This intermediate layer acts as a processing hub, where the transformation of information occurs. Depending on the precision required, this layer can be structured as either a single-layer or multi-layer hidden-layer configuration. Subsequently, the final hidden layer relays the refined data to the output layer, which completes the learning cycle. The output layer then further processes this information before presenting the results back to the external world. If the actual output value differ from the anticipated output, the gradient descent technique is employed to retroactively distribute the error to each layer, adjusting their respective weights. This process extends progressively back to the hidden and input layers. Through the repetitive cycle of forward propagation and reverse error dissemination, the weightings of the individual layers are meticulously honed to mirror the neural network's connectivity objectives accurately. The process continues until the output error decreases below a pre-set threshold or a pre-set number of learning iterations is reached. Through this laborious process, the BP neural network autonomously fine-tunes itself, enhancing the forecast accuracy of the model. Such enhancement is essential in addressing the intricate and fluctuating nature of financial markets.

D. LONG SHORT-TERM MEMORY (LSTM)

Long short-term memory (LSTM) was proposed by Hochreiter and Schmidhuber [26] and was recently improved by Alex Graves [26]. LSTM solves the gradient disappearance problem by designing an elaborate network structure. LSTM designs the memory cells, which can add or remove information by the input gate (i_t), forget gate (f_t), output gate (o_t). c_{t-1} and c_t respectively indicate the cell state at time $t-1$ and $t \cdot g_t$ add information to cell state. The input and hidden state are represented by x_t and h_t at time t. Cells and gates are updated according to Equations (5)-(9).

$$i_t = \sigma\left(W_i x_t + R_i h_{t-1} + b_i\right) \tag{5}$$
$$f_t = \sigma\left(W_f x_t + R_f h_{t-1} + b_f\right) \tag{6}$$
$$o_t = \sigma\left(W_o x_t + R_o h_{t-1} + b_o\right) \tag{7}$$
$$g_t = tanh\left(W_g x_t + R_g h_{t-1} + b_g\right) \tag{8}$$
$$c_t = f_t \cdot c_{t-1} + g_t \cdot i_t \tag{9}$$
$$h_t = o_t \cdot tanh\left(c_t\right) \tag{10}$$

$\sigma(\cdot)$ denotes the sigmoid function, W and R respectively indicate input weights and recurrent weights, b represent bias. Weights are updated by back propagation trough time algorithm. The forget gate selectively discards the information in the past cell state (c_{t-1}), as shown in Eq. (9). The input gate selectively records new information in the cell state (c_t), as presented in Eqs. (7) and (8). The output gate determines how much of the current cell's information is assigned to the next cell, as noted in Eq. (10).

E. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Networks (CNN) represent another category of feed-forward architecture which primarily process their input as bi-dimensional matrices. They are typically composed of a sequence of successive convolutional and subsampling layers, followed one or multiple hidden layers and culminating in an output layer. The initial layers of convolution and subsampling are iteratively stacked to extract high-level feature vectors in a single dimension. These feature vectors are processed by the hidden and output layers, which function akin to a fully connected multilayer perceptron [15].

In this architecture, convolutional layers encompass a multiple filters, also known as convolutions, that are applied to the input from the previous layer. The kernel weights of these convolution filters are optimized throughout the training phase. In this context subsampling or pooling layers serve to diminish the dimensionality of the features, thereby providing a robustness mechanism against noise.

III. PROPOSED MODEL

The introduction of feature fusion in our framework addresses the complex and non-linear nature of gold price time series data. Traditional single models, such as ARIMA and GARCH, are often inadequate for capturing the intricate patterns in the data due to their linear assumptions. Even individual deep learning models like LSTM or CNN, while powerful, can suffer from limitations such as overfitting or an inability to capture both short-term and long-term dependencies effectively.

Feature fusion combines the strengths of multiple models, leveraging their unique capabilities to create a more robust predictive model. Specifically, we employ variational mode decomposition (VMD) to decompose the time series into more manageable components, which are then processed by a combination of backpropagation (BP), long short-term memory (LSTM), and convolutional neural networks (CNN). This approach ensures that the model can capture both the temporal dependencies and the underlying patterns in the data more effectively than any single model alone.

The core of our research lies in the design of a comprehensive structure known as the Feature Fusion Module (FFM). Illustrated in Figure 1. Contrived to process the input data and generate feature vectors, the Feature Fusion Module consists of three distinct branches, each adept at processing a seven-dimensional input vector to produce a 128-dimensional feature vector. In the first branch— referred to as the left branch—the input vector is induced and backpropagated through a fully connected layer. Backpropagation is used in this branch as a traditional algorithm that effectively

FIGURE 1. Feature processing framework.

reduces prediction error by optimizing the weights during model training and has proved to be very effective in training machine learning models, including neural networks. Next comes the intermediate branch, which employs a convolutional network to process the input vectors. Specifically, a one-dimensional convolutional layer is employed, generating a 7×64 feature vector. This vector is expanded to a 448 dimensions and then further processed through a fully connected layer, culminating in a 128-dimensional feature vector. Convolutional Neural Network (CNN) is deployed in this branch because of its superior capability to identify spatial relationships in data, making it particularly suitable for processing time series data like gold price trends. Finally, the right branch contains a Long Short-Term Memory (LSTM) network. The LSTM network extracts features from a 7×1 input vector, forming a 64-dimensional feature vector, which is subsequently manipulated through a fully connected layer, thus yielding a 128-dimensional feature vector. The LSTM is particularly useful for processing data such as gold price trends because of its ability to remember patterns over long time horizons, which is crucial for our model, they allow for more accurate predictions by taking into account long-term dependencies in the time series data.

Next, we splice the three produced 128-dimensional feature vectors are then concatenated to form a singular 384-dimensional feature vector. Afterwards, this vector is processed through a series of consecutive fully connected layers, resulting in a sequence of feature vectors (128, 64, and 32 dimensions, respectively), which are finally compressed into a one-dimensional feature vector.

In conclusion, Feature fusion plays a crucial role in the gold price prediction model we constructed. It provides the possibility of integrating various complementary information collected from multiple feature extraction techniques. By amalgamating the outputs from different branches of backpropagation, convolutional neural networks, and LSTM networks, the Feature Fusion Module successfully builds a comprehensive feature representation. This representation

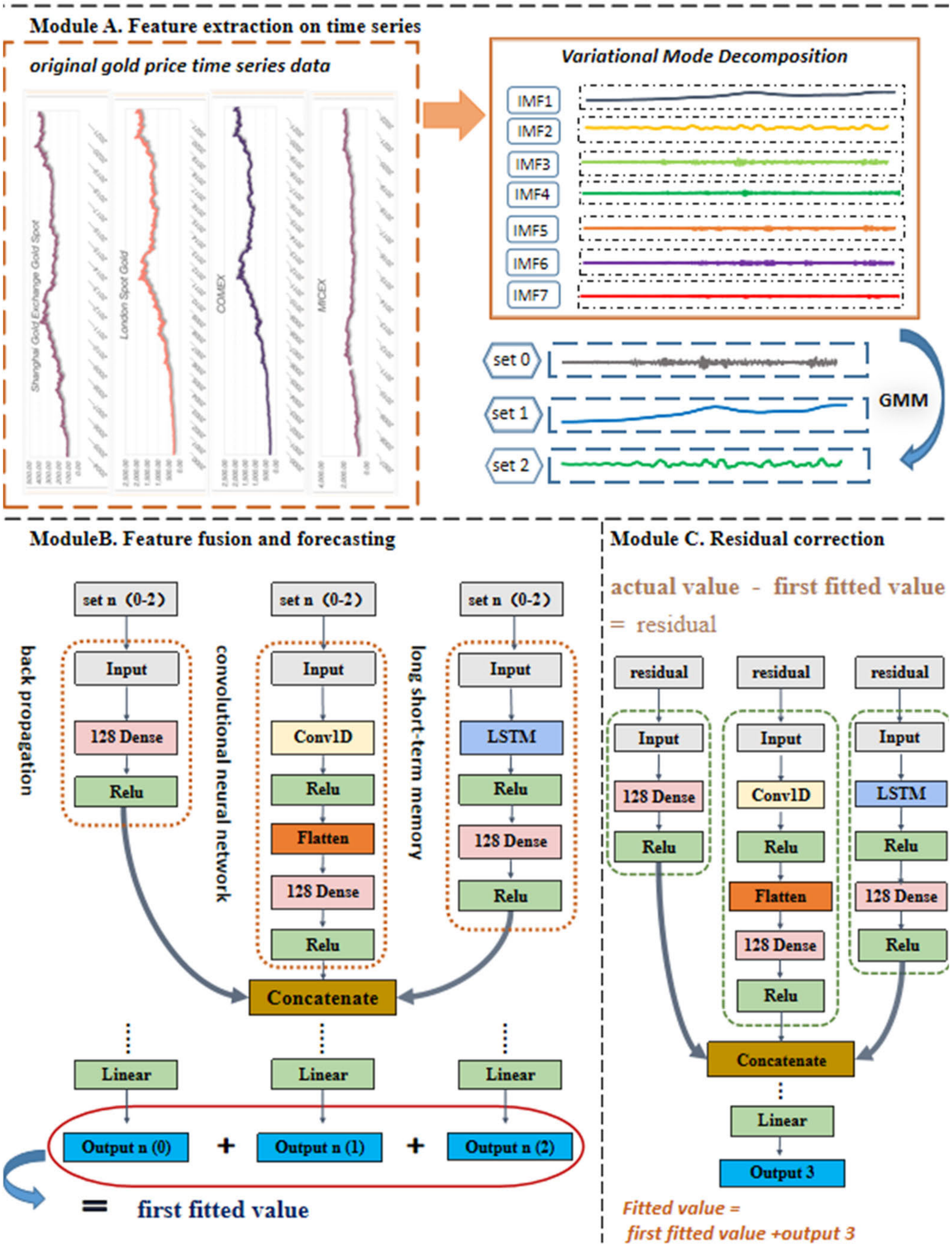

FIGURE 2. Fusion model framework.

captures the complex and diverse patterns present in the time series data of gold prices.

A. FUSION MODEL FRAMEWORK

In this study, we propose a fusion modelling framework that integrates data preprocessing techniques, optimization algorithms, and machine learning methods, aimed at accurate forecasting of gold price time series data. With the seamless integration of three unique modules, this innovative approach collectively enhances the prediction performance. Together, these modules not only capture key features of the data, but also optimise the predictive output of the model (Figure 2).

Specifically, Module A is the primary component of this fusion model, which focuses on data extraction and preprocessing. In this key step, the raw gold price time series data is converted into a format suitable for further analysis. Given that time series data are typically non-stationary, we employ a variational pattern decomposition to process the raw data into seven subseries, effectively separating out underlying trends and cyclical patterns. Subsequently, a Gaussian Mixture Model approach is applied to process these subsequences, ultimately transforming them into three distinct data sets. This process not only simplifies the data structure but also ensure that the newly generated datasets accurately reflected the fundamental characteristics of the original time series data.

Next, Module B centres on developing a composite model called BP-CNN-LSTM, which combines the strengths of three distinct machine learning methods: Backpropagation (BP), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). The approaches are linked to each other through a fully connected layer, with the aim of exploiting their unique capabilities and complementing each other's shortcomings. The three preprocessed data sets derived from Module A are then meticulously trained with the BP-CNN-LSTM integrated model, producing three output results. An optimization algorithm such as Genetic Algorithm or Particle Swarm Optimization is subsequently utilized to assign weights to the predictions of each model. His step helps to determine the optimal model configuration and derive the final predicted values. Then the residuals between the initial predicted values and the actual observed values are calculated.

In the end, Module C completes the proposed fusion model framework by implementing a comprehensive residual correction process. The goal of this stage is to improve the prediction accuracy of the model by examining the differences between the initial predicted values generated by Module B and the actual values. To accomplish this, residuals are used as inputs and undergo secondary training through the BP-CNN-LSTM integrated model in order to capture residual patterns or correlations that may not be adequately revealed by the initial training.

Upon completing the secondary training, the model generates Output 3, which further improves the accuracy of the prediction results. Following this, the initial predictions obtained from Module B are combined with Output 3 to o obtain a residual-corrected second version of the fitted values. This process effectively integrates residual correction into the overall orecasting process, resulting in more accurate and reliable gold price forecasts. A coherent and transparent model structure guarantees that it maintains the interpretability of the model while incorporating the advantages of advanced machine learning techniques.

The fusion modelling framework proposed in this study takes full advantage of the combined strengths of data preprocessing, feature fusion, and machine learning methods, offers a systematic and robust approach to gold price prediction. By integrating these elements into a coherent and efficient framework, the model captures the complex dynamics of gold price time series data and addresses the limitations that may be encountered when using each method individually. Taken together, the model becomes a fully-featured and powerful tool for gold price forecasting, and is expected to significantly improve the accuracy and reliability of forecasting efforts in the financial sector. Its innovative architecture and the synergistic application of multiple techniques sets a new benchmark for gold price prediction and provides valuable insights for future research in the field of time series analysis and prediction.

IV. SIMULATION AND DISCUSSION

In this section, in order to comprehensively evaluate the effectiveness of a two-stage deep integration model based on feature fusion and residual correction in gold price prediction, we choose four major gold markets as experimental object: AuT+D, London Gold Spot (US dollar), COMEX gold futures (active contract) and MICEX gold futures (active contract), s. This section exhaustively describes the experimental process including performance comparisons between different machine learning models, and presents the final results and their discussion.

A. DATA COLLECTION

The experimental dataset for this study were obtained from the Wind Information database (https://www.wind.com.cn). Four principal gold markets were selected as the experimental targets, including the Shanghai Gold Exchange Gold Spot: Closing Price: AuT+D, London Spot Gold (denominated in US Dollars), Futures Closing Price (Active Contract) from COMEX Gold, and Futures Closing Price (Active Contracts) from MICEX Gold. These datasets encompass four distinct markets and their respective ranges, after cleaning, outlier removal and data preprocessing, are listed in Table 1.

TABLE 1. Time range of gold market data.

Gold price	Dataset Range	Numbers	Training subset	Testing subset
Shanghai Gold Exchange Gold Spot	2004-09-27 ~ 2022-05-26	4602	3682	920
London Spot Gold	2000-07-11 ~ 2022-05-25	5693	4554	1139
COMEX Gold	2000-07-11 ~ 2022-05-25	5693	4554	1139
MICEX Gold	2007-03-19 ~ 2022-05-24	3967	3173	794

In this case, the gold price time series were partitioned into two sections: a training subset, which accounts for 80% of the time series and was utilized for constructing forecasting models, another testing subset, which accounts for the remaining 20 percent of the time series, is used to validate the forecasting performance of the hybrid model. This approach assured a rigorous evaluation of the proposed hybrid model's accuracy and effectiveness.

B. EVALUATION OF PREDICTION ACCURACY

Most published studies currently employ a variety of performance evaluation criteria to demonstrate the predictive accuracy of the model. These metrics include mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), mean square error (MSE), and

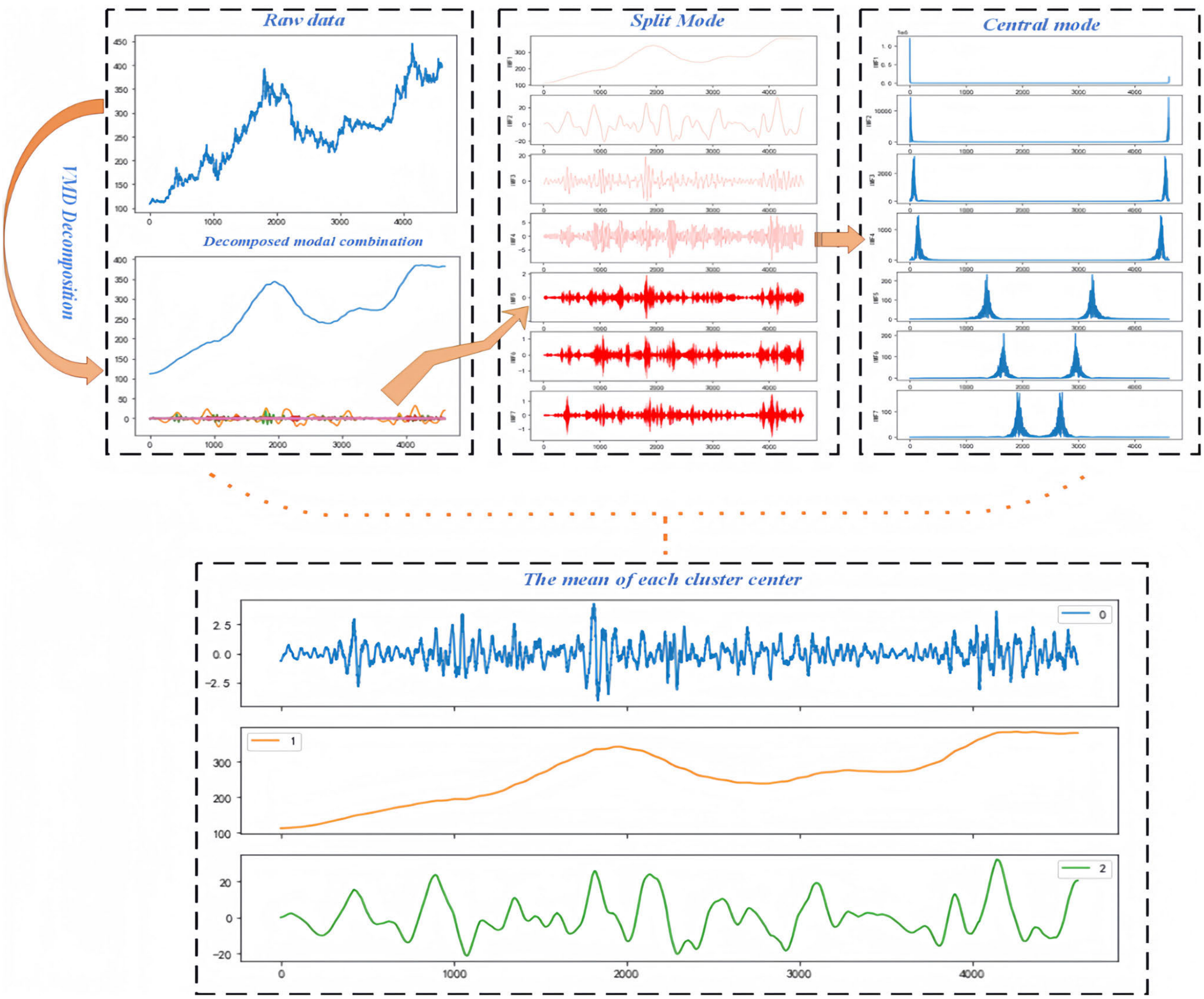

FIGURE 3. VMD decomposition model.

coefficient of determination (R^2). Lower values of MAE, RMSE, MAPE, and MSE indicate better predictive models. Conversely, higher values of R^2 signify superior model performance.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_{PRE(i)} - y_{ACT(i)}\right| \tag{11}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{PRE(i)} - y_{ACT(i)}\right)^2} \tag{12}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{PRE(i)} - y_{ACT(i)}}{y_{ACT(i)}}\right| \times 100\% \tag{13}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{PRE(i)} - y_{ACT(i)}\right)^2 \tag{14}$$

$$R^2 = 1 - \frac{\sum_i \left(y_{PRE(i)} - average\left(y_{PRE}\right)\right)^2}{\sum_i \left(y_{ACT(i)} - average\left(y_{PRE}\right)\right)^2} \tag{15}$$

where N is the size of testing dataset, y_{average} is the mean value of y, $y_{\text{ACT}(i)}$ and $y_{\text{PRE}(i)}$ are the i_{th} actual and forecasting values.

C. EXPERIMENTAL PROCESS

1) VMD DECOMPOSITION

Given the inherent volatility and non-stationary nature of gold price data, the high level of noise commonly found in financial time series data, and the nonlinearity and complexity of gold price movements, the variational mode decomposition (VMD) method provides a robust solution [11], [18], [24], [27], [28]. This method is able to segregate various underlying trends and periodic patterns in the data efficiently, thus deepening our understanding of the characteristics of the data and enhancing the forecasting accuracy of the process. The VMD decomposition mode is as shown in Figure 3.

D. DATA ANALYSIS

1) FORECASTING THE PRICE OF GOLD

In this study, three benchmark models and five recognized performance evaluation metrics were used to assess the predictive ability of the current hybrid forecasting model.

TABLE 2. Experimental results in shanghai gold exchange gold spot.

Market	Model	MSE	MAE	RMSE	R^2	MAPE
Shanghai Gold Exchange Gold Spot	BP-train	5.21	1.6039	2.2825	0.9988	0.0068
	BP-test	10.3993	2.2767	3.2248	0.9937	0.0063
	LSTM-train	6.1949	1.7621	2.489	0.9985	0.0076
	LSTM-test	10.3993	2.2767	3.2248	0.9937	0.0063
	CNN-train	6.4775	1.8159	2.5451	0.9985	0.008
	CNN-test	13.5242	2.6604	3.6775	0.9919	0.0073
	BP-CNN-LSTN-train	5.0281	1.579	2.2423	0.9988	0.0067
	BP-CNN-LSTM-test	10.1062	2.2617	3.179	0.9939	0.0062

TABLE 3. Experimental results in london spot gold.

Model	MSE	MAE	RMSE	R^2	MAPE
BP-train	122.7637	7.4611	11.08	0.9994	0.0081
BP-test	248.9281	11.441	15.778	0.9962	0.007
LSTM-train	142.9921	8.0648	11.958	0.9993	0.0087
LSTM-test	316.3692	13.2151	17.787	0.9952	0.008
CNN-train	161.9153	9.4441	12.725	0.9992	0.0129
CNN-test	273.4234	12.1231	16.536	0.9958	0.0074
BP-CNN-LSTN-train	117.5241	7.2698	10.841	0.9994	0.0079
BP-CNN-LSTM-test	242.5457	11.2532	15.574	0.9963	0.0069

TABLE 4. Experimental results in COMEX Gold.

Market	Model	MSE	MAE	RMSE	R^2	MAPE
COMEX Gold	BP-train	86.0057	6.1737	9.2739	0.9996	0.0066
	BP-test	185.0242	9.7258	13.602	0.9972	0.0059
	LSTM-train	104.4357	6.8206	10.219	0.9995	0.0073
	LSTM-test	324.095	13.5994	18.003	0.995	0.0081
	CNN-train	108.1047	7.0257	10.397	0.9995	0.008
	CNN-test	236.1998	11.0068	15.369	0.9964	0.0067
	BP-CNN-LSTN-train	83.6408	6.0692	9.1455	0.9996	0.0065
	BP-CNN-LSTM-test	175.6793	9.5391	13.254	0.9973	0.0058

TABLE 5. Experimental results in MICEX Gold.

Market	Model	MSE	MAE	RMSE	R^2	MAPE
MICEX Gold	BP-train	122.3411	8.1389	11.061	0.9982	0.0068
	BP-test	238.1695	11.7109	15.433	0.9924	0.0067
	LSTM-train	147.4852	8.9802	12.144	0.9979	0.0075
	LSTM-test	306.5525	13.5874	17.509	0.9902	0.0078
	CNN-train	158.245	9.2366	12.58	0.9977	0.0077
	CNN-test	301.5735	13.126	17.366	0.9903	0.0075
	BP-CNN-LSTN-train	120.9784	8.1113	10.999	0.9983	0.0067
	BP-CNN-LSTM-test	240.5556	11.8331	15.51	0.9923	0.0068

The results of the detailed performance metrics are displayed in Tables 2-5. Clearly, the current hybrid model achieves much lower values of MSE, MAE, RMSE, MAPE, and higher values of R^2, demonstrating its superior predictive ability

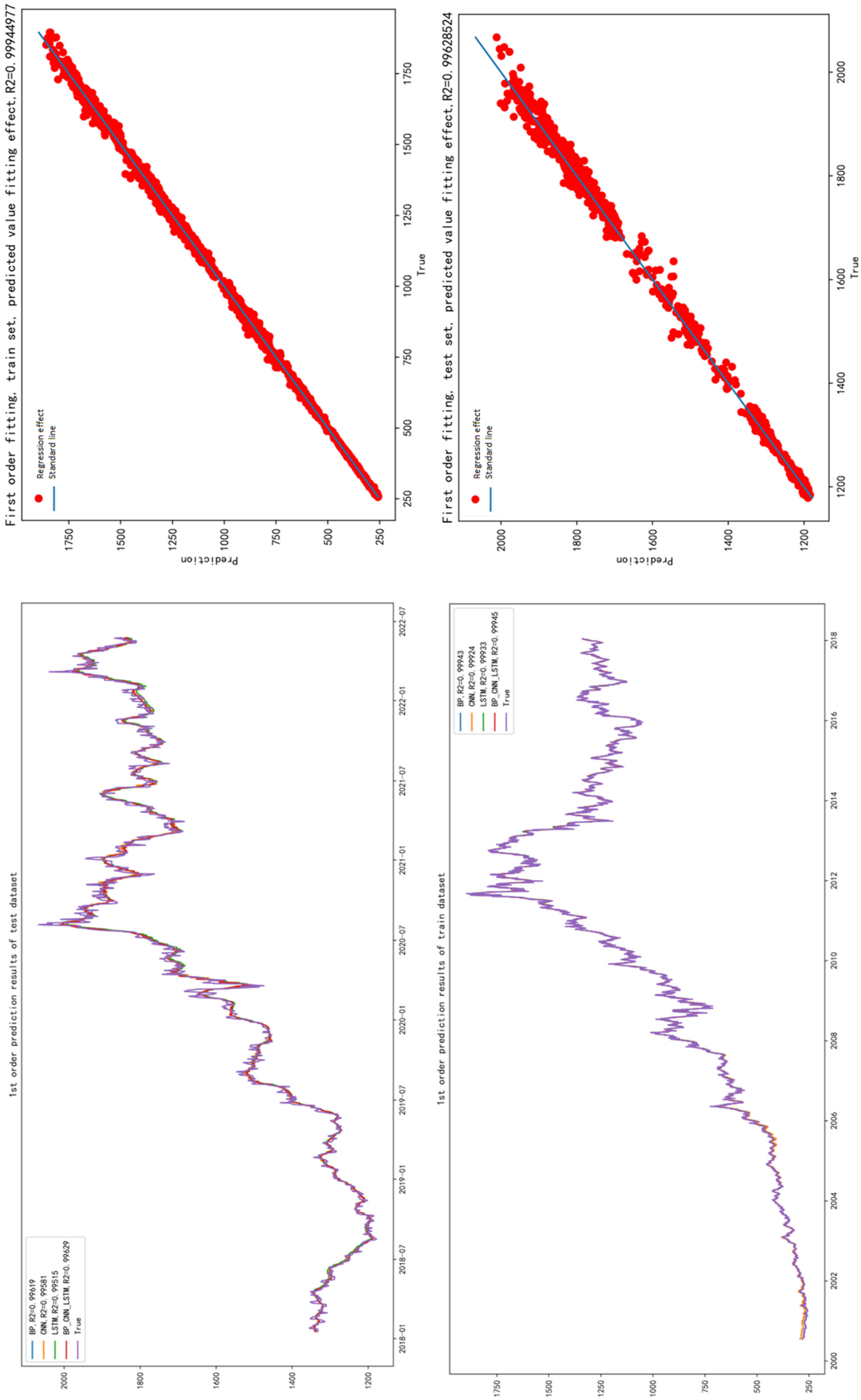

FIGURE 4. One-stage fitting multi-model prediction comparison.

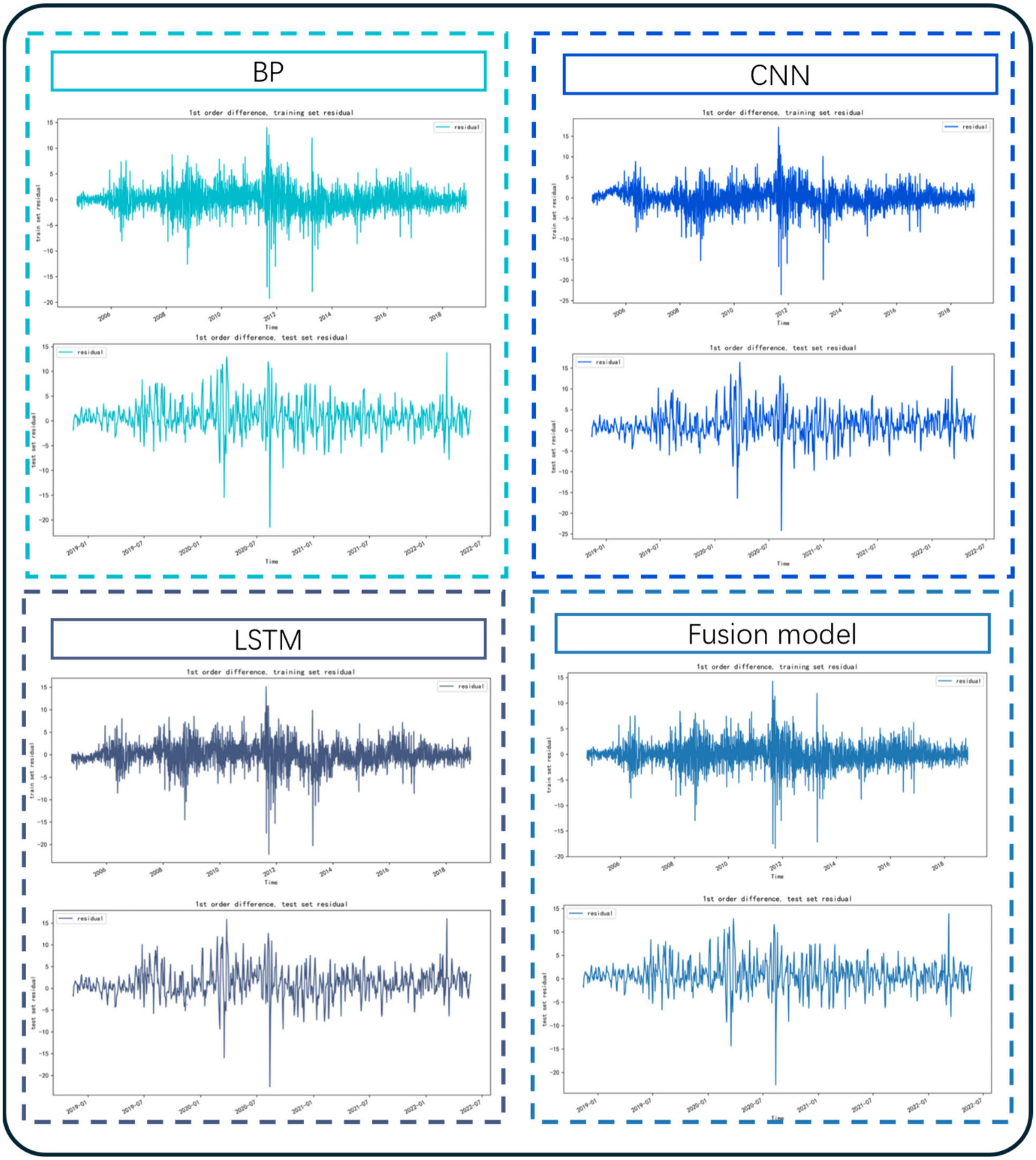

FIGURE 5. Three methods and fusion model residual extraction.

and more reliable and stable forecasting results. According to the data in Table 2, the results depicts instability when a single model is used to forecast the gold spot price on the Shanghai Gold Exchange. Specifically, the MAPE values for BP-test, LSTM-test, and CNN-test are 0.0063, 0.0063, and 0.0073 respectively, and these values are higher than that of the hybrid BP-CNN-LSTM model (0.0062). Notably, the MAPE values for the hybrid BP-CNN-LSTM model in London Spot Gold, COMEX Gold, and MICEX Gold are 0.0069, 0.0058, and 0.0068 respectively, which perform better than their corresponding single models. In addition, when other performance metrics such as MSE, MAE and RMSE are considered, the predictive performance of the fused BP-CNN-LSTM model also outperforms the other single models as shown in Figure 4. This result indicates that the proposed hybrid model has significant advantages in gold

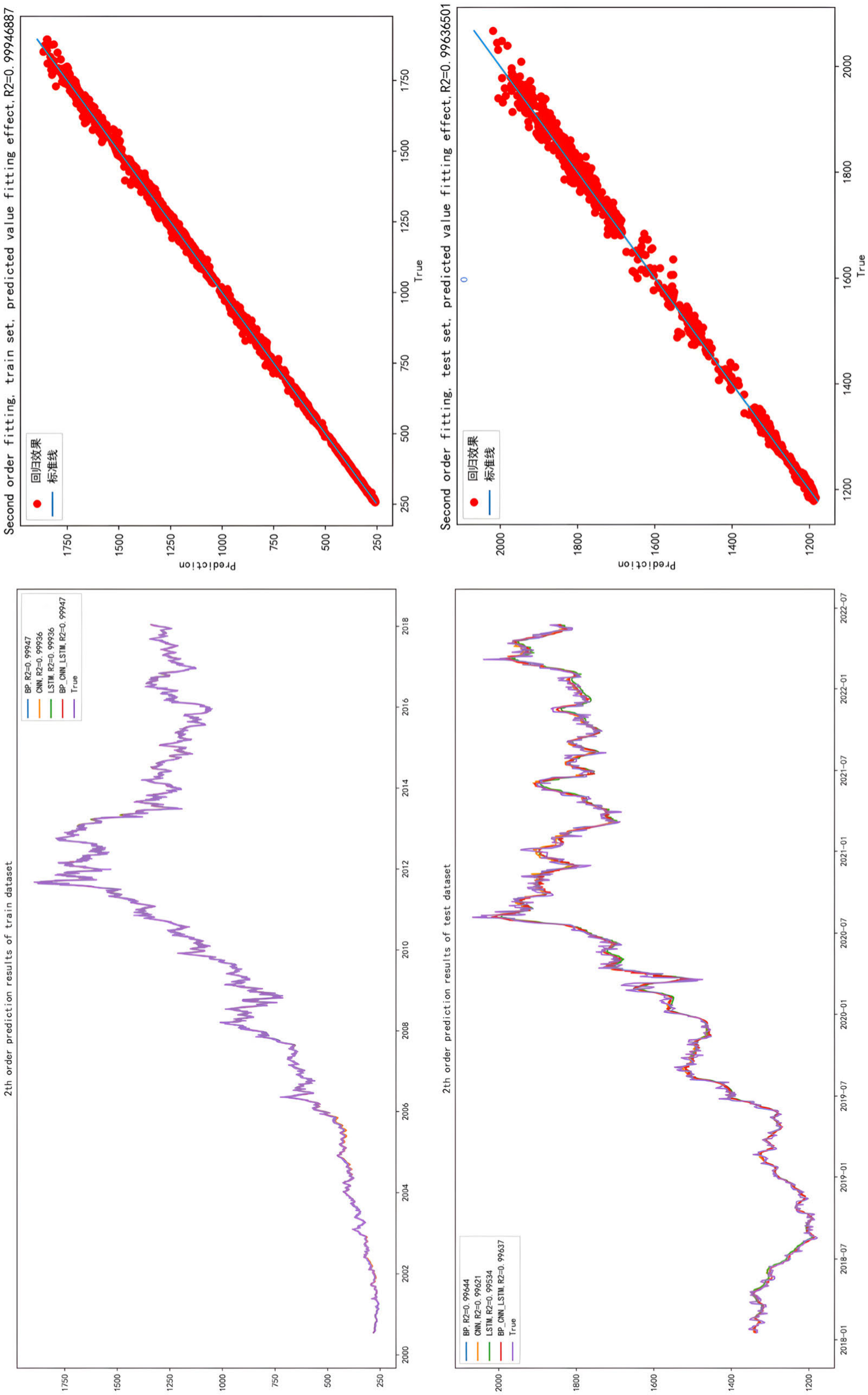

FIGURE 6. **Two-stage fitting multi-model prediction comparison.**

TABLE 6. The comparison between first-stage and second-stage hybrid models.

Market	Model	MSE	MAE	RMSE	R^2	MAPE
Shanghai Gold	First-stage BP-CNN-LSTM	10.1062	2.2617	3.1790	0.9939	0.0062
Exchange Gold Spot	Second-stage BP-CNN-LSTM	9.6574	2.2098	3.1076	0.9942	0.0061
London Spot Gold	First-stage BP-CNN-LSTM	242.5457	11.2532	15.5738	0.9963	0.0069
	Second-stage BP-CNN-LSTM	242.5457	11.2532	15.5739	0.9963	0.0069
COMEX Gold	First-stage BP-CNN-LSTM	175.6793	9.5391	13.2544	0.9973	0.0058
	Second-stage BP-CNN-LSTM	164.9928	9.2938	12.8450	0.9975	0.0056
MICEX Gold	First-stage BP-CNN-LSTM	240.5556	11.8331	15.5098	0.9923	0.0068
	Second-stage BP-CNN-LSTM	229.3081	11.5136	15.1429	0.9926	0.0066

price prediction and can provide more accurate and stable prediction results.

2) RESIDUAL CORRECTION AND OPTIMIZATION

Although the results of the first-stage experiments are impressive, it is recognised that there is further scope for improving the prediction accuracy. Towards this end, a novel methodology is introduced, whereby the hybrid model is optimized by training the residuals of the first-stage experiment to improve the final results with a view to obtaining more accurate predictions. The methodology involves training the residuals from the four major gold markets to produce the final fitted values. Figure 5 illustrates a comparison of the residuals extracted by the three different machine learning methods as well as the fusion model when dealing with the test and training sets.

As indicated in Figure 6 and Table 6, the hybrid BP-CNN-LSTM model of the second stage outperforms the hybrid model of the first stage in terms of MSE, MAE, RMSE, MAPE, and R^2 values.

According to the data in Table 6, the MSE values of the second-stage BP-CNN-LSTM model are significantly lower than those of the first-stage BP-CNN-LSTM model in the four major gold markets, which are 9.6574, 242.5457, 164,9928, and 229.3081, respectively. Particularly in the COMEX gold market, the MAPE values of the first-stage and second-stage hybrid BP-CNN- LSTM models have MAPE values of 0.9973 and 0.9975, respectively, a result that suggests that the second-stage model has superior predictive ability. In other words, by further operating on the residuals of the first-stage hybrid model, we achieve a significant improvement in the predictive performance. Our results indicate that the proposed hybrid model outperforms traditional single prediction models in terms of MSE, MAE, RMSE, MAPE, and R^2. These findings are consistent with the results reported by Liu et al. [11] who demonstrated the effectiveness of hybrid models in capturing the nonlinearities and complexities inherent in financial time series data. Moreover, the superior performance of our model compared to that of He et al. [27] underscores the importance of incorporating advanced feature extraction and residual correction techniques. Our results not only confirm the advantages of hybrid models but also highlight the significance of refining residuals for improving predictive accuracy. This discussion aligns with previous research by Liang et al. [20] and further validates the robustness of our proposed framework in diverse market conditions.

V. CONCLUSION

Overall, this research begins by highlighting the increasing importance of gold price forecasting for various stakeholders, such as policymakers, financial investors, and others. The development of a more accurate prediction model will undoubtedly help these stakeholders to make more informed decisions and strategies in a volatile market. Faced with the challenges posed by the highly dynamic gold market, our research successfully integrates the strengths of CNN, BP, and LSTM models to overcoming their respective shortcomings to provide an excellent forecasting framework. The key innovation in the research is to optimally process the residuals generated from the first-stage experiment. By comparing the performance of the first-stage and second-stage experiments, it is confirmed that the second stage experiments are able to achieve more accurate prediction results. Moreover, potential interference from chance factors is minimised through the selection of four mainstream gold markets as the study object.

In summary, on the one hand, the proposed hybrid model provides precise gold price forecasts and valuable insights for various stakeholders, and on the other hand, it represents an innovative approach to time series prediction. The adaptability and accuracy of the model also means that it has the potential to be applied to a variety of fields, such as stock markets and machine production, which is expected to bring significant social benefits. Nevertheless, the current study still has some limitations, like not fully considering relevant influencing factors and market environments, which could play a crucial role in forecasting. Future research could address these shortcomings to further enhance the predictive capabilities of the hybrid model. Despite the promising results, this study has certain limitations. One of the primary limitations is the model's dependency on historical data, which may not fully capture sudden market shifts caused by unforeseen geopolitical events or economic crises. Additionally, the model's performance could be affected by the choice of hyperparameters and the initial setup of the training process. Future research should focus on incorporating more adaptive algorithms that can dynamically adjust to real-time data and market conditions.

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