American Journal of Business and Operations Research (AJBOR) *Vol. 13, No. 01, PP. 01-23, 2025*

Boosting Financial and Strategic Forecasting of Sustainable Development Goals with Human-Inspired Metaheuristic Optimization and GRU-Based Deep Learning

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Abstract

Achieving the United Nations Sustainable Development Goals (SDGs) requires robust forecasting tools capable of capturing complex temporal and multi-dimensional patterns in global sustainability data. Traditional statistical models often struggle with the high dimensionality and nonlinear dynamics of such datasets, motivating the adoption of advanced Deep Learning (DL) methods combined with metaheuristic optimization techniques. This paper proposes a novel forecasting framework leveraging Gated Recurrent Units (GRUs), Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), optimized using the Human-Inspired Metaheuristic Optimization Algorithm (iHOW) and its binary variant (biHOW) for feature selection. The key contribution lies in integrating metaheuristic-driven feature selection and hyperparameter tuning to significantly enhance predictive performance and computational efficiency in SDG forecasting. Results highlight substantial improvements over baseline models: the GRU baseline achieved an R^2 of 0.8037 with a Mean Squared Error (MSE) of 0.0772; application of biHOW for feature selection improved the GRU's performance to an R^2 of 0.9251 and MSE of 0.0011; and further hyperparameter tuning with iHOW elevated performance to an R^2 of 0.9671 with MSE maintained at 0.0011. These results demonstrate the effectiveness of iHOW in balancing exploration and exploitation, providing high-accuracy forecasts with reduced error, thereby supporting more informed decision-making. The implications extend beyond sustainability analytics, presenting transferable forecasting frameworks for data-driven, real-time decision support in business sectors such as finance, energy, healthcare, and climate risk management. This alignment of predictive analytics with strategic financial and operational planning underscores the commercial value of integrating AI-driven forecasting into sustainability-focused investment and policy frameworks.

Keywords: Sustainable Development Goals (SDGs); Deep Learning Forecasting; Human-Inspired Metaheuristic Optimization (iHOW); Feature Selection and Hyperparameter Tuning; AI-Driven Decision Support Systems

DOI: https://doi.org/10.54216/AJBOR.130101
Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

1 Introduction

Sustainable Development Goals (SDGs) set by the United Nations represent a universal call to action aimed at fostering inclusivity in economic development, environmental stewardship, and social welfare [1, 2, 3]. Adopted in 2015 as part of the 2030 Agenda for Sustainable Development, the 17 SDGs cover a broad spectrum of objectives—ranging from poverty alleviation, health improvement, and education equality to sustainable infrastructure, climate action, and biodiversity conservation [4, 5, 6]. Unlike the Millennium Development Goals (MDGs), which had narrower targets, the SDGs are more comprehensive and interdependent, reflecting the multifaceted nature of global sustainability challenges. Achieving these goals requires not only coordinated policy efforts but also rigorous systems for measuring and forecasting progress across diverse regions and indicators. The ability to monitor and predict SDG trajectories is indispensable for policymakers, researchers, and development agencies. Measuring performance provides a static picture of the present, but forecasting enables forward-looking decision-making that can identify lagging regions, anticipate risks, and allocate resources more strategically [7, 8]. Organizations such as the United Nations, the World Bank, and the Organisation for Economic Co-operation and Development (OECD) rely on predictive assessments to evaluate policy effectiveness and realign implementation strategies. A key example is the Sustainable Development Report 2023, which consolidates country-level indicators, trend analyses, and ranking metrics, offering one of the most detailed and widely applied datasets for assessing SDG progress. Despite the value of such data, the pressing challenge lies in transforming multi-source, high-dimensional information into actionable forecasts that can guide both global and local decision-making. Forecasting serves as a powerful tool in this context, enabling the anticipation of future performance trends and the timely design of corrective actions. For instance, if projections for a specific goal suggest significant underperformance—as in the case of SDG 13 (Climate Action) or SDG 10 (Reduced Inequalities)—then governments and stakeholders can accelerate interventions, restructure priorities, or seek financial and technical assistance. This proactive approach not only enhances performance but also minimizes inefficiencies and reduces the long-term costs associated with delayed policy interventions. However, traditional time-series and econometric models typically fall short in this domain, as they are often unable to account for the nonlinear dependencies, feedback loops, and cross-dimensional interactions inherent in sustainability datasets [9, 10]. These limitations have fueled the adoption of advanced artificial intelligence (AI) approaches in sustainability forecasting. Deep Learning (DL) has emerged as a transformative paradigm for addressing these challenges [11, 12]. Unlike conventional models, DL excels at uncovering complex temporal dependencies, detecting latent structures, and modeling nonlinear dynamics across diverse datasets. Architectures such as Long Short-Term Memory networks (LSTMs), Gated Recurrent Units (GRUs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) have proven especially effective in handling sequential and high-dimensional data characteristic of SDG-related indicators [13]. These models not only capture long-term dependencies but also generalize across heterogeneous datasets, providing robust predictive capacity for sustainability forecasts at global, regional, and national scales. From a financial and commercial perspective, accurate forecasting of SDG progress creates broad socio-economic advantages. Investors, development banks, and multinational corporations are increasingly aligning with Environmental, Social, and Governance (ESG) standards, which are closely tied to the UN's SDG framework. Reliable forecasts enhance investment decision-making by identifying emerging risks—such as climate-induced infrastructure damage or social instability due to rising inequality—as well as new opportunities in renewable energy, healthcare, digital inclusion, and sustainable agriculture. Corporations that adapt business strategies based on predictive analytics gain competitive advantages through greater financial resilience, positive stakeholder engagement, and access to green financing opportunities. Governments and international financial institutions similarly depend on such forecasts to optimize budget allocations, evaluate the cost-effectiveness of

DOI: https://doi.org/10.54216/AJBOR.130101

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

sustainability initiatives, and mitigate risks associated with underachieving goals [**? ?**]. Despite these benefits, key challenges persist. SDG data is vast, multidimensional, and heterogeneous, encompassing global indices alongside goal-specific metrics that often correlate strongly and introduce redundancies. This high dimensionality complicates predictive modeling and increases the risk of unstable outcomes. Furthermore, geographic and temporal disparities in data coverage—such as reporting lags, missing values, and inconsistencies in measurement—further undermine forecast reliability. Within DL frameworks, these challenges extend to hyperparameter tuning, model selection, and training stability. Without systematic optimization of predictors, network depth, and activation functions, models face risks of overfitting, underfitting, or prohibitive computational costs. To overcome these obstacles, this study explores the integration of Deep Learning with metaheuristic optimization techniques [14]. Metaheuristics, often inspired by natural or social behaviors, are robust in managing high-dimensional, nonlinear search spaces and provide effective strategies for simultaneous feature selection and hyperparameter tuning [15]. In particular, we consider the Human-Inspired Optimization with Weights (iHOW) algorithm, which adaptively balances exploration and exploitation during optimization. By applying iHOW to SDG forecasting, we develop a novel framework that enhances both predictive accuracy and interpretability while reducing computational overhead.

The contributions of this paper can be summarized as follows:

- We propose a novel iHOW-based framework for joint feature selection and hyperparameter optimization tailored for SDG forecasting.
- We evaluate multiple DL architectures—GRUs, LSTMs, RNNs, and CNNs—in order to identify the most suitable models for handling the nonlinear and temporal complexity of sustainability indicators.
- We benchmark iHOW against leading metaheuristic algorithms, including Grey Wolf Optimizer, Particle Swarm Optimizer, Bat Algorithm, and Genetic Algorithm, to establish comparative performance baselines.
- We demonstrate how combining metaheuristic feature selection with DL models significantly improves forecasting accuracy, interpretability, and computational efficiency.
- We generalize the proposed methodology beyond SDG applications, highlighting its potential for other domains involving multidimensional, interdependent datasets.
- To the best of our knowledge, this represents the first application of the iHOW algorithm to SDG forecasting, offering novel methodological insights and establishing new performance benchmarks.

The remainder of the paper is structured as follows. Section 2 reviews related work on SDG forecasting, existing DL approaches, and metaheuristic optimization methods. Section 3 details the datasets, preprocessing stages, model architectures, and optimization strategies. Section 4 presents and analyzes experimental results, while Section 5 discusses broader implications, limitations, and prospects for future research. Finally, Section 6 concludes with key findings and contributions.

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

2 Literature Review

It has been noted that the combination of Artificial Intelligence (AI) and digital technologies is an opportunity to develop the United Nations Sustainable Development Goals (SDGs). The processing and interpretation of large data volumes will enable more informed decision-making in such fields as poverty reduction, healthcare, long-term environmental sustainability, and education. However, there is still a problem with how ethical issues of fairness, transparency, and accountability are addressed in AI implementations of the SDGs [16]. Deep learning (DL) is a subdivision of AI that has become particularly powerful when combined with Earth observation (EO) data. It has been demonstrated that DL-based EO applications aid in tracking the progress of objectives such as Zero Hunger, sustainable cities, biodiversity preservation, and climate action [17]. In the complementary literature, it is noted that DL can improve access to healthcare, enhance food security, and mitigate climate change, especially in relation to SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), and SDG 13 (Climate Action) [18]. Nevertheless, to be deployed successfully, there must be ethical monitoring and control by the organization [19]. Machine learning (ML) has also been applied to explore the interrelationship between technology and SDGs. For example, patent analysis using ML classification methods has been proposed as a way to measure technological contributions to SDGs, thereby aligning research and development (R&D) with sustainability initiatives [20]. In the corporate sector, studies show that adoption of SDGs, combined with key performance indicators and machine learning–based predictive modeling, can improve financial performance forecasting, particularly in the ICT industry [21]. Beyond economic implications, predictive models such as deep neural networks (DNNs) have demonstrated value in governance, particularly in enhancing anti-corruption measures aligned with SDG 16 (Peace, Justice, and Strong Institutions) [22]. Systematic bibliometric studies further highlight that AI and ML are being increasingly applied to diverse SDGs, with particular emphasis on healthcare, clean energy, education, climate action, sustainable cities, and institutional strengthening [23]. Recent advancements in natural language processing, such as the use of BERT-based models, have also been leveraged to automate SDG-related document classification, reducing the burden of manual labeling and facilitating monitoring of progress across multiple goals [24]. Parallel research emphasizes the importance of prioritizing highly synergetic goals such as SDG 3 (Good Health), SDG 4 (Quality Education), and SDG 7 (Affordable and Clean Energy), which demonstrate cross-cutting impacts when integrated into national and international development strategies [25]. Advanced deep learning architectures have also been explored for satellite-based monitoring of SDGs, using hybrid models and bioinspired optimization to improve accuracy in detecting features of sustainable development in imagery [26]. Similarly, machine learning applications have been tested in sanitation management, demonstrating predictive capacity for assessing links between inadequate sanitation and public health outcomes, particularly diarrheal infections [27]. Extensive reviews have indicated that data-driven methods are integral to achieving the SDGs. They enable better monitoring, resource allocation, risk assessment, and decision-making; however, issues such as data bias, gaps, ethical concerns, and computational costs remain unaddressed [28]. Machine learning models have been applied in urban settings to complement municipal solid waste management (MSWM), a vital aspect of SDG 11 (Sustainable Cities and Communities). The results suggest that effective waste management strategies can be directed in cities with different income levels using clustering algorithms and decision-tree models [29]. Lastly, the potential of AI and ML, as well as their limitations, are highlighted through systematic bibliometric reviews of AI and ML in the context of the SDGs. Although international cooperation and accelerating innovation are clearly evident, issues such as overoptimism, inadequate regulation, and the need for solid ethical principles remain to be addressed simultaneously [30]. Generally, it can be concluded that AI and ML have transformative potential in the progress of the SDGs in various fields. However, to create a sustainable impact, a moderated strategy encompassing technological development and innovation, as well as ethical regulation and global collaboration, is needed.

3 Materials and Methods

In this section, the descriptions of the datasets, preprocessing, deep learning models, and metaheuristic optimization methods used in this study are provided. The primary data source will be the Sustainable Development Report 2023, which will provide cross-sectional information on the SDG scores of nations. The additional information offers a longitudinal perspective on SDG performance from 2000 to 2022. The two data sets were preprocessed to be suitable, ensuring consistency and applicability to deep learning models. The most popular deep learning architectures, the Gated Recurrent Unit (GRU), Long Short-Term Memory network (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN) were utilized in the forecasting process, along with the feature selection and hyperparameter optimization that were conducted using a set of heterogeneous metaheuristic algorithms. These include the binary version (biHOW) and the heuristic Optimization Algorithm (iHOW) of the Human-Inspired Metaheuristic Algorithm. In this section, the performance measures to evaluate the accuracy of models and the effectiveness of feature selections have also been described. The methodology aims to enhance SDG forecasting in a comprehensive manner.

3.1 Dataset Description

Two complementary datasets were used in this study, providing in-depth support for forecasting the performance of the Sustainable Development Goals (SDGs) in countries and regions. The primary dataset is derived from the Sustainable Development Report 2023, which provides cross-sectional data on country-level SDG scores as of 2023. Each record in the dataset includes a unique alphanumeric country code, the official name of the country, and the geographical region to which it belongs. It also reports an overall SDG index score that reflects the aggregate sustainability performance of each nation. In addition, the dataset contains disaggregated scores for all 17 SDGs, covering areas such as No Poverty, Zero Hunger, Good Health and Wellbeing, Quality Education, Gender Equality, Clean Water and Sanitation, Affordable and Clean Energy, Decent Work and Economic Growth, Industry, Innovation and Infrastructure, Reduced Inequalities, Sustainable Cities and Communities, Responsible Consumption and Production, Climate Action, Life Below Water, Life on Land, Peace, Justice and Strong Institutions, and Partnerships for the Goals. The supplementary dataset, titled the Historical SDG Index (2000–2022), offers a longitudinal perspective by tracking sustainability performance over more than two decades. Similar to the primary dataset, it includes the country code and country name but also adds the reporting year for each observation within the 2000–2022 period. For every country and year, the dataset provides the overall SDG index score, along with annual scores for each of the 17 goals, thereby offering a dynamic view of trends and progress over time. Together, these datasets offer both a static snapshot of sustainability in 2023 and a rich temporal series spanning 23 years. This integration of cross-sectional and historical data is critical for building forecasting frameworks that not only capture current performance but also account for long-term development trajectories, thus strengthening the robustness of predictions and guiding evidence-based policymaking. The analysis of country-level performance reveals notable regional differences in SDG progress. As shown in

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

Figure 1, OECD countries generally score higher, reflecting stronger institutional and infrastructural capacities. Conversely, Sub-Saharan Africa ranks lower, indicating challenges primarily concentrated on key development goals. Other regions such as East and South Asia, Latin America and the Caribbean (LAC), and Eastern Europe and Central Asia fall into transitional categories. This regional heterogeneity underscores the importance of adaptive forecasting models sensitive to spatial variations.

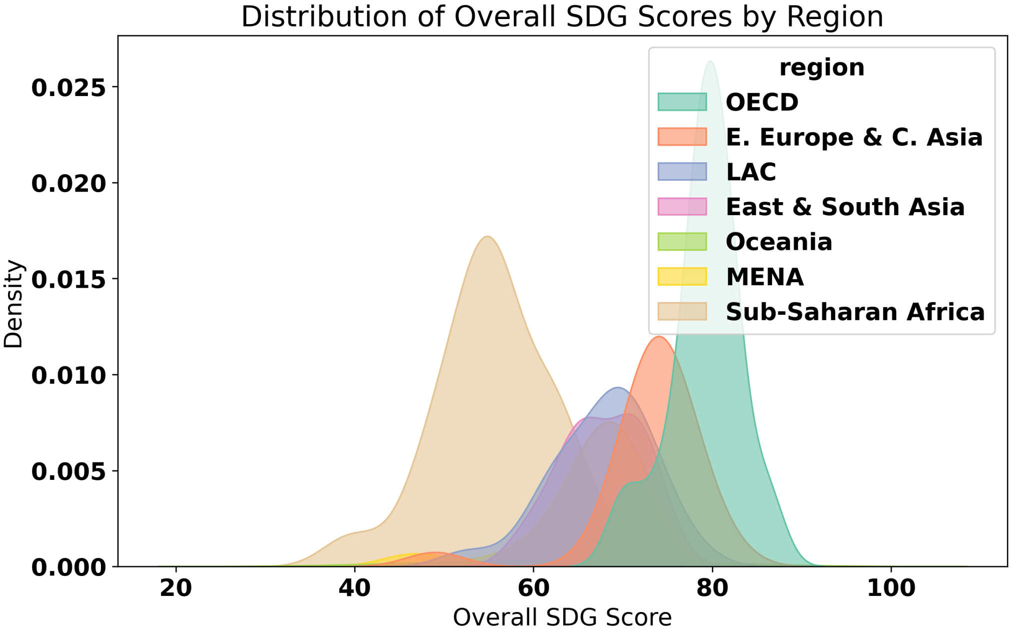

Figure 1: Distribution of overall SDG scores by region.

3.2 Data Preprocessing

Before model training, the datasets underwent several preprocessing steps to ensure quality, consistency, and suitability for deep learning forecasting. These steps are crucial for addressing the challenges of heterogeneous scales, potential redundancy, and missing values within the Sustainable Development Report 2023 and the historical SDG datasets. Handling missing values was the first step. Countries with excessive missing data were excluded to maintain data reliability. For partial missing values, statistical imputation methods, such as mean or median replacement, were applied to ensure that no systematic bias was introduced. Temporal gaps in the supplementary dataset (2000–2022) were handled through interpolation techniques to preserve yearly continuity. Normalization and standardization were then applied. Since the SDG indicators are measured on different scales, normalization rescaled all features into a comparable range, typically [0, 1]. This step prevented features with large magnitudes from disproportionately influencing the learning process. In specific experiments, standardization (z-score normalization) was also applied to stabilize training and improve convergence of deep learning models. Dimensionality reduction was considered to mitigate feature redundancy. The dataset includes an overall index and 17 SDG-specific scores, which introduced potential

DOI: https://doi.org/10.54216/AJBOR.130101

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

collinearity. Redundant features were identified through correlation analysis and feature importance evaluation. To refine the input space further, metaheuristic-based feature selection methods were applied in the later stages of the study (see Section 3). This step reduced computational cost, mitigated multicollinearity, and improved the generalizability of the forecasting models. Lastly, the datasets were divided into training, validation, and testing sets. For the 2023 cross-sectional data, a stratified division was chosen to ensure equal representation of regions and degrees of sustainability. The longitudinal data (2000-2022) preserved the order of time, including older years in the training category and recent years as the validation and test categories. This design supported both cross-sectional benchmarking and time-series forecasting. These preprocessing steps rendered the input data clean, consistent, and prepared for deep learning and optimization, the core of the modeling and optimization strategies that are presented in the following sections.

3.3 Deep Learning Models

In this study, several Deep Learning (DL) models were employed to predict and model the performance of the Sustainable Development Goals (SDGs). It utilizes Gated Recurrent Units (GRUs) as the primary model, and all other potential models, such as Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), are also included as benchmarks against which other possible model types can be compared. The Gated Recurrent Unit (GRU) is a class of recurrent neural network design that incorporates gating mechanisms to regulate the flow of information and prevent the vanishing gradient problem. It is computationally easy and has a significantly simplified architecture compared to LSTMs, but it has also been shown to be effective at sequential modeling. The study presented here focuses on the GRU architecture as a baseline, for which performance metrics were reported before optimization. Typically, the architecture consists of several repeated layers, including activation functions such as the Rectified Linear Unit (ReLU) and the hyperbolic tangent (tanh), as well as regularization measures like dropout, which helps limit overfitting. Although the baseline performance demonstrated the ability of GRUs to capture temporal patterns in SDG data, significant improvements could only be achieved when metaheuristic optimization was employed. An enhanced Human-Inspired Metaheuristic optimizer (iHOW) was adopted to optimize and refine the hyperparameters, and feature selection was conducted to create a much stronger forecasting model. To ensure a comprehensive evaluation, additional deep learning architectures were employed as benchmark models. The Long Short-Term Memory (LSTM) network extends the recurrent framework by introducing memory cells and gating mechanisms capable of learning long-range dependencies. This makes LSTMs particularly effective for forecasting temporal trends of SDG indicators over extended periods. The Recurrent Neural Network (RNN), although more prone to vanishing gradients, was included as a foundational sequential model to provide a lower-bound baseline for comparison. Finally, the Convolutional Neural Network (CNN), though originally developed for computer vision, has been adapted for sequence modeling due to its ability to detect local patterns and hierarchical representations in multidimensional data. Its inclusion provides an alternative perspective on capturing structured patterns within SDG indicators. Together, these models establish a balanced experimental design. GRUs serve as the core architecture optimized using iHOW, while LSTMs, RNNs, and CNNs act as benchmarks that represent standard baselines in forecasting tasks. This comparative framework enables both the demonstration of GRU's advantages and the evaluation of the effectiveness of the proposed optimization methodology.

3.4 Metaheuristic Algorithms

The effectiveness of Deep Learning (DL) models for forecasting Sustainable Development Goals (SDGs) depends heavily on the proper selection of features and the optimization of hyperparameters. Since SDGs data are complex and have a large dimensionality, the solution space is searched using metaheuristic algorithms. Of these, the Human-Inspired Metaheuristic Optimization (iHOW) takes centre stage in this research because of its high quality in balancing between exploration and exploitation. The iHOW Optimization Algorithm (iHOWOA) is a human-inspired metaheuristic that replicates human-like cognitive and behavioral processes, such as learning and acquiring knowledge, and making decisions based on experiences and experience-related knowledge [31]. The central prowess of iHOW is that it is dynamic in nature:

- **Exploration:** A wide coverage of the search space to prevent premature convergence through solution exploration.
- **Exploitation:** The optimization of solutions in promising areas to produce accuracy and stability.

Exploration phase.
To avoid premature stagnation during search, iHOW produces candidate solutions that are uniformly distributed throughout the search space. The equation of the position update can be formulated as:

$$DS^{t+1} = r_1 \cdot DS_1 + r_1 \cdot r_2 \cdot DS_2 + r_1 \cdot r_2 \cdot r_3 \cdot DS_3, \tag{1}$$

where DS^{t+1} is the updated exploration state at iteration $t+1$, and DS_1, DS_2, DS_3 represent the exploration components. Parameters r_1, r_2, r_3 are learning rates that control the magnitude of exploration.

Exploitation phase.
In exploitation, iHOW refines promising solutions by focusing on the best-performing regions of the search space. The position update equation is given by:

$$X^{t+1} = X^t + \left(K^{t+1} + DS^{t+1}\right) \cdot r, \tag{2}$$

where X^{t+1} is the updated solution at iteration $t+1$, X^t is the current solution, K^{t+1} is the knowledge state, and r is a random control parameter. Additional refinements are performed with:

$$X_2^{t+2} = X_2^t + r_3 \cdot r_4 \cdot \left(K^t + LS^{t+1}\right), \tag{3}$$

$$X_3^{t+3} = X_3^t + \left(r_3 \cdot r_4 \cdot r_5 \cdot K^t + DS^{t+1} + LS^{new}\right), \tag{4}$$

which enable the algorithm to intensively search around knowledge-enhanced candidate solutions.

The adaptive knowledge factor K decreases over iterations according to:

$$K = 2 - 2 \times \left(\frac{\text{iteration count}}{\text{maximum iterations}}\right), \tag{5}$$

ensuring a smooth transition from global exploration to local exploitation. The general structure of iHOW can be summarized in the following pseudo-code:

Algorithm 1 Pseudo-code of the iHOW Optimization Algorithm

```
Initialize population size, knowledge factor $K$, learning rates $(r1, r2, r3, ...)$, and maximum iterations.
Randomly generate initial population of candidate solutions.
for each iteration until maximum iterations do
    Exploration: Update exploration states $DS^{t+1}$ using Eq. (1).
    Learning: Update learning states $LS^{t+1}$ from accumulated knowledge.
    Knowledge Acquisition: Integrate $DS^{t+1}$ and $LS^{t+1}$ to update knowledge state $K^{t+1}$.
    Exploitation: Refine candidate solutions using Eqs. (2)–(4).
    Evaluate all solutions and update the global best $X_{best}$.
end for
Return $X_{best}$ as the final optimized solution.
```

To validate its effectiveness, iHOW is compared against several well-established metaheuristic algorithms, including:

- Grey Wolf Optimizer (GWO) – inspired by the social hierarchy and hunting strategy of wolves.
- Particle Swarm Optimizer (PSO) – based on swarm intelligence and collective behavior.
- Bat Algorithm (BA) – modeled on the echolocation behavior of bats.
- Biogeography-Based Optimizer (BBO) – simulating species migration across habitats.
- Whale Optimization Algorithm (WOA) – inspired by bubble-net feeding of whales.
- Multiverse Optimization (MVO) – based on cosmological concepts of multiple universes.
- Satin Bowerbird Optimizer (SBO) – mimicking mating and nest-building behaviors.
- Genetic Algorithm (GA) – based on natural selection, crossover, and mutation.

This comparative framework ensures that the advantages of iHOW are rigorously demonstrated not only in terms of prediction accuracy but also in exploration–exploitation trade-off, computational efficiency, and robustness across multiple datasets.

3.5 Evaluation Metrics

The effectiveness of the proposed forecasting framework was assessed using two categories of evaluation metrics. The initial one is regression-based measures of performance, which assess the accuracy and reliability of the predictions of the Deep Learning (DL) models. The second category involves feature selection metrics, which measure the efficiency and stability of the metaheuristic algorithms in identifying the most relevant subset of input variables. A combination of these measures guarantees that the predictive accuracy and efficiency of optimization are thoroughly evaluated. Regression measures all assess the extent to which model predictions align with observed values. Redder values of MSE, RMSE, MAE, and MBE imply more

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

Table 1: Regression metrics for evaluating model performance

Metric	**Equation**
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i \rvert$
Mean Bias Error (MBE)	$MBE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
Correlation Coefficient (r)	$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}$
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Relative RMSE (RRMSE)	$RRMSE = \frac{RMSE}{\bar{y}} \times 100$
Nash–Sutcliffe Efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Willmott's Index (WI)	$WI = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert y_i - \bar{y}\rvert + \lvert \hat{y}_i - \bar{y}\rvert)^2}$

minor differences between the predicted and observed performance, thereby indicating higher predictive accuracy. The correlation coefficient (r) will be used to estimate the strength of the linear predictive relationship between predictions and data, and the coefficient of determination (R²) will be used to establish the percentage of observed data variation (data explained) by the model. RRMSE is an operation of RMSE, compared with the mean of the observations, permitting cross-comparisons of scales. The Nash-Sutcliffe Efficiency (NSE) is used to evaluate the model's performance in comparison to the mean of the observed values. Conversely, the Willmott Index (WI) is used to determine the degree to which the model conforms to the observed values, with an index of 1 representing ideal conformance.

Table 2: Measurements of feature selection to assess optimization performance

Metric	**Equation**
Average Error (AE)	$AE = \frac{1}{M}\sum_{j=1}^{M}\frac{1}{N}\sum_{i=1}^{N}\left(V_i - \hat{V}_i\right)^2$
Average Select Size (ASS)	$ASS = \frac{1}{M}\sum_{j=1}^{M}\lvert S_j \rvert$
Average Fitness (AF)	$AF = \frac{1}{M}\sum_{j=1}^{M}F_j$
Best Fitness (BF)	$BF = \min_{j=1,2,\ldots,M} F_j$
Worst Fitness (WF)	$WF = \max_{j=1,2,\ldots,M} F_j$
Standard Deviation Fitness (StdF)	$Std(F) = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}\left(F_j - \bar{F}\right)^2}$

Measures of feature selection indicate the quality, stability, and efficiency of optimization results. The lower the value of the Average Error, the more plausible the predictive performance of the algorithm is on the

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

specific subset of selected features. When the Average Select Size is smaller, this indicates that the algorithm can represent data in compact forms, thereby reducing model complexity. Average Fitness is the quality of average solutions during multiple runs. Best Fitness and Worst Fitness are the best and worst solutions of the algorithm, respectively. Finally, stability of the optimization process is quantified by the Standard Deviation of Fitness; values below one imply that the same performance is observed when the experiment is repeated. A combination of such metrics offers a metric that not only ensures the accuracy of feature selection but also the efficiency of computations and their ease of understanding.

4 Results

This section presents the laboratory results, which will be divided into three stages: a comparison of the deep learning models in the baseline, the results of feature selection, and the outcome of the optimized models. The purpose of the presented study is to evaluate how the use of various metaheuristic optimization methods can facilitate the predictability of Sustainable Development Goal (SDG) performance. The baseline performance of Gated Recurrent Units (GRUs), Long Short-term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) is compared. The comparison can be used as a benchmark to assess the strengths and weaknesses of each architecture in terms of capturing the trends associated with the SDGs. Subsequently, the findings of feature selection using different metaheuristic algorithms are presented, with a particular focus on the enhancements of dimensionality reduction without compromising model performance. Finally, the above-mentioned optimized models are addressed, i.e., tuned through Human-Inspired Metaheuristic Optimization (iHOW) and other metaheuristic algorithms, such as Genetic Algorithm (GA), Greylag Goose Optimization (GGO), and Whale Optimization Algorithm (WOA): it is demonstrated that the above-mentioned optimization techniques can considerably enhance the predictive capabilities of GRU-based models.

4.1 Baseline Model Comparison

To establish a reference point for subsequent optimization and feature selection experiments, the raw performance of the baseline Deep Learning (DL) models was evaluated. Table 3 summarizes the regression metrics for Gated Recurrent Units (GRUs), Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs).

Table 3: Baseline performance metrics of deep learning models before feature selection and optimization.

Model	**MSE**	**RMSE**	**MAE**	**MBE**	**r**	**R^2**	**RRMSE**	**NSE**	**WI**
GRUs	0.0772	0.2881	0.2470	0.0053	0.7911	0.8037	21.6404	0.9126	0.8699
LSTM	0.0955	0.3486	0.2992	0.0092	0.6479	0.6605	23.8215	0.8976	0.7096
RNN	0.1138	0.4091	0.3514	0.0132	0.5048	0.5174	24.9943	0.8400	0.5493
CNN	0.1321	0.4695	0.4036	0.0171	0.3616	0.3742	25.4037	0.8159	0.3890

The results demonstrate clear differences in predictive performance across the four baseline architectures. GRUs achieved the best overall accuracy, with the lowest error metrics (MSE, RMSE, and MAE) and the

DOI: https://doi.org/10.54216/AJBOR.130101

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025

highest correlation coefficient (r), coefficient of determination (R^2), and Willmott's Index (WI). These results highlight the ability of GRUs to effectively capture sequential dependencies in the Sustainable Development Goal (SDG) dataset while maintaining computational efficiency. LSTMs also performed reasonably well, but their accuracy lagged behind GRUs, indicating that while they are capable of modeling long-term dependencies, their added complexity did not translate into superior predictive skill for this dataset. RNNs showed a further decline in performance, primarily due to their susceptibility to vanishing gradient problems, which limits their ability to learn long-range dependencies effectively. CNNs recorded the weakest performance across all metrics, suggesting that while convolutional filters can detect local patterns, they are less effective for temporal forecasting of SDG indicators when compared with recurrent-based models. Overall, this baseline comparison confirms that recurrent models, particularly GRUs, provide a stronger foundation for forecasting SDG performance. However, the gap between baseline results and the desired level of accuracy underscores the necessity of further optimization and feature selection, which are explored in subsequent sections. To better understand the distribution and variability of the evaluation metrics used in this study, we combined kernel density estimation (KDE) with boxplots to capture both the spread and central tendency of the results. Figure 2 presents this mixed visualization for nine key performance indicators, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), coefficient of determination (R^2), Relative Root Mean Squared Error (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott's Index (WI). The KDE plots illustrate the probability density of each metric, while the superimposed boxplots highlight the median, quartiles, and potential outliers. This dual representation provides a more comprehensive view of how the models behave across multiple runs, enabling both statistical robustness checks and visual interpretation of error and agreement patterns.

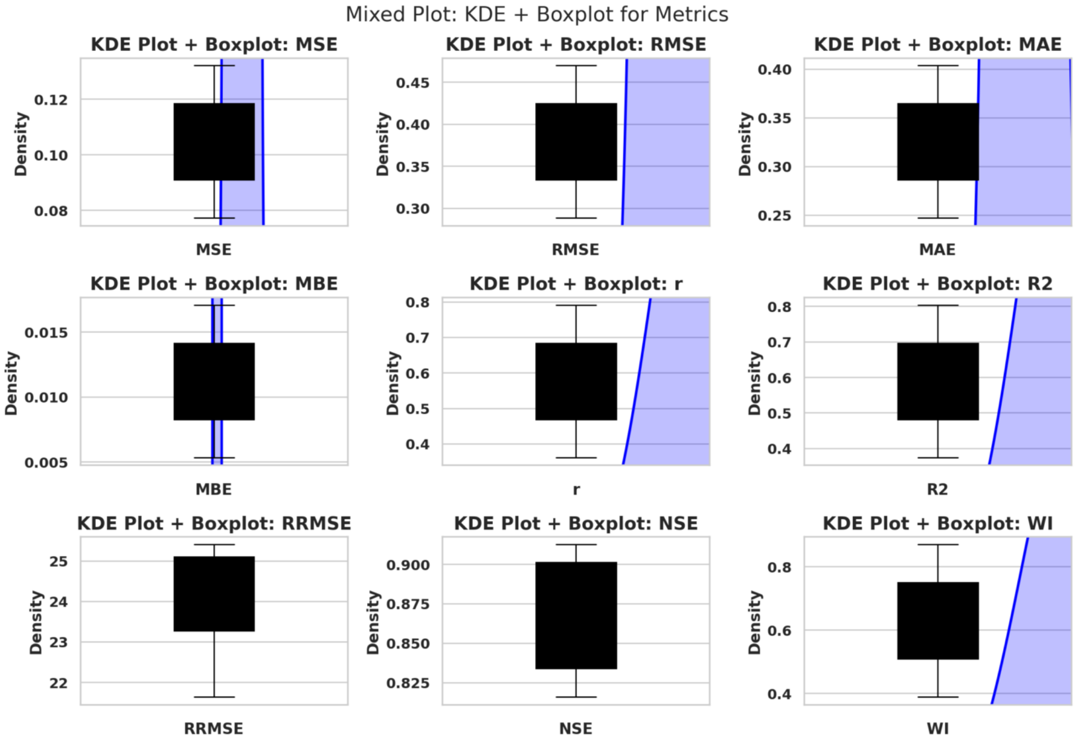

Figure 2: Mixed KDE and boxplot visualization of regression metrics.

In order to examine the underlying distributions of the evaluation metrics in greater detail, violin plots with kernel density estimation (KDE) were employed. Figure 3 illustrates the distribution of nine key performance indicators, namely Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), coefficient of determination (R^2), Relative Root Mean Squared Error (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott's Index (WI). Each violin plot combines a boxplot with a smoothed density curve, providing both summary statistics and a visualization of distributional shape. This dual representation would not only exhibit the median and variability of the measures, but also skewness and multimodality, which can provide further insight into the behavior and stability of the models when repeated.

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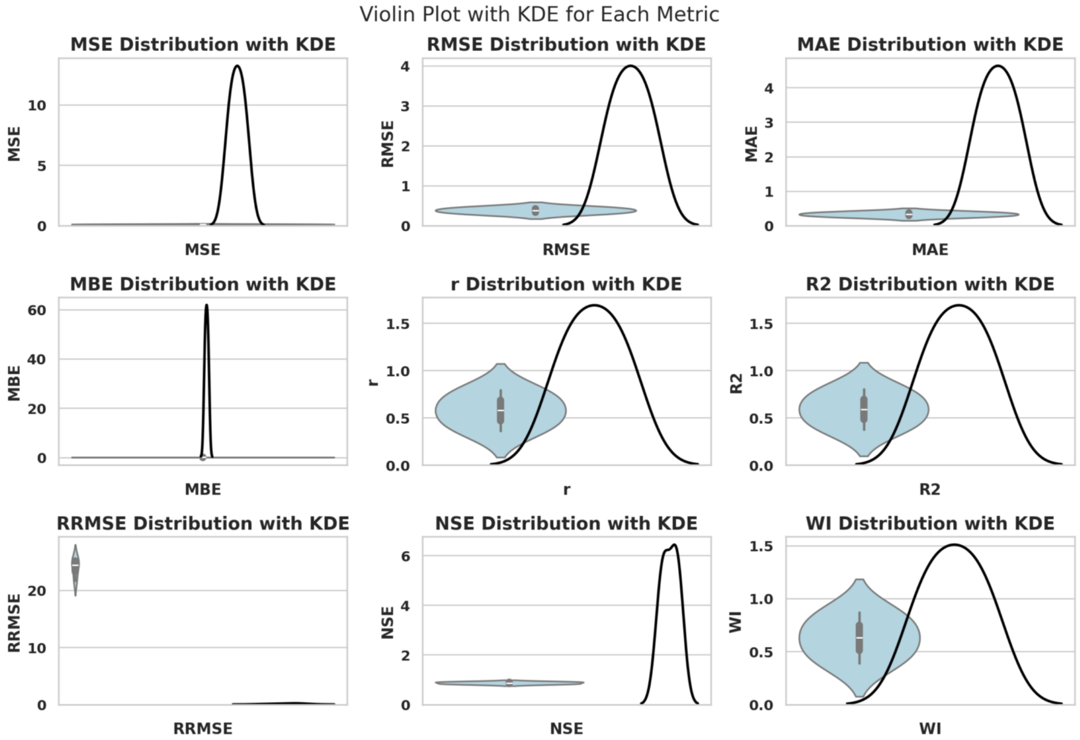

Figure 3: Violin plot visualization of distributions for evaluation metrics with KDE.

4.2 Feature Selection Results

To evaluate the efficiency of various meta-heuristic algorithms in feature selection, several binary versions of state-of-the-art optimizers were tested before hyperparameter optimization. Table 4 presents the comparative findings in terms of different evaluation measures, including average error, subset size, and fitness values.

Table 4: Feature selection results before optimization for different metaheuristic algorithms

Metric	biHOW	bHHO	bGWO	bPSO	bBA	bWAO	bBBO	bMVO	bSBO
Average Error	0.3330	0.3578	0.4419	0.5354	0.5450	0.5352	0.5036	0.5121	0.5437
Average Select Size	0.2858	0.4934	0.6715	0.6372	0.7766	0.8006	0.8010	0.7337	0.8075
Average Fitness	0.3962	0.4200	0.4731	0.5622	0.5851	0.5700	0.5679	0.5919	0.6019
Best Fitness	0.2980	0.3403	0.4266	0.5425	0.4748	0.5341	0.5576	0.5171	0.5450
Worst Fitness	0.3965	0.4072	0.5366	0.6102	0.5764	0.6102	0.6441	0.6351	0.6247
Standard Deviation Fitness	0.2185	0.2308	0.2938	0.3740	0.3839	0.3762	0.4189	0.4247	0.4349

The results reveal that the Human-Inspired Metaheuristic Optimization (biHOW) consistently outperformed other metaheuristic algorithms in terms of both accuracy and efficiency. It achieved the lowest average

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error and the smallest feature subset size, indicating that it can effectively reduce dimensionality without compromising predictive performance. Additionally, biHOW achieved the highest fitness and a reduced variation level in numerous runs, as indicated by its comparatively minor standard deviation. Conversely, more feature subsets were chosen, and the error value was considerable in algorithms such as binary Satin Bowerbird Optimizer (bSBO) and binary Whale Optimization Algorithm (bWAO), which underscores their lower ability to perform successful dimensionality reduction in the given context. The Binary Gray Wolf Optimizer (bGWO) and Binary Particle Swarm Optimizer (bPSO) exhibited medium performance, albeit with high error rates and instability. Overall, these results underscore the superiority of biHOW as a more efficient optimizer for feature selection in Sustainable Development Goal prediction.

4.3 Deep Learning Performance After Feature Selection

After applying feature selection through metaheuristic optimization, the performance of the Deep Learning (DL) models improved significantly across all metrics. Table 5 presents the results for Gated Recurrent Units (GRUs), Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs).

Table 5: Deep Learning model performance after feature selection

Model	**MSE**	**RMSE**	**MAE**	**MBE**	**r**	R^2	**RRMSE**	**NSE**	**WI**
GRUs	0.0011	0.0039	0.0033	0.0128	0.9243	0.9251	10.6578	0.9542	0.9240
LSTM	0.0014	0.0046	0.0040	0.0132	0.9153	0.9161	12.6669	0.9111	0.8842
RNN	0.0016	0.0054	0.0047	0.0136	0.9064	0.9072	13.6134	0.8746	0.8554
CNN	0.0018	0.0062	0.0054	0.0140	0.8974	0.8982	14.5245	0.8550	0.8345

The findings indicate that the feature selection process significantly reduced the error statistics in all models. GRUs again recorded the best results, producing the lowest MSE, RMSE, and MAE, as well as the highest correlation coefficient (r), coefficient of determination (R^2), and Willmott Index (WI). These findings demonstrate that GRUs can work exceptionally well in identifying the underlying structure of the SDG dataset when irrelevant or redundant features are removed. LSTMs also exhibited notable improvements, though their accuracy remained slightly lower than that of GRUs. This suggests that while LSTMs are capable of handling long-range temporal dependencies, their complexity does not necessarily translate into superior performance for the SDG forecasting problem. RNNs and CNNs showed improved accuracy relative to their baseline results but continued to lag behind GRUs and LSTMs. The relatively weaker performance of CNNs reinforces the conclusion that convolutional architectures, while effective in capturing spatial patterns, are less suited for sequential forecasting tasks such as SDG prediction. Overall, the application of feature selection streamlined the learning process for all models, reducing redundancy and enhancing predictive efficiency. The gains observed in correlation-based metrics (r, R^2) and agreement-based indices (NSE, WI) underscore the value of integrating feature selection with DL architectures in sustainability forecasting. Importantly, the improvements highlight that optimization-driven feature selection is a critical step toward achieving both accuracy and interpretability in predictive modeling. Understanding the interrelationships among performance metrics is essential for evaluating forecasting models in a holistic manner. Figure 4 presents a clustered heatmap of correlations between nine evaluation metrics, including correlation

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coefficient (r), coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), Willmott's Index (WI), Relative Root Mean Squared Error (RRMSE), Root Mean Squared Error (RMSE), Mean Bias Error (MBE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). The heatmap reveals two dominant clusters: accuracy and agreement-based measures (r, R^2, NSE, WI) are strongly and positively correlated with one another, while error-based measures (RRMSE, RMSE, MBE, MSE, MAE) form a second group with high positive correlations. Notably, these two clusters exhibit strong negative correlations with each other, reflecting the natural trade-off between higher accuracy/efficiency and lower error magnitudes. This clustering highlights the redundancy among certain metrics while confirming the consistency of the evaluation framework in distinguishing well-performing models from weaker ones.

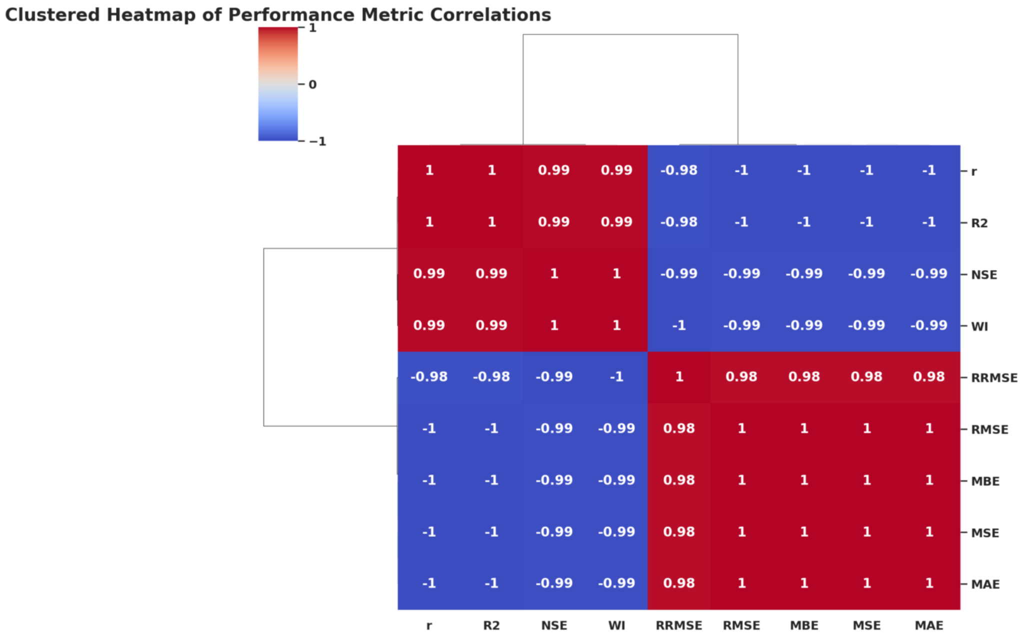

Figure 4: Clustered heatmap of correlations among performance metrics.

4.4 Optimized Models

To further enhance predictive accuracy, the Gated Recurrent Unit (GRU) architecture was optimized using several metaheuristic algorithms. Table 6 presents the results of the optimized models, where the GRU was tuned using the Human-Inspired Metaheuristic Optimization (iHOW), Genetic Algorithm (GA), Greylag Goose Optimization (GGO), and Whale Optimization Algorithm (WOA).

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Table 6: Performance of optimized GRU models using different metaheuristic algorithms

Model	**MSE**	**RMSE**	**MAE**	**MBE**	**r**	R^2	**RRMSE**	**NSE**	**WI**
iHOW + GRUs	0.0011	0.0038	0.0033	0.0127	0.9663	0.9671	7.9497	0.9865	0.9705
GA + GRUs	0.0013	0.0046	0.0040	0.0131	0.9573	0.9581	9.9588	0.9576	0.9307
GGO + GRUs	0.0016	0.0054	0.0046	0.0135	0.9484	0.9492	10.9053	0.9211	0.9019
WOA + GRUs	0.0018	0.0062	0.0053	0.0139	0.9394	0.9402	11.8164	0.9015	0.8810

The results clearly demonstrate the advantage of optimization, with all algorithms improving the baseline GRU model. Among the compared methods, the iHOW-optimized GRU achieved the best performance across nearly all metrics. It recorded the lowest error values (MSE, RMSE, and MAE), the highest correlation coefficient (r), and the strongest agreement indices (R^2, NSE, and WI). These outcomes highlight iHOW's superior ability to balance exploration and exploitation during the optimization process, resulting in more effective hyperparameter tuning and feature selection. The GA-optimized GRU also performed competitively, achieving substantial improvements compared to the unoptimized baseline, though it remained slightly behind iHOW. The GGO and WOA optimizers provided further gains over baseline GRUs but were less effective than iHOW and GA, as indicated by their higher error values and lower correlation-based metrics. Notably, WOA achieved the weakest performance among the optimized models, suggesting that its search strategy was less effective in navigating the high-dimensional parameter space of GRUs for SDG forecasting. In summary, the comparative analysis confirms that iHOW is the most effective optimization algorithm for enhancing GRU performance. Its human-inspired learning and adaptive search strategy provide more stable convergence, superior accuracy, and stronger generalization, establishing it as the best-performing optimizer for the forecasting framework proposed in this study. To further investigate the similarity between optimized forecasting models, hierarchical clustering was applied to the performance metrics of the GRU-based architectures optimized with different metaheuristic algorithms. Figure 5 shows the resulting dendrogram, which clusters the models by their pairwise differences in predictive behavior. The clustering demonstrates that GA + GRUs and GGO + GRUs form a close cluster, indicating that they share similar optimization tendencies and predictive profiles. However, iHOW + GRUs do not lie so closely to each other, as they exhibit unique performance gains and a better balance of exploration and exploitation. WOA + GRUs fall in the middle range, exhibiting moderate deviation from the other optimizers. This hierarchical visualization both emphasizes the distinctiveness of iHOW in moving GRU optimization, and also demonstrates structural similarities and differences between other metaheuristic methods.

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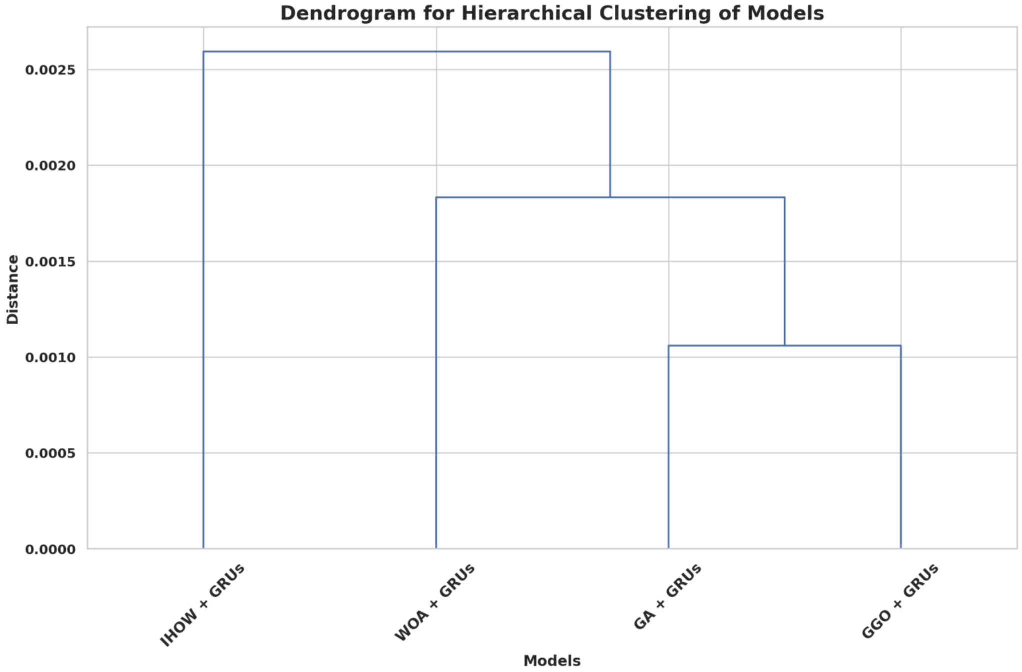

Figure 5: Hierarchical clustering dendrogram of optimized GRU models using different metaheuristic algorithms.

To provide a holistic visualization of model performance across multiple evaluation metrics, a radar plot was constructed. Figure 6 simultaneously represents nine key measures, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), correlation coefficient (r), coefficient of determination (R^2), Relative Root Mean Squared Error (RRMSE), Nash–Sutcliffe Efficiency (NSE), and Willmott's Index (WI). By mapping all metrics onto a single circular scale, the radar plot enables an intuitive comparison of strengths and weaknesses, highlighting dimensions where the model performs exceptionally well and others where further optimization may be required. This integrated view facilitates balanced assessment by emphasizing not only error minimization but also correlation strength and overall predictive agreement.

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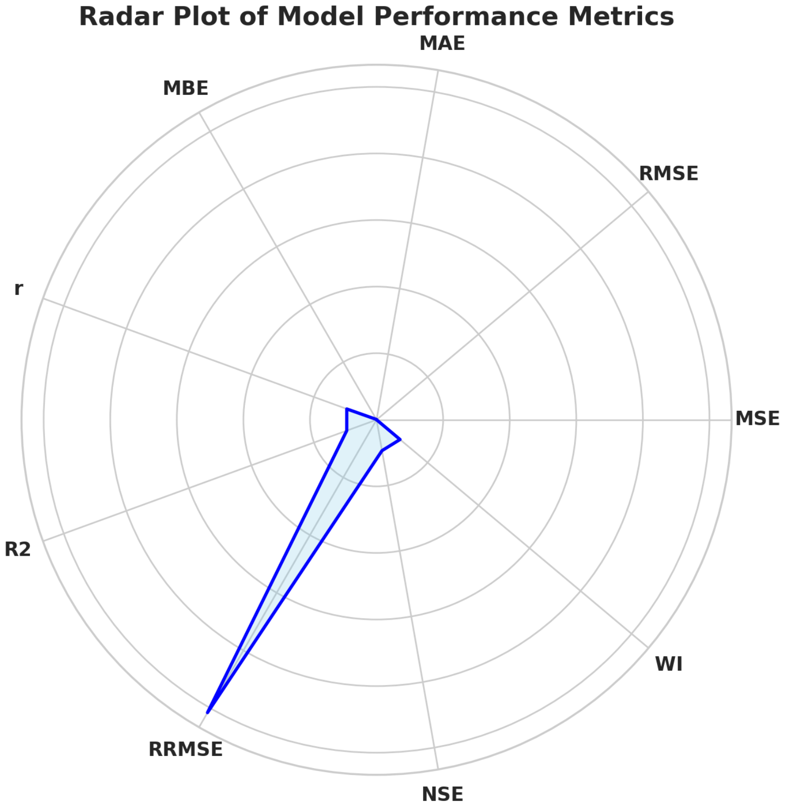

Figure 6: A radar diagram to visualize model performance using various measures of evaluation.

5 Discussion

This study demonstrates the substantial potential of integrating advanced deep learning architectures with metaheuristic optimization algorithms to enhance the forecasting accuracy and efficiency of Sustainable Development Goals (SDGs). In particular, the use of Gated Recurrent Units (GRUs) optimized via the Human-Inspired Metaheuristic Optimization algorithm (iHOW) yields superior predictive performance compared to other deep learning models and optimization techniques. The results convincingly show that applying metaheuristic-driven feature selection and hyperparameter tuning significantly reduces prediction errors and improves model stability, as evidenced by improvements in key regression metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The observed dominance of GRU-based models aligns with their intrinsic capacity to efficiently capture long-term temporal dependencies while maintaining a comparatively low computational footprint relative to complex architectures like LSTMs. Moreover, the ability of iHOW to balance exploration and exploitation during optimization facilitates robust avoidance of local minima and ensures fine-tuning of model parameters, which is critical given the high dimensionality and heterogeneity of the SDG dataset. The notable improvements in forecasting accuracy after joint feature selection and hyperparameter optimization confirm that dimensionality reduction and tailored model configuration are essential for managing the challenges posed by correlated and redundant input features. From a broader perspective, these methodological advancements carry important implications for policy-makers, international development agencies, and financial institutions. Accurate and timely forecasting of SDG progress allows governments and stakeholders to identify priority intervention areas, optimize resource allocation, and design effective policy responses — potentially reducing inefficiencies and accelerating achievement timelines. Additionally, enhanced forecasting models can serve as critical decision-support tools for investors and private sector actors increasingly incorporating Environmental, Social, and Governance (ESG) criteria aligned with SDGs into their risk assessments and strategic planning. Precise SDG forecasts enable better anticipation of emerging systemic risks, growth opportunities, and compliance requirements, which ultimately supports sustainable business practices and fosters confidence among stakeholders. Financially, improved SDG forecasts contribute to more informed capital allocation by investors seeking to align portfolios with sustainability objectives, as well as by organizations optimizing their sustainability-linked financing strategies. Enhanced predictive insights can also facilitate the quantification of economic co-benefits associated with achieving SDGs, supporting stronger business cases for green investments and public-private partnerships. Furthermore, the scalability and adaptability of the proposed framework suggest applicability beyond sustainability analytics, extending to commercial domains such as energy demand forecasting, climate risk modeling, and healthcare prognosis, which carry substantial economic stakes. However, despite these promising outcomes, some practical limitations warrant consideration. Firstly, the reliance on pre-compiled datasets constrains the model's responsiveness to real-time events, an increasingly important requirement in dynamic policy and market environments. Secondly, the computational expense associated with metaheuristic optimization—although justified by performance gains—may limit deployment in resource-constrained settings or require dedicated computational infrastructure. Thirdly, the inherent variability and regional heterogeneity of SDG indicators suggest that further tailoring or domain-specific adaptation may be necessary to capture localized patterns effectively. Looking forward, research efforts could focus on integrating streaming data sources such as satellite imagery, social media signals, and real-time economic indicators to enhance model reactivity. Advances in hybrid optimization strategies and adaptive parameter control mechanisms could reduce computational demands while maintaining optimization quality. Additionally, embedding these predictive frameworks into interactive decision-support platforms could enhance accessibility and facilitate stakeholder engagement across government, finance, and civil society. In conclusion, by marrying the representational power of deep learning with the search efficiency of metaheuristic algorithms, this study establishes a robust and versatile approach to SDG forecasting. This integration not only advances the scientific understanding of sustainable development trajectories but also opens new pathways for financial innovation and strategic planning aligned with global sustainability imperatives.

6 Conclusion and Future Work

The proposed study presents a robust forecasting framework for Sustainable Development Goals (SDGs) by combining advanced deep learning models with cutting-edge metaheuristic optimization algorithms. Employing data from the Sustainable Development Report 2023 and the historical SDG index, the research demonstrates that sophisticated architectures, notably Gated Recurrent Units (GRUs) optimized via the Human-Inspired Metaheuristic Optimization (iHOW), outperform traditional models in accuracy, computational efficiency, and resilience. Compared against other deep learning algorithms such as Long Short-Term Memory networks (LSTMs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks

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(CNNs), the GRU-based models consistently achieved superior predictive performance. Moreover, among several metaheuristic optimizers, iHOW stood out by effectively balancing exploration and exploitation, leading to enhanced feature selection and hyperparameter tuning. Beyond the methodological contributions, these findings carry significant implications for the financial sector. Accurate and timely forecasting of SDG progress can revolutionize investment analysis and risk management frameworks by providing actionable insights into sustainability trends that materially affect markets and corporate valuations. Financial institutions increasingly incorporate Environmental, Social, and Governance (ESG) considerations—closely aligned with SDGs—into their decision-making processes. Reliable SDG forecasts empower asset managers to better assess sustainability risks, identify growth opportunities linked to emerging green technologies, and optimize portfolios toward long-term resilience. Furthermore, companies leveraging precise SDG projections can improve compliance with evolving regulatory standards and enhance stakeholder trust, thereby gaining competitive advantage in increasingly sustainability-conscious markets. The capability to integrate sophisticated AI-driven forecasting into financial analytics thus has the potential to catalyze more sustainable capital flows and accelerate the transition toward greener economies. Nonetheless, challenges remain that warrant future research. The reliance on precompiled datasets limits model adaptability to real-time shifts, a critical requirement for dynamic financial markets and policy environments. Computational demands of metaheuristic-driven optimization may pose scalability barriers, although algorithmic innovations and hardware advances could mitigate these concerns. Moreover, heterogeneity across geographic regions and economic sectors suggests the need for localized model customization to capture distinctive sustainability trajectories and financial impacts accurately. Future studies should explore integrating diverse real-time data streams—including satellite imagery, social media, and high-frequency economic indicators—to enable continuous forecasting updates. Advancing hybrid and adaptive metaheuristic methods promises efficiency gains, facilitating broader deployment in commercial financial applications. Additionally, embedding forecasting models within interactive decision-support platforms can enhance transparency and usability for financial analysts, regulators, and corporate strategists alike. In conclusion, this research establishes a powerful and practical AI-based paradigm for SDG forecasting with clear extensions to financial analytics. By uniting predictive accuracy, computational efficiency, and interpretability, the framework advances both sustainable development science and financial decision-making, opening exciting avenues for future innovations at the intersection of sustainability and finance.

References

[1] Shahryar Sorooshian. The sustainable development goals of the united nations: A comparative midterm research review. *Journal of Cleaner Production*, 453:142272, 2024.

[2] Hasibul Islam. Nexus of economic, social, and environmental factors on sustainable development goals: The moderating role of technological advancement and green innovation. *Innovation and Green Development*, 4(1):100183, 2025.

[3] Naveed Ahmad, Sarminah Samad, and Shahzad Mahmood. Sustainable pathways: the intersection of csr, hospitality and the united nations' sustainable development goals. *Current Issues in Tourism*, 27(22):3924–3943, 2024.

[4] Kgosietsile Velempini. Assessing the role of environmental education practices towards the attainment of the 2030 sustainable development goals. *Sustainability*, 17(5), 2025.

[5] Prof. Dr. Eng. Mutambara. *UN Sustainable Development Goals (SDGs)*, pages 47–80. Springer Nature Switzerland, Cham, 2025.

[6] David W South and Savas Alpay. Analyzing global progress on united nations sustainable development goals 7 and 13—clean energy and climate action. *Climate and Energy*, 41(9):23–32, 2025.

[7] Cem Işık, Serdar Ongan, Dilek Ozdemir, Jiale Yan, and Oğuzhan Demir. The sustainable development goals: Theory and a holistic evidence from the usa. *Gondwana Research*, 132:259–274, 2024.

[8] Vincenzo Varriale, Antonello Cammarano, Francesca Michelino, and Mauro Caputo. The role of digital technologies in production systems for achieving sustainable development goals. *Sustainable Production and Consumption*, 47:87–104, 2024.

[9] Sharmin Nahar. Modeling the effects of artificial intelligence (ai)-based innovation on sustainable development goals (sdgs): Applying a system dynamics perspective in a cross-country setting. *Technological Forecasting and Social Change*, 201:123203, 2024.

[10] Nicholas Sawers, Nigel Bolster, and Andrew Bastawrous. The contribution of artificial intelligence in achieving the sustainable development goals (sdgs): what can eye health can learn from commercial industry and early lessons from the application of machine learning in eye health programmes. *Frontiers in public health*, 9:752049, 2021.

[11] Virender Kadyan, TP Singh, and Chidiebere Ugwu. *Deep Learning Technologies for the Sustainable Development Goals*. Springer, 2023.

[12] P Ilamathi and S Chidambaram. Integration of hyperspectral imaging and deep learning for sustainable mangrove management and sustainable development goals assessment. *Wetlands*, 45(1):9, 2025.

[13] Zhencheng Fan, Zheng Yan, and Shiping Wen. Deep learning and artificial intelligence in sustainability: A review of sdgs, renewable energy, and environmental health. *Sustainability*, 15(18), 2023.

[14] Bahriye Akay, Dervis Karaboga, and Rustu Akay. A comprehensive survey on optimizing deep learning models by metaheuristics. *Artificial Intelligence Review*, 55(2):829–894, 2022.

[15] Mehrdad Kaveh and Mohammad Saadi Mesgari. Application of meta-heuristic algorithms for training neural networks and deep learning architectures: A comprehensive review. *Neural Processing Letters*, 55(4):4519–4622, 2023.

[16] Jhansi Bharathi Madavarapu, Balaram Yadav Kasula, Pawan Whig, and Sandeep Kautish. Ai-powered solutions advancing un sustainable development goals: a case study in tackling humanity's challenges. In *Digital Technologies to Implement the UN Sustainable Development Goals*, pages 47–67. Springer, 2024.

[17] Claudio Persello, Jan Dirk Wegner, Ronny Hänsch, Devis Tuia, Pedram Ghamisi, Mila Koeva, and Gustau Camps-Valls. Deep learning and earth observation to support the sustainable development goals: Current approaches, open challenges, and future opportunities. *IEEE Geoscience and Remote Sensing Magazine*, 10(2):172–200, 2022.

[18] Nitu Yadav and Savita Kumari Sheoran. The role of deep learning in attaining the sustainable development goals. In *2024 First International Conference on Technological Innovations and Advance Computing (TIACOMP)*, pages 437–443, 2024.

[19] Redouane Lhiadi, Abdelali Kaaouachi, and Abdessamad Jaddar. The role of applications deep learning in achieving sustainable development goals. In *Emerging Trends in ICT for Sustainable Development: The Proceedings of NICE2020 International Conference*, pages 71–78. Springer, 2021.

[20] Arash Hajikhani and Arho Suominen. Mapping the sustainable development goals (sdgs) in science, technology and innovation: application of machine learning in sdg-oriented artefact detection. *Scientometrics*, 127(11):6661–6693, 2022.

[21] Ariana Chang, Tian-Shyug Lee, and Hsiu-Mei Lee. Applying sustainable development goals in financial forecasting using machine learning techniques. *Corporate social responsibility and environmental management*, 31(3):2277–2289, 2024.

[22] Ananya Misra, Emmanuel Okewu, Sanjay Misra, and Luis Fernández-Sanz. Deep neural network model for evaluating and achieving the sustainable development goal 16. *Applied Sciences*, 12(18), 2022.

[23] Aakash Singh, Anurag Kanaujia, Vivek Kumar Singh, and Ricardo Vinuesa. Artificial intelligence for sustainable development goals: Bibliometric patterns and concept evolution trajectories. *Sustainable Development*, 32(1):724–754, 2024.

[24] Jade Eva Guisiano, Raja Chiky, and Jonathas De Mello. Sdg-meter: A deep learning based tool for automatic text classification of the sustainable development goals. In *Asian conference on intelligent information and database systems*, pages 259–271. Springer, 2022.

[25] Atie Asadikia, Abbas Rajabifard, and Mohsen Kalantari. Systematic prioritisation of sdgs: Machine learning approach. *World Development*, 140:105269, 2021.

[26] Chatrabhuj and Kundan Meshram. Proposed design of an augmented deep learning model for estimation of sustainable development goals via satellite image analysis. *Environment, Development and Sustainability*, pages 1–27, 2024.

[27] Achara Taweesan, Thammarat Koottatep, Thongchai Kanabkaew, and Chongrak Polprasert. Application of machine learning in sanitation management prediction: Approaches for achieving sustainable development goals. *Environmental and Sustainability Indicators*, 22:100374, 2024.

[28] Nadine Bachmann, Shailesh Tripathi, Manuel Brunner, and Herbert Jodlbauer. The contribution of data-driven technologies in achieving the sustainable development goals. *Sustainability*, 14(5), 2022.

[29] Achara Taweesan, Thongchai Kanabkaew, Nawatch Surinkul, and Chongrak Polprasert. Integrating clustering algorithms and machine learning to optimize regional snapshot municipal solid waste management for achieving sustainable development goals. *Environmental Advances*, 19:100607, 2025.

[30] A Jiran Meitei, Pratibha Rai, and SS Rajkishan. Application of ai/ml techniques in achieving sdgs: a bibliometric study. *Environment, Development and Sustainability*, 27(1):281–317, 2025.

[31] El-Sayed M El-Kenawy, Faris H Rizk, Ahmed Mohamed Zaki, Mahmoud Elshabrawy, Abdelhameed Ibrahim, Abdelaziz A Abdelhamid, Nima Khodadadi, Ehab M ALmetwally, and Marwa M Eid. ihow optimization algorithm: a human-inspired metaheuristic approach for complex problem solving and feature selection. *Journal of Artificial Intelligence in Engineering Practice*, 1(2):36–53, 2024.

Received: March 03, 2025 Revised: June 05, 2025 Accepted: August 08, 2025