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Gold Price Forecast Based on the Least Square Support Vector Machine

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Abstract: Statistical models are used to forecast the price of gold. Utilize time-series based forecasting to ascertain how the past has an impact on the future. Forecasting is the process of creating theories about likely future occurrences, and forecasting models are capable of foreseeing such occurrences. Due to the worth of gold, systems for forecasting its price have garnered a lot of attention in the scientific and industrial realms. This study will forecast gold prices from 1 January 2021 to 12 may 2023 using a LSSVM model. Predictions of the price of gold are made using the proposed hybrid, Least square support vector machine (LSSVM) model. The analysis relies on the commonly used metrics of mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) for assessing the performance of time-series forecasting. Performance evaluations using real data obtained from the MarketWatch gold prices show that the proposed LSSVM model outperforms other traditional statistical methods. The solution to problems involving time series forecasting has been greatly aided by the proposed method, which is also a very precise tool.

Keywords*: Least Square Support Vector Machine, Gold Price, Forecasting, Parameter, training.*

1. Introduction

Planning for the future and making business decisions both heavily rely on time series forecasting. For economic analysis, it is a crucial instrument. Everywhere, including in the forecasting of the weather, the stock market, and sales, historical data must be analysed. Simon J etal.(2006) [1] present the first step in examining patterns affected by extreme weather events and climate changein power demand and the electricity network. Along with developing a reliable method to precisely predict the daily load for planning purposes, similar to most traditional models, it is crucial for us to also produce a trustworthy long-term projection.

Liu et al. (2009) [2] described the currency and financial characteristics of gold make its futures more significant than those of other commodities. Therefore, the research on gold futures is significant both theoretically and practically. The parameters of the Hadavandi et al. (2010) [3] proposed PSO-based time series model for gold price prediction are calculated in this study using the PSO algorithm. Utilizing daily gold price observations to test the proposed model's capabilities, we compare the results to those obtained using earlier techniques using mean absolute error (MAE). Hussein et al. (2011) [4] described a system that will help gold investors choose when it is best to buy or sell gold in the future. The system created is based on already-existing time series of gold data and artificial neural network-based techniques.

Kusumawardhani et al. (2011) [5]described that the system being modelled is a Markov process with unknown parameters, hidden Markov models (MMM) are a type of stochastic model. Finding the hidden parameters from the parameters that are visible is the difficult part. Jian-Hui et al. (2012) [6] proposed the Wavelet transform (WT), which employs SVR to anticipate detail signals and approximation signals and decomposes the function into some signal. This method is more developed than the previous practises. Each forecasting component will eventually obtain the resultant prediction.

Yazdani-Chamzini et al. (2012) [7] described how the gold price was modelled using the ANFIS and ANN models, in contrast to the more popular ARIMA statistical model.ANFIS, which Makridou et al. (2013) [8] proposed, outperforms all other methods in terms of accuracy, demonstrating the potential of neural fuzzy-based modeling for predicting the price of gold.Kangaran et al. (2013) [9] described the prediction of gold prices on the Forex market as the main goal. It used two ANN prediction machine models: one that uses the output of the network as input, and the other that does not. Li et al. (2014) [10] proposed a brand-new artificial bee colony (ABC) algorithm and wavelet neural network (WNN) are integrated to address the problem of forecasting the price of gold. The traditional roulette selection approach is disregarded in this upgraded algorithm.

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Contribution of the research

- In this paper, an innovative LSSVM time series prediction model is presented.
- The proposed model was applied to forecast the price of gold in India and resulted in a trustworthy forecast.
- The outcome of the training and forecasting for gold prices using an LSSVM model.
- The results demonstrate that over the time period of gold prices from 1 January 2021 to 12 May 2023, the proposed method outperforms the other traditional statistical techniques.

The organization of this paper is structured as follows. part II summarizes the linked works. In part III, present the implementation of theLSSVM models utilized in this paper. part IV will present the performance measurement. Finally, the results are discussed in part V.

2. Literature Review

Given the growing demand for gold in India, a model like that proposed by Navin et al. (2015) [11] must be developed that encapsulates the structure and predicts how the gold market will behave and how prices will change. Support vector regression and decision tree modelling are the best techniques for determining gold prices. Christina et al. (2015) [12] have proposed type-2 neuro-fuzzy modelling is used to predict the price of gold. Self-Constructing Clustering is used to partition the historical gold price data into a number of clusters and generate some type-2 fuzzy rules. The outcome of the type-2 neuro-fuzzy modelling used to estimate the price of gold is contrasted with that of the widely utilised ARIMA method.

In order to predict daily gold prices, Dubey et al. (2016) [13] created time-series gold price prediction models using SVR and ANFIS approaches. The support vector model was developed using the epsilon support vector regression approach, while the adaptive neural fuzzy inference systems were created using grid partition and subtractive clustering techniques.Sivalingam et al (2016) [14] have proposed Extreme Learning Machine (ELM), a learning algorithm with high learning capabilities, is utilised in this paper to train single hidden layered feed forward neural networks.Wen et al. (2017) [15] have proposed CEEMD algorithm outperforms the EMD method in this paper's initial comparison of the two algorithms for analysing gold price volatility. The complementary ensemble empirical mode decomposition is then used to dissect the historical price of global gold into price components at various frequencies, allowing this study to derive a short-term volatility, a shock from major events, and a long-term price. Tripathy et al. (2017) [16]have proposed ARIMA (Auto Regressive Integrated Moving Average) model is used in the current study to anticipate India's gold price over a 25-year period, from July 1990 to February 2015. According to the study, the price of gold over the previous month has a big influence on the price of gold right now.

Hafeziet.al (2018) [17] tries to advance an intelligent gold price forecasting model built on artificial neural networks (ANNs). A meta-heuristic algorithm known as the BAT algorithm is included in the suggested intelligent network to enable ANN to track fluctuations. Bin Khamis et al. (2018) [18] have proposed ANN trained using the back propagation algorithm and a hybrid forecasting model combining genetic algorithms and artificial neural networks. The neurons in artificial neural networks are optimized using genetic algorithms.

Singla etal.(2019) [19] formula for estimating India's CPI projections from May to December 2018. The all-India CPI statistics for the months of January 2013 and April 2018 were used in this study. Using the modeller approach, models were fitted by experts in SPSS, and the data were reviewed.Alameer etal. (2019) [20] the proposed an improvement in forecasting accuracy over the GWO-NN, ARIMA, GA-NN, and PSO-NN models, as well as a reduction in mean square error for each.A comprehensive analysis of the research on the use of DL studies to forecast financial time series is provided by Sezer et al. (2020) [21]. We divided the studies into groups according to the DL models they used, such as LSTM, CNN, and DBN. We also divided the studies into groups according to the forecasting applications they were intended for, such as index, and commodity forecasting (LSTM).

Jaiswal etal. (2020) [22] a review of the available soft computing techniques used for stock market forecasting, along with a comparison and potential solutions. It is clear from the reviewed articles that researchers have worked very hard to develop fusion forecast representations, and they have also put a lot of effort into using broadcasting data to anticipate the stock market. Surendra J et.al, 2021 [23] mainly concentrated on estimating gold prices from 2020 to 2029, noted the unexpected rise in gold price in 2020 due to numerous reasons, and its impact on forecasting gold prices using ARIMA model. The proper ARIMA model (0, 2, 3) is discovered by studying the partial autocorrelation function and autocorrelation function are two types of autocorrelation functions to the chosen differenced series, and gold price forecasts are created. IoannisSyrris etal. (2021) [24] comes to predicting the returns and volatility of gold price series, a hybrid ARIMA-GARCH model outperforms either an ARIMA or GARCH model by itself. In conclusion, GARCH models required to be used in order to capture the extreme volatility of the gold commodity, despite the fact that ARIMA models have demonstrated the ability to capture the autoregressive process.RasmitaRautray etal. (2021) [25], have described the contrasted with PSNN learning based on DE and PSO.

Kamalovet.al,(2021) [26] have proposed LSTM, NN, and AR models' predicting abilities for time series with linear lags are assessed. The results of the tests demonstrate that NN models outperform AR models despite AR models having a natural advantage in modelling linearly lagged data.Hajek et al. (2022) [27] have proposed a fuzzy rule-based forecasting model that has a module that looks at different aspects of news events. In order to predict gold prices one and five days in advance for investors, this system uses historical data to achieve a highly interpretable trading approach. Yang et al. (2022) [28] have proposed three models are subjected to a comparative analysis in the first phase. The evaluation of how cryptocurrency affects the models is demonstrated in the second stage. Our results show that all three methods benefit from the extra cryptocurrency data, with the SVR model outperforming the other two methods. In order to estimate annual gold prices using the Autoregressive Distribution Lag technique, Madziwa et al. (2022) [29] used treasury gold demand and lagged gold prices as covariates. All of the variables were found to be ordered by a single integrator when unit roots were checked using the Phillips Perron and improved Dickey Fuller techniques. Baser et al. (2023) [30] have described development of artificial intelligence recently and improved computer equipment's capabilities have demonstrated the effectiveness of price prediction systems. In many markets, machine learning (ML) is utilised to anticipate prices.

3. Proposed of Least Square Support Vector Machine Gold Prices Forecasting

This section discusses the dataset and proposed forecasting techniques for the same time series of the daily gold price. The forecasting models will be discussed after the dataset has been introduced.

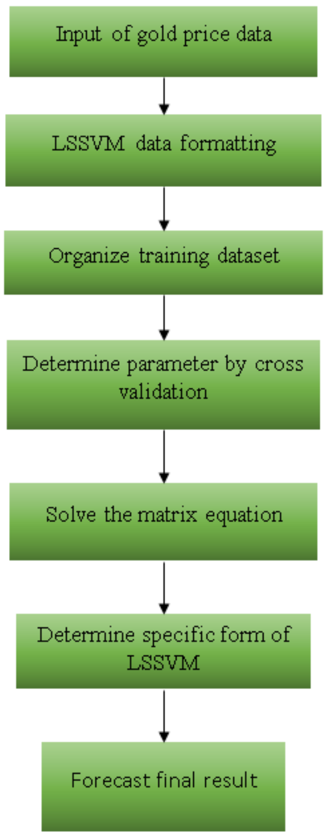


Fig:1 Flow chart of LSSVM model

The flowchart in Figure 1 provides a basic explanation of the LS-SVM model's operation. From 2021 through 2023, we gathered data on gold prices. gold price training and forecasting using a single LSSVM model. Predictions of the price of gold are made using the proposed hybrid, LSSVM model. Finally, the performance of the LSSVM model was compared to that of other forecasting models using a dataset for India.

3.1 Dataset

The years 2021 to 2023, we collected gold price data. More specifically, we downloaded the MarketWatch database's daily prices for COMEX Gold futures [37].

The primary international gold benchmark is the COMEX Gold price. Previous research has looked at a range of input variables as potential predictors of fluctuations in the price of gold, as previously indicated. These input variables' closing prices from the day before were gathered from the MarketWatch database, which is freely accessible. These input variables' closing prices from the previous day were gathered from the free MarketWatch database.

3.2 Proposed system is based onLeast Square Support Vector Machine

A supervised learning technique built on the idea of structural risk minimization (SRM), the support vector machine (SVM) [38] was created in 1995 by Vladimir Vapnik and colleagues at AT&T Bell Laboratories. Signal processing, pattern recognition, and non-linear regression can all use the SVM model since it has a propensity to handle dynamic, non-linear, and complex time-series data. Since SVM is utilised to approximate accurately non-linear relationships between input and output variables, the dominating methodology of least square support vector machine (LS-SVM) has been derived from it. LS-SVM is very useful in resolving issues pertaining to non-linear classification and regression. By using a least squares loss function and equality constraints rather than inequality constraints, LSSVM [39] solves a quadratic optimisation problem. Think about a training dataset (i_x,i_y) that has output $y_i \in R$ and input $x_i \in R^n$. SVM models in feature space have the following forms:

$$y(x) = w^T \emptyset(x) + b \qquad (1)$$

where the input data is mapped into a higher dimensional feature space by the non-linear mapping $\phi(x)$. By rewriting the regression issue as, LSSVM offers a least squares variant to SVM regression.

$$min\ R(w, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 (2)$$

subject to the restrictions on equality

$$y(x) = w^T \emptyset(x_i) + b + e_i, \ \ i = 1,2, \ldots., n \qquad (3)$$

The construction of the Lagrange function is used to solve this optimisation problem as

$$L = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{n} e_i^2 - \sum_{i=1}^{n} \alpha_i \{w^T \emptyset(x_i) + b + e_i - y_i\} \qquad (4)$$

If α_i represents Lagrange multipliers, γ represents a regularisation parameter, ω, b represents model parameters, and e represents the training set's error vector. By partially differentiating with regard to w, b, e_i, and α_i, it is possible to arrive to the solution of equation (4).

$$\frac{\partial L}{\partial W} = 0 \to w = \sum_{i=1}^{n} \alpha_i \, \emptyset(x_i) \qquad (5)$$

$$\frac{\partial L}{\partial b} = 0 \to \sum_{i=1}^{n} \alpha_i = 0 \qquad (6)$$

$$\frac{\partial L}{\partial e_i} = 0 \to \alpha_i = \gamma e_i \qquad (7)$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \to w^T \emptyset(x_i) + b + e_i - y_i = 0, i = 1,2, \ldots., n \qquad (8)$$

Afterward, the weight w can be expressed as a combination of the Lagrange multipliers and the relevant data training x_i.

$$w = \sum_{i=1}^{n} \alpha_i \, \emptyset(x_i) = \sum_{i=1}^{n} \gamma e_i \emptyset(x_i) \qquad (9)$$

The following result is produced by plugging the result of (9) into (1):

$$y(x) = \sum_{i=1}^{n} \alpha_i \emptyset(x_i)^T \emptyset(x_i) + b = \sum_{i=1}^{n} \alpha_i k(x_i, x) + b \qquad (10)$$

where the following is the definition of a positive definite kernel:

$$k(x_i, x) = \emptyset(x_i)^T \emptyset(x_i) \qquad (11)$$

One can determine the α vector and b by resolving a series of linear equations:

$$\begin{bmatrix} 0 & 1^T \\ 1 & \emptyset(x_i)^T \emptyset(x_j) + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \qquad (12)$$

Where $y = [y_1, \ldots, y_n]$, $1 = [1, \ldots., 1]$, $\alpha = [\alpha_1, \ldots, \alpha_n]$

Finally, the resulting LSSVM model for function estimation is as follows:

$$y(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) \, k(x_i, x) + b \, (13)$$

where b is derived from the complementarity of the KKT conditions and α_i, α_i^* are solutions to the aforementioned quadratic programming problem. It is clear that the support vectors with coefficients $(\alpha_i - \alpha_i^*)$ that are not zero define the decision function.

In actuality, a larger ε leads to fewer support vectors and, thus, a sparser solution. Additionally, the precision of training points will be worse the larger the ε. Consequently, ε can be used to manage the balance between closeness to training data and solution sparsity.

Several well-liked kernel functions are listed in [41, 42]:

a) The high dimensional feature space that is nonlinearly transferred from the input space x is represented by the kernel function K (x_i, x).

b) polynomial kernel: $K(x_i, x) = ((x_i)^T x + 1)^d$ where d is the kernel's degree in the polynomial.

c) Numerous studies have shown that the Radial basis function (RBF) performs well. RBF is therefore employed in this study as the kernel function. RBF is provided by

$$k(x_i, x) = exp(-\sigma \|x_i - x\|^2), \qquad (14)$$

where σ represents the kernel's settings.

The correctness of the final solution is impacted by the structure of the high-dimensional feature space (x), which is dependent on kernel function parameters. The flowchart in Figure 1 provides a basic explanation of the LS-SVM model's operation.

Figure 1 depicts the model's detailed steps. They are as follows:

(1) Prepare the training data.

(2) The kernel parameter σ and regularisation parameter γ, which significantly affect the model's performance, should be determined prior to training. The model's performance quality is substantially governed by the two parameters [43]. To locate the location where the cross validation error is the minimum, the approach iteratively modifies the two parameters.

(3) After determining the kernel parameters σ and regularisation parameters γ, solve equation (12) to obtain α and b.

(4) Follow α and b into (13) to determine the exact LS-SVM form.

(5) The price of gold is calculated with a final forecast.

3.3 PERFORMANCE ASSESSMENT OF THE MODELS

Both the training data and the forecasted data are analysed in order to assess how well each model performs. The outcome of this investigation is evaluated using statistical measures. the analysis based on the metrics mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), all of which are frequently used to assess the performance of time-series forecasting [40]. The RMSE, which is sensitive to significant differences between the forecast value and the actual value, provides a good reflection of the accuracy of the forecasting result. MAE can be used to address the problem of positive and negative errors cancelling one another. The following are the three indicators' calculation formulas. The accuracy of the forecasting result can be more accurately reflected by MAPE because it considers both the relationship between the error and the actual outcome as well as the variance between forecast and actual value.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{N}(A_t - P_t)^2}{N}} \qquad (15)$$

$$\text{MAE} = \frac{\sum_{t=1}^{N}|A_t - P_t|}{N} \qquad (16)$$

$$MAPE = \frac{100}{N\sum_{t=1}^{N}\left|\frac{A_t - P_t}{P_t}\right|} \qquad (17)$$

where A_t and P_t represent the actual and anticipated price of gold at time t, respectively. The criteria to choose which model is the best to use for modelling and forecasting are relatively low MAE, MAPE and RMSE values. Data normalisation is frequently done prior to the training procedure. The following is the linear transformation formula for [0, 1]:

$$y_t == \frac{x_t}{x_{max}} \qquad (18)$$

where x_{max} denotes the highest values among the original data, and $y_t$and x_t denote the normalised and original data, respectively.

4. Experimental Result and Discussion

The forecasted price of gold in India was used to evaluate the proposed method LSSVM. All experiments' settings and the dataset's description are provided. The outcomes of LSSVM were also contrasted with those of the original ANFIS, LSTM, and ARIMA.

4.1 Dataset Description

The daily 2021 to 2023, we collected gold price data. More specifically, we downloaded the MarketWatch database's daily prices for COMEX Gold futures. The primary international gold benchmark is the COMEX Gold price.In this work, the data modelling techniques LS-SVM are used to forecast daily out-of-sample data points that will provide an estimate of a future increase in the confirmed gold price. Time series forecasting usually makes use of these well-known data.

Table 1 Daily gold price descriptive statistics.

Statistic	Value
Skewness	- 0.5509
SD	6.8776
Maximum	133.10
Mean	118.4784
Kurtosis	2.6991
Median	119.325
Minimum	100.50

While Fig. 2 shows the daily gold prices, Table 1 provides descriptive statistics that include the following measurements to describe the nature of the distribution: minimum, mean, maximum, median, standard deviation (SD), skewness, and kurtosis.

Fig 2. Gold price of India from 2021 to 2023

A total of 640 observations covering the years 2021 to 2023 are used to calculate the price of gold. The dataset will be split into two sets: a training set that includes the first 90% of values and a test set that contains the remaining 10%. The test set is used to evaluate the proposed strategy with other models, while only the training set is utilised for model selection and parameter optimisation. Table 1 provides details about the series spread among the training and forecasting sets.

Table 1 The set of data utilised in forecasting techniques.

Series	Data	Training set	Forecasting set
A	MarketWatch database's daily prices 2021 to 2023 for COMEX Gold	640	40

4.2. LSSVM testing is done on the data

Numerous successful implementations of this model depend on the choice of the number of inputs that correspond to the number of variables. Finding the ideal amount of inputs is a critical yet challenging problem. In this section, we simply used one LSSVM model to analyse the datasets. For a hybrid model, we used the same parameters as the LSSVM's parameter.

4.2.1 Implementation of LSSVM

Because it often achieves greater performance, we used the Radial Basis Function (RBF) kernel in our experiment, where δ^2 is the RBF kernel's bandwidth. There is no theory that can be applied to determine how many inputs should be chosen. The datasets for this study's analysis used the number inputs (I), 2, 4, 6, 8 and 12. δ^2 and the margin γ are set to 50 and 10 for the kernel bandwidth, respectively. LSSVM was chosen for this reason since it has equality constraints. Thus, the answer is discovered by resolving a set of linear equations. LSSVM can be resolved using scalable and effective methods, such as those based on conjugate gradient.

4.2.2. Result

Table 2 displays the outcomes of the training and forecasting using a single LSSVM model. The statistical outcomes for forecasting and training using LSSVM models are listed in Table 2. The lowest RMSE and MAE are determined from four inputs for forecasting data. The values of MAPE and RMSE decrease to some extent as the input in the first layer rises from 2 to 12, and the training impact of the model improves proportionally. The model has reached its optimal state when the input value hits 12, at which point all three errors display the lowest values. The errors immediately decreased, especially when the input was 12. Table 2 The outcome of training and predicting with an LSSVM model

Series data	Input	Training			Forecasting		
		MAE	RMSE	MAPE	MAE	RMSE	MAPE
A	2	0.0319	0.0433	0.0492	0.0237	0.0322	0.0483
	4	0.0237	0.034	0.0327	0.0193	0.0294	0.0312
	6	0.0238	0.0341	0.0364	0.017	0.0265	0.0336
	8	0.0229	0.0325	0.0338	0.018	0.0275	0.0347
	12	0.0196	0.0243	0.0273	0.0086	0.0178	0.0297

In the meantime, the data for A was also computed. For forecasting, the lowest RMSE, MAPE, and MAE are derived from inputs equal to six, while the lowest RMSE, MAPE, and MAE from the observation were determined using inputs equal to twelve (see Table 2).

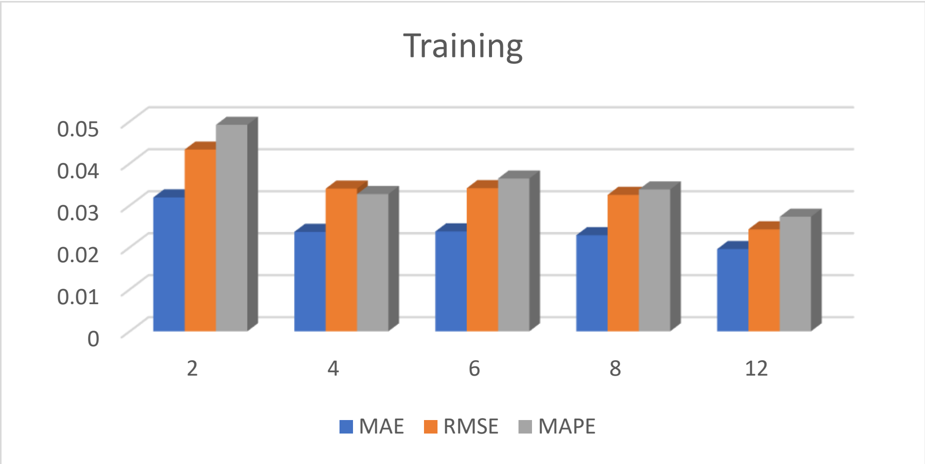


Fig. 3. LSSVM training values using various input numbers

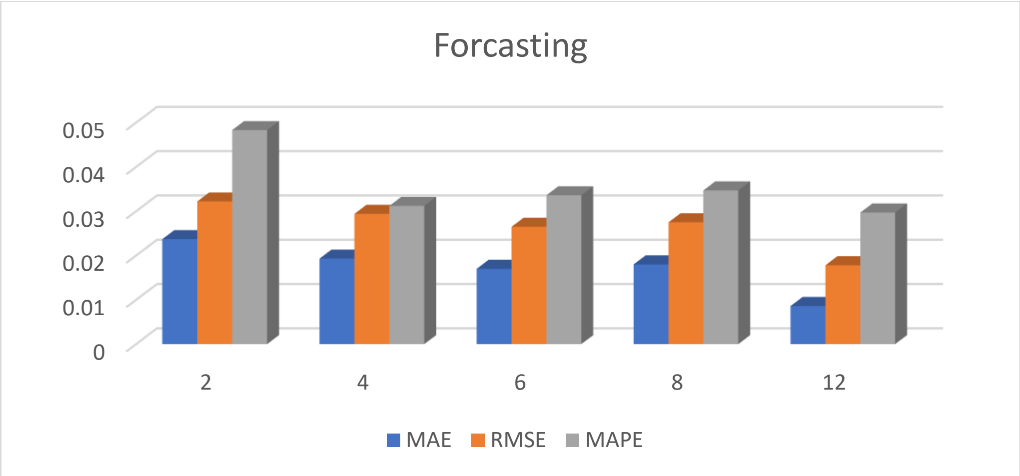


Fig. 4. LSSVM forecasted values with various input numbers

Figures 3 and 4 display the training value and predicted values produced by the input-layer LSSVM model with various input numbers. The 12 input layer values in the LSSVM provide the best training and forecasting results for the gold price. When the number of input layers falls, it is clear that the model's prediction accuracy is greatly improved by reducing model complexity. Additionally, the LSSVM's sigmoid function activation function, the ideal learning rate of 0.01, and the ideal momentum of 0.2. The LSSVM's optimal parameters were used as the starting point for all subsequent results that are reported in this research when contrasting them with those from other models.

4.3 Comparison

A hybrid LSSVM model's training and forecasting performance were compared to those of the other model for comparison's sake. Tables 3 and 4 compare the training and forecasting accuracy of several methodologies using three statistical measures for a set of datasets. The outcomes further demonstrate that the LSSVM model outperforms alternative approaches for A series data. This indicates that a hybrid LSSVM model is more capable in terms of RMSE and MAE during predicting and training. The outcome of this experiment demonstrated that one LSSVM greatly outperformed another. The outcome might be explained by the fact that LSSVM provide a superior prediction.

Table 3 Training outcome of performance comparison of LSSVM and various data series approaches

Data	Model	Training		
		MAE	RMSE	MAPE
A	ARIMA [31]	12.6782	8.9945	0.9725
	LSTM[32]	-	4.18	2.40
	ANFIS [33]	0.012	5.94	-
	Proposed LSSVM	0.009	2.13	0.721

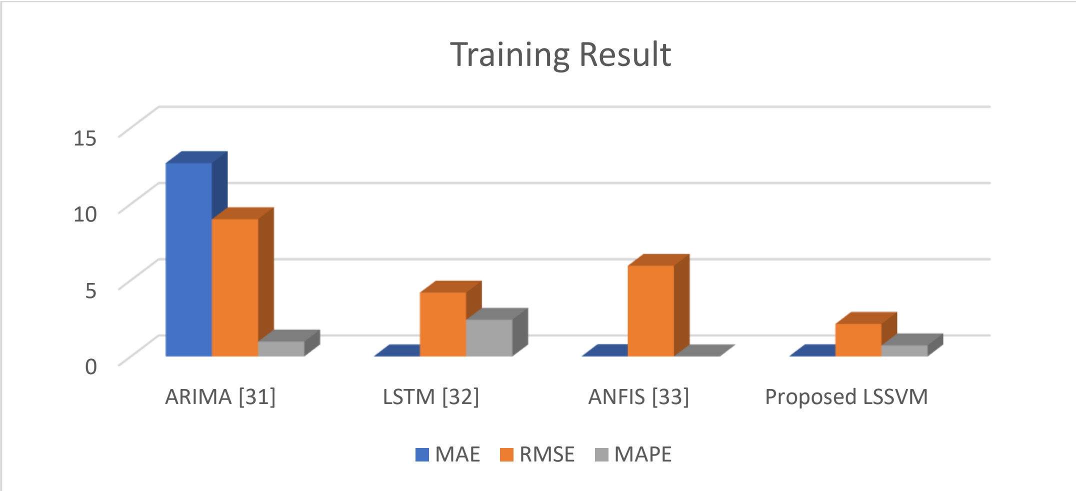


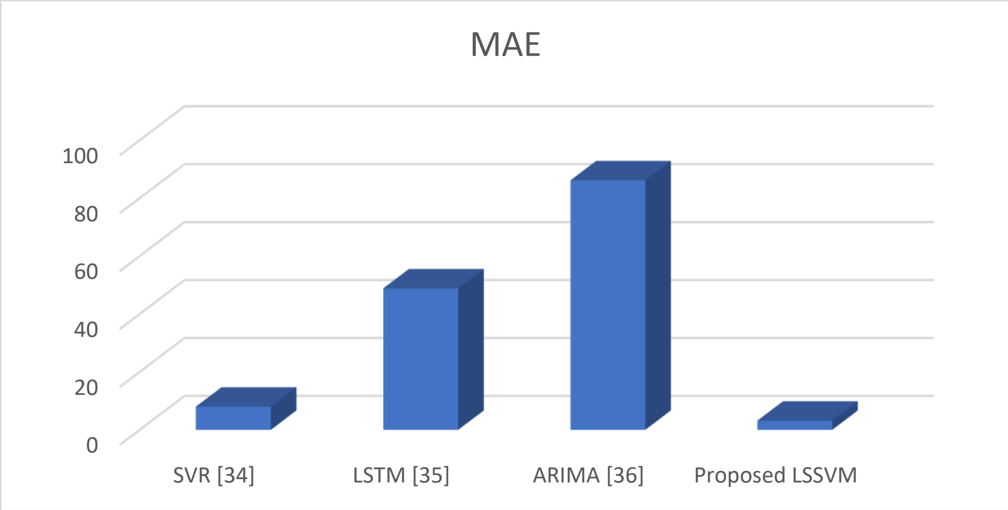
Fig 5 Training outcome of performance comparison between LSSVM and other techniques

Fig. 5 shows how the LSSVM models performed during the training phase. Daily gold COMEX prices from MarketWatch database used for time series forecasting. Gold price values from January 1, 2021, to December 5, 2023, are used in this experiment as historical data and are displayed in Table 4. The proposed model's outcomes were contrasted with the anticipated values offered by the SVR model in addition to the LSSVM comparison. SVR's absolute and relative mistakes, as well as its total error level, are inferior than those of LSSVM model.

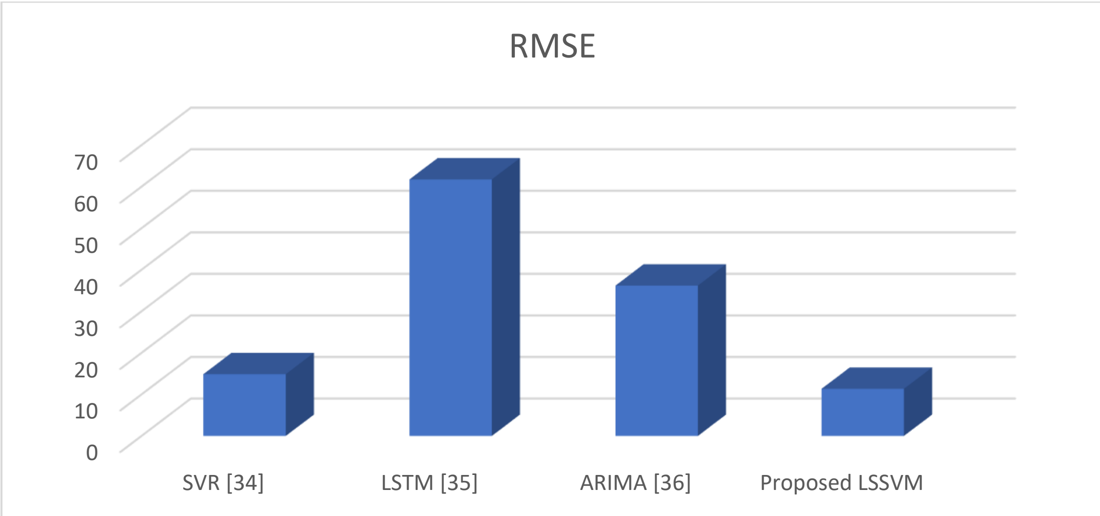
Table 4. Comparison of the performance of LSSVM with various data series forecasting techniques

Data	Model	Forecasting		
		MAE	RMSE	MAPE
A	SVR[34]	8.021052	14.85914	0.0063055
	LSTM [35]	48.85	61.728	3.48
	ARIMA [36]	86.15	36.1795	28.975
	Proposed LSSVM	3.183	11.329	0.00371

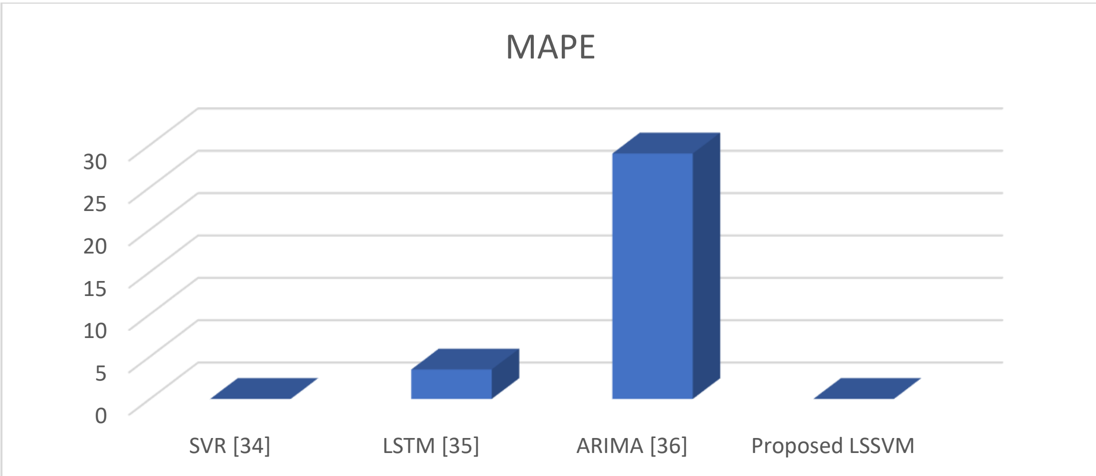
The proposed method, LSSVM, outperformed SVR, LSTM, and ARIMA in every way when it came to predicting the price of gold in India. Figure 4 displays the predicting RMSE, MAE, and MAPE values for each algorithm utilised in India.



(a) MAE



(b) RMSE



(c)MAPE

Fig 6. Forecasting performance of different models: a) RMSE b) MAPE

In Table 4, the effectiveness of each approach is contrasted. According to Table 4, the proposed model's RMSE and MSE are both less than those of the other models. As a result, the LSSVM model we propose in this research could significantly improve forecast precision.

Both the mean absolute percentage error (MAPE) and the root mean squared error (RMSE) of the suggested model are smaller than those of the rival models. As a result, the FTS model suggested in this research might contribute to increasing forecast precision. Finally, these comparison findings demonstrate that LSSVM outperforms the other two models. In other words, the proposed LSSVM is effective for predicting gold prices.

We also used the reference models [34, 35, 36] to anticipate gold prices concurrently for comparison's sake. Figure 5 displays each model's forecasted outcomes.

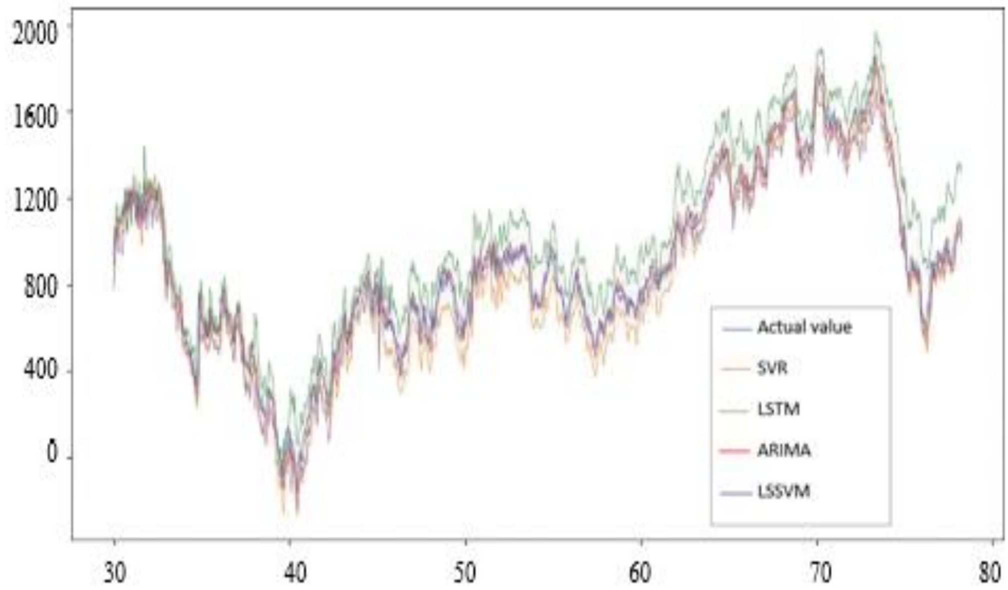


Fig 7. Real and forecasting data of India's gold prices.

Table 5 lists the outcomes of LSSVM forecasting for India for the daily from 2021 to August 2023. The forecasted values in this table appear to be comparable to the observation values, which is a sign of reliability.

Table 5. LSSVM forecasting values of India gold prices for daily

Data	Actual	Forecasted	Date	Actual	Forecasted	Date	Actual	Forecasted
5/15/2023	**-**	2039.20	03/01/2023	1,845.40	1862.70	12/15/2022	1,787.80	1791.20
5/14/2023	**-**	2035.20	02/28/2023	1,836.70	1842.80	12/14/2022	1,818.70	1820.10
5/13/2023	**-**	2032.40	02/27/2023	1,824.90	1831.70	12/13/2022	1,825.50	1834.70
05/12/2023	2,019.80	2024.40	03/02/2023	1,840.50	1849.70	12/12/2022	1,792.30	1797.20
05/11/2023	2,020.50	2028.40	03/01/2023	1,845.40	1849.80	12/09/2022	1,810.70	1822.70
05/10/2023	2,037.10	2041.30	02/28/2023	1,836.70	1839.80	12/08/2022	1,801.50	1816.60
05/09/2023	2,042.90	2048.70	02/27/2023	1,824.90	1835.80	12/07/2022	1,798.00	1799.90
05/08/2023	2,033.20	2040.60	02/24/2023	1,817.10	1828.20	12/06/2022	1,782.40	1788.90
05/05/2023	2,024.80	2031.40	02/23/2023	1,826.80	1832.30	12/05/2022	1,781.30	1792.80
05/04/2023	2,055.70	2061.40	02/22/2023	1,841.50	1852.80	12/02/2022	1,809.60	1811.70
05/03/2023	2,037.00	2041.30	02/21/2023	1,842.50	1850.70	12/01/2022	1,815.20	1828.80
05/02/2023	2,023.30	2029.20	02/17/2023	1,850.20	1859.60	11/30/2022	1,759.90	1767.80
05/01/2023	1,992.20	1998.30	02/16/2023	1,851.80	1861.80	11/29/2022	1,748.40	1758.70
04/28/2023	1,999.10	2008.30	02/15/2023	1,845.30	1848.70	11/28/2022	1,740.30	1747.30
04/27/2023	1,999.00	2001.80	02/14/2023	1,865.40	1867.70	11/25/2022	1,754.00	1767.80
04/26/2023	1,996.00	1999.60	02/13/2023	1,863.50	1869.70	11/23/2022	1,745.60	1754.70
04/25/2023	2,004.50	2013.90	02/10/2023	1,874.50	1880.60	11/22/2022	1,739.90	1745.90
04/24/2023	1,999.80	2008.30	02/09/2023	1,878.50	`1882.50	11/21/2022	1,739.60	1754.30
04/21/2023	1,990.50	1998.80	02/08/2023	1,890.70	1895.60	11/18/2022	1,754.40	1761.90
04/20/2023	2,019.10	2021.30	02/07/2023	1,884.80	1889.50	.	.	.
04/19/2023	2,007.30	2012.50	02/06/2023	1,879.50	1882.50	.	.	.
04/18/2023	2,019.70	2032.00	02/03/2023	1,876.60	1878.60	.	.	.
04/17/2023	2,007.00	2017.00	02/02/2023	1,930.80	1939.60	.	.	.

04/14/2023	2,015.80	2019.60	02/01/2023	1,942.80	1948.50	.	.	
04/13/2023	2,055.30	2059.00	01/31/2023	1,945.30	1950.60	02/16/2021	1,799.00	1811.70
04/12/2023	2,024.90	2034.30	01/30/2023	1,922.90	1928.70	02/12/2021	1,823.20	1834.80
04/11/2023	2,019.00	2020.20	01/27/2023	1,929.40	1930.40	02/11/2021	1,826.80	1838.70
04/10/2023	2,003.80	2012.90	01/26/2023	1,930.00	1940.30	02/10/2021	1,842.70	1852.60
04/06/2023	2,026.40	2029.30	01/25/2023	1,942.60	1947.40	02/09/2021	1,837.50	1841.80
04/05/2023	2,035.60	2038.40	01/24/2023	1,935.40	1936.50	02/08/2021	1,834.20	1844.80
04/04/2023	2,038.20	2042.80	01/23/2023	1,928.60	1931.40	02/05/2021	1,813.00	1854.70
04/03/2023	2,000.40	2012.80	01/20/2023	1,928.20	1931.40	02/04/2021	1,791.20	1798.70
03/31/2023	1,986.20	1989.00	01/19/2023	1,923.90	1928.50	02/03/2021	1,835.10	1839.90
03/30/2023	1,997.70	1999.00	01/18/2023	1,907.00	1913.50	02/02/2021	1,833.40	1846.70
03/29/2023	1,966.90	1969.30	01/17/2023	1,909.90	1911.60	02/01/2021	1,863.90	1879.40
03/28/2023	1,973.50	1978.80	01/13/2023	1,921.70	1928.89	01/29/2021	1,850.30	1869.10
03/27/2023	1,953.80	1958.80	01/12/2023	1,898.80	1899.00	01/28/2021	1,837.90	1851.90
03/24/2023	1,983.80	1887.90	01/11/2023	1,878.90	1881.60	01/27/2021	1,844.90	1856.50
03/23/2023	1,995.90	1998.40	01/10/2023	1,876.50	1880.40	01/26/2021	1,850.90	1867.40
03/22/2023	1,949.60	1953.70	01/09/2023	1,877.80	1883.50	01/25/2021	1,855.20	1861.70
03/21/2023	1,941.10	1949.80	01/06/2023	1,869.70	1872.50	01/22/2021	1,856.20	1859.80
03/20/2023	1,982.80	1987.89	01/05/2023	1,840.60	1844.60	01/21/2021	1,865.90	1878.80
03/17/2023	1,973.50	1982.30	01/04/2023	1,859.00	1861.40	01/20/2021	1,866.50	1875.10
03/16/2023	1,923.00	1928.00	01/03/2023	1,846.10	1850.40	01/19/2021	1,840.20	1862.70
03/15/2023	1,931.30	1937.40	12/30/2022	1,826.20	1830.20	01/15/2021	1,829.90	1832.60
03/14/2023	1,910.90	1920.80	12/29/2022	1,826.00	1830.40	01/14/2021	1,851.40	1853.70
03/13/2023	1,916.50	1920.40	12/28/2022	1,815.80	1821.40	01/13/2021	1,854.90	1863.30
03/10/2023	1,867.20	1869.90	12/27/2022	1,823.10	1828.60	01/12/2021	1,844.20	1857.20
03/09/2023	1,834.60	1839.80	12/23/2022	1,804.20	1811.60	01/11/2021	1,850.80	1861.30
03/08/2023	1,818.60	1823.40	12/22/2022	1,795.30	1798.70	01/08/2021	1,835.40	1842.50
03/07/2023	1,820.00	1829.00	12/21/2022	1,825.40	1830.80	01/07/2021	1,913.60	1919.70
03/06/2023	1,854.60	1860.30	12/20/2022	1,825.40	1831.50	01/06/2021	1,908.60	1925.60
03/03/2023	1,854.60	1859.40	12/19/2022	1,797.70	1799.50	01/05/2021	1,954.40	1958.30
03/02/2023	1,840.50	1843.60	12/16/2022	1,800.20	1812.40	01/04/2021	1,895.10	1899.20

The best forecasts for the daily gold price were made using LSSVM. In addition, the curve of anticipated outcomes along with the original data on gold prices for India, and the green area in these figures only includes the anticipated outcomes for the next threedays.

5. Conclusion

This study proposes a different method for predicting time series of gold prices. Predictions of the price of gold are made using the proposed hybrid, LSSVM model. To evaluate the accuracy of the LSSVM model as well as the value of gold price period from 1/1/2021 to 12/5/2023. The main objective of determine the LSSVM model most suitable parameters using a set of historical gold price data as training, and then to apply the best method with the minimum fitness function to the testing set. Using data on gold prices from India, the proposed forecasting LSSVM-accuracy was evaluated. In conclusion, these comparison results demonstrate that the LSSVM model outperforms the other three models. The results of the experiment show that LSSVM is better to other methods. These findings go counter to the LSSVM models' greater use in the literature. But our findings show that, at the very least for financial time series forecasting, LSSVM models are a viable alternative.

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Declaration Statement

Availability Of Data

Downloaded the COMEX daily prices of Gold from the Market Watch database.

Competing Interest

There is no competing interest in conducting this research.

Funding

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Authors Contributions

In this work, the data modelling techniques LS-SVM are used to forecast daily out-of-sample data points that will provide an estimate of a future increase in the confirmed gold price.

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Ethical Approval

NICHE (Nooral Islam College of Higher education) checked plagiarism and given ethical approval for publishing.

Consent To Participate

Participants were informed about the study's purpose, procedure, potential risks.

Consent To Publish

Participants were informed about the possibility of their data being included and publish in this research paper