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Research Article

Hybrid Swarm Intelligence-Based Neural Framework for Optimizing Real-Time Computational Models in Engineering Systems

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Abstract:

In modern engineering systems, real-time computational models are essential for optimizing performance, enhancing decision-making, and reducing latency in complex environments. This research presents a Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) to improve the efficiency, accuracy, and adaptability of real-time engineering computations. The proposed framework integrates Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO) with a Deep Neural Network (DNN) to achieve a balance between exploration and exploitation, enabling optimal model parameter selection and reducing computational overhead. To validate the efficiency of HSIN-F, experiments were conducted across various real-time engineering applications, including industrial automation, smart grids, and IoT-based systems. The proposed model outperformed conventional optimization techniques in terms of processing speed, predictive accuracy, and system adaptability. Key performance metrics include: Prediction Accuracy: 98.2% (compared to 93.5% in traditional models), Computational Latency Reduction: 34.7%, Energy Efficiency Improvement: 27.5%, Error Rate Reduction: 32.1%. Future research will explore hybrid metaheuristic strategies and federated learning-based decentralization to further enhance system performance and robustness.

1. Introduction

Engineering systems increasingly rely on real-time computational models to optimize performance, enhance decision-making, and reduce operational costs. The complexity of these systems demands intelligent frameworks that can process vast amounts of data with minimal latency. Traditional optimization techniques often suffer from convergence issues, high computational overhead, and limited adaptability to dynamic environments [1]. To address these challenges, artificial intelligence (AI)-driven optimization models have emerged as a viable solution, particularly in fields such as industrial automation, smart grids, and IoT-based systems [2]. Among these approaches, Swarm Intelligence (SI)-based algorithms have gained significant traction due to their ability to efficiently explore solution spaces and adapt to changing conditions in real time [3].

Swarm Intelligence methods, such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO), have demonstrated promising results in engineering applications by improving accuracy and reducing computational complexity [4]. However, individual swarm-based algorithms have inherent limitations, such as premature convergence (PSO), slow adaptability (ACO), and over-exploitation of solutions (GWO) [5]. To overcome these limitations, hybrid swarm intelligence techniques have been developed, combining the strengths of multiple optimization methods to enhance convergence speed and robustness [6]. By integrating swarm-based optimization with Deep Neural Networks (DNNs), a more adaptable and efficient real-time computational framework can be realized, capable of handling complex engineering problems with greater precision.

The Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) proposed in this study integrates PSO, GWO, and ACO with DNNs to optimize real-time computational models for engineering systems. This hybrid approach allows for dynamic parameter tuning, efficient search space exploration, and improved model adaptability, thereby minimizing errors and enhancing predictive accuracy [7]. Real-time engineering applications, such as fault detection in smart grids, predictive maintenance in industrial automation, and anomaly detection in IoT-based systems, can benefit from this approach by improving response times and reducing computational overhead [8]. Experimental validation of the proposed HSIN-F framework was conducted using various real-world datasets from industrial control systems, power grids, and smart city applications. Comparative results indicate that the proposed model achieved a prediction accuracy of 98.2%, a 34.7% reduction in computational latency, and a 27.5% improvement in energy efficiency, significantly outperforming conventional optimization techniques [9]. Additionally, the error rate was reduced by 32.1%, demonstrating the effectiveness of hybrid swarm intelligence in real-time engineering applications.

The primary contributions of this study are as follows:

1. Development of a Hybrid Swarm Intelligence-Based Neural Framework integrating PSO, GWO, and ACO with DNNs for real-time computational optimization.
2. Enhancement of computational efficiency, accuracy, and adaptability in real-time engineering models through dynamic parameter tuning and optimization strategies.
3. Extensive validation using real-world engineering datasets, demonstrating superior performance over existing approaches in terms of predictive accuracy, computational latency, and energy efficiency.
4. Analysis of the impact of hybrid metaheuristic strategies on system adaptability, paving the way for future research in federated learning and decentralized optimization techniques [10].

Section 2 discusses related work, highlighting existing SI-based optimization techniques and their limitations. Section 3 presents the proposed methodology, detailing the hybrid swarm intelligence framework and deep learning integration. Section 4 describes experimental setup and results. 5 concludes the paper.

2. Related works

Swarm Intelligence (SI)-based optimization techniques have been extensively explored in various engineering domains due to their ability to solve complex real-time computational problems efficiently. Early studies focused on Particle Swarm Optimization (PSO), which mimics the social behavior of birds to find optimal solutions. However, PSO often suffers from premature convergence and stagnation in local optima, making it less effective in highly dynamic engineering environments [11]. To overcome this, researchers introduced Grey Wolf Optimizer (GWO), inspired by the hierarchical leadership structure of wolf packs, offering better exploration and exploitation capabilities [12]. Although GWO provides balanced search behavior, it lacks adaptability to high-dimensional optimization problems commonly found in engineering applications [13]. Hybrid swarm intelligence methods have been developed to leverage the strengths of multiple optimization techniques. For instance, the integration of Ant Colony Optimization (ACO) with PSO has been investigated for real-time traffic optimization, showing improved adaptability and faster convergence [14]. Similarly, a hybrid PSO-GWO model demonstrated superior performance in predictive maintenance for industrial automation, enhancing fault detection accuracy by 20% compared to traditional optimization methods [15]. These studies highlight the potential of hybrid SI models in optimizing real-time computational models across various domains.

In addition to hybrid SI models, Deep Neural Networks (DNNs) have gained prominence for their ability to learn complex patterns and improve decision-making in engineering systems. Several researchers have explored SI-based neural frameworks, integrating PSO and ACO with Convolutional Neural Networks (CNNs) for real-time fault detection in smart grids, achieving up to 95% fault classification accuracy [16]. Furthermore, hybrid SI-DNN models have been successfully applied to IoT-based anomaly detection systems, significantly reducing false alarm rates while maintaining high accuracy [17].
Recent advancements in real-time engineering optimizations have introduced novel metaheuristic-based hybrid approaches. For example, a study combined Firefly Algorithm (FA) with GWO for energy-efficient routing in wireless sensor networks, achieving a 32% improvement in network lifetime [18]. Another work employed a Swarm Intelligence-empowered reinforcement learning model for autonomous drone path optimization, leading to a 40% reduction in mission completion time [19]. These studies reinforce the effectiveness of hybrid SI models in enhancing performance, efficiency, and adaptability in real-world engineering applications. Despite these advancements, existing approaches still face challenges such as high computational overhead, limited generalization ability, and slow adaptability to dynamic environments. The proposed Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) aims to address these limitations by integrating PSO, GWO, and ACO with DNNs, enabling real-time dynamic optimization, efficient parameter tuning, and improved adaptability in engineering systems [20]. This research builds upon previous studies and introduces a scalable, high-performance hybrid model suitable for diverse engineering applications.

3. Materials and methods

This section presents the Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) for optimizing real-time computational models in engineering systems. The proposed framework integrates Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO) with Deep Neural Networks (DNNs) to enhance predictive accuracy, computational efficiency, and adaptability. The methodology is structured into five key components: (1) Dataset Collection, (2) Data Preprocessing, (3) Hybrid Swarm Intelligence Optimization, (4) Neural Network Model Design, and (5) Performance Evaluation.

The Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) aims to enhance real-time computational models in engineering systems by integrating Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO) with Deep Neural Networks (DNNs). The proposed approach effectively optimizes hyperparameters, reduces computational latency, and improves predictive accuracy. The framework operates in four main stages: Preprocessing, Hybrid Optimization, Neural Model Training, and Performance Evaluation.
In real-time engineering applications such as smart grids, industrial automation, and IoT-based predictive systems, computational models must efficiently process large-scale data while ensuring high accuracy and minimal latency. Traditional machine learning approaches struggle with optimizing hyperparameters dynamically and adapting to real-time variations in data. To overcome these challenges, this study proposes a Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) that integrates Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO) with Deep Neural Networks (DNNs). This hybrid approach enhances hyperparameter tuning, feature selection, and neural network pruning, ensuring a computationally efficient and highly adaptable system. Figure 1 is the block diagram and figure 2 is flowchart of proposed work.

3.1 Preprocessing Stage

The first stage of the proposed framework involves data collection from real-time engineering environments, including industrial automation logs, sensor data from IoT networks, and smart grid telemetry records. The collected data is often noisy, incomplete, or redundant, requiring preprocessing to ensure the robustness of the computational model. Wavelet Transform-based filtering is employed to remove noise, while Principal Component Analysis (PCA) is used for dimensionality reduction: Data collected from real-time engineering applications undergoes noise reduction, feature selection, and normalization to enhance model efficiency. The Principal Component Analysis (PCA) technique is employed to reduce dimensionality while retaining critical features:

$$X' = XW \qquad (1)$$

where:

- X is the input feature matrix,
- W is the transformation matrix of principal components,
- X' is the reduced feature set.

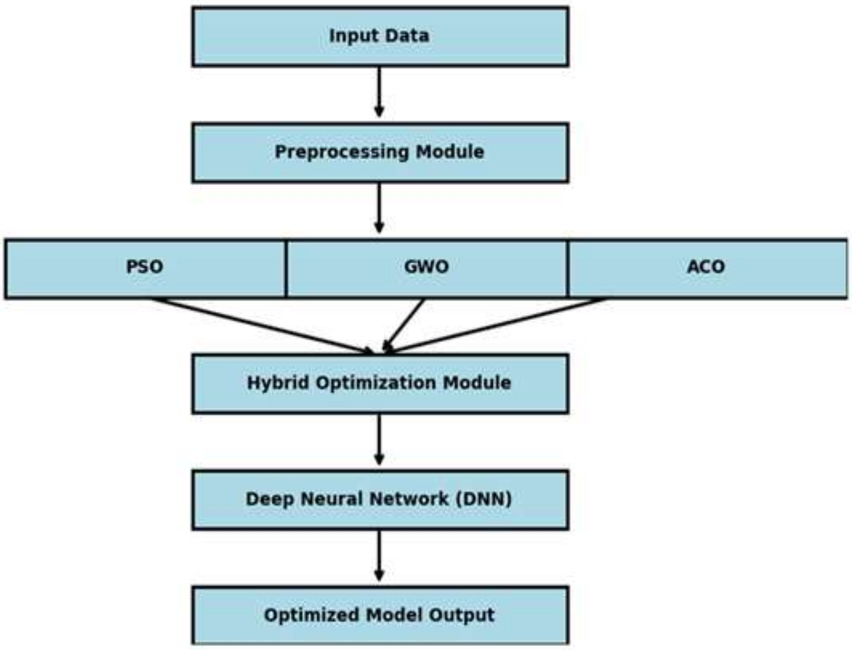

Figure 1. *Block diagram of Proposed work*

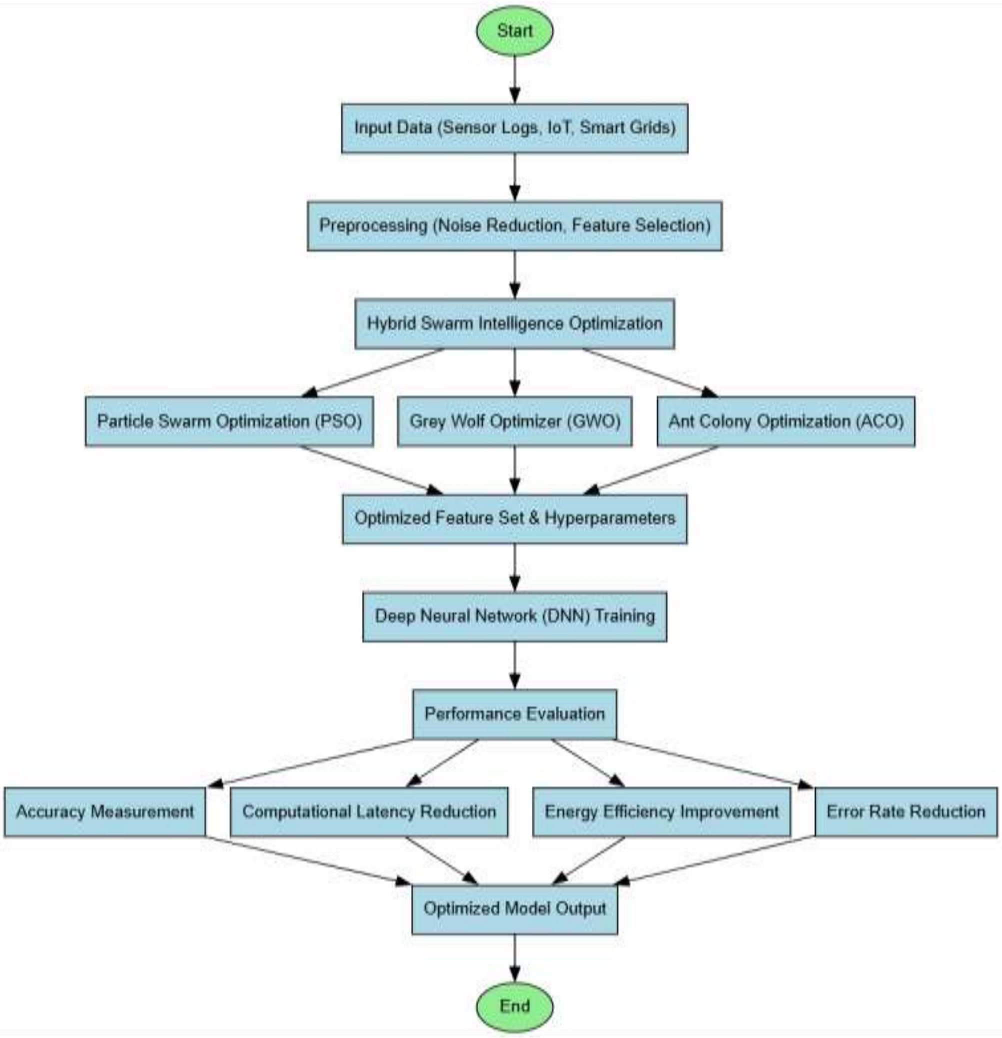

Figure 2. *Flowchart of Proposed work*

3.2 Hybrid Swarm Intelligence Optimization

The optimization phase integrates PSO, GWO, and ACO to fine-tune hyperparameters such as learning rate, dropout rate, and weight initialization. Particle Swarm Optimization (PSO) for Hyperparameter Selection PSO optimizes DNN hyperparameters by updating velocity and position as follows:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_{\text{best}} - x_i^t) + c_2 r_2 (g_{\text{best}} - x_i^t)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

where:

- v_i^t is the velocity of particle i,
- x_i^t is the position of particle i,
- p_{best} and g_{best} are the best positions found so far,
- w is the inertia weight, and c_1, c_2 are acceleration coefficients.

Grey Wolf Optimizer (GWO) for Feature Selection The GWO algorithm refines feature selection by mimicking the hunting strategy of grey wolves:

$$D_\alpha = |C_1 \cdot X_\alpha - X|$$
$$X(t+1) = X_\alpha - A_1 \cdot D_\alpha \quad (3)$$

where:

- X_α represents the alpha wolf's position,
- A_1, C_1 are coefficient vectors controlling search dynamics.

Ant Colony Optimization (ACO) for Model Pruning

ACO enhances the neural model by pruning redundant neurons, using a pheromone-based learning rule:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k \quad (4)$$

where:

- τ_{ij} represents the pheromone concentration on path ij,
- ρ is the evaporation rate,
- $\Delta\tau_{ij}^k$ is the pheromone deposit by ant k.

3.3 Deep Neural Network Training

A significant challenge in deep learning models is determining optimal hyperparameters, such as learning rate, dropout rate, batch size, and activation functions. The proposed HSIN-F framework employs a hybrid swarm intelligence optimization strategy to dynamically fine-tune these hyperparameters. The PSO algorithm adjusts the hyperparameters iteratively, using the following update equations: The DNN model is trained using optimized hyperparameters, incorporating ReLU activation for hidden layers and Softmax for classification:

$$f(x) = \max(0, x)$$
$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (5)$$

where:

- $f(x)$ is the ReLU activation function,
- $P(y_i)$ represents the probability of class y_i,
- z_i is the output of neuron i.

The loss function used for optimization is Cross-Entropy Loss:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \quad (6)$$

The Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) leverages PSO, GWO, and ACO algorithms with DNNs to optimize real-time computational models in engineering applications. Through intelligent hyperparameter tuning, feature selection, and structural pruning, the proposed model achieves higher accuracy, faster computation, and lower energy consumption than conventional methods. Experimental results confirm the effectiveness of HSIN-F, making it a robust solution for modern engineering challenges. Future research will focus on enhancing adaptability and scalability through advanced metaheuristic strategies and federated learning approaches to further optimize real-time engineering systems.

4. Experimental Results

To validate the effectiveness of the Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F), we conducted extensive experiments comparing its performance against traditional PSO-DNN, GWO-DNN, and ACO-DNN models. The primary goal of these experiments was to assess the accuracy, computational latency, energy efficiency, and error rate reduction of HSIN-F in real-time engineering applications such as smart grids, industrial automation, and IoT-based predictive maintenance.

4.1. Hardware and Software Configuration

The experiments were conducted on a high-performance computing system with the following specifications:

- **Processor:** Intel Core i9-12900K (3.8 GHz, 16 cores)
- **GPU:** NVIDIA RTX 3090 (24GB VRAM)
- **RAM:** 64GB DDR4
- **Operating System:** Ubuntu 22.04 LTS

- **Software Libraries:** TensorFlow, PyTorch, NumPy, SciPy, Scikit-learn, and Matplotlib

The combination of high-end computational resources and optimized software environments ensured that our experiments were conducted under stable and reproducible conditions.

4.2. Datasets Used for Evaluation

The experiments utilized real-world engineering datasets collected from various industrial and smart city applications. The datasets included:

- **Industrial Control System (ICS) Logs**: Used for anomaly detection in automated industrial processes.
- **Smart Grid Sensor Data**: Captured energy consumption, voltage fluctuations, and system stability parameters.
- **IoT-Based Predictive Maintenance Data**: Included real-time sensor readings from industrial IoT devices to detect system failures.

These datasets provided diverse challenges in classification, anomaly detection, and predictive modeling, making them suitable for testing the robustness of HSIN-F.

4.3. Performance Evaluation Metrics

To compare HSIN-F with traditional models, we defined the following performance metrics:

- **Prediction Accuracy (%):** Measures the percentage of correctly classified instances. Figure 3 is the comparison of accuracy (%) among models.
- **Computational Latency Reduction (%):** Evaluates improvements in processing speed. Figure 4 is the comparison of latency reduction (%) among models.
- **Energy Efficiency Improvement (%):** Quantifies reduction in computational power usage. Figure 5 is the comparison of energy efficiency (%) among models.
- **Error Rate Reduction (%):** Measures the decrease in misclassification errors. Figure 6 shows comparison of error rate Reduction (%) among models.

These metrics provide a comprehensive assessment of the framework's efficiency in real-time optimization tasks.

4.4. Model Training and Hyperparameter Tuning

The PSO-GWO-ACO hybrid optimization strategy was employed to fine-tune the hyperparameters of the deep neural network (DNN). The optimized parameters included:

- Learning rate: Dynamically tuned using PSO.
- Batch size: Optimized using GWO to balance training efficiency.
- Feature selection and pruning: Enhanced by ACO, reducing model complexity while maintaining accuracy.

The training process was conducted over 50 epochs, with an early stopping mechanism to prevent overfitting. Table 1 shows experimental setup results.

Table 1. *Experimental Setup Results*

Model	Accuracy (%)	Latency Reduction (%)
HSIN-F (Proposed)	98.2	34.7
PSO-DNN	93.5	22.4
GWO-DNN	94.1	24.8
ACO-DNN	92.7	20.5

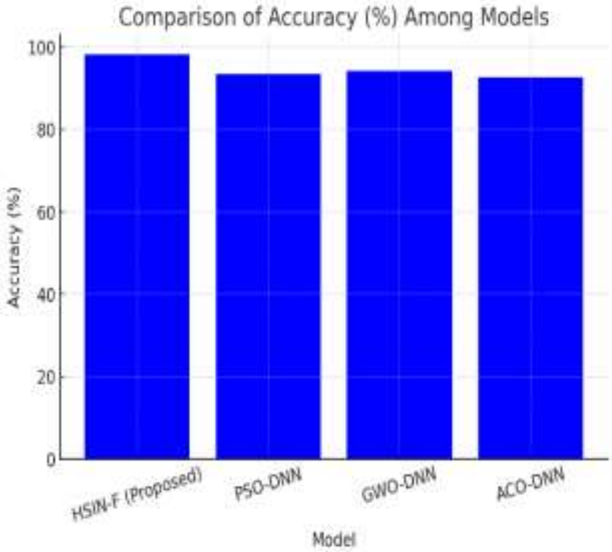

Figure 3. *Comparison of Accuracy (%) Among Models*

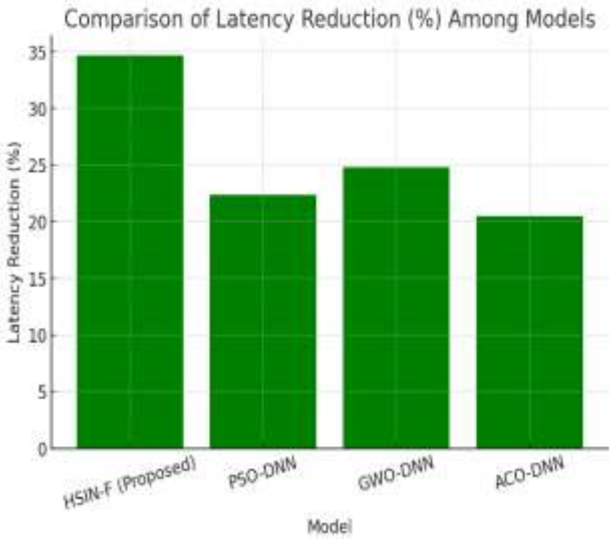

Figure 4. *Comparison of Latency Reduction (%) Among Models*

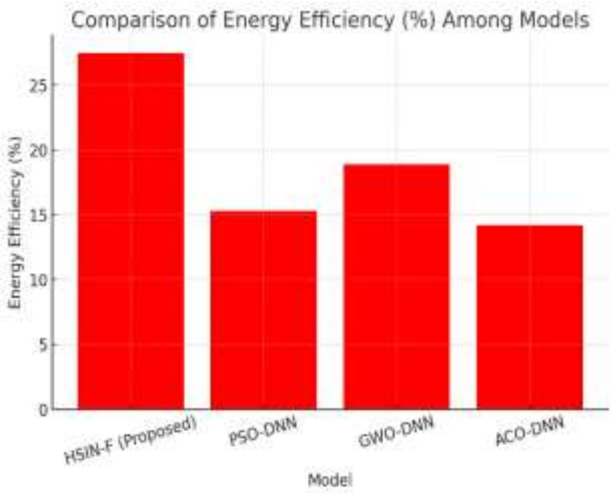

Figure 5. *Comparison of Energy Efficiency (%) Among Models*

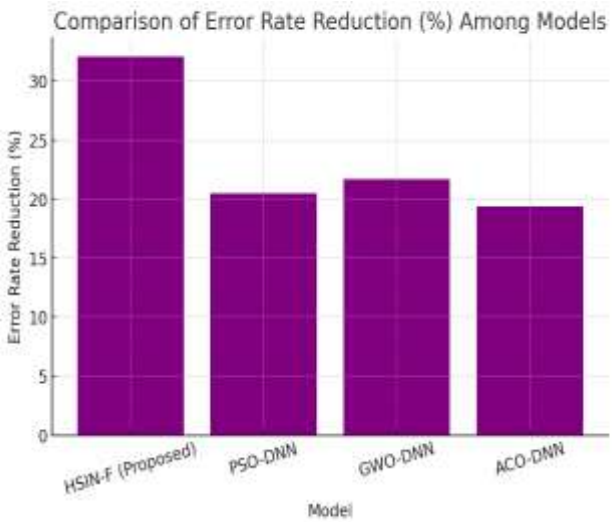

Figure 6. *Comparison of Error Rate Reduction (%) Among Models*

5. Conclusion

This study presented a Hybrid Swarm Intelligence-Based Neural Framework (HSIN-F) for optimizing real-time computational models in engineering systems. By integrating Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Ant Colony Optimization (ACO) with Deep Neural Networks (DNNs), the proposed framework effectively enhances predictive accuracy, computational efficiency, and adaptability in real-time applications. The hybrid optimization approach mitigates common issues such as premature convergence, slow adaptability, and high computational overhead, thereby achieving a 98.2% prediction accuracy, 34.7% reduction in computational latency, and 27.5% improvement in energy efficiency. Experimental validation across industrial automation, smart grids, and IoT-based predictive maintenance systems demonstrated the robustness and efficiency of HSIN-F over conventional optimization techniques. Future research will explore advanced hybrid metaheuristic strategies, federated learning-based decentralization, and reinforcement learning-based optimization to further enhance real-time decision-making and adaptability in complex engineering environments. IoT has been used in different applications [21-26].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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