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Artificial Intelligence-Based Prediction of Modified Solar Still Productivity Using FGSVM and LOOCV

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Abstract

Accurate prediction of freshwater productivity is key to design and optimise solar desalination systems. A Fuzzy Gaussian Support Vector Machine (FGSVM) model is developed in this paper to predict the hourly distillate yield of a sponge-augmented Modified Solar Still (MSS) under real climatic conditions. The experimental data were obtained from the single slope solar still integrated with sponges that enhance evaporation through increase in water retention, capillary action and effective use of thermal energy. Field experiments were conducted at Raghogarh, Guna, India (24°39'N, 77°19'E) using 40 kg of basin water mass. Input parameters were the basin water temperature (Tw), inner glass cover temperature (Tci), solar radiation intensity (I) and the temperature difference between basin water and glass cover (Tw - Tci). The hourly freshwater productivity was used as output variable. To ensure a robust model validation with a limited experimental dataset, training and testing were done using Leave-One-Out Cross Validation (LOOCV). The efficiency of the proposed FGSVM model was evaluated by Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R2). The model gave an RMSE of 14.775, MAE of 11.224 and R2 of 0.980 which indicated an excellent agreement between observed and predicted productivity values. The results show that the FGSVM model can well capture the nonlinear thermal behaviour of the MSS, and the freshwater yield can be predicted accurately. Therefore, the proposed approach can be used as a reliable artificial intelligence tool for productivity forecasting, reducing experimental effort and supporting the development of intelligent and efficient solar desalination systems.

1.Introduction

Rapid urbanisation, industrialisation, population increase, and climate change have made freshwater shortage one of the world's most urgent problems [1]. Only a small portion of the water resources on Earth are suitable for drinking, even though around 97% of them are salty [2]. As a result, experts from all over the world are paying close attention to the development of sustainable and energy-efficient desalination technology [3-5]. Solar stills are regarded as one of the most promising desalination techniques because of their straightforward design, little maintenance needs, and capacity to harness solar energy that is readily available [6-8]. However, the comparatively poor freshwater production and thermal efficiency of traditional solar stills sometimes limit their broad implementation [9].

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Arunkumar et al. have reviewed various changes to enhance heat absorption, thermal storage, evaporation rate, and condensation processes in solar still systems to get over these restrictions [10]. To improve distillate yield and thermal performance, a variety of sensible heat storage materials, phase change materials, wicks, fins, porous media, saltwater bottles, glass bottles filled with sand, jute fabrics, honeycomb structures, ultrasonic forgers, and magnetic materials have been successfully used [11-16]. Because of their high-water retention capacity, increased evaporative surface area, and enhanced heat localisation properties, sponge-based materials have lately become popular as efficient thermal energy storage and capillary augmentation media.

The prediction of freshwater productivity is still a difficult job because sun desalination processes include highly nonlinear heat and mass transport phenomena, despite significant efforts being made to improve solar still performance experimentally [17]. Esmaeili et al. has suggested several interrelated factors, such as basin water temperature, glass cover temperature, solar radiation intensity, ambient circumstances, and temperature gradients, affect a solar still's output [18-20]. These intricate nonlinear interactions are frequently difficult for traditional mathematics and regression-based models to adequately describe, especially when experimental datasets are small [21,22].

Barmavatu et al. has suggested that recent advances in machine learning (ML) and artificial intelligence (AI) have shown great promise for simulating nonlinear thermal systems. Renewable energy and desalination systems have effectively used techniques including Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM), Random Forests, and Gaussian Process Regression [23-27]. Among these techniques, Support Vector Machine-based regression models are especially well-suited for small experimental datasets due to their superior generalisation capabilities and lower overfitting risk. Furthermore, the handling of uncertainties and imprecise connections that frequently occur in experimental thermal systems is made possible by the integration of fuzzy logic into machine learning frameworks [28]. The benefits of fuzzy logic and Support Vector Regression are combined with a Gaussian Radial Basis Function (RBF) kernel in the Fuzzy Gaussian Support Vector Machine (FGSVM). While fuzzy principles provide resilience against uncertainties and fluctuations found in experimental observations, the Gaussian kernel effectively captures nonlinear connections between input and output variables. As a result, FGSVM provides better prediction performance for thermal systems with nonlinear and unpredictable behaviour [29].

The scarcity of datasets is a significant obstacle to experimental solar still research. When there are few data available, traditional train-test splitting techniques may result in performance estimates that are skewed. The current study uses Leave-One-Out Cross Validation (LOOCV) to overcome this problem. Because each observation is used once for testing and all other observations are used for training, LOOCV is regarded as one of the most stringent validation methods for small datasets [30].

To estimate the hourly freshwater production of a sponge-augmented Modified Solar Still (MSS) operating under actual climatic circumstances, the main goal of the current work is to create a Fuzzy Gaussian Support Vector Machine (FGSVM) model. Hourly distillate yield was chosen as the objective output variable, and experimental measurements of basin water temperature, inner glass cover temperature, solar radiation intensity, and temperature differential between basin water and glass cover were used as input factors. Leave-One-Out Cross Validation and statistical measures such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used to assess the prediction accuracy of the generated model. The suggested method seeks to lessen reliance on lengthy experimental studies while offering a precise and trustworthy artificial intelligence framework for predicting solar still production.

2.Experimental setup Dataset Preparation

In November and December of 2024, the experimental investigation was carried out at Jaypee University of Engineering and Technology (JUET), Guna, India (24°39′N, 77°19′E). FRP material that was 5 mm thick was used to create a single slope Modified Solar Still (MSS) with a basin size of 1 m². To improve solar energy absorption, the stills inside surfaces were painted black, and a clear

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glass cover measuring 4 mm in thickness was placed at a 15.6° inclination. Inside the basin, 35 cotton thread cylindrical sponges were evenly distributed in a zigzag manner to enhance evaporation and heat energy storage. Each sponge was covered with black dye to improve solar absorptivity and had an average height of 13.2 cm and a diameter of 3 cm.

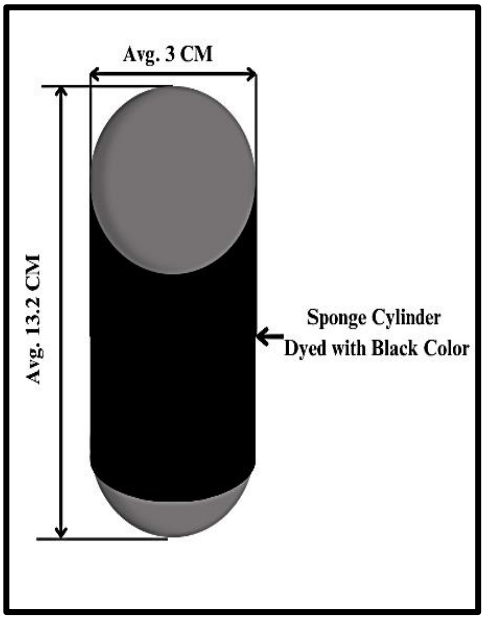


Figure 1. Diagrammatic of a sponge.

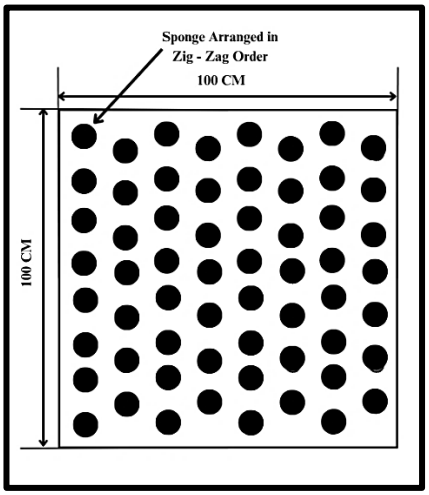


Figure 2. Arrangement of sponges in MSS

K-type thermocouples coupled to a DTC324A-2 temperature indicator were used to record the temperature of basin water (Tw), inner glass cover (Tci), ambient air (Ta), and other places. An LX-107 solar power meter was used to measure solar radiation intensity (I), and a graduated cylinder was used to quantify hourly freshwater productivity (Mew). Measurement reliability was assessed using type-B uncertainty analysis. A 40 kg basin water mass was used for the experiments, and hourly measurements were made between 9:00 and 21:00.

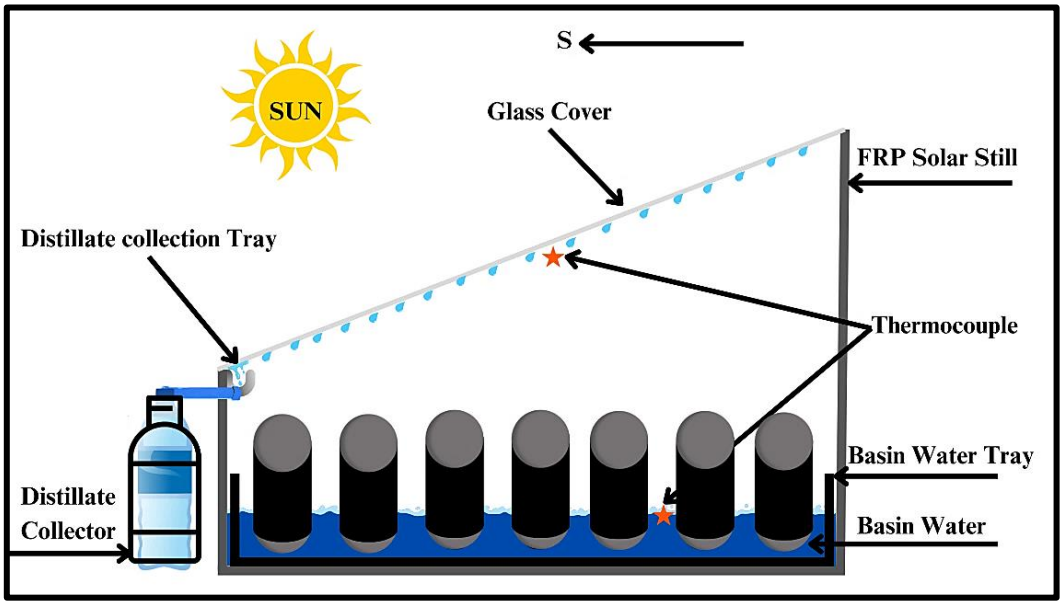


Figure 3. Diagrammatic representation of MSS.

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Basin water temperature (Tw), inner glass cover temperature (Tci), ambient temperature (Ta), solar radiation intensity (I), and hourly distillate production (Mew) made up the experimental dataset. To enhance the predictive power of the model, an extra element was created: the temperature differential between the glass cover and basin water (Tw − Tci). The Fuzzy Gaussian Support Vector Machine (FGSVM) model was created and validated using these parameters. Leave-One-Out Cross Validation (LOOCV) was used to optimise data utilisation and guarantee dependable prediction performance because of the small sample size.

3.Mathematical Modeling of Fuzzy Gaussian Support Vector Machine (FGSVM)

3.1 Input and Output Variables

The modified solar still's experimental parameters were used to create the FGSVM model. The expression for the input feature vector is:

$$X = [T_w,\ T_{ci},\ I,\ (T_w - T_{ci})] \quad (1)$$

where:

- T_w = basin water temperature (°C)
- T_{ci} = inner glass cover temperature (°C)
- I = solar radiation intensity (W/m²)
- $(T_w - T_{ci})$ = temperature difference between basin water and inner glass cover (°C)

The freshwater productivity per hour is the desired output variable.

$$Y = M_{ew} \quad (2)$$

where M_{ew} is the hourly distillate yield (mL/h).

3.2 Fuzzy Logic Formulation

Each experimental observation's fuzzy membership value is shown as follows:

$$\mu(X_i) \in [0,1] \quad (3)$$

where the degree of membership of the i^{th} sample is indicated by $\mu(X_i)$. During training, the fuzzy membership function lessens the impact of ambiguous or noisy data.

3.3 Support Vector Regression (SVR)

The regression functions that SVR uses is provided by:

$$f(X) = w^T \phi(X) + b \quad (4)$$

where:

- w = weight vector
- b = bias term
- $\phi(X)$ = nonlinear transformation function

The goal of optimization is:

$$\min\left(\frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} (\xi_i + \xi_i^*)\right) \quad (5)$$

subject to:

$M_{ew,i} - f(X_i) \le \varepsilon + \xi_i \quad f(X_i) - M_{ew,i} \le \varepsilon + \xi_i^*\ \xi_i, \xi_i^* \ge 0$

where:

- C = penalty parameter
- ε = insensitive loss function
- ξ_i, ξ_i^* = slack variables

The term

$$\frac{1}{2} \parallel w \parallel^2 \quad (6)$$

SVR works effectively with less datasets because it regulates model complexity. The model prevents overfitting while preserving high prediction accuracy by minimizing this term.

3.4 Gaussian Kernel Function

A Gaussian Radial Basis Function (RBF) kernel was used because of the extremely nonlinear relationship between thermal parameters and productivity:

$$K(X_i, X_j) = \exp(-\gamma \parallel X_i - X_j \parallel^2) \quad (7)$$

where:

- γ = kernel width parameter

The model can learn intricate nonlinear correlations between T_w, T_{ci}, I, and M_{ew} due to the Gaussian kernel, which maps the data into a high-dimensional feature space. The main factor contributing to FGSVM's superior prediction performance is its kernel.

3.5 Fuzzy Gaussian Support Vector Machine (FGSVM)

Once fuzzy memberships are included, the optimization issue is as follows:

$$\min\left(\frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} s_i\,(\xi_i + \xi_i^*)\right) \quad (8)$$

where:

- s_i = fuzzy membership value of the i^{th} observation

The fuzzy weights increase prediction resilience and lessen the impact of ambiguous experimental samples.

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3.6. Leave-One-Out Cross Validation (LOOCV)

LOOCV does N separate training-validation cycles for a dataset with N observations:

$$N_{LOOCV} = N \quad (9)$$

For each iteration:

$$Training = N - 1 \; Testing = 1$$

This procedure is repeated until each observation has been utilized as a testing sample exactly once. LOOCV maximizes data utilization and offers a trustworthy assessment of model performance because the MSS dataset only has 13 observations.

1.7 Performance Evaluation Criteria

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(M_{ew,i}^{obs} - M_{ew,i}^{pred}\right)^2} \quad (10)$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|M_{ew,i}^{obs} - M_{ew,i}^{pred}\right| \quad (11)$$

Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(M_{ew,i}^{obs} - M_{ew,i}^{pred}\right)^2}{\sum_{i=1}^{N}\left(M_{ew,i}^{obs} - \overline{M}_{ew}\right)^2} \quad (12)$$

where:

- M_{ew}^{obs} = observed hourly distillate yield
- M_{ew}^{pred} = predicted hourly distillate yield
- $\overline{M}_{ew}$ = mean observed distillate yield

The values obtained for the constructed MSS model were:

- RMSE = 14.775
- MAE = 11.224
- $R^2 = 0.980$

demonstrating a high degree of consistency between the projected and actual freshwater production.

FGSVM was chosen because it offers three benefits:

- Overfitting in short datasets is avoided by using $\frac{1}{2}\| w \|^2$ to minimise structural risk.
- Nonlinear heat and mass transport behaviour in solar stills is well-modelled by the Gaussian Kernel $K(X_i, X_j)$.
- Fuzzy Membership Weights s_i, which lessen the effects of environmental variations and measurement error.

Because of these features, FGSVM is especially well-suited for tiny experimental solar still datasets, which accounts for the study's strong prediction accuracy (R^2=0.980).

2. Observations, result and discussions.

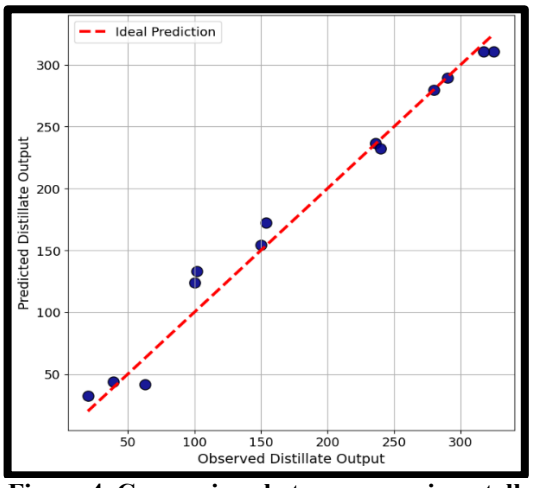


Figure 4. Comparison between experimentally observed and FGSVM-predicted hourly distillate productivity of the modified solar still.

The hourly distillate production of the improved solar still as predicted by FGSVM and empirically observed is compared in Fig. 4. Over the course of the whole working time, it is evident that the projected values closely match the experimental trend. Freshwater production rose steadily in the morning, peaked in the afternoon, and then fell as solar radiation intensity dropped. The FGSVM forecast was about 310 ml h^{-1}, but the maximum actual distillate production was about 325 ml h^{-1}. In a similar vein, the model effectively represented the fluctuations in production during low-yield times in the morning and evening. The ability of the suggested FGSVM model to precisely depict the nonlinear thermal behaviour of the modified solar still is demonstrated by the strong agreement between the observed and predicted curves.

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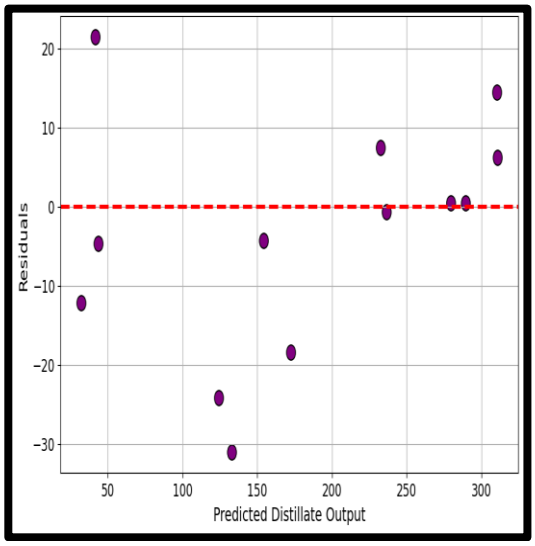


Figure 5. Residual analysis of the FGSVM model obtained using Leave-One-Out Cross Validation.

Figure 5 displays the FGSVM model's residual distribution as determined by Leave-One-Out Cross Validation (LOOCV). The residual values show no systematic trend and are dispersed randomly about the zero-error line. Most residuals fall within ±15 ml h^{-1}, suggesting modest model bias and strong forecast consistency. Some observations have somewhat bigger residuals, especially when production fluctuates quickly, but these deviations are still within acceptable bounds. Despite the small experimental dataset, the constructed FGSVM model has good generalisation capabilities and does not suffer from severe overfitting, as confirmed by the random distribution of residuals.

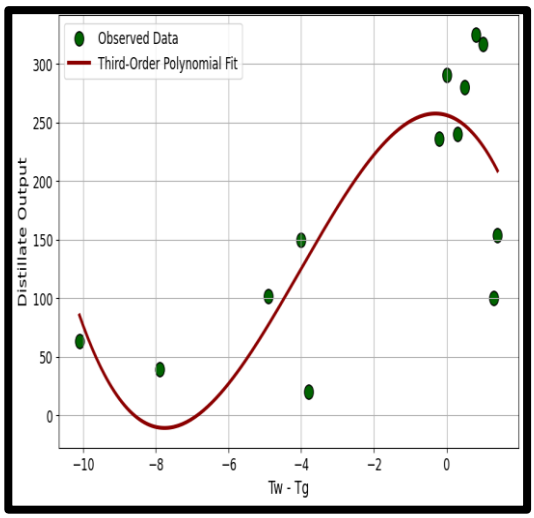


Figure 6. Relationship between temperature difference ($T_w - T_{ci}$) and freshwater productivity with third-order polynomial fitting.

Figure 6 shows how freshwater production is affected by the temperature differential between basin water and inner glass cover (Tw-Tci). To determine the underlying link between the independent variable and distillate output, a third-order polynomial fitting was used. The findings show a significant nonlinear correlation between freshwater output and temperature variation. The evaporation-condensation process becomes more efficient as the temperature differential rises, leading to increased productivity. The distillate yield is quite sensitive to heat gradients created between the condensing glass surface and the basin water, as confirmed by the polynomial trend. The significance of having (Tw-Tci) as one of the input parameters in the FGSVM model is further supported by this discovery.

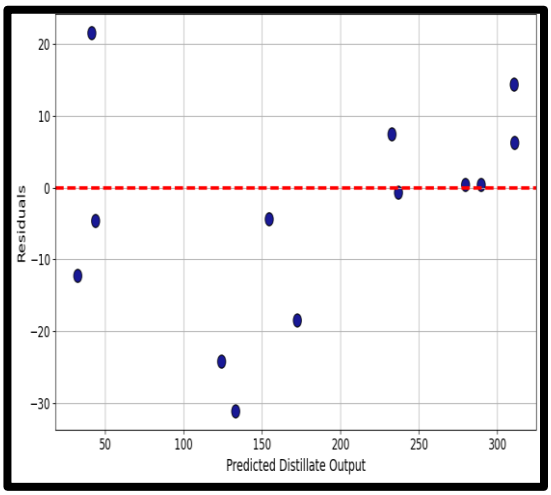


Figure 7. Scatter plot showing the agreement between experimentally observed and FGSVM-predicted distillate productivity.

The scatter plot between experimentally observed and FGSVM-predicted distillate values is displayed in Fig. 7. Excellent agreement between experimental observations and model predictions is demonstrated by the bulk of data points being centred around the ideal prediction line. The points' closeness to the 45° reference line shows that the prediction errors stay low across the solar still's operational range. The scatter distribution demonstrates that both high and low production circumstances are adequately captured by the suggested model.

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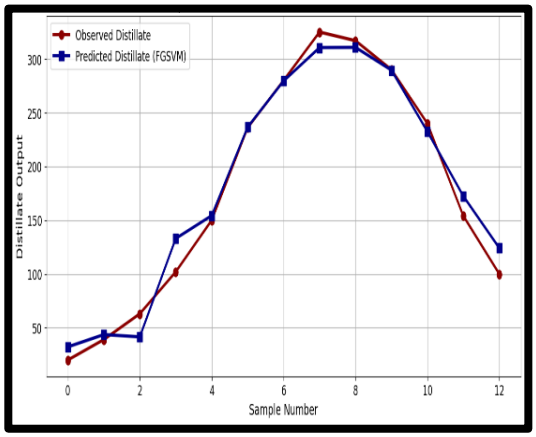


Figure 8. Statistical performance evaluation of the developed FGSVM model using RMSE, MAE, and R^2 indicators.

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used to assess the predictive power of the FGSVM model. RMSE = 14.775 ml h^{-1}, MAE = 11.224 ml h^{-1}, and R^2 = 0.980 were the results. The high coefficient of determination shows that the constructed model explains almost 98% of the variation in freshwater productivity, while the low RMSE and MAE values show slight differences between experimental and projected outputs as shown in figure 8. The combination of fuzzy logic, Gaussian kernel-based support vector regression, and LOOCV validation offer a dependable framework for forecasting solar still productivity using sparse experimental observations, as demonstrated by the outstanding statistical indicators.

3. Conclusion

Employing experimental data gathered under actual climate circumstances, a Fuzzy Gaussian Support Vector Machine (FGSVM) model was effectively created to forecast the hourly freshwater production of a sponge-augmented Modified Solar Still (MSS). Hourly distillate yield (Mew) was regarded as the output parameter, while basin water temperature (Tw), inner glass cover temperature (Tci), solar radiation intensity (I), and temperature differential (Tw-Tci) were utilized as input variables. Leave-One-Out Cross Validation (LOOCV) was used to optimize data utilization and offer trustworthy model validation because of the small experimental dataset. With RMSE, MAE, and R^2 values of 14.775 ml h^{-1}, 11.224 ml h^{-1}, and 0.980, respectively, the constructed FGSVM model demonstrated exceptional prediction ability. The ability of the suggested model to precisely represent the nonlinear thermal behavior of the MSS is demonstrated by the strong agreement between the observed and anticipated distillate outputs. The findings verify that a strong and dependable framework for predicting solar still productivity is provided by combining fuzzy logic, Gaussian kernel-based support vector regression, and LOOCV. As a result, the suggested FGSVM model may be used efficiently for solar desalination system performance predictions and optimization while lowering the requirement for in-depth experimental research.

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