A Comparative Study of Artificial Neural Network (ANN) and Support Vector Regression (SVR) on Forecasting: A Review

Hussein H. Saleh*

*Ministry of education, Iraq

*Corresponding Author: hunzgz@yahoo.com

Received 20 Jan. 2025, Accepted 17 May. 2025, Published 30 June. 2025.

DOI: 10.52113/2/12.01.2025/132-142

Abstract: Forecasting outcomes of any system is essential for a better understanding and optimal management of the fluxes occurring in system operations. Machine Learning (ML) approaches can solve complex relationships among collected data that are hard to describe using forecasting models. This paper aims to give an overview of many described prediction methodologies that use Artificial Neural Networks (ANN) and Support Vector Regression (SVR) under the diversity of the dataset and understand the performance of each method. To improve the forecasting performance, the author proposed depending on some performance indicators, such as The Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and coefficient of determination R^2. Concludes that SVR generally outperforms ANN in forecasting of groundwater quality, drought indices, oil production, and illuminance prediction. The ANN shows better performance in certain scenarios, such as predicting wheat moisture content, solar energy, and monthly streamflow.

***Keywords*:** Machine learning, prediction, artificial neural network, support vector regression, forecasting.

1. Introduction

Methods diversity of ML and the powerful results are made from these methods, as strong prediction tools to solve various problems in different fields [1]. Many researchers used ML methods to predict climate elements such as solar radiation, rainfall, and wind speed, whereas others used them for the estimation of oil production, gold price, tourism demand, drought indices, and river follow [2].

This review article presents many published research studies in the last few years that deal with ML methods, ANN and SVR in any field of forecasting. For each article research, the author extracts the kinds of variables used, evaluation indicators, and analyzes the power and limitations points. To confirm the best forecasting performance between ANN and SVR, the author extracts the evaluation factors used for each research article, which gives us a general idea about each technique in the context of prediction, and then understanding the strengths and weaknesses performance.

Figure 1 presents research papers for estimation that use the ANN and SVR methods published from 2015 to 2024 according to the Science Direct Platform. The more than ten thousand research papers that used ANN technique in a year indicate the popularity of this technique in comparison with other ML techniques [3]. While both ANN and SVR have been widely studied, there is a lack of systematic reviews comparing their performance across diverse fields. This paper aims to fill this gap by synthesizing recent research and identifying the strengths and limitations of each method.

2. Machine learning

The ML is one of the artificial intelligence specializations that deal with systems that can learn from the dataset and is widely used in many fields. It can be represented as models to solve problems that are impossible to represent using traditional methods. In the context of forecasting, ML techniques are particularly valuable for capturing complex, nonlinear relationships in data, which traditional statistical methods may fail to model effectively. The main mechanism of ML techniques finds the relations between input and output variables even if the representations are impossible; for these features, ML is used in many fields as classification and regression problems, computer vision, spam filtering, pattern recognition, medicine, and weather forecasting. Figure 2 presents the structure and steps of the ML method [4].

3. ANN method

An ANN is one of the ML techniques, and it was inspired by the learning algorithm of the human brain [5]. An ANN consists of multiple processing nodes or neurons connected across three layers: the input layer, which receives input features; the hidden layer, which acts as a bridge between both input and output layers; and the output layer, where the final predictions are made, as shown in Figure 3. The structure of the problem is determined by the number of nodes in each layer. Also, this computational system uses a much more complex term named deep learning and has proven far more effective than earlier methodologies for a broad class of problems [6].

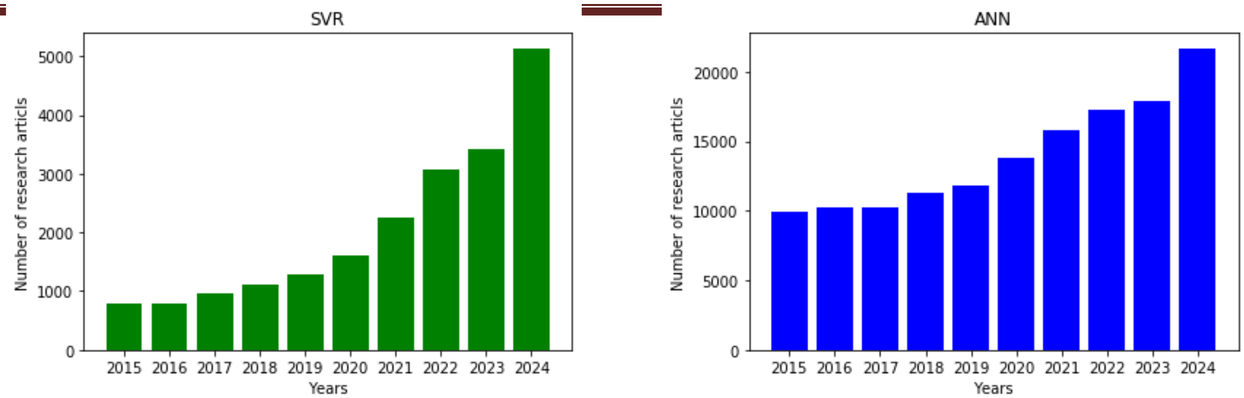

Figure 1. The number of research papers for ten years.

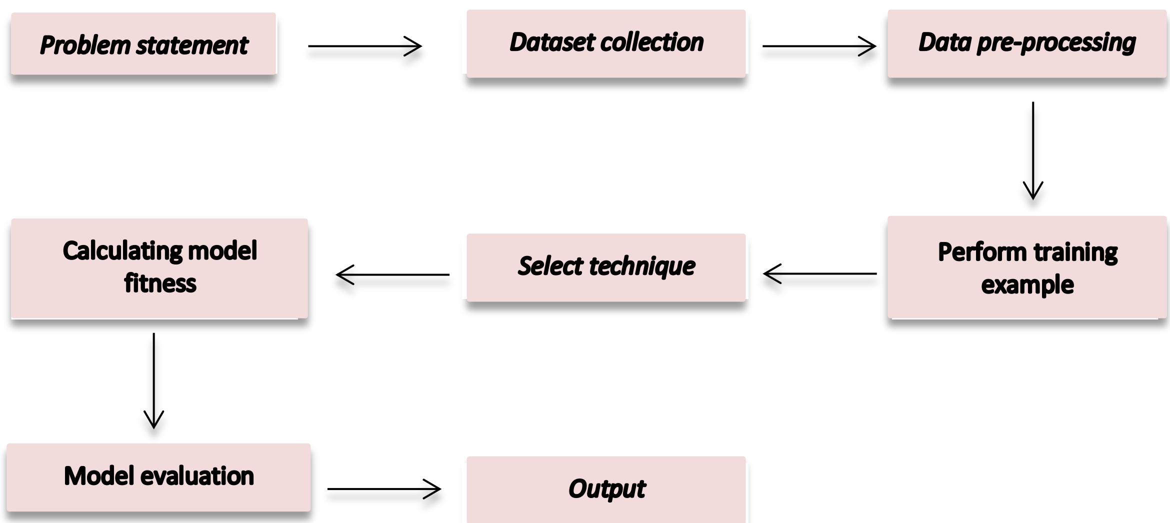

Figure 2. Structure of ML methods.

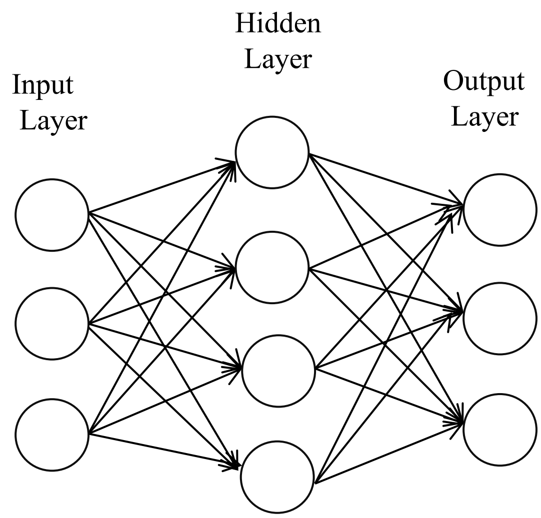

Figure 3. The common architectures of ANN.

4. SVR method

The SVR is a set of ML methods generally used for linear and nonlinear classification, regression, and outlier detection tasks. It is more effective in high-dimensional spaces where the number of dimensions is greater than the number of samples. Also, avoid overfitting during the training process [7]. The supervised learning algorithm has different kernel functions for both provided and specified custom kernels as follows:

- Linear kernel: (x, x'), where unlabeled input x' and each of the training inputs x.
- Radial basis function (RBF) kernel: $(-y\ \|x - x'\|^2)$, where y is determined by parameter gamma.
- Polynomial kernel: $(y(x, x') + r)^m$, where d is determined by parameter degree and r is coefficient.
- Sigmoid kernel: $\tanh(y(x, x') + r)$, r is determined by coefficient.

To establish the kernel function, the SVM needs to have fewer established user-defined parameters. The regularization parameter c, also known as the cost. This constant control is a trade-off between an estimation error and the weight vector norm $\|w\|$ [8]. The second functionality of the SVM is regression, also named as support vector regression, which can be easily understood by first assuming linear data [9].

5. Method

In this literature review, the author has tried to follow a systematic methodology based on the number of methods: research, reading, analysis, and summary. The article consists of a targeted selection of research that predicts using ANN and SVR techniques, including the types of datasets to be considered in the analysis. Also, understand the structure and characteristics of ML techniques that have been proposed in this paper.

6. Analysis

The author denoted two main terms, ANN and SVR, to search for twenty recent articles that used different datasets to predict the variables in the fields of energy, agriculture, industry, economy, and oil. The selected papers are read, extracted interesting and relevant information is extracted to make an analysis and come out with a comparison. Furthermore, specified performance criteria and the structure process for both proposed methods. ANN and SVR are ML algorithms that model nonlinear relationships by minimizing the error between input and output variables. These techniques have been used over the past few years due there flexibility, efficiency, and reliability. In certain scenarios, SVR outperforms ANN, SVR is effective in high-dimensional spaces, performs best performance with smaller datasets, robustness to outliers, has easier interpretability, and is highly effective in high-dimensional spaces, while the ANN technique is highly flexible and can model a wide range of functions, requires a significant amount of data for effective training, and can be computationally intensive, especially for deep networks.

7. Conclusion and outlook

As shown in the present research articles in Table 1, two methods of ML have been compared by citing, understanding capabilities, and the limitations. Furthermore, based on reading and searching the research articles that used ANN and SVR methods to forecast various problems and distinguish the advantages and limitations of each technique. Several researchers used a combination of optimization input variables methods as a hybrid gamma test and genetic algorithm, to optimize the prediction results. Four kernels with various properties granted the SVR method advantages over ANN methods. Also, many authors frequently used the SVR method to study the energy and generate power from the climate elements like solar radiation and wind speed. This article review explains the outperformance of the SVR method in many research articles. Further, the ANN is an unstable predictor producing differing outcomes at different iterations for the same optimum variables, dataset partitions, and data size, while SVM maintains its stability. In general, the accuracy of these techniques upon the quality of the training dataset that used in the training step. Many articles depend on specific preprocessing steps, such as normalization and feature selection, which are considered powerful tools for improving the quality of the dataset. Actually, several researchers used hybrid ML methods with complex structures as a set of algorithms to generate high-level models. These combined models have the best performance forecasting, providing high precision and opening up new avenues for scientific research. As future work, the author suggests studying applying ANN and SVR to emerging fields like healthcare or climate change, and understanding the performance of each technique in these fields.

Table 1. List of representative research articles related to forecasting models using ANN and SVR methods.

References	Prediction objective	Variables	Metrics	Another employed Techniques	Results
[10]	Water surface	Cross-sectional area, depth, volume of rivers	MSE	Multiple Linear Regression (MLR)	SVR > ANN
[11]	Rainfall	Daily rainfall averages	MSE and RMSE	Empirical Mode Decomposition (EEMD)	SVR > ANN
[12]	Ground water level	Ground water levels	MSE, RMSE, and correlation coefficient (R)	NA	SVR > ANN
[13]	River flow	Monthly river flow data	MSE, RMSE, and correlation coefficient (CC)	NA	SVR > ANN
[14]	Gold Price	Major indices in the US, popular cryptocurrencies, silver, USD index (United States Dollar against Euro), and the gold prices	MSE, RMSE, and MAPE	Long Short-Term Memory (LSTM)	SVR > ANN
[15]	Streamflow	Streamflow data	MSE and RMSE	MLR	SVR = ANN
[16]	Reservoir volume	Levels of water volumes at two reservoirs	MSE and RMSE	LSTM	LSTM > SVR and ANN
[17]	Carbon dioxide emissions	CO2 emissions, Foreign direct investment, industrial activity, Trade, Urban population, Gross domestic product, Energy consumption, Coal, and Oil.	MSE and RMSE	Random Forest (RF) and ridge regression (Ridge)	SVR > ANN
[18]	Stock market	Daily stock price data	MSE and RMSE	Autoregressive integrated moving average (ARIMA)	SVR = ANN
[19]	Heat wave days	Air temperature, geopotential height, relative	MSE and RMSE	Random Forest (RF) and eXtreme gradient	All models recommended

		humidity, U-wind, and V-wind		boosting (XGBoost)	
[20]	Wheat moisture content	Air temperature, relative humidity, wind speed, and precipitation	RMSE and R^2	NA	ANN > SVR
[21]	Ground water quality	Ca^{2+} Mg^{2+} Na^{+} Cl^{-} SO_4^{2-} HCO_3^{-} and pH	RMSE and R^2	Multi-nonlinear regression	SVR > ANN
[22]	Solar energy	Solar irradiance and the temperature	RMSE, MAE, and Mean Absolute Scaled Error (MASE)	Decision Tree (DT), Random Forest (RF), Generalized Additive Model (GAM) and Extreme Gradient Boosting (XGBOOST)	ANN > SVR
[23]	Drought Indices	Temperature, relative humidity, wind, and rain percentage	MSE and RMSE	NA	SVR > ANN
[24]	Tourism demand	The number of domestic and foreigner tourists	MAPE, MAE, and MSE	LSTM and Gated Recurrent Unit (GRU)	LSTM and GRU > SVR > ANN
[25]	Monthly streamflow	Ensembles of precipitation, runoff, and temperature	Kling-Gupta efficiency coefficient (KGE), Nash-Sutcliffe Efficiency coefficient (NSE), and Normalized Root Mean Square Error (NRMSE)	MLR, RF, and XGBoost	ANN > SVR
[26]	Oil production in unconventional reservoirs	The tubing head pressure, nozzle size, and water rate were utilized	RMSE	Decline Curve Analysis (DCA) and LSTM	SVR > ANN
[27]	Rainfall	Average weekly rainfall data aggregated	RMSE and MAE	Decision Tree, Random Forest Algorithm and Long Short-Term Memory	Another employed Techniques > SVR and ANN
[28]	Illuminance prediction	Air temperature, relative humidity, global horizontal irradiance, diffuse horizontal irradiance, and global horizontal illuminance	Mean relative error	k-Nearest Neighbor	SVR > ANN

[29]	PV Power Generation	Power generation data, atmospheric temperature, solar irradiance, and module temperature.	NRMSE	ARIMA, ANFIS, and GA	All techniques are recommended

References

[1] Bouabdallaoui, D., Haidi, T. and El Jaadi, M., 2023, Review of current artificial intelligence methods and metaheuristic algorithms for wind power prediction, Indonesian Journal of Electrical Engineering and Computer Science, 29(2), pp.626-634.

[2] Aruna, M., Ashwini, N., Hema, P., Kolla, V.J., Singh, K.U. and Kumar, S.S., 2025, Predicting home appliance electricity usage in low energy consumption houses with high accuracy using SVR and BP-ANN machine learn, In Challenges in Information, Communication and Computing Technology (pp. 587-591). CRC Press.

[3] Karsavran, Y., 2024, Evaluation of the performance of SVR and ANN Models in Sea Water Level Prediction for the Izmir Coast of the Aegean Sea, International Journal of New Findings in Engineering, Science and Technology, 2(1), pp.1-7. https://doi.org/10.61150/ijonfest.2024020101

[4] Voyant, C., Notton, G., Kalogirou, S., Nivet, M.L., Paoli, C., Motte, F. and Fouilloy, A., 2017, Machine learning methods for solar radiation forecasting: A review, Renewable energy, 105, pp.569-582. https://doi.org/10.1016/j.renene.2016.12.095

[5] Goel, A., Goel, A.K. and Kumar, A., 2023, The role of artificial neural network and machine learning in utilizing spatial information, Spatial Information Research, 31 (3), 275–285 [online]. https://doi.org/10.1007/s41324-022-00494-x

[6] Maier, H.R., Galelli, S., Razavi, S., Castelletti, A., Rizzoli, A., Athanasiadis, I.N., Sànchez-Marrè, M., Acutis, M., Wu, W. and Humphrey, G.B., 2023, Exploding the myths: An introduction to artificial neural networks for prediction and forecasting, Environmental modelling and software,

167, p.105776. https://doi.org/10.1016/j.envsoft.2023.105776

[7] Waqas, M., Humphries, U.W., Wangwongchai, A., Dechpichai, P. and Ahmad, S., 2023, Potential of artificial intelligence-based techniques for rainfall forecasting in Thailand: a comprehensive review, Water, 15(16), p.2979. https://doi.org/10.3390/w15162979

[8] Benti, N.E., Chaka, M.D. and Semie, A.G., 2023, Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects, Sustainability, 15(9), p.7087. https://doi.org/10.3390/su15097087

[9] Sina, A. and Kaur, D., 2023, An accurate hybrid approach for electric short-term load forecasting, IETE Journal of Research, 69(5), pp.2727-2742. https://doi.org/10.1080/03772063.2021.1905085

[10] Soebroto, A.A., Cholissodin, I., Pratiwi, D.E. and Putra, G.P.W., 2022, Comparative Study of SVR, Regression and ANN Water Surface Forecasting for Smart Agriculture, HABITAT, 33(01), pp.86-92. https://doi.org/10.21776/ub.habitat.2022.033.1.9

[11] Xiang, Y., Gou, L., He, L., Xia, S. and Wang, W., 2018, A SVR–ANN combined model based on ensemble EMD for rainfall prediction, Applied Soft Computing, 73, pp.874-883.

[12] Mirarabi, A., Nassery, H.R., Nakhaei, M., Adamowski, J., Akbarzadeh, A.H. and Alijani, F., 2019, Evaluation of data-driven models (SVR and ANN) for groundwater-level prediction in confined and unconfined systems, Environmental Earth Sciences, 78, pp.1-15.

[13] Kalteh, A.M., 2013, Monthly river flow forecasting using artificial neural network and support vector regression models coupled with wavelet transform, Computers and Geosciences, 54, pp.1-8. https://doi.org/10.1016/j.cageo.2012.11.015

[14] Yang, J., De Montigny, D. and Treleaven, P., 2022, May. ANN, LSTM, and SVR for gold price forecasting. In 2022 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr) (pp. 1-7). IEEE. https://doi.org/10.1109/CIFEr52523.2022.9776141

[15] Abbasi, M., Dehban, H., Farokhnia, A., Roozbahani, R. and Bahreinimotlagh, M., 2022, Long-term streamflow prediction using hybrid SVR-ANN based on Bayesian model averaging, Journal of Hydrologic Engineering, 27(11), p.05022018. https://doi.org/10.5281/zenodo.4678663.

[16] Özdoğan-Sarıkoç, G., Sarıkoç, M., Celik, M. and Dadaser-Celik, F., 2023, Reservoir volume forecasting using artificial intelligence-based models: artificial neural networks, support vector regression, and long short-term memory, Journal of Hydrology, 616, p.128766. https://doi.org/10.1016/j.jhydrol.2022.128766

[17] Wang, C., Li, M. and Yan, J., 2023, Forecasting carbon dioxide emissions: application of a novel two-stage procedure based on machine learning models, Journal of Water and Climate Change, 14(2), pp.477-493. https://doi.org/10.2166/wcc.2023.331

[18] Sharma, D., Singla, S.K. and Sohal, A.K., 2021, Stock market prediction using ARIMA, ANN and SVR. In ICCCE 2020: Proceedings of the 3rd International Conference on Communications and Cyber Physical Engineering (pp. 1081-1092), Springer Singapore.

[19] Bhoopathi, S., Sumanth, K., Akanksha, L. and Pal, M., 2024, Evaluating the performance of ANN, SVR, RF, and XGBoost in the prediction of maximum temperature and heat wave days over Rajasthan, India, Journal of Hydrologic Engineering, 29(6), p.04024044. https://doi.org/10.1061/JHYEFF.HEENG-6243

[20] Abdollahpour, S., Kosari-Moghaddam, A. and Bannayan, M., 2020, Prediction of wheat moisture content at harvest time through ANN and SVR modeling techniques, Information Processing in Agriculture, 7(4), pp.500-510. https://doi.org/10.1016/j.inpa.2020.01.003

[21] Alnuwaiser, M.A., Javed, M.F., Khan, M.I., Ahmed, M.W. and Galal, A.M., 2022, Support vector regression and ANN approach for predicting the ground water quality, Journal of the Indian Chemical Society, 99(7), p.100538. https://doi.org/10.1016/j.jics.2022.100538

[22] Ledmaoui, Y., El Maghraoui, A., El Aroussi, M., Saadane, R., Chebak, A. and Chehri, A., 2023, Forecasting solar energy production: A comparative study of machine learning algorithms, Energy Reports, 10, pp.1004-1012.

https://doi.org/10.1016/j.egyr.2023.07.042

[23] Piri, J., Abdolahipour, M. and Keshtegar, B., 2023, Advanced machine learning model for prediction of drought indices using hybrid SVR-RSM. Water Resources Management, 37(2), pp.683-712. https://doi.org/10.1007/s11269-022-03395-8

[24] Laaroussi, H. and Guerouate, F., 2020, November. Deep learning framework for forecasting tourism demand. In 2020 IEEE international conference on technology management, operations and decisions (ICTMOD) (pp. 1-4). IEEE. https://doi.org/10.1109/ICTMOD49425.2020.9380612

[25] Akbarian, M., Saghafian, B. and Golian, S., 2023, Monthly streamflow forecasting by machine learning methods using dynamic weather prediction model outputs over Iran, Journal of Hydrology, 620, p.129480. https://doi.org/10.1016/j.jhydrol.2023.129480

[26] Wen, S., Wei, B., You, J., He, Y., Xin, J. and Varfolomeev, M.A., 2023, Forecasting oil production in unconventional reservoirs using long short term memory network coupled support vector regression method: A case study, Petroleum, 9(4), pp.647-657. https://doi.org/10.1016/j.petlm.2023.05.004

[27] Khairudin, N.B.M., Mustapha, N.B., Aris, T.N.B.M. and Zolkepli, M.B., 2020, September. Comparison of machine learning models for rainfall forecasting, In 2020 international conference on computer science and its application in agriculture (ICOSICA) (pp. 1-5). IEEE. https://doi.org/10.1109/ICOSICA49951.2020.9243275 fd

[28] Ferrari, S., Lazzaroni, M., Piuri, V., Salman, A., Cristaldi, L., Rossi, M. and Poli, T., 2012, September. Illuminance prediction through extreme learning machines, In 2012 IEEE Workshop on Environmental Energy and Structural Monitoring Systems (EESMS) (pp. 97-103). IEEE. https://doi.org/10.1109/EESMS.2012.6348407

[29] Wu, Y.K., Chen, C.R. and Abdul Rahman, H., 2014, A novel hybrid model for short-term forecasting in PV power generation, International Journal of Photoenergy, 2014(1), p.569249. https://doi.org/10.1155/2014/569249