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Optimization Method of Teaching Program under the Concept of Sustainable Environmental Development of Renewable Energy Based on Artificial Intelligence Internet

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ABSTRACT

The increasing global demand for energy, coupled with concerns about environmental sustainability, has underscored the need for a transition toward renewable energy sources. A well-structured teaching program under the framework of sustainable development in renewable energy seeks to give students the information, abilities, and critical thinking needed to solve energy-related problems sustainably. This research proposes AI-powered personalized learning, innovative real-time integration of diverse data, and adaptive teaching strategies to enhance student understanding regarding renewable energy concepts. The sheep flock-optimized innovative recurrent neural network (SFO-IRNN) will recommend relevant topics and resources based on students' performance. Renewable energy teaching data from assess-

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ments are combined with real-time IoT-based renewable energy data. This dataset contains renewable energy education using AI-driven teaching methods and internet-based learning. The data was preprocessed by handling missing values and min-max scaling. The data features were extracted using Fourier Transform (FT). Further application of 10-fold cross-validation will increase the reliability of the model as it can evaluate its performance metrics like accuracy, F1-score, recall, and precision on different subsets of student data, which improves its robustness and prevents overfitting. The findings showed that the proposed method is significantly better, which ensures that the students have a deeper theoretical and practical understanding of renewable energy technologies. In addition, integrating real-time IoT data from renewable energy sources gives students a chance to do live simulations and problems that would enhance analytical thinking and hands-on learning. The research shows that AI provides context-aware guidance on sustainable energy infrastructure, enhancing interactive and personalized learning.

Keywords: Teaching Program; Artificial Intelligence (AI); Sustainability; Sheep Flock Optimized Innovative Recurrent Neural Network (SFO-IRNN); Renewable Energy; Environmental

1. Introduction

Increasing energy demand on a global scale, together with increasing environmental concerns, has made solutions to sustainable energy more pressing than ever before. With the decline in fossil fuel reserves and an increasingly evident environmental impact, the transition to renewable energy sources, such as solar and wind, has picked up impetus and gained credibility. The challenge to meet this transition lies in integrating renewable energy education into school curricula to provide future generations with highly relevant, cogent, and research-backed analysis in leading the global energy transformation [1]. Education is a prime mover in ensuring that there is increased adoption of renewable energy and sustainability processes. By providing students with the required knowledge, skills, and tools to understand all aspects of energy systems, environmental impact, and sustainable practices, education programs will inspire a generation of leaders in renewable energy innovation. Specifically, with the recent developments in technology, this is where it will be particularly important to understand how artificial intelligence (AI) and energy systems merge, as this could lead to transformative, sustainable solutions for the world's energy problems [2].

Machine learning (ML) has continuously developed an advanced integration of AI to provide a personalized learning experience. These systems were designed to serve the same functional objectives akin to that of a one-on-one tutor while dynamically responding to a student's needs and capabilities and tracking the learners' progress. Even the advanced AI can customize the learning process because the models are getting real-time data. While solving problems of renewable energy education, ML can give students real-time information about energy systems, thus making complex subjects very engaging [3]. With the introduction of AI and the Internet of Things (IoT) in educational platforms, there are innumerable opportunities for personalized learning for students. AI provides personalized Content and pacing for every individual student while IoT sensors provide real-time data from renewable energy sources. Such a blend allows for an interactive, dynamic learning experience in which students engage with live energy systems and obtain a better understanding of solar power, wind energy, and smart grids. Such a combination provides better theoretical and practical learning experiences [4].

Some of the most exciting promises of AI in education lie in personalization. AI systems utilize student interaction data to adapt content, suggest learning materials, and provide real-time feedback to help students with complicated topics. For renewable energy education, personalized learning ensures that students are reaching the very pertinent information according to their level of understanding and interest. AI-based systems can also diagnose knowledge gaps and pinpoint resources to fill such gaps [5]. Most students have a tough time wrapping their minds around the system of energy, smart grids, and sustainable technologies because of their extreme abstractness. Apart from this, renewable energy is an extremely dynamic and ever-changing field; with this evolution, it is not easy for an education curriculum to cater to all development aspects. Thus, there is an urgent need to introduce new methods of teaching that can cope with these challenges while also aiding in promoting an understanding of the topics amongst students [6].

These adaptive features integrate great possibilities of increasing students' engagement through AI-based systems, whereby personalization of learning is enabled by what each student needs to keep fully engaged in the process of learning [7]. These systems can keep students motivated through their learning journey while swallowing interactive problem-solving tasks that prompt personalized feedback. Also, the introduction of interactive features such as energy simulations in real time and challenges tied to live renewable energy data will allow students to dive into and conceptually engage with the material. This will lead to deeper learning and a better understanding of renewable energy systems [8]. The goal of this research was to develop an advanced AI for ensuring students' performance, which incorporates the Sheep Flock Optimized Innovative Recurrent Neural Network (SFO-IRNN) for personalized learning, real-time IoT data from renewable energy sources, and creating a platform to facilitate increasing student interest and comprehension of the sustainable energy technologies.

The research is structured as follows: Phase 2 provides literature investigation, Phase 3 defines the procedure, Phase 4 focuses on the evaluation of performance and discussion, and Phase 5 concludes the overall evaluation.

2. Related Works

Assessed the long-term impact of training in entrepreneurship and innovation for undergraduate and graduate students majoring in clean energy [9]; an evaluation model was suggested. The model built an environmental analysis indices technique and improved the generalized regression neural networks (GRNN) algorithm using the self-projection adaptation-vector field search (SPA-VFS) and Anarchy Bat algorithms. Simulations were used to validate the model's reliability and integrity in science. Examining the long-term growth of 19 Asian countries in digitization [10], factors like academic freedom, nepotism, energy use, urbanization, financial complexity, business, human resources, and the use of renewable energy were considered. The method suggested prioritizing information and communication technology (ICT) use, trade integration, saving energy, intelligent development, and fair resource use.

The aim was to assess how different technological tools could enhance the teaching of physics [11]. The outcomes demonstrated that these technologies outperformed the shortcomings of conventional teaching approaches by improving student participation, awareness, and reasoning skills. The challenges were inadequate professional development programs, uneven device use, and teacher preparation. The developments in ML and deep neural networks (DNN) that predicted the production of green energy were examined [12]. The method highlighted the significance of solid models for a sustainable energy future while going over its advantages, disadvantages, difficulties, and potential research avenues.

The ethical ramifications of AI along with its possible detrimental impacts on the surroundings and society at large were covered [13]. To promote green energy, it suggested feasible AI. The model identified eight key areas of AI assessment on energy administration with qualitative analysis and context-specific topic modeling. Along with incorporating remedies like elbow approaches to address obstacles, it suggested 14 potential training strands.AI has the potential to completely transform training, and education by enhancing mobility, efficacy, and future viability through a range of subject areas [14]. AI could maximize resources and knowledge, improving the efficiency and enjoyment of learning. AI and green education together could produce a comprehensive, profitable strategy for sustainable development. AI could increase the reliability of educational materials, create more effective teaching strategies, and assess the results of sustainable development projects.

A model based on ML and reinforcement learning was used to create a sustainable green energy management system (SGEMS) that optimized solar power and energy consumption on green campuses [15]. Real-time energy analysis and decision-making were made possible by the superior performance of the extreme gradient boosting (XGBoost) method and reinforced learning. The scalable solution raised energy efficiency and lessened dependability on exterior grids, establishing a standard for upcoming green campus projects. In 2020–2022, Irish educators, supporters of underwater solar power, and environmental participants discussed improving post-primary educational resources [16]. For students ages 15 to 17, a dual-language transfer year unit was developed with a focus on English and Irish. According to a multidisciplinary case study, stakeholder input was crucial for program efficacy and engagement. The research recommended a web-based Deep Learning (DL) platform for a nationwide impact.

Research carried out in Beijing, China, discovered a U-shaped relationship between humidity and the amount of electricity used by undergraduates [17]. Days with temperatures above 30°C saw a 16.8% increase in electricity consumption, while days with temperatures below –6 °C saw a six percent increase. Building characteristics such as a window course and level heights impacted the relationship. The findings suggest that, especially in urban centers like Beijing, Tianjin, and Hebei, building walls could represent a better way to cut energy consumption and become ready for higher temperatures.

Investigate the impact of environmental education on the ecologic education of 15-year-olds in Colombia, taking into consideration a variety of factors such as financial standing, a student's scientific community ability, parent features, and school-level features [18]. The results indicated insufficient evidence that environmental instruction increased environmental awareness, and showed little association with environmental engagement. The study also concluded that instruction and energy-efficient technologies alone were not sufficient and that environmental education was not ideal.

To find the best ways to balance energy consumption and the condition of the interior in Taiwanese elementary schools was suggested [19]. It examined how the flow rate and temperature set-point affected the standard of the atmosphere and suggested the best trade-off strategies. Beijing and Hong Kong have the greatest per-hour expense performance when set-point and airflow are combined optimally, taking into account cooling energy and academic performance. To improve student achievement in hot-humid climate regions, the research offered administrators recommendations.

The energy-saving measures in student residence halls from a psychological perspective [20]. A new variable, individual ethical norms, and the theory of planned behavior (TPB) formed the basis of the suggested theoretical framework. The outcomes proved that students' intentions to conserve energy were positively correlated with their actions, with personal ethics having the largest impact. Gender and temperature perceptions mitigated the impact of energy-saving intention on behavior. The findings supported the value of moral perspectives and provided insight into how students exploit their power in college residence halls.

The experiment investigated an intervention to boost intermediate school student engagement in energy concepts employing both simulation and real-world research [21]. The strategy included the influenced investigation exercises as well as group discussions. The students outperformed the control group based on engagement along with enhanced learning outcomes. The research used an evidence-based approach, showing that increased interest enhanced learning outcomes and raised the likelihood that other challenging scientific concepts could gain greater significance.

The impact of science, technology, engineering, arts, and mathematics (STEAM) education on seventh-grade students' conceptual grasp of force and energy concepts was examined [22]. The findings indicated that STEAM instruction improved students' conceptual knowledge, lowered misconceptions, and raised post-test scores. The content adds to the body of research on how STEAM education helped conceptual understanding.

Investigate the relationship between solar energy and Hungary's ecological awareness [23]. The relationship surveyed 2180 primary, middle, and university pupils in the Gyöngyös microregion. The results showed that intellectual well-being was more significant for students than protecting the environment. There was no increase in views on the environment or awareness among college students. It was believed that using renewable energy was too expensive for low-income families.

Examined energy awareness among Vietnamese high school students with a focus on the factors influencing energy-saving behavior [24]. The results showed an inadequate amount of knowledge, an increased valued opinion, and an intent to conserve energy. As journalism is the primary source of energy information, students in educational institutions use more energy-efficient techniques.

The effectiveness of STEM-PBL integrated engineering designing a process (EDP) in cost-effective building units, with an emphasis on enhancing students' ability to compute, was suggested [25]. STEM-EDP outperformed traditional STEM techniques in terms of student performance and engagement, creating superior conceptual abilities, and utilizing basic, accessible technologies for meaningful learning.

3. Materials and Methods

This section involves the framework of SFO-IRNN to offer personalized, adaptive learning experiences in renewable energy education and enhance the student's performance. **Figure 1** depicts the methodology flow to recommend relevant topics and resources based on students' performance.

3.1. Data Collection

The data collected from 500 students across different engineering courses help to determine the effects of AI-assisted teaching on renewable energy education [26]. The data includes information about student engagement in AI-supported learning programs, awareness of sustainability topics, and academic achievement in renewable energy courses. Data points show interaction metrics, such as time spent on tasks, completion rates, and real-time assessment responses. The combination of this information, along with IoT-based renewable energy data, allows for an in-depth analysis of how personalized and AI-enhanced learning impacts students in sustainability education. Research included 500 participants with a mean age of 24.86 years. The gender distribution was 55% female and 45% male. The participants were roughly evenly split between private (52.4%) and state (47.6%) institutions. The participants came from different departments, such as Civil (142), Computer Science (125), Electrical (119), and Mechanical (114). In AI adaptation, 180 students had a high level, 156 had a medium, and 164 had a low.

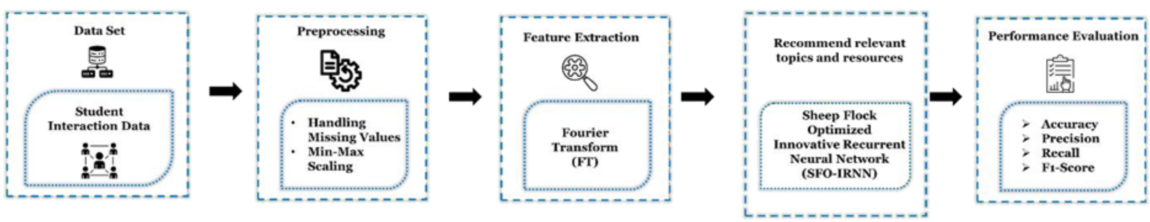

Figure 1. Framework of SFO-ARNN.

3.2. Data Preprocessing

The data was preprocessed using two techniques handling missing values and min-max scaling to suggest related subjects and materials based on the student.

✹ Handling Missing Values

The technique is one of the most critical rituals in the line of data preprocessing, especially in an educational dataset. In educational datasets, the reasons for missing values can range from incomplete student performance to experience gained through missing IoT sensor data from the renewables. Multiple forwarding strategies can be applied: imputation techniques by mean, median, and mode, predictive models to estimate missing values or even an advanced option. These assist in ensuring that the dataset remains conformed to integrity, therefore enhancing the accuracy and reliability of the educational recommendations.

✹ Min-Max Scaling

The technique used to normalize data while rescaling feature values to a certain range is preferable within [0,1], as given in

$$cld=\frac{-i}{-i} \tag{1}$$

Where stands for the data point when collected characteristic. $_i$is the number that determines the minimum value of the feature. Represents the value of the maximal feature. The result,$_d$ is the transformed value for the given data that is in the range. The variables in a dataset are measured on different scales or units to prevent them from submerging because of their higher value. It has large or small values in the data that affect the scaling of other values. Handling missing values and Min-Max scaling are essential preprocessing steps that ensure data consistency and normalization, making them crucial for effective model performance.

While outlier detection is useful, handling missing data and scaling can have a more immediate impact on improving data quality and ensuring algorithms work optimally.

3.3. Feature Extraction Using Fourier Transform (FT)

Digital signal processing has greatly benefited from the FT method. The convolutions required to construct digital filters, the correlations required to implement matched filters, and the Fourier analysis required to produce spectrograms can be efficiently carried out using the methodology. The forms of the foundation, ranging from predicting student performance to optimizing learning pathways, observing student well-being, assessing the efficacy of training, predicting dropout rates, and providing educational management with real-time decision-making capabilities, are provided by correlation, convolution, and spectrum analysis procedures. Depending on how many independent variables were used to transform the function, one or more dimensions are employed to express the FT theorem. The FT of a function *F(q)* in the time (or spatial) domain *f(i)*is defined as Equation (2).

$$F(q)=\int_{-\infty}^{+\infty} f(i)e^{j2\pi qi}di \tag{2}$$

Where $i=\sqrt{-1}$ and *q* are the variable frequency. *F(q)* is obviously a complex function. The magnitude *H(q)* and Phase *(q)* of *F(q)* are calculated in the event that both imagined and actual elements are specified as $F_i(q)$ and $F_g(q)$, respectively,

$$H(q)=|F(q)|=\sqrt{F_g^2(q)+F_i^2(q)} \tag{3}$$

$$\psi\,(q)=tan^{-\left[\frac{F_g(q)}{F_i(q)}\right]} \tag{4}$$

Frequently, *F(q)* is shown in the Equation (5) polar form.

$$F(q)=H(q)e^{i\psi(q)} \tag{5}$$

The inverse Ft Equation (6) is used to recreate the function *F(i)*.

$$F(i)=\int_{-\infty}^{+\infty} f(i)e^{j2\pi qi}dq \tag{6}$$

The FT pair is denoted by *F(i)* and *F(q)*. A two-dimensional function *F(i,y)* has the following Fourier transforms pair equivalently:

$$F(q,v)=\int\int_{-\infty}^{+\infty} f(i,y)e^{-j2\pi(qi+qy)}didy \tag{7}$$

$$F(i,y)=\int\int_{-\infty}^{+\infty} f(q,v)e^{j2\pi(qi+qy)}dqdv \tag{8}$$

Where the frequencies for *i* and *y*, respectively, are represented by *q* and *v*, and a similar calculation is used to determine the Fourier Transform's magnitude and phase. Here,f(i,y)f(i, y)f(i,y) is the original spatial domain function (e.g., an image or motion signal), F(q,v)F(q, v)F(q,v) is the frequency domain representation, qqq and vvv represent the frequency components corresponding to the spatial variables iii and yyy, respectively. FT is particularly optimal for the feature extraction process as it effectively analyzes frequency components of signals, which is essential for identifying patterns in time-series data. While other techniques like wavelet transform or PCA may be useful in different contexts, Fourier Transform provides a more direct and efficient method for the specific types of data and objectives in this study.

3.4. To Recommend Relevant Topics and Resources Based on the Students Using Sheep Flock-Optimized Innovative Recurrent Neural Network (SFO-IRNN)

The SFO-IRNN is a hybrid AI model that unites the flocking behavior of sheep with recurrent neural networks. This unique approach optimizes the RNN learning process by representing the adaptive, collaborative, and natural movement of sheep within a flock for better real-time data processing and personalized learning.

3.4.1. Innovative Recurrent Neural Network (IRNN)

Consider the sequence $\{\mathbf{M_1}, \mathbf{M_2}, ...\mathbf{M_u}\}$ where the kind of variable $\boldsymbol{M_u}$ (scalar or vector) depends on the situation. A recurrent function in a recurrent neural network determines hidden states $\boldsymbol{z_u}$, as described in equation (9). This process is vital for computational teaching where the model is modified according to a student's performance with real-time changes for optimizing learning outcomes.

$$z_u = IRNN(z_{u-1}, M_u) \tag{9}$$

Hidden states encode the data in transmitted input entries that are most important for producing the intended outputs. Because the variables of the recurrent function remain constant during the sequence indicated and may be trained by backpropagation. However, due to gradient disappearance, typical *R* cells cannot create particularly long-term interdependence. Therefore, recurrent skipping is employed to exploit the recurring structure in the input information. The integration of instructional program dynamics and student performance data further increases the system's capacity to adjust to each learning need, optimizing the recommendation of education

$$z_u = IRNN(z_{u-w}, M_u) \tag{10}$$

In Equation (10), the provided data is used as the source of the period value.

3.4.2. Sheep Flock Optimization (SFO)

The SFO is inspired by the grazing behavior of a flock of sheep and goats that follow a shepherd while in search of fertile pastures. The goal of that algorithm is to optimize solutions by mimicking the search for the best pasture, wherein each animal represents a potential solution. SFO is superior to techniques such as PSO or GA in analyzing the teaching program from the perspective of sustainable environmental growth in renewable energy because it has a higher probability of supporting the unique dynamics of the analysis.

The key components of the SFO were depicted in the following features for using flexible teaching techniques to improve students' comprehension of sustainable energy concepts.

Grazing Radius of Sheep: A dynamic range for alterations of teaching programs through each cycle of the optimization was designed. The applicable dynamic range is decided by as shown in equation (11), and the total number of iterations. The dynamic range of sheep, which reproduce the optimization processes driven by the AI, and repeat human adaptation to the learning of AI, is dependent on the current iteration and the total number of iterations. SFO undergoes extreme change at every decisive iteration, allowing for a transition of the optimization from a broad search for educational methods (exploratory stage) to a focus on exploiting the teacher strategies as effectively as possible using the improvements gained with the AI's adjustment to learning new strategies.

$$qH_{sheep} = 0.001 \times (upper\ bound - lower\ bound) \times S \tag{11}$$

Time Influence Factor: The time influence factor is computed to decrease with time (iterations) to manage how AI systems and real learners adapt to evolving teaching strategies. SFO aids in transitioning the educational approach from an initial broad exploration of techniques into a focused refinement of the most usable approaches for sustainable development in renewable energy. As it decreases, AI and human systems focus their attention on the best possible educational solutions, thus converging toward the best teaching strategies, as given in

$$S = 1 - \left(\frac{iteration}{max\ iteration}\right) \tag{12}$$

Movement of Sheep: The global best teaching strategies to aid the educational 249 optimization process. The local best solutions (individual educational optimization) to outgrow on convergence are 250 based on specific learning contexts and experiences. The interactions occur between the AI-driven models and the 251 human learners, supporting the search by collective knowledge, and data from learners' progress is displayed in equations (13–15).

$$u_{sh1,1} = (1-s) \times D \times Rand\ (1, Dim) \times (W_{HBest} - W) \tag{13}$$

$$u_{kbest,1} = D \times Rand\ (1, Dim) \times (W_{kbest} - W) \tag{14}$$

$$u_{other,1} = D \times Rand\ (1, Dim) \times (W_{Randomsheep} - W \tag{15}$$

Where $u_{sh1,1}$: Movement of a learner towards the global best solution. $u_{kbest,1}$: Movement of a learner towards its own best solution (local best). $u_{other,1}$: Movement of a learner towards a randomly selected learner's position for exploration. *S*: Scaling factor, *D*: Distance factor (affects step size), *Randd (1,Dim)*: Random factor for direction, W_{HBest}: Global best position, W_{kbest}: Local best position, $W_{Randomsheep}$: Position of a randomly chosen learner, and *W*: Current position of the learner.

Position Update and Velocity Calculation: Every cycle of the algorithm, the positions of the AI models, and the human learners are updated based on a global set of local best educational solutions. Velocity is added to the current position to find the new position, guaranteeing continuous refinement of the teaching strategies toward maximized learning outcomes.

Updating of Optimal Solutions: Every iteration updates the global and local best educational strategies through the current positions of AI-driven models and human learners. Global best is the significant educational strategy found by the entire optimization process, while local best solutions are tailored to individual learners. Such updates ensure that the educational optimization process improves and approaches closure to a more effective solution many times. **Figure 2** displays how the SFO is applied to personalize learning by recommending relevant renewable energy topics based on individual student performance. SFO enhances the adaptive learning system by optimizing the AI's capability of predicting and responding to each learner's needs in real-time.

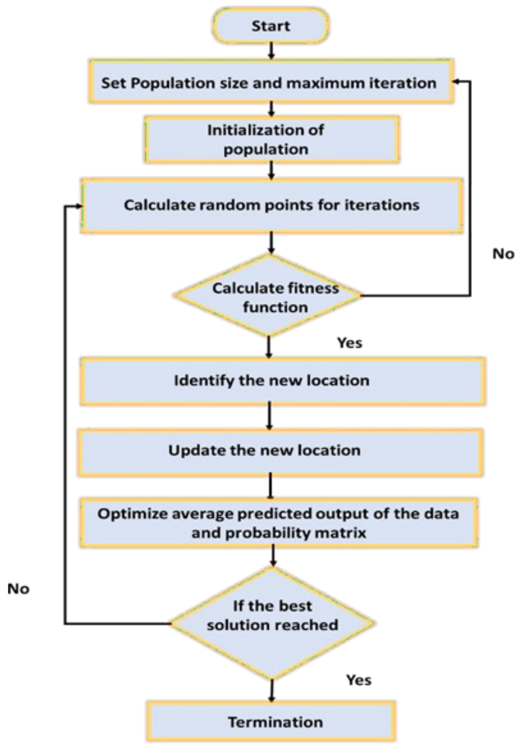

Figure 2. Flow Chart of SFO.

Hybrid algorithm that combines the collective behaviour of sheep flocking with advanced neural network techniques. This optimization approach mimics the natural coordination and adaptability of sheep flocks to enhance the efficiency and precision of recurrent neural networks (RNNs). By leveraging the flocking behaviour's dynamic search capabilities, SFO-IRNN optimizes learning processes in real-time, enabling personalized, context-aware recommendations based on student performance and interaction data for more effective educational outcomes. **Algorithm 1** displays the process of SFO IRNN.

Algorithm 1: SFO-IRNN

Initialize population size N, max iterations Max_iter, bounds (upper, lower), and time factor T
Initialize positions X_sheep and velocities V_sheep, Global_best = random position, LocalBest_sheep = sheep's initial position.
For iteration = 1 to Max_iter:
TrainIRNN (Global_best)
Evaluate Performance (IRNN_model, X_sheep)
If performance improves:
Global_best = new IRNN optimized solution
For iteration = 1 to Max_iter:
T = 1 – (iteration / Max_iter)
For each sheep
v_sheep = Update Velocity (X_sheep, GlobalBest, LocalBest_sheep, T)
X_sheep = X_sheep + v_sheep
Evaluate and Update the Best Position for sheep
TrainIRNN (GlobalBest)
If ConvergenceCriteriaMet (GlobalBest):
Break
Return GlobalBest □

4. Result and Discussion

The findings indicate the superior performance of SFO-IRNN, ensuring that students develop a deep and practical understanding of renewable energy technologies.

4.1. Experimental Setup

The experimental apparatus in the project employs Python as its principal programming language with the use of Tensorflow and PyTorch libraries for AI-based optimization algorithms. The system requires a minimum of 16 GB RAM, along with a multi-core processor, Intel i7, to efficiently run deep learning models and optimization computations.

4.2. Evaluation Criteria

The outcomes were derived based on the (10-fold) cross-validation based on the evaluation of performance metrics.

- **Accuracy** is the total performance of the AI system to correctly identify normal and abnormal renewable energy, as given in

$$Accuracy=\frac{true\ positive+true\ negative}{total\ instances} \tag{16}$$

✹ **Precision** is the proportion of correctly predicted abnormal sustainable development among all instances predicted as abnormal, which is given in

$$Precision=\frac{truepositive}{true\ positive+false\ positive} \tag{17}$$

✹ **Recall** is that the model identifies abnormal resources while minimizing sustainable development in

$$Recall=\frac{true\ positive}{true\ positive+false\ positive} \tag{18}$$

F1-Score is the balance expressed in equation (19) between precision and recall, indicating how well the model weighted between them for evaluation of students' performance.

$$F1\text{–}score=2\times\frac{precsion\times recall}{precision+recall} \tag{19}$$

Table 1 and **Figure 3** display the numerical outcomes for the cross-validation (10-fold) for the AI-based model in renewable energy education (**Figure 3(a)** and **(b)**). Each fold includes performance metrics, which provide an in-depth performance analysis of the model on different subsets of the data. Results show reliably high performance across folds, with minimal variation in precision and recall. In a nutshell, it is confirmed that the model is reliable in prediction accuracy and evaluation metrics used and is, therefore, robust in personalized renewable energy education.

Table 1. Numerical Values of Cross Validation (10-Fold).

Fold	Accuracy	Recall	F1 Score	Precision
1	0.9914	0.9548	0.9672	0.9600
2	0.9400	0.9400	0.9405	0.9419
3	0.9700	0.9700	0.9599	0.9730
4	0.9800	0.9700	0.9698	0.9207
5	0.9700	0.9700	0.9713	0.9777
7	0.9300	0.9700	0.9710	0.9757
7	0.9700	0.9700	0.9700	0.9700
8	0.9700	0.9600	0.9700	0.9500
9	0.9700	0.9700	0.9580	0.9719
10	0.9875	0.9567	0.9675	0.9500

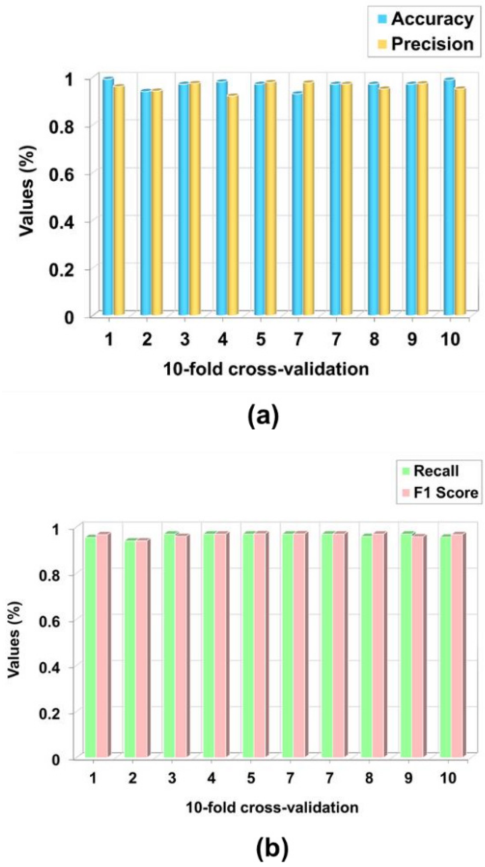

Figure 3. Outcomes of (10-Fold) Cross Validation. **(a)** Accuracy and Precision. **(b)** Recall and F1-Score.

Table 2 provides a statistical summary of the evaluation metrics regarding the AI-powered model on renewable energy education. Mean values and standard deviations are presented, which deal with the performance in terms of accuracy, precision, recall, and F1-score. These usefully portend the model's general effectiveness in making accurate predictions regarding student engagement and learning outcomes. The values suggest that the model is well-performing, reliable, and balanced across all evaluated student performance.

Table 2. Statistical Summary of Evaluation Metrics.

Metric	Mean	Standard Deviation
Accuracy	0.9770	±0.0173
Precision	0.9760	±0.0165
Recall	0.9790	±0.0173
F1 Score	0.9751	±0.0172

The impressive mean accuracy rate (97.70%) and low standard deviation (±1.73%) indicate the strong ability of the model to well classify student performance and activity across different sets of data. Similarly, the similarly close precision value (97.60%) and recall value (97.90%) demonstrate that the model, in addition to identifying significant student patterns with correct accuracy, prevents false negatives. F1 Score (97.51%), or harmonic mean of precision and recall, also confirms that the model possesses great balance between sensitivity and specificity. Low variance across all the measures indicates strong and generalizable performance, further contributing to the reliability of the model in real-world education.

The ROC-AUC curve indicates the classification ability of the proposed SFO-IRNN model for five classes, as Shown in **Figure 4**. The AUC for all classes is high, which reflects the good accuracy of the model in separate classes. The Proximity of the curve to the top-left corner indicates high true positive rates with low false positives, which verifies the strength and robustness of the model in multi-class prediction.

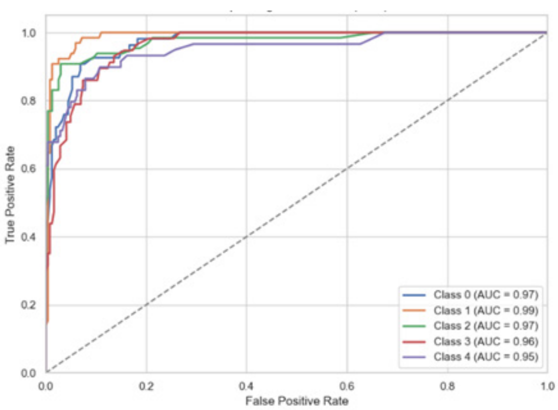

Figure 4. ROC-AUC Curve Based on Proposed SFO-IRNN.

The improved paradigm aims to optimize the performance of a system based on many factors such as customer satisfaction, system response, scalability, fidelity of the contents, etc. Contrasting with anticipated values (anticipated or designed) and measured values (true outcome) captures the disparity of the system's performance as shown in **Figure 5**. An example is that user satisfaction had been predicted as 85% but actual values at 82%, where there has been room for improvement. Also, the system response time was larger than the target value, and scalability should be enhanced to support more users. These variations from target values are precious information, which can further be used to make the adjustments required to meet the target values so that the overall system performance and user experience are enhanced.

Student performance scores across different ages, genders, and departments were calculated using the proposed SFO-IRNN method during AI-assisted teaching of renewable energy (**Figure 6**). **Figure 6a** shows student performance scores categorized by age and gender. Both male and female students exhibit comparable performance distributions, indicating that the proposed method achieves balanced learning outcomes across genders. **Figure 6b** presents student performance scores by department. Students from the Mechanical, Computer Science, Civil, and Electrical departments all show strong engagement, with those in Electrical and Computer Science performing slightly better. These results suggest that the model is broadly effective across a range of academic disciplines.

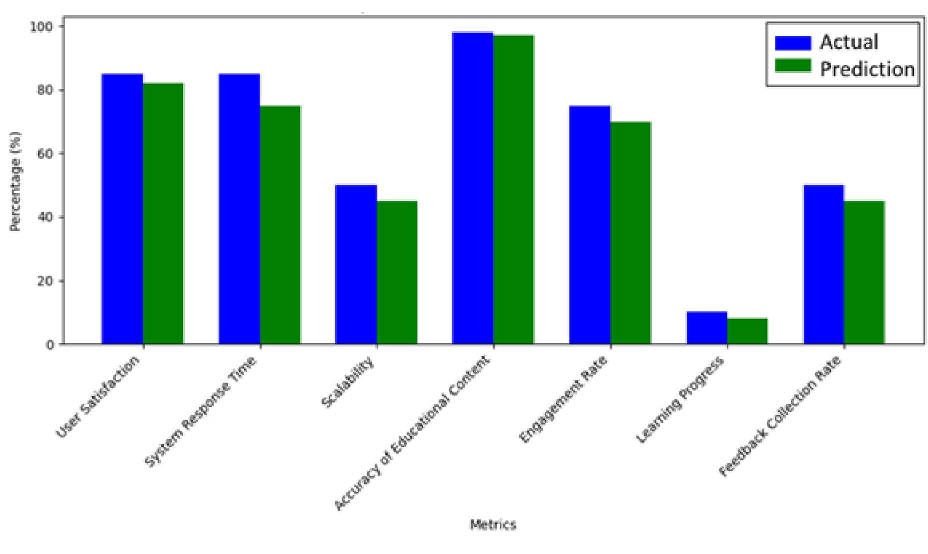

Figure 5. Performance Evaluation Comparison of Prediction vs. Actual Values.

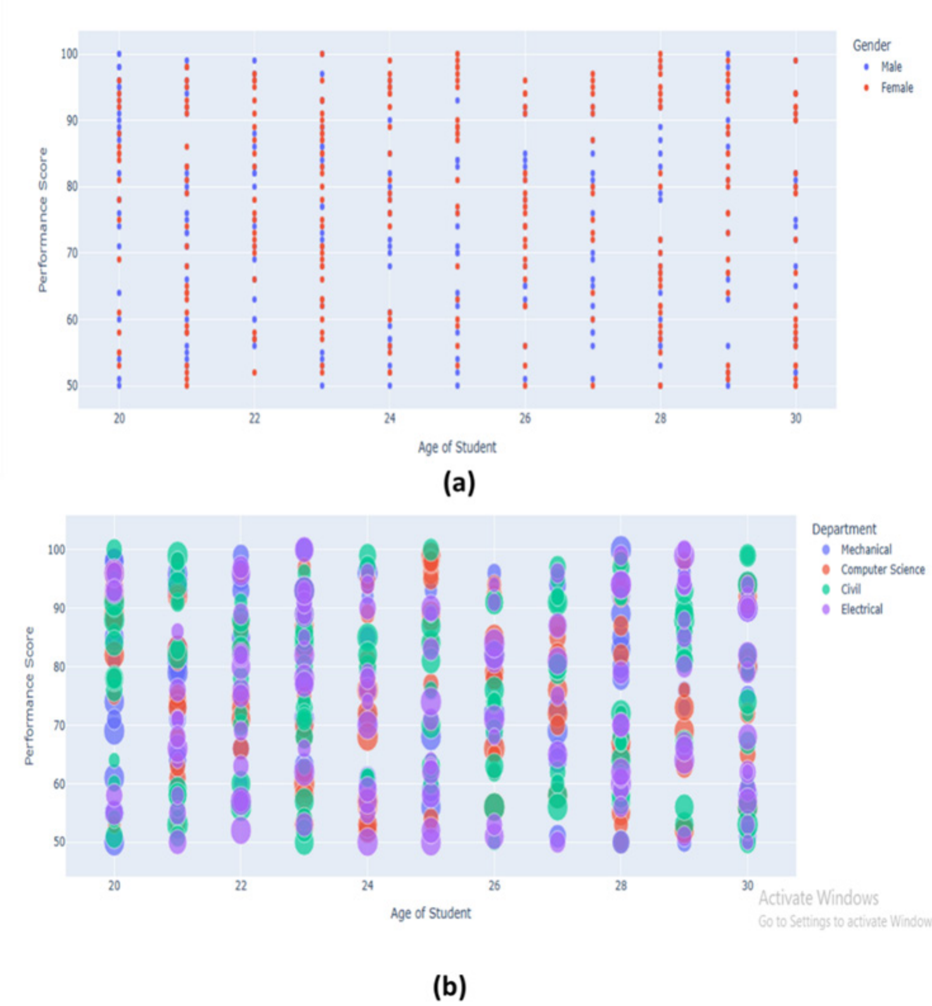

Figure 6. Age and Performance Score Comparison: (**a**) Gender-Based Comparison. (**b**) Department-Based Comparison.

4.3. Discussion

Examined the optimization of learning programs in renewable energy based on sustainable environmental development principles as a guideline. In light of the help provided by the Internet and artificial intelligence, the research seeks to optimize the efficiency and responsiveness of education strategies in this area. The SFO-IRNN uses cross-fold validation for the evaluation of an AI-powered learning system in renewable energy education. The substantiation provided by (10-fold) cross-validation also formulates solid outcomes for the performance metrics, therefore having a comprehensive assessment of the method's ability to adapt and personalize learning. The experiments show that the model performs consistently with minimum variance, indicating its effectiveness in customized learning contexts. In addition, the statistical summary also improves the model's balance and reliability when identifying diverse facets of student engagement and learning achievements. GRNN requires complex implementation [9], which demands specialized technical competencies, resulting in difficulty when used by the general scholarly population. The implementation of multiple complex algorithms leads to enhanced cost and complexity in computations and difficulties for practical use. The features of the model show reduced effectiveness when working with inconsistent or insufficient data quality from input sources. The suggested research overcomes the conventional teaching constraints by integrating AI-driven personalized learning, IoT real-time information, and adaptive strategies. Unlike fixed strategies, it provides dynamic data-driven learning that suits individual students' requirements. It increased participation, experiential learning, and critical analysis. The

SFO-IRNN model guarantees high performance with improved deeper understanding of renewable energy through live simulation and interactive learning.

5. Conclusions

The SFO-IRNN framework has assurances to be an innovative way to charge into renewable energy education with the potential to provide an engaging and personalized, adaptive learning course. The proposed system blends the use of AI-based recommendations of content with real-time IoT data obtained from renewable energy sources to create an interactive environment for students, promoting critical thinking and problem-solving skills. The data was preprocessed with handling missing values and min-max scaling. The data features were extracted using FT. The dynamic and efficient optimization of teaching strategies making use of the SFO algorithm could ensure the balance between the exploration and exploitation of the best educational approaches. The further use of (10-fold) cross-validation enhances the reliability of the model as it could evaluate its performance metrics like accuracy, f1-score, recall, and precision on different subsets of student data, thus improving its robustness and preventing overfitting. This method provides an innovative, scalable platform for enhancing renewable energy education. Students can logically relate theoretical knowledge to the real-world challenges faced. The results affirm the effectiveness of SFO-IRNN in improving learning outcomes, engagement, and hands-on knowledge of sustainable energy technologies. The current system heavily relies on real-time IoT data, that cannot always be accessible in some places. Besides, the complexity of the SFO-IRNN model may require higher computational resources. Future improvements could expand the system by integrating more diverse renewable energy sources and additional AI algorithms for increased predictive accuracy. Further research could then be directed towards exploring ways to improve the system's scalability and real-time adaptability. The online demo platform can be expanded to support real-time data integration, multi-language interfaces, advanced analytics dashboards, and broader educational applications, enabling scalable adoption in diverse learning environments and fostering enhanced personalization for global educational initiatives.

Author Contributions

Conceptualization, B.N. and K.B.S.; methodology, G.P.P.; software, K.S.K.; validation, K.B.S., G.P.P. and R.V.S.; formal analysis, G.P.P.; investigation, R.V.S.; resources, V.P.K.P.; data curation, K.S.K.; writing—original draft preparation, K.B.S.; writing—review and editing, B.N.; visualization, K.S.K.; supervision, B.N.; project administration, V.P.K.P.; funding acquisition, B.N. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

All data supporting the findings of this study are included in the article.

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Conflicts of Interest

The authors declare no conflict of interest.

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