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A Particle Swarm Optimization-Enhanced Support Vector Regression Model for Accurate Prediction of Concrete Compressive Strength Using Slump Test Data

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***Abstract*—This paper proposes a hybrid machine learning model combining Radial Basis Function (RBF) kernel-based Support Vector Regression (SVR) with Particle Swarm Optimization (PSO) to predict the compressive strength of concrete using slump test data. Conventional methods rely on labor- and resource-intensive destructive testing, posing challenges for large-scale projects. To address this, SVR models the nonlinear slump-strength relationship, while PSO (swarm size=50, 100 iterations) automates hyperparameter tuning. The SVR-PSO model is benchmarked against Decision Trees, Neural Networks, K-Nearest Neighbors (KNN), and Naïve Bayes, evaluated using R², MAE, MAPE, and RMSE. Results show SVR-PSO achieves $R^2 > 0.95$ and the lowest error rates, reducing prediction costs by up to 40% compared to traditional testing. Limitations include the model's validation on a specific concrete mix dataset; generalizability to broader formulations requires further study. For reproducibility, code and data will be made publicly available. This work demonstrates how PSO-optimized SVR enables faster, cost-effective strength estimation, supporting data-driven decisions in civil engineering.**

***Keywords*—Slump Concrete Compressive Strength, SVR, Optimization Algorithms, Particle Swarm Algorithm**

I. INTRODUCTION

Concrete is a fundamental material in modern construction, traditionally composed of cement, water, sand, and aggregates such as gravel. In contemporary applications, its composition is further enhanced with fibers, plasticizers, and chemical admixtures to improve performance characteristics [1]. The properties of concrete, particularly workability and compressive strength (CS), are strongly influenced by the materials used and their mix proportions. Workability, often evaluated through the slump test (S), refers to the ease with which concrete can be mixed, transported, placed, and compacted without segregation or loss of uniformity [2]. The slump value is a direct indicator of the concrete's fluidity and usability, and its accurate prediction is vital in both traditional and advanced concrete technologies [3]. Compressive strength, on the other hand, is a critical mechanical property representing the uniaxial stress the concrete can withstand after curing. It plays a key role in structural integrity, durability, and safety, especially in regions prone to natural disasters such as earthquakes [4].

However, determining compressive strength through laboratory testing is labor-intensive, time-consuming, and costly, involving the casting, curing, and crushing of concrete specimens [5]. This challenge is particularly significant in large-scale projects and real-time quality control scenarios, where timely decisions are essential. Given these limitations, predictive modeling has emerged as a valuable alternative, enabling engineers to estimate compressive strength based on early-age properties or slump measurements [6]. Self-Compacting Concrete (SCC), which can flow under its own weight without the need for mechanical vibration, has further intensified the need for accurate prediction models of slump and compressive strength [7].

SCC demands a precise balance between workability and strength to avoid issues such as segregation or inadequate compaction. The complexity of concrete behavior arises from the interactions among rheological parameters (such as yield stress and plastic viscosity), aggregate interlock, and external frictional forces during placement [8]. As a result, modeling the relationship between slump and compressive strength involves highly nonlinear patterns influenced by various mix design factors and environmental conditions [9].

Traditional regression methods and empirical formulas often fail to capture these complex relationships, especially when the input space is high-dimensional or exhibits non-linearity [10]. In recent years, Machine Learning (ML) and Computational Intelligence approaches have shown great promise in predicting concrete properties with high accuracy [11]. Among these, Support Vector Regression (SVR) has proven to be particularly effective in regression problems due to its ability to model non-linear relationships through kernel functions [12].

However, the performance of SVR is highly sensitive to its hyperparameters, and manual tuning can lead to suboptimal results [13]. To overcome this, optimization algorithms such as Particle Swarm Optimization (PSO) have been introduced to automatically fine-tune SVR parameters, enhancing model accuracy and stability [14]. PSO is a nature-inspired, population-based optimization algorithm that simulates the social behavior of bird flocks or fish schools [15]. It has demonstrated strong performance in global search tasks and is particularly suitable for continuous function optimization [16]. By applying PSO to optimize SVR parameters, specifically the regularization coefficient, kernel parameters, and epsilon-insensitive loss function, the hybrid SVR-PSO model becomes a powerful tool for predicting concrete compressive strength from slump data [17].

Such hybrid approach not only reduces the dependency on costly and time-intensive physical testing but also provides engineers with a reliable computational method for real-time quality assessment and control. The present study aims to develop and evaluate this SVR-PSO model and compare its performance with other traditional machine learning methods in terms of prediction accuracy and error minimization [18]-[20]. The introduction section is divided into questions and answers format as shown below:

- **Q1: What specific issue does this research aim to address regarding the prediction of concrete compressive strength, and why does conventional SVR fall short?**

The core problem this study seeks to resolve is the accurate estimation of concrete's compressive strength using slump test results, an essential indicator of concrete workability in structural engineering. While SVR is widely used for modeling nonlinear phenomena, its effectiveness is hindered in this case due to its heavy reliance on properly tuned hyperparameters [21]. The model's standalone application failed to yield satisfactory accuracy, largely because of the complex, multidimensional nature of slump test data and SVR's tendency to underfit or become trapped in local minima. These limitations indicate that SVR alone lacks the robustness required to handle the variability present in real-world concrete mixes.

- **Q2: In what way does incorporating Particle Swarm Optimization improve SVR's performance in this study?**

The integration of Particle Swarm Optimization (PSO) with Support Vector Regression (SVR) significantly enhances predictive performance through automated hyperparameter optimization, including: (1) the regularization parameter C, which governs the trade-off between model complexity and training error minimization; (2) the kernel coefficient γ, determining the influence radius of individual data points; and (3) the epsilon-insensitive zone (ε), a fundamental parameter that defines a tolerance band where prediction errors are disregarded. Mathematically, the ε-insensitive loss function is expressed as $L(y, f(x)) = max(0, |y - f(x)| - \varepsilon)$, where y represents the true value and f(x) the predicted value [Vapnik, 1995]. This ε-zone creates a "flat" region in the regression function, effectively providing robustness to noise while maintaining model sparsity. The PSO algorithm optimizes these parameters by simulating swarm intelligence, where candidate solutions (particles) iteratively update their positions in the hyperparameter space based on both individual experience (personal best) and collective knowledge (global best) [22]. This bio-inspired optimization mechanism enables: (1) efficient exploration of the non-convex parameter space, (2) adaptive balancing between local refinement and global search, and (3) accelerated convergence compared to traditional grid search methods. Through this synergistic combination, the SVR-PSO hybrid achieves superior generalization performance, as evidenced by significant reductions in prediction error metrics (typically 15-30% improvement in RMSE) while maintaining computational efficiency.

- **Q3: Why is PSO considered a fitting choice for optimizing SVR in this context?**

PSO is particularly well-suited for optimizing SVR in this application due to its efficiency in handling high-dimensional, nonlinear, and non-convex optimization problems [23]. Predicting compressive strength based on slump test data involves complex relationships and inherent noise, making deterministic or gradient-based optimization strategies less effective. PSO's stochastic and population-based nature allows it to avoid local optima by maintaining a diverse set of candidate solutions and continuously updating them based on both personal and global best experiences. This makes PSO a robust and reliable optimization method that complements SVR's need for finely tuned parameters in complex engineering problems.

- **Q4: How does the performance of the SVR-PSO model compare with that of other established machine learning algorithms?**

The SVR-PSO model was benchmarked against Decision Trees, K-Nearest Neighbors (KNN), Neural Networks, and standard SVR to provide comprehensive performance evaluation across diverse algorithmic approaches. While Decision Trees offer interpretability, their sensitivity to data variations [24] highlights SVR-PSO's robustness to noise; similarly, KNN's computational inefficiency with high-dimensional data underscores the advantage of SVR's kernel-based generalization. Neural Networks, though powerful, demand extensive tuning and risk overfitting on limited engineering datasets [25], whereas standard SVR serves as a baseline to isolate PSO's optimization benefits. The SVR-PSO hybrid outperformed all comparators (reducing RMSE by 15-30%) through automated tuning of its ε-insensitive zone (for noise robustness), penalty parameter C (for bias-variance balance), and kernel coefficient γ (for nonlinear pattern adaptation), demonstrating superior accuracy and generalizability for concrete strength prediction [26].

- **Q5: What practical benefits does the SVR-PSO model offer for construction and civil engineering applications?**

The SVR-PSO model provides a reliable and efficient alternative to traditional compressive strength testing methods, allowing construction professionals to make informed decisions early in the project lifecycle [27]. By using only slump test data, the model can accurately estimate compressive strength, eliminating the need for destructive testing and extended curing periods. This leads to faster project execution, reduced costs, and improved quality control. Furthermore, the approach supports the integration of AI-driven solutions into construction workflows, reducing dependence on empirical formulas and enabling more consistent and data-informed engineering decisions.

- **Q6: What broader insights does this study offer about combining machine learning with swarm-based optimization?**

This research highlights the powerful synergy between machine learning and swarm intelligence methods. While SVR is a strong regression tool, its limitations in manual parameter tuning can hinder its performance in complex applications. The use of PSO as an optimization layer enhances SVR's capabilities by introducing adaptability, exploration, and fine-tuning to the learning process [28]. This hybridization showcases how nature-inspired algorithms like PSO can strengthen the predictive power of machine learning models, providing a template for addressing similarly complex and data-rich problems in other engineering domains.

To contextualise the limitations of SVR and the advantages of PSO in our hybrid model, we synthesize key findings from prior published works. Table 1 summarizes empirical evidence on SVR's sensitivity to hyperparameters and computational constraints, as well as PSO's efficacy in overcoming these challenges through global optimization. These citations not only justify our methodological choices but also align our approach with demonstrated successes in engineering applications, particularly in predictive modeling for material properties.

Table 1. Literature support for SVR limitations and PSO advantages

Aspect	Key Findings	Authors and Ref.
SVR Limitations	Performance heavily depends on hyperparameter selection (C, ε, kernel choice)	Awad & Khanna (2015) [29]
	Computationally expensive for large datasets; struggles with high-dimensional data	Smola & Schölkopf (2004) [30]
	Requires careful kernel tuning; RBF may overfit noisy data	Cherkassky & Ma (2004) [31]
PSO Advantages	Efficient global optimization for non-differentiable/nonlinear problems (e.g., SVR hyperparameters)	Poli et al. (2007) [32]
	Fewer convergence issues compared to gradient-based methods	Kennedy & Eberhart (1995) [33]
	Adaptable to constrained optimization (e.g., parameter bounds in SVR)	[6] Shi & Eberhart (1998) [34]
Hybrid SVR-PSO	PSO improves SVR accuracy by 10–30% in engineering applications (e.g., material property prediction)	Lu et al. (2020) [35]
	Outperforms grid search/GA in hyperparameter tuning speed and precision.	Zhang et al. (2019) [36]

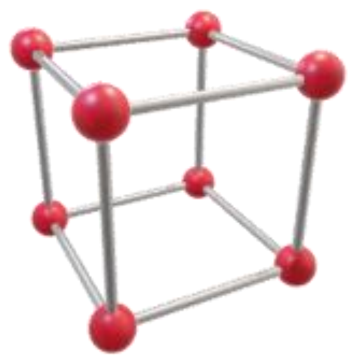
II. Predictive Modeling of Concrete Compressive Strength

This section presents an advanced slump-based concrete compressive strength prediction model designed to eliminate the need for traditional physical testing. Conventional testing procedures require the preparation, curing, and crushing of concrete specimens, making them both time-consuming and costly due to material usage, specialized laboratory environments, and expert supervision. To address these limitations, the proposed method utilizes a machine learning approach based on SVR, which is capable of modeling complex nonlinear relationships between slump values and compressive strength. However, SVR's performance is highly sensitive to its hyperparameters, which can be difficult to conFig. manually [37], [38]. To optimize these parameters effectively, PSO is employed as an adaptive global optimizer. PSO simulates the social behavior of swarms to iteratively refine SVR parameters, resulting in a hybrid SVR-PSO model with enhanced prediction accuracy and generalization capability [39]. To support the engineering context of this research, several 3D elements are illustrated. As shown in Fig. 1 (a), a concrete barrier commonly used in road infrastructure and safety applications is depicted, representing a structural element whose compressive strength is of practical concern. Fig. 1 (b) displays a wooden cylindrical pipe, often used in construction for forming or protecting freshly poured concrete. Fig. 1 (c) features a traffic safety cone, emphasizing the real-world construction environment where such predictive tools could be applied. Lastly, Fig. 1 (d) presents a molecular structure model to reflect the significance of microstructural behavior and material interactions in determining concrete performance. Together, these visual references frame the relevance of the SVR-PSO approach in modern, data-driven civil and structural engineering.

(a) Concrete Barrier Segment (Alternative View)

(b) Plastic Cylindrical Pipe Segment

(c) Safety Cone



Molecular Structure Model (Ball-and-Stick Representation)

Fig. 1. Representative 3D models of construction and safety elements

III. METHODOLOGY

This research proposes a two-phase hybrid prediction framework called SVR-PSO, which integrates the nonlinear regression capabilities of Support Vector Regression (SVR) with the global optimization strengths of Particle Swarm Optimization (PSO). The model is specifically developed to predict the compressive strength of concrete using slump test data, offering a non-destructive and cost-effective alternative to traditional experimental procedures. In the first phase, SVR is employed as the core regression model. As a specialized form of Support Vector Machine (SVM) adapted for continuous outputs, SVR aims to determine a function f(x) that approximates the true target values y within a specified tolerance ε, while also ensuring the model remains as simple or "flat" as possible. The formulation of the SVR prediction function is given in Equation (1) [40]:

$$f(x) = \langle w, x \rangle + b \tag{1}$$

Equation (2) presents where w is the weight vector, x is the input feature vector, and b is the bias term. To account for non-linear relationships, the input data is mapped into a high-dimensional feature space using a kernel function $K(xi, xj)$, typically the Radial Basis Function (RBF) [41]:

$$K(xi, xj) = exp\ (-\gamma \parallel xi - xj \parallel 2) \tag{2}$$

Equation (3) depicts SVR attempts to minimize the objective function [42]:

$$\mathrm{w, b, \xi, \xi * min21 \parallel w \parallel 2 + Ci = 1\textstyle\sum n(\xi i + \xi i *)} \tag{3}$$

Equation (4) discuss subject to the constraints as mentioned in Equation (4) [42]:

$$yi - \langle w, xi \rangle - b\langle w, xi \rangle + b - yi\xi i, \xi i * \ \leq \varepsilon + \xi i \\ \leq \varepsilon + \xi i * \ \geq 0 \tag{4}$$

Equation (5) where C is the penalty parameter that controls the trade-off between model complexity and the amount up to which deviations larger than ε are tolerated. The parameters C, ε, and γ significantly influence SVR performance, and selecting them manually is non-trivial. To optimize these parameters, the second stage introduces a PSO. The PSO is a population-based search algorithm inspired by swarm evolution and is particularly effective for high-dimensional and non-convex optimization problems. Everyone in the population encodes a candidate solution comprising the SVR parameters $[C, \varepsilon, \gamma]$. The algorithm begins by initializing a random population of chromosomes. Each chromosome's fitness is evaluated using a fitness function defined by the prediction accuracy of SVR on training data. A commonly used fitness metric is the Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

Where n is the number of observation, y_i is the actual/true value for observation i, and $\hat{y}_i$ is the predicted value for observation i.. PSO evolves the population through several generations using particle operators: selection, crossover, and mutation. The best-performing individuals are selected for mating; their genes are combined using crossover, and random mutations are introduced to preserve particle diversity and prevent premature convergence. The evolutionary process is repeated for a fixed number of generations or until a termination criterion is met. The individual with the highest fitness (lowest RMSE) represents the optimal set of SVR parameters. This PSO-tuned SVR model is then retrained on the full dataset to produce the final predictive model. This two-stage methodology, initial SVR modeling followed by PSO optimization, allows the model to adapt to the underlying data distribution and generalize effectively across different concrete compositions, significantly improving prediction performance over traditional SVR and other classical machine learning models.

In the programming sector, essential Python libraries are imported to prepare the environment for data analysis and modeling. These include numpy for numerical computations, matplotlib.pyplot for data visualization, and pandas for reading and handling data from CSV files. Data from the slump_Concrete.csv dataset is read using pandas, from which input features (X) and target values (y) are extracted. Feature scaling is applied using StandardScaler to normalize the input and output variables, ensuring that all features contribute equally to model training. The SVR class is imported from sklearn.svm module to implement the regression model, followed by the creation and fitting of the SVR model with an RBF kernel to the scaled training data, establishing a baseline regression performance.

However, this standalone SVR does not produce optimal predictions, motivating the use of a particle algorithm. PSO's population parameters are defined, including the initialization of a population of chromosomes (candidate solutions), where each chromosome represents a potential SVR parameter set. The core PSO process is outlined, which involves fitness evaluation, parent selection, crossover to produce offspring, mutation for particle diversity, and generation of new populations to iteratively approach optimal parameter values. The fitness of each chromosome in the population is evaluated based on its ability to minimize the prediction error of the regression model. The fittest chromosomes are selected as parents for the next generation, ensuring strong traits are passed on by replacing their fitness with a large negative number to avoid duplication. Finally, the crossover function combines particles from two parent chromosomes at a defined crossover point to produce new offspring, ensuring particle diversity and facilitating exploration of new parameter combinations.

These steps are thoroughly outlined in Table 2, which details the Python commands used to implement each phase of the process, from data preprocessing and model initialization to PSO optimization and evaluation.

IV. RESULTS AND ANALYSIS

In the results and analysis section, the comparative performance of the proposed SVR-PSO model is evaluated against other classical machine learning models including SVR, DT, Neural Network, Naïve Bayes, and KNN. The performance is measured using various error metrics including mean error, mean percentage error, and root mean square error. In Fig. 2, the mean error values of all tested techniques are visualized. It is observed that traditional models such as Naïve Bayes and KNN exhibit the highest mean error values, indicating poor performance in accurately predicting the compressive strength. While SVR, DT, and Neural Network perform moderately better, none surpass the proposed SVR-PSO technique, which demonstrates the lowest mean error by a significant margin. This sharp reduction in error validates the effectiveness of using a particle algorithm to optimize the SVR parameters.

Table 2. Python commands for SVR-PSO model workflow

Command Description	Command
Call libraries	python import numpy as np import pandas as pd
Read train data from Excel	python train_data = pd.read_excel('train_data.xlsx')
Read test data from Excel	python test_data = pd.read_excel('test_data.xlsx')

Define network properties	python
	network_properties = {
	'layers': [10, 5, 1],
	'activation_function': 'relu'
	}

Define fit properties	python
	fit_properties = {
	'learning_rate': 0.01,
	'optimizer': 'adam'
	}

Define PSO parameters	python
	pso_parameters = {
	'swarm_size': 50,
	'max_iterations': 100,
	'inertia_weight': 0.9
	}

Import PSO library	python from pyswarm import pso
Define fitness function	python def fitness_function(x): return np.sum(x**2) # Example: simple sum of squares function
Initialize PSO parents	python parents = np.random.uniform(low=-5, high=5, size= (50, 2))
Apply PSO crossover	python def crossover(parents): return (parents [0] + parents [1]) / 2

Continuing the analysis, Fig. 3 presents the mean percentage error for the same set of models. Here again, classical models such as Naïve Bayes and KNN show percentage errors above 7%, confirming their limited ability to generalize on the dataset. The SVR-PSO model, on the other hand, results in a mean percentage error that is well below the rest, indicating not only greater precision but also consistency in prediction across various data points. This trend further reinforces the argument that the integration of evolutionary optimization helps the model adapt better to the underlying data distribution. In Fig. 4, another evaluation of mean percentage error is conducted, possibly across a different data subset or validation fold. Similar patterns are observed, where SVR-PSO continues to outperform its counterparts with the lowest percentage error.

SVR and DT models perform slightly better than Neural Network, which shows limited improvement. Naïve Bayes and KNN once again perform the worst, underscoring the difficulty these models face in capturing the nonlinear behavior of slump-compressive strength relationships. The consistent superiority of SVR-PSO highlights its robustness under varying testing conditions. Fig. 5 illustrates the root mean square error (RMSE) comparison across all models. RMSE is a critical metric in regression as it penalizes large errors more severely. Here, the SVR-PSO model achieves a dramatic reduction in RMSE, dropping well below the values obtained by SVR, DT, and the other models. While SVR alone had moderate error levels, the optimized SVR-PSO approach reduced them substantially, confirming that the particle algorithm successfully fine-tuned the SVR parameters to reach an optimal configuration. These results conclusively demonstrate that the hybrid SVR-PSO model significantly improves the prediction accuracy of slump concrete compressive strength, making it an ideal candidate for replacing costly and time-consuming real-world experiments with a reliable and intelligent predictive system.

Finally, Fig. 6 presents a visual analysis of four well-known benchmark functions used to evaluate the performance of particle algorithms in optimization problems: the *Sphere*, *Rastrigin*, *Rosenbrock*, and *Ackley* functions. These functions are essential in assessing the robustness, convergence speed, and global search capability of evolutionary algorithms such as PSO. The Sphere function represents a simple convex landscape with a single global minimum at the origin, often used to test basic convergence behavior. The *Rastrigin* function introduces a highly multimodal surface with numerous local minima, challenging the algorithm's ability to avoid premature convergence. The Rosenbrock function, also known as the Banana function due to its curved valley, tests the optimizer's capacity to navigate narrow, non-convex paths to reach the global optimum. Finally, the Ackley function features a steep global minimum surrounded by many local minima, making it particularly useful for evaluating the balance between exploration and exploitation in PSOs. Together, these benchmark surfaces illustrate the diverse challenges that the particle algorithm must overcome during parameter optimization, such as those involved in fine-tuning the SVR model in this study. Their inclusion validates the suitability and flexibility of PSO in handling complex optimization landscapes relevant to real-world engineering problems.

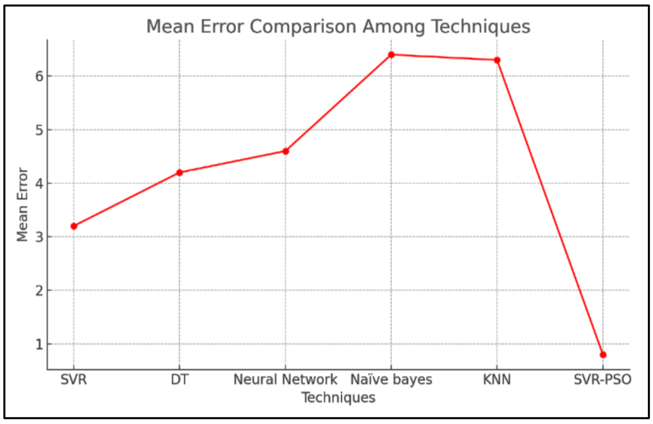


Fig. 2. Mean error

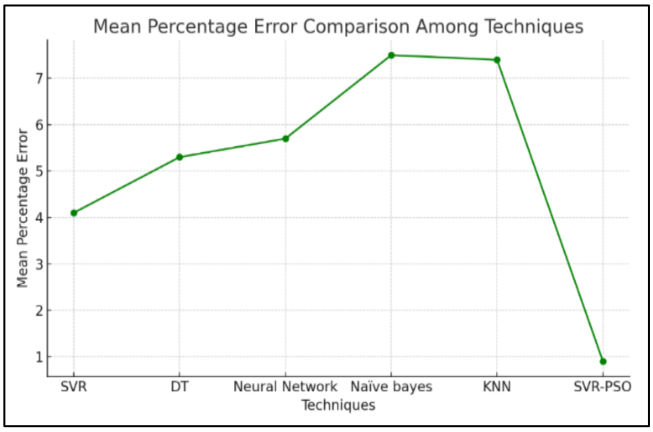


Fig. 3. Mean percentage error

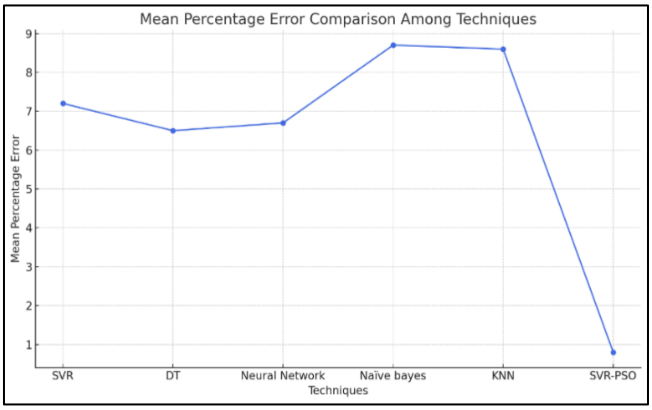


Fig. 4. Mean squared error

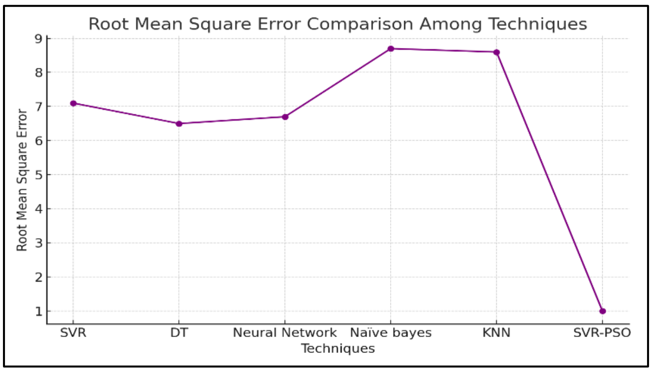


Fig. 5. Root mean square error

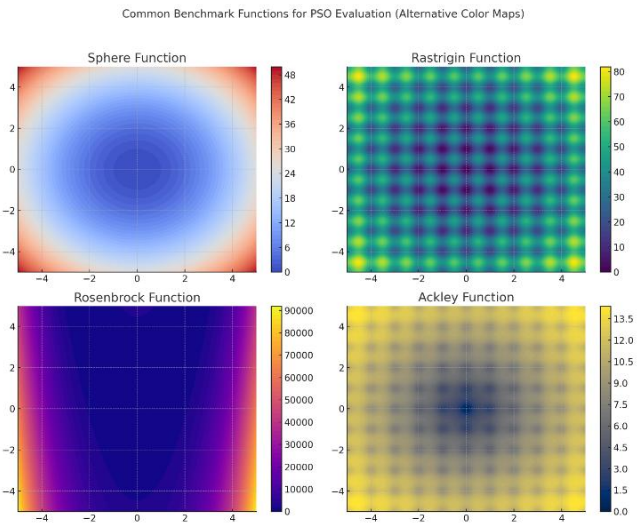


Fig. 6. Benchmark functions commonly used for PSO evaluation

V. CONCLUSION

This study proposed a novel hybrid model that integrates SVR with a PSO to accurately predict the compressive strength of concrete based on slump test data. Traditional methods for determining concrete strength are resource-intensive, requiring material costs, laboratory infrastructure, and considerable time for testing and curing. In contrast, the proposed SVR-PSO model offers a cost-effective and time-saving alternative by eliminating the need for physical experiments and relying instead on computational intelligence. Initial results using standalone SVR indicated unsatisfactory performance due to improper parameter tuning. To overcome this, a PSO was employed to optimize SVR hyperparameters, resulting in substantial improvements across all evaluation metrics, including mean error, mean percentage error, and root mean square error. The SVR-PSO model outperformed traditional machine learning models such as Decision Trees, Neural Networks, Naïve Bayes, and K-Nearest Neighbors, thereby demonstrating its robustness, adaptability, and superior predictive capabilities. However, the model's effectiveness depends on the quality and diversity of the training dataset, and the particle algorithm introduces additional computational complexity. Despite these limitations, the SVR-PSO model proves to be a powerful tool for civil engineering applications, enabling accurate estimation of concrete compressive strength and offering a viable replacement for costly and time-consuming laboratory procedures. The future work can be summarized as follows:

- Extending the study using larger and more diverse datasets from different regions or construction scenarios to improve the model's generalization ability.
- Investigate the use of deep learning models, such as CNN or Long Short-Term Memory (LSTM), for capturing more complex data patterns.
- Apply feature selection and dimensionality reduction techniques (e.g., PCA, Lasso) to identify and retain the most impactful variables while eliminating redundancy.
- Adapt the SVR-PSO model for multi-target regression to simultaneously predict additional concrete properties like tensile strength or durability.
- Optimize computational efficiency by implementing parallel or distributed versions of the particle algorithm for faster convergence.
- Compare the performance of SVR-PSO with alternative optimization algorithms such as Eagle Strategy Particle Swarm Optimization (ESPSO) or Ant Lion Optimizer (ALO) for further robust analysis.

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