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Original Article

Metaheuristic-Based Support Vector Machines for Exchange Rate Forecasting

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Abstract *- Given the dynamic and complex landscape of financial markets, accurately predicting financial time series presents considerable hurdles. This research explores the utilization of an evolutionary approach called Particle Swarm Optimization (PSO) to fine-tune the biases and weights of Support Vector Machine (SVM) models. This novel methodology leads to the development of an SVM-PSO hybrid model crafted through meticulous optimization strategies. This research evaluates the effectiveness of SVM-PSO by forecasting the final values of two prominent currency exchange rates. Additionally, this research constructs two comparative models, SVM-GD and SVM-GA, by training an equivalent SVM model using GD and GA techniques. The performances of all the models are gauged by RMSE and MSE metrics. Our results indicate that SVM-PSO surpasses SVM-GD in accuracy, representing a significant leap forward. This underscores the potency of the evolutionary PSO algorithm in tackling the intricacies inherent in time series forecasting for exchange rates.*

Keywords *- PSO, SVM, Metaheuristic algorithm, Financial Time series forecasting, Exchange rate forecasting.*

1. Introduction

Due to the dynamic and often unpredictable nature of financial markets [20], accurately forecasting the prices of Financial Time Series (FTS) poses a significant challenge. Researchers have been drawn to this challenge, emphasizing the importance of predicting FTS volatility and the critical need for accurate future forecasts. To tackle these challenges, researchers have proposed various methods, including ARMA [1-2], ARIMA [3-4], ANN, and ANFIS [5]. These methods fall into two main categories: data-driven and conceptual methods, with the primary difference lying in their reliance on input data volume. In recent years, data-driven methods, particularly ANNs, have gained traction due to their reduced dependency on input data volume and lower complexity [8]. ANNs, inspired by the human nervous system, are known for their high predictive power and flexibility, making them widely applicable across various domains. Studies have shown their effectiveness in solving engineering problems, such as those in water resources engineering, owing to their precise simulation and estimation of nonlinear functions [9]. Another notable data-driven process is the SVM model, which offers distinct advantages over ANN models [6]. SVMs, as a machine learning method, simplify complex processes, simulate nonlinear behaviors, and provide essential information for making informed decisions. This healthy method addresses uncertainty in prediction problems effectively [7]. Initially developed by Vapnik [36], SVM models have found applications in classification and regression problems. Additionally, evolutionary algorithms have shown increased efficiency in training various ML models compared to traditional methods [35], highlighting the evolving landscape of methodologies in addressing FTS prediction challenges.

While various hybrid SVM models have been suggested for predicting FTS, our focus is on evolutionary learning-based SVMs for forecasting. To address this gap, this study introduces an evolutionary-based nonlinear SVM method. In our approach, this study stabilizes the input weights and hidden biases of SVM using PSO, resulting in a hybrid model named SVM-PSO. This study applies the SVM-PSO model to forecast the closing prices of two widely traded currency exchange rates. For comparison, this study also develops two alternative models called SVM-GD and SVM-GA. The performances of all the models were evaluated using the MSE and RMSE metrics.

The succeeding sections of this article are ordered as follows: Section 2 provides an in-depth summary of existing literature, exploring relevant studies in the field. Moving forward, Section 3 comprehensively outlines the materials and methods employed in this work, offering a detailed insight into the research approach. In Section 4, the focus shifts to an exploration of the datasets utilized, shedding light on their sources and relevance. Section 5 then delves into the experimental setup, offering a detailed account of the methodology used and presenting a thorough analysis of the obtained results. The penultimate section, Section 6, engages in a thoughtful discussion of concluding remarks. Finally, the article concludes with a comprehensive list of references.

2. Related Works

Based on SVM, numerous researchers have explored various aspects of financial forecasting, acknowledging the complexity of this domain. These investigations span a wide range of applications, including Software Refactoring Prediction [10], forecasting data leakage risks [11], predicting Breast Cancer [12-13], forecasting retweets [14], predicting floods [15], Soil-Moisture-Content prediction [16], anticipating stock prices [17], projecting results in the Wordle Word Guessing Game [18], predicting dam failure peak outflow [19], projecting flood discharge [20], forecasting groundwater levels [21], localizing Partial Discharge [22], predicting failure time series using Empirical Mode Decomposition (EEMD) [23], predicting FTS [24], forecasting Walmart stock prices [25], bandwidth prediction [26], evaluating the performance of Rockburst prediction [27], and predicting ground temperature[28].

Similarly, Reddy [29] explored exchange rate forecasting using the RIMA method. Lee [30] investigated stock market volatility utilizing GARCH, while Zong [31] utilized a combination of MLP, CNN, LSTM, and hybrid SVM for stock index forecasting. Hercog [32] employed a metaheuristic-based ANN for cryptocurrency forecasting, while Nayak [33] applied a higher-order neural network for exchange rate prediction. Nayak et al. [34] explored the use of an Improved CRO Algorithm-based DNM for intelligent financial forecasting. Taking cues from the existing literature, this research integrated a PSO algorithm with SVM. This fusion resulted in the creation of a hybrid SVM-PSO model, which was utilized to predict the closing prices of two widely traded currency exchange rates. Additionally, this study trained the SVM using GA and GD algorithms and applied the resulting SVM-GA and SVM-GD models to the same forecasting task.

3. Materials and Methods

3.1. Support Vector Machine (SVM)

Vapnik pioneered SVM as a groundbreaking solution capable of tackling both regression and classification problems [36]. Praised for its efficacy in data regression and classification tasks [38-39], SVM distinguishes itself from traditional ML methods plagued by issues such as local minima, slow convergence rates, the necessity for diverse training data, and problems of underfitting/overfitting [40-41]. Leveraging the principles of SRM, SVM effectively surmounts these hurdles. The output function of SVM is denoted by equation (1).

$$F(x) = \sum_{i-1}^{N} (\alpha_i - \alpha_i^*) K(x, z) + b_i \quad (1)$$

Where, $(\alpha_i - \alpha_i^*)$ represents Lagrange factors, the inner product of the function represents by $K(x, z)$ according to mercer theorem [20], and the bias represented byb_i.

As a computational algorithm, SVM utilizes examples to learn and identify the optimal classifier function or hyperplane for separating two classes within the input space. The architecture of the SVM model is visually illustrated in Figure 1.

3.2. Particle Swarm Optimization (PSO)

Kennedy and Eberhart introduced the PSO algorithm in 1995 [42], which has since become a widely adopted optimization tool. Operating as a form of swarm intelligence, PSO takes cues from the collaborative behavior observed in bird flocks as they search for optimal locations to secure food. Initially inspired by the social dynamics of bird flocks, it has evolved into a foundational model for understanding collective behavior in nature. Algorithm 1 illustrates the working principles of PSO. Authors interested in exploring the intricacies of PSO functionality and its application to FTS prediction can gain valuable insights from references [27] and [44]. Notably, this algorithm supports multi-point search and is adept at handling continuous optimization problems. Therefore, the PSO algorithm is selected for determining constraints in the SVM to enhance its performance.

Algorithm1: Working principles of PSO

1. Initialize Population:
   Produce an initial population of individuals with random genes.
2. Evaluate Fitness:
   For each individual in the population:
      Calculate its fitness value based on a fitness function.
3. Repeat for a specified number of generations or until convergence:
4. Selection:
      Choose individuals from the population for reproduction based on their fitness (higher fitness = higher chance of selection).
5. Crossover:
      Perform crossover (breeding) between selected individuals to create offspring.
6. Mutation:
      Apply mutation to some of the offspring to introduce diversity in the population.
7. Evaluate Fitness:
      Calculate fitness for the new offspring population.
8. Elitism:
      Select top individuals from the current population based on fitness to survive unchanged to the next generation.
9. Replace Population:
      Replace the current population with the combined offspring and elite individuals.
10. Output:
   Return the best individual or the population with the highest fitness as the optimized solution.

3.3. Genetic Algorithm (GA)

GA [45], invented by John Holland in the 1960s at the University of Michigan, is a heuristic search and optimization technique inspired by natural selection and genetics. It mimics evolutionary processes to generate high-quality solutions to complex optimization and search problems. Just as genes evolve to adapt species to their environment, genetic algorithms evolve solutions to diverse problems, making them valuable tools across fields such as engineering and finance for innovative problem-solving strategies. Algorithm 2 illustrates the working principle of GA. Interested readers can explore references [46-47] to gain a comprehensive understanding of GAs and their application in training ANNs for FTS.

Algorithm2: Working principles of GA

1. Initialize Population:
   Construct an initial population of individuals with random genes.
2. Evaluate Fitness:
   For each individual in the population:
      Calculate its fitness value based on a fitness function.
3. Repeat for a specified number of generations or until convergence:
4. Selection:
   Choose individuals from the population for reproduction based on their fitness (higher fitness = higher chance of selection).
5. Crossover:
   Perform crossover (breeding) between selected individuals to create offspring.
6. Mutation:
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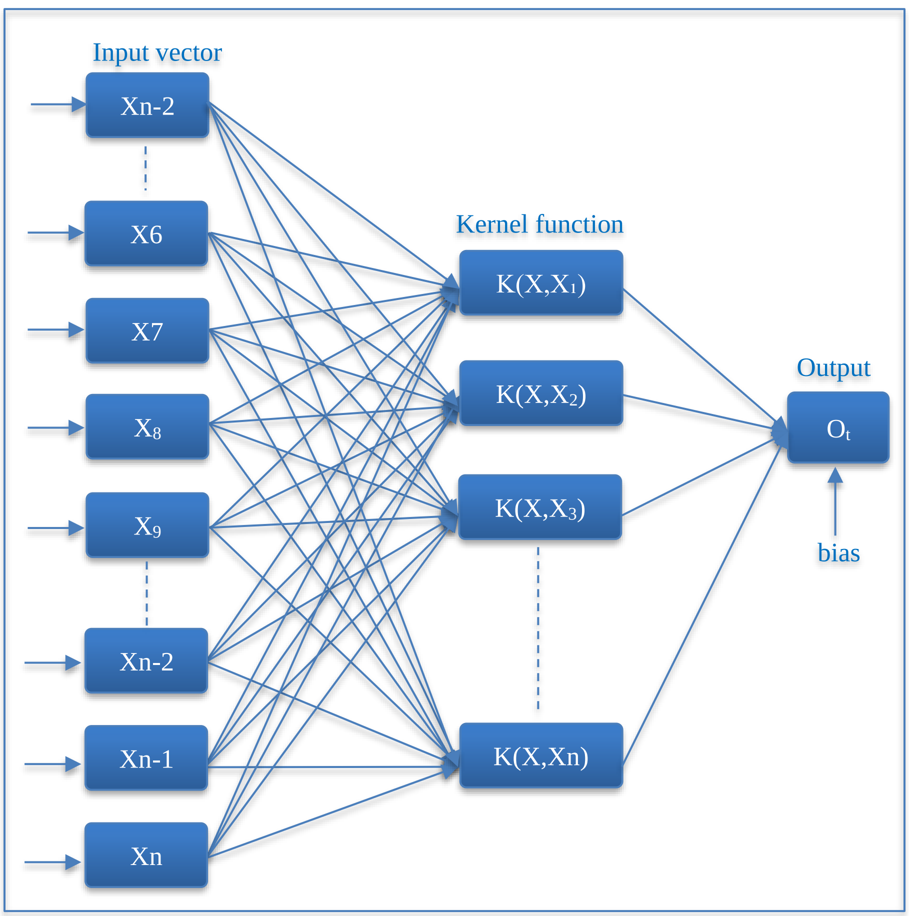

Fig. 1 Support vector machine architecture

3.4. Gradient Descent Algorithm

The representation of the operational notion of the GD method [43] can be seen in Algorithm 3.

Algorithm 3: Working Principle of GD

1. Initialize Parameters:
   Put initial position randomly or based on prior knowledge.
   Define step size (learning rate) and convergence criteria.
2. Repeat until convergence or maximum iterations reached:
3. Calculate Gradient:
   Compute the gradient of the objective function at the current position.
4. Update Position:
   Adjust the current position in the direction opposite to the gradient.
   Scale the step size to control the descent speed.
5. Check Convergence:
   Evaluate convergence criteria (e.g., small change in position, reaching a specified error threshold).
6. End Optimization:
   Stop when convergence criteria are met or after a maximum number of iterations.
7. Output:
   Return the final position, which represents the optimized solution.

4. Training SVM Using PSO

The training error improvement leads to dynamic adjustments of the 'γ' and 'C' values using PSO. The objective is to find the most suitable parameters that result in the lowest error. Consequently, an optimization process is initiated to identify the optimal parameters for the SVM. Once these optimized parameters are determined, they are employed in the retraining of the SVM model. The SVM model is then ready for the identification of fresh samples during the testing phase, following the training period. This involves selecting a testing set through element selection from the original dataset. Subsequently, testing patterns are imputed into the trained multilayer SVM [20] model. The overall steps involved in the parameter optimization of the SVM are described in Algorithm 4 as follows.

Algorithm 4: PSO-Based Training

1. Begin with an initial set of parameters for 'γ ' and 'C '
2. Train the PSO-based SVM model using SRM to minimize training error.
3. Utilize PSO to dynamically adjust the values of 'γ ' and 'C ' during the training stage.
4. Identify the most suitable parameters that result in the least training error.
5. Apply the optimized parameters to retrain the SVM model.
6. Testing Set Selection: Select a testing set through feature selection from the original dataset.
7. Apply testing patterns into the trained SVM.
8. Conduct testing using test data

5. About the Data

For the timeframe spanning from Jan 24, 2023, to Jan 24, 2024, daily currency data was collected from http://www.yahoo.finance/quotes on exchanges between INR and USD, as well as EUR and USD. The statistical properties of EUR-USD and INR-USD are provided in Table 1. Following that, sigmoid normalization [30] was applied to each of the datasets as a pre-processing step. Open, Close, High, Adj Close, and Low input features were applied as input features to both the SVM-PSO and SVM-GD models. This research employed a sliding window technique [32] with a window size of 3, maintaining a split ratio of 50:50 between the training dataset and the testing dataset. This facilitated the partitioning of the selected characteristics into training and testing datasets, simplifying the training and evaluation of our prediction model. The suggested metaheuristic method for SVM is founded on a unique learning approach inherent to SVM. It utilizes a foundational model with a single kernel layer. PSO was developed to determine the weights associated with hidden-input and hidden-output neurons, as well as the bias vectors between them, within the SVM framework. Furthermore, the same SVM model was also trained using the GD algorithm.

Table 1. Statistical properties of dataset

Data	Statistical property	Close
EUR-USD	count	261.0000
	mean	1.082836
	std	0.016325
	min	1.047230
	25%	1.070183
	50%	1.085270
	75%	1.094739
	max	1.123760
	Kurtosis	-0.600205
	Skewness	-0.055143
INR-USD	count	262.0000
	mean	0.012106
	std	0.000089
	min	0.011738
	25%	0.012023
	50%	0.012094
	75%	0.012184
	max	0.012349
	Kurtosis	0.000443
	Skewness	0.114951

6. Simulation and Results

The experimentation for both models was conducted on Google Colab within a Windows 10 environment. Employing an iterative approach, for PSO, the population size was set at 50, and after extensive iterative experimentation, the maximum number of iterations was established at 100. All other algorithmic parameters for PSO were selected following the specifications outlined in [42]. Similarly, all the ideal parameters of GA were selected as specified in [46], keeping the population size and iterations the same as chosen for PSO.

Regarding the GD algorithm, a learning rate of 0.01 was utilized. The input features for all the models comprised Open, Close, High, Low, and Adj Close data across all datasets. These models were then applied to forecast the closing prices of exchange rates for both 1-day and 10-day ahead intervals. To assess the forecasting accuracy of each model, the MSE [26] and RMSE metrics were used.

The testing errors, represented by MSE and RMSE values over 20 runs for both datasets and both time frames, were meticulously recorded and are presented in Table 2. These metrics serve as crucial indicators of the performance and reliability of the proposed hybrid models in predicting currency exchange rates. In addition to documenting individual MSE and RMSE values for both models across 1-day and 10-day forecasting periods, this study computed average MSE and average RMSE values for a more comprehensive comparison. The results of this comparison are visually depicted through a bar chart in Figure 2. This graphical representation offers a concise and clear summary of the comparative performance between the two hybrid models in predicting closing prices of exchange rates over various time frames.

For illustrative purposes, Figures 3 and 4 showcase the 1-day ahead forecast plots for INR-USD and EUR-USD, respectively.

6.1. Results Comparison with Existing Models

We conducted a performance comparison between our proposed SVM-PSO model and several state-of-the-art hybrid SVM models such as EMD-SVM [24], DIFF-SVM [26], LS-SVM [25], and PSO-SVM [20]. In this comparison, we calculated the average value of the error metrics for several models, including our proposed model, without regard to specific datasets or forecasting horizons. Our analysis encompassed various prediction areas and datasets, and we observed that our model generally outperformed some of these models. Detailed results are provided in Table 3 for reference.

Table 2. Avg. MSE and Avg. RMSE Scores (20 runs) comparison

Model	Error	Period	INR-USD	EUR-
SVM-PSO	MSE	1-day	0.1145	0.1156
		10-day	0.0978	0.0895
SVM-GA		1-day	0.4568	0.5628
		10-day	0.7859	0.8956
SVM-GD		1-day	0.9985	1.8956
		10-day	0.9879	1.9895
SVM-PSO	RMSE	1-day	0.3383	0.3400
		10-day	0.3126	0.2992
SVM-GA		1-day	0.6757	0.7502
		10-day	0.8864	0.9468
SVM-GD		1-day	0.9993	1.3767
		10-day	0.9939	1.4111

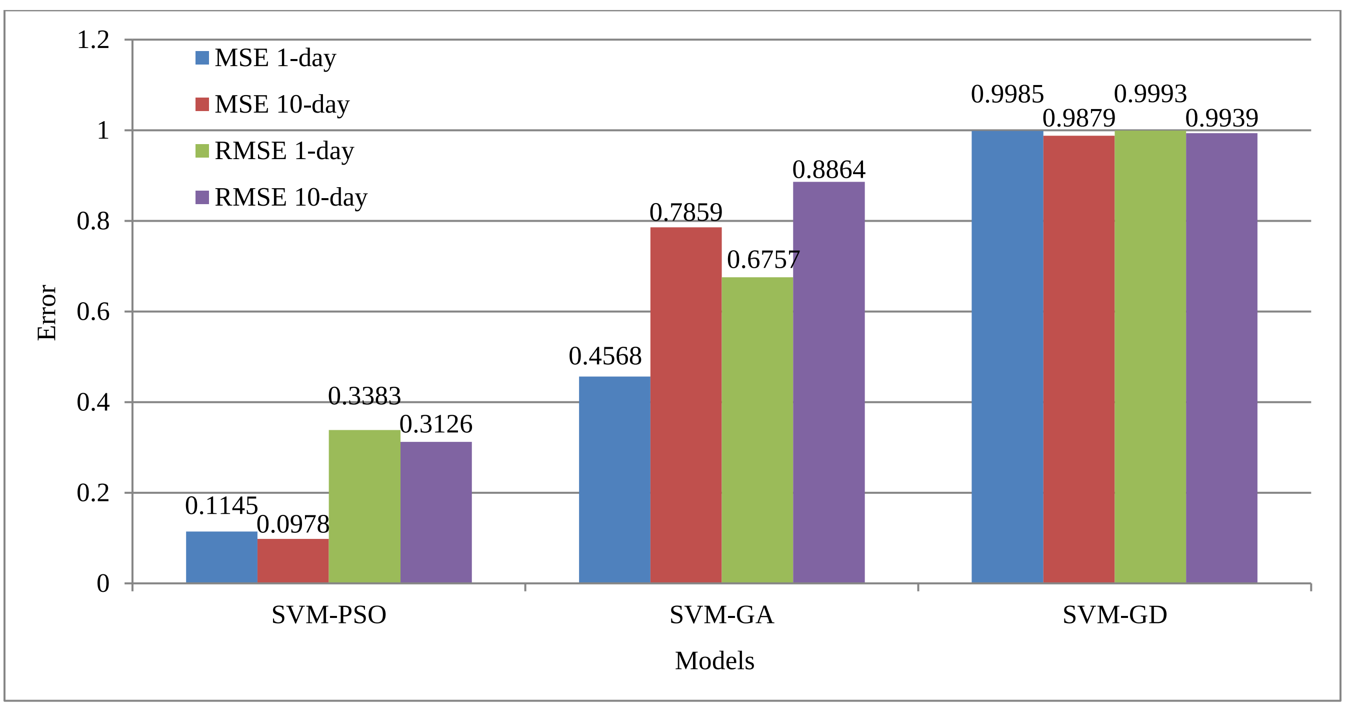

Fig. 2 Error comparison plot

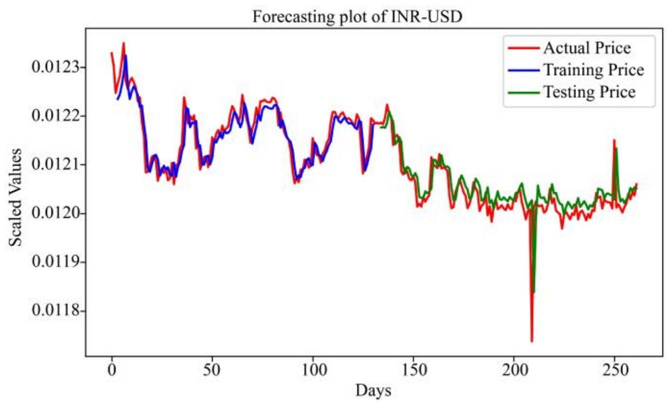

Fig. 3 Forecast Plot of SVM-PSO for INR-USD

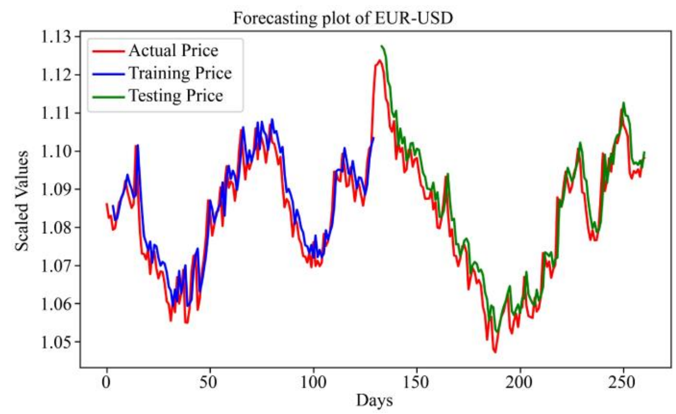

Fig. 4 Forecast Plot of SVM-PSO for EUR-USD

Table 3. Result comparison with existing models

Ref.	Model	Metrics	Values
[24]	EMD-SVM	RMSE	0.6219
		MAE	0.4606
		MAPE	1.72%
		R^2	0.9947
[26]	DIFF-SVM	MAD	6.45
		MSE	131.27
[25]	LS-SVM	Avg.MSE	320.1308
		Avg.MAE	13.2611
		Avg. R^2	-1.0273
[20]	PSO-SVM	Avg. NSE	0.96849
		Avg. RMSE	0.01039
		Avg. R^2	0.96204
Proposed	SVM-PSO	Avg.MSE	**0.1044**
		Avg. RMSE	**0.3225**

7. Conclusion

In this study, PSO was utilized as a metaheuristic to train an SVM. This innovative approach facilitated the optimization of optimal weights and biases, leading to the creation of a unique hybrid model known as SVM-PSO. The SVM-PSO hybrid model showcased its effectiveness by accurately predicting the closing prices of two widely monitored currency exchange rates. Concurrently, this research created SVM-GA and SVM-GD alternate models for the same task. Evaluation based on the MSE and RMSE metrics unequivocally highlighted the superior forecasting accuracy of SVM-PSO, underscoring the efficacy of the PSO algorithm in addressing the intricacies of exchange rate time series forecasting. Looking ahead, this study aimed to explore opportunities for enhancing the network's topology and implementing more efficient hybrid training techniques to further refine prediction accuracy. While the SVM-PSO model excels in forecasting closing prices of currency exchange rates, it is essential to acknowledge certain limitations. The proposed model has not been tested on other financial time series, hyperparameter tuning has not been conducted, and technical indicators were not been incorporated into the input. Addressing these limitations will be a focal point of our future research, ensuring a more comprehensive and robust approach to financial time series forecasting.

Abbreviations

Autoregressive Integrated Moving Average	(ARIMA)
Artificial Neural Network	(ANN)
Adaptive Neuro-Fuzzy Inference System	(ANFIS)
Machine Learning	(ML)
Financial Time Series	(FTS)
Support Vector Machines	(SVM)
Multilayer Perceptron	(MLP)
Convolutional Neural Network	(CNN)
Long Short Term Memory	(LSTM)
Dendritic Neuron Model	(DNM)
Chemical Reaction Optimization	(CRO)
Particle Swarm Optimization	(PSO)
Gradient Descent	(GD)
Structural Risk Minimization	(SRM)
Mean Squared Error	(MSE)
Root Mean Squared Error	(RMSE)

References

[1] James B. McDonald, “Partially Adaptive Estimation of ARMA Time Series Models,” *International Journal of Forecasting*, vol. 5, no. 2, pp. 217–230, 1989. [CrossRef] [Google Scholar] [Publisher Link]

[2] Jorge Ludlow, and Walter Enders, “Estimating Non-Linear ARMA Models using Fourier Coefficients,” *International Journal of Forecasting*, vol. 16, no. 3, pp. 333–347, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yushu Shao, “Prediction of Moderna Adjusted Closing Stock Price Trend Using ARIMA Model,” *2nd International Conference on Finance, Investment and Business Analysis*, vol. 44, pp. 108–114, 2023. [CrossRef] [Publisher Link]

[4] Rahul Mangalampalli et al., “Stock Prediction Using Hybrid ARIMA and GRU Models,” *International Journal of Engineering Research and Technology*, vol. 9, no. 5, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Mohammad Bagher Menhaj, Computational Intelligence, AmirKabir University of Technology (in persian), 2009.

[6] Jun Liu et al., “Prediction of Autogenous Shrinkage of Concretes by Support Vector Machine,” *International Journal of Pavement Research and Technology*, vol. 9, no. 3, pp. 169–177, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[7] Wenjian Wang, Changqian Men, and Weizhen Lu, “Online Prediction Model Based on Support Vector Machine,” *Neurocomputing*, vol. 71, no. 4-6, pp. 550–558, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[8] L.M. Marangon Lima, E. Popova, and P. Damien, “Modeling and Forecasting of Brazilian Reservoir Inflows via Dynamiclinear Models,” *International Journal of Forecasting*, vol. 30, no. 3, pp. 464–476, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[9] Roohollah Noori et al., “Comparison of ANN and Principal Component Analysis-Multivariate Linear Regression Models for Predicting the River Flow Based on Developed Discrepancy Ratio Statistic,” *Expert Systems with Applications*, vol. 37, no. 8, pp. 5856–5862, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mohammed Akour, Mamdouh Alenezi, and Hiba Alsghaier, “Software Refactoring Prediction Using SVM and Optimization Algorithms,” *Processes*, vol. 10, no. 8, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Qian Cao, “An Enterprise Financial Data Leakage Risk Prediction Based on ARIMA-SVM Combination Model,” *International Journal of Applied Systemic Studies*, vol. 1, no. 1, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Sijun Chen, “Breast Cancer Prediction Based on RF-SVM,” *Applied and Computational Engineering*, vol. 8, no. 1, pp. 657–666, 2023. [CrossRef] [Publisher Link]

[13] Tianji Dai et al., “ICS-SVM: A User Retweet Prediction Method for Hot Topics Based on Improved SVM,” *Digital Communications and Networks*, vol. 8, no. 2, pp. 186–193, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ike Fitriyaningsih , and Yuniarta Basani, “Flood Prediction with Ensemble Machine Learning using BP-NN and SVM,” *Journal of Technology and Computer Systems*, vol. 7, no. 3, pp. 93–97, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Min-Wei Huang et al., “SVM and SVM Ensembles in Breast Cancer Prediction,” *PLOS ONE*, vol. 12, no. 1, pp. 1-14, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ying Huang, “Improved SVM-Based Soil-Moisture-Content Prediction Model for Tea Plantation,” *Plants*, vol. 12, no. 12, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Haoyu Ji, “Stock Price Prediction Based on SVM, LSTM, ARIMA,” *International Conference on Portfolios, Global Marketing and Economic Environment*, vol. 35, pp. 267–272, 2022. [CrossRef] [Publisher Link]

[18] Ruichen Liu, Yinxi Li, and Mengdan Li, “Result Prediction of Wordle Word Guessing Game Based on SVM And BP Neural Network Multi-Input-Multi-Output Regression Prediction Model,” *Highlights in Science, Engineering and Technology*, vol. 70, pp. 175–182, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Mohammad Nobarinia et al., “Dam Failure Peak Outflow Prediction through GEP-SVM Meta Models and Uncertainty Analysis,” *Water Supply*, vol. 21, no. 7, pp. 3387–3401, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sandeep Samantaray, Abinash Sahoo, and Ankita Agnihotri, “Prediction of Flood Discharge Using Hybrid PSO-SVM Algorithm in Barak River Basin,” *MethodsX*, vol. 10, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Sandeep Samantaray, Abinash Sahoo, and Deba Prakash Satapathy, “Prediction of Groundwater-Level Using Novel SVM-ALO, SVM-FOA, and SVM-FFA Algorithms at Purba-Medinipur, India,” *Arabian Journal of Geosciences*, vol. 15, no. 8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Permit Mathuhu Sekatane, and Pitshou Bokoro, “Partial Discharge Localization through k-NN and SVM,” *Energies*, vol. 16, no. 21, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Haiyan Sun et al., “Hybrid SVM and ARIMA Model for Failure Time Series Prediction based on EEMD,” *International Journal of Performability Engineering*, vol. 15, no. 4, pp. 1161-1170, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[24] Kai Tang, “Financial Time Series Prediction Based on EMD-SVM,” *International Conference on Financial Market and Enterprises Management Engineering*, vol. 30, pp. 218–227, 2022. [CrossRef] [Publisher Link]

[25] Chenguang Yan, “Stock Price Prediction of Walmart Based on Combination of SVM and LS-SVM Models,” *International Conference on Economics, Mathematical Finance and Risk Management*, vol. 38, pp. 363–371, 2023. [CrossRef] [Publisher Link]

[26] Xu Yanling, Wu Baolin, and Yang Liushan, “A Network-Adapative SVC Streaming Strategy with SVM-Based Bandwidth Prediction,” *International Journal of Future Computer and Communication*, vol. 3, no. 3, pp. 205–209, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[27] Jian Zhou et al., “Performance Evaluation of Rockburst Prediction Based on PSO-SVM, HHO-SVM, and MFO-SVM Hybrid Models,” *Mining, Metallurgy & Exploration*, vol. 40, pp. 617-635, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Shiyu Zhou et al., "Prediction of the Ground Temperature with ANN, LS-SVM and Fuzzy LS-SVM for GSHP Application," *Geothermics,* vol. 84, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[29] A.S. Babu, and S.K. Reddy, "Exchange Rate Forecasting Using ARIMA, Neural Network and Fuzzy Neuron," *Journal of Stock & Forex Trading,* vol. 4, no. 3, pp. 1-5, 2015. [Google Scholar] [Publisher Link]

[30] Hojin Lee, "Forecasting Performance of Asymmetric GARCH Stock Market Volatility Models," *SSRN Electronic Journal,* vol. 13, no. 2, pp. 109-143, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[31] Xiangyu Zong, "MLP, CNN, LSTM and Hybrid SVM for Stock Index Forecasting Task to INDU and FTSE100," *SSRN Electronic Journal*, pp. 1-37, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[32] D. Hercog, "Generalised Sliding Window Protocol," *Electronics Letters,* vol. 38, no. 18, pp. 1067-1068, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[33] Sarat Chandra Nayak, "Development and Performance Evaluation of Adaptive Hybrid Higher Order Neural Networks for Exchange Rate Prediction," *International Journal of Intelligent Systems and Applications,* vol. 9, no. 8, pp. 71–85, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[34] Sarat Chandra Nayak, Satchidananda Dehuri, and Sung-Bae Cho, "Intelligent Financial Forecasting with an Improved Chemical Reaction Optimization Algorithm Based Dendritic Neuron Model," *IEEE Access,* vol. 10, pp. 130921–130943, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[35] S. Chakravarty et al., "An Evolutionary Functional Link Neural Fuzzy Model for Financial Time Series Forecasting," *International Journal of Applied Evolutionary Computation,* vol. 2, no. 3, pp. 39–58, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[36] Vladimir N. Vapnik, *The Nature of Statistical Learning Theory,* Springer New York, 1995. [Google Scholar] [Publisher Link]

[37] John G. Vlachogiannis, and Kwang Y. Lee, "Multi-Objective Based on Parallel Vector Evaluated Particle Swarm Optimization for Optimal Steady-State Performance of Power Systems," *Expert Systems with Applications,* vol. 36, no. 8, pp. 10802–10808, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[38] Sandeep Samantaray, and Abinash Sahoo, "Estimation of Runoff through BPNN and SVM in Agalpur Watershed," *Frontiers in Intelligent Computing: Theory and Applications*, pp. 268–275, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[39] Sandeep Samantaray, and Abinash Sahoo, "Assessment of Sediment Concentration through RBNN and SVM-FFA in Arid Watershed, India," *Smart Intelligent Computing and Applications,* pp. 701–709, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[40] Weizhen Lu et al., "Air Pollutant Parameter Forecasting Using Support Vector Machines," *Proceedings of the 2002 International Joint Conference on Neural Networks*, Honolulu, HI, USA, pp. 630–635, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[41] R. Salat, and S. Osowski, "Accurate Fault Location in the Power Transmission Line Using Support Vector Machine Approach," *IEEE Transactions on Power Systems,* vol. 19, no. 2, pp. 979-986, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[42] J. Kennedy, and R. Eberhart, "Particle Swarm Optimization," *Proceedings of ICNN'95-International Conference on Neural Networks,* Perth, WA, Australia, vol. 4, pp. 1942–1948, 1995. [CrossRef] [Google Scholar] [Publisher Link]

[43] Shun-Ichi Amari, "Backpropagation and Stochastic Gradient Descent Method," *Neurocomputing,* vol. 5, no. 4–5, pp. 185–196, 1993. [CrossRef] [Google Scholar] [Publisher Link]

[44] Guo Zhiqiang, Wang Huaiqing, and Liu Quan, "Financial Time Series Forecasting Using LPP and SVM Optimized By PSO," *Soft Computing,* vol. 17, no. 5, pp. 805–818, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[45] John H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, The MIT Press, 1992. [CrossRef] [Google Scholar] [Publisher Link]

[46] Muhammad Latif, and Sri Herawati, "Combined EEMD and ANN Improved by GA for Tourist Visit Forecasting," *Bulletin of Electrical Engineering and Informatics,* vol. 11, no. 2, pp. 947–954, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[47] K. Sudha, Neeraj Kumar, and Poras Khetarpal, "GA-ANN Hybrid Approach for Load Forecasting," *Journal of Statistics and Management Systems,* vol. 23, no. 1, pp. 135–144, 2020. [CrossRef] [Publisher Link]