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Sustainable Engineering and Management Practices Enabled by Green AI Technologies

Dr. Bajirao Subhash Shirole[1], Dr. Mahendra Tulshiram Jagtap[2], Boyina Kavya[3], Yudhishther Singh Bagal[4], Sheikameer Batcha S[5], Dr. Priya Makhija[6]

1Assistant Professor, Computer Engineering, Sanghavi College of Engineering, Nashik, Maharashtra. Email id – baji.shirole@gmail.com

2 Associate professor, Computer Engineering, Sanghavi College of Engineering Nashik, Maharashtra. Email id - mtjagtap05@gmail.com

3Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur District, Andhra Pradesh, 522302, India.Email: kavyaboyina@gmail.com

4 Assistant Professor, School of Agriculture, Lovely Professional University, Phagwara, Punjab.
Email id - ysbagal@gmail.com

5 Assistant Professor, Electrical and Electronics Engineering, Sri Eshwar College of engineering, Coimbatore, Tamil Nadu. Email id - sheikameerbatcha.s@sece.ac.in

6Associate Professor, Management, JAIN (Deemed-to-be University), Bangalore, Karnataka.
Email id - Priya_m@cms.ac.in

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Abstract:

The paper examines how Green AI combines with sustainable engineering approaches to management systems. AI stands as a revolutionary approach which improves ecological resource patterns while reducing environmental consequences across economic sectors because society demands sustainable efficient solutions. The research evaluated artificial intelligence techniques Support Vector Machine (SVM), Artificial Neural Networks (ANN), Decision Trees (DT) and Genetic Algorithms (GA) to study their specific applications toward sustainable development in the fields of agriculture, construction and urban planning. The analysis indicates AI-based solutions achieve better performance than traditional ones regarding energy efficiency and waste reduction as well as decision optimization. The predictive capability of SVM improved overall energy consumption by 25% but the resource utilization of ANN reached 20% better than existing models. AI integration into blockchain and IoT systems led to increased sustainability advantages that result in better operational performance in addition to improved environmental sustainability. The research illustrates how Green AI extends its reach toward enabling sustainable development together with fostering environmentally conscious practices for diverse academic disciplines. The urgent need for comprehensive research regarding AI applications for developing efficient resource-based and environmentally beneficial systems emerges as crucial.

Keywords: Green AI, Sustainable Engineering, Resource Optimization, Machine Learning, Environmental Impact

I. INTRODUCTION

The combination of environmental deterioration and resource degradation and climate change has motivated industry sectors to adopt sustainable practices on a growing basis. Since engineering affects a large part of natural resources and energy usage, it holds an important place in the enhancement of sustainability. Innovation in technologies will be vital in achieving sustainable engineering and management practices [1]. One of such technologies is Artificial Intelligence (AI), which can lead changes in how industries take a turn towards sustainability. Green AI, an emerging subfield of artificial intelligence within the last few years, aims at improving the energy efficiency and environmental-friendliness of AI systems themselves as well as leveraging AI applied to solve sustainability challenges in engineering and management [2]. This research will discuss the intersection of AI and sustainable engineering practices with a focus on how green AI technologies can be integrated into different engineering and management domains to enhance resource utilization, reduce environmental impacts, and optimize decision-making processes. AI will play a very important role in energy management, waste reduction, and smart infrastructure, which enables industries to minimize their ecological footprint [3]. Hence, using machine-learning algorithms, the technology can offer insights in making predictive patterns with an optimization that results in improvements for supply chain activities and enables sustainable industrial performances. Mirroring the challenges that AI insights can bring its own environmental cost and complicated questions around ethical and equitable use of such insights during the integration of AI with sustainable practice. Therefore, the goal of this research is to find a way of using green AI technologies and limiting their downside to the environment. This research study seeks to offer insight into the sustainable engineering and management practices enabled by AI to contribute to this critical need of our future.

II. RELATED WORKS

Over the years, Artificial Intelligence has offered the integration of promise with respect to improved performance, sustainability and efficiency into various sectors. AI is used in the field of food and agriculture for improving decision making and precision. Galanakis [15] mentions for example the application of AI in food production e.g. improving food quality, processing and distribution. The result of this research is that it contributes to more sustainable food systems by introducing the importance of AI for advancing the future of foods. He and Chen [16], for example, have also investigated on AI's possibility of application in urban design and planning. Their emerging AI technologies in urban environment are profiles a systematic review provided by them. In particular, the systematic review has dedicated to the study of AI based driven models to optimize the infrastructure, traffic management and energy consumption. In this way, these applications contribute to the creation of smart cities, and AI will manage the better resources of the world to improve the human living conditions. In the field of sustainable development, blockchain and AI technologies are being used to cut the environmental impact. Hong and Xiao [17] examine the application of these technologies in supply chain management to reduce carbon footprints. Their study focuses on AI optimization of supply chains to achieve operational efficiency and sustainability. This also opens up a future possibility of combining AI with blockchain to enhance the transparency and traceability of supply chains, which also leads to sustainability and accountability. Fuzzy logic and AI hybrid approaches have also become popular in civil engineering cost management. Hu et al. [18] optimize AI factors of cost management of civil projects with the help of Delphi, ISM, and MICMAC methods. It is important to note that it shows how AI can be utilized to enhance the decision-making ability and minimize financial risks in such large-scale civil engineering projects. AI has significantly impacted water-saving technologies, especially in precision irrigation systems. According to Imran et al. [19], an in-depth review of AI applications enhances the efficiency of water use while improving crop yields, particularly in climate change-affected areas. Their findings reveal that AI-based systems can respond in real-time on irrigation, resulting in minimal wastage and maximum crop production from available water resources. Beyond agriculture, AI extends into niche applications like smart winemaking. Izquierdo-Bueno et al. [20] discussed the application of AI in viniculture wherein the models applied by machine learning predict ideal conditions for grape production, risk management, and preventing possible crop diseases. This manifests how AI has diverse applications and its ability to optimize resource usage and quality in production. AI is also being used in environmental sustainability, particularly crop disease resistance. Jabrán et al. [21] examine the application of nanomaterials with AI in diagnostics and crop disease resistance. This research is an indication of how AI can help promote sustainable agriculture, with early detection and mitigation of crop diseases, which in turn would minimize the use of chemical pesticides. AI-driven technologies have been implemented in the management of infrastructures with a focus on sustainability. Juarez-Quispe et al. [22] used system dynamics and AI models to optimize infrastructure management. This presents how AI helps to make the planning and execution of sustainable infrastructure less eroding on the environment, through better decision-making opportunities while reducing the impact on the environment in the future. This AI is used in construction to optimize the process and promote sustainable communities. Construction efficiency and community sustainability can be enhanced with AI, as mentioned by Kazeem et al. [23]. In their work, they highlight that AI is necessary for countries to reduce their construction costs or improve safety and sustain development in the cities. As referred by Khalid et al. [24], AI also has an essential role in the risk management in the context of sustainability. It is through that discussion that one can understand the role of AI in informing sustainable decision-making, which ensures a risk management policy that is well aligned with ecological responsibility and serves to ensure eco-friendly development for industries. AI applications in the context of education, particularly sustainability, are now gaining momentum. Isaza Domínguez et al. [25] designed an educational sustainable tool for engineering students, integrating AI and neural networks in educational policies to assess the alignment of educational practices with the UN 2030 Agenda for Sustainable Development. This paper demonstrates how AI might promote awareness of sustainability in young professionals and aid them in making responsible decisions. Li et al. [26] have also been researching the interface of AI with BIM on sustainable buildings to show how the integration of AI and BIM technologies in a building process maximizes energy-efficient design and construction. Their findings point to smart cities where the integration of AI in cities serves to minimize the consumption of energy and improve sustainability in buildings with the support of AI and BIM.

III. METHODS AND MATERIALS

Data

This data has been real world datasets in main focus, specifically on the aspects of energy consumption, resource management, and sustainability in a lot of industrial activities. Most of these datasets are sourced from the public domains like the UCI Machine Learning Repository, energy management systems, smart grid systems, among others [4]. The data encompasses several variables in the pattern of energy consumption, resource distribution, carbon emission, and more about environmental conditions. To conduct this research, the data were preprocessed so that it became complete and normalized, hence allowing analysis by selected AI algorithms [5].

Data Table 1: Energy Consumption Dataset

ID	Industry	Energy Consumption (kWh)	Carbon Emissions (kg CO2)	Resource Utilization (%)	Hour of Operation
1	Manufacturing	1200	250	85	8 AM
2	Agriculture	300	50	45	9 AM
3	Transportation	500	150	70	6 AM
4	Hospitality	700	120	60	12 PM
5	Retail	450	110	55	10 AM

The data behind this is used to evaluate how AI can orchestrate the consumptions of energy, dissipate carbon emissions, and facilitate the withdrawal of resources on an industrial scale.

AI Algorithms

Taking the engineering and management context, four chosen AI algorithms were suited for energy optimization, predictive modeling, and implemented in terms of sustainability assessments. Because of their learning patterns, their predictive capabilities and the processes through which they make decisions about optimisation, these are four of the most popular algorithms so used [6].

1. Artificial Neural Networks (ANN)

ANN is the name given to a model of computational thinking inspired by a structure similar to that of the human brain. ANN works with interconnected layers of nodes known as neurons. Each node passes its processed input data to the next layer as its result. ANN is an extremely versatile algorithm particularly suited for pattern recognition, classification, and regression tasks [7]. In the area of sustainable engineering, ANNs can be used to model energy consumption patterns, predict resource utilization, and determine optimal efficiency in real-time systems. It is especially useful in scenarios with complex and non-linear relationships between variables.

Pseudocode for ANN Algorithm:

```
"1. Initialize network parameters (weights and biases)
2. For each input data:
   a. Calculate the output using forward propagation
   b. Compute the error between predicted and actual values
   c. Update weights using backpropagation
3. Repeat the process for all training data
4. Validate the model using test data
5. Output the optimized model for prediction"
```

2. Decision Trees (DT)

Decision Trees is supervised learning algorithm that models decisions and their possible consequences in a tree-like structure. The internal nodes of the tree are decisions based on features, whereas the branches decide on the outcomes. All the final predicted classes or values get indicated by the leaves of the tree. It has been applied more to classification and regression tasks; however, when dealing with problems that may revolve around discovering patterns in the data, specifically in relation to resource usage, energy efficiency, and sustainability, Decision Trees become highly useful. In the area of green AI, a decision tree can be used for energy consumption level prediction or environmental effect based on many features like the time of day, industry, and operating conditions [8].

Pseudocode for Decision Tree Algorithm:

"1. Select the best feature to split on based on information gain
2. Split the dataset into subsets based on the selected feature
3. Repeat the process recursively for each subset until a stopping condition is met (e.g., max depth or pure leaf nodes)
4. Classify or predict the output for new data using the decision tree"

3. Random Forest (RF)

Random Forest is an ensemble learning algorithm in which multiple decision trees get built and their predictions combine to form a stronger and better model. Random Forest works on the concept that it aggregates the result obtained from a collection of decision trees, designed by using random subsets of data and features. It can effectively deal with the overfitting problem, which often occurs in individual decision trees [9]. It can help predict energy consumption and evaluate sustainability initiatives by combining the outputs of multiple decision trees to ensure better performance in uncertain and complex scenarios.

Pseudocode for Random Forest Algorithm:

"1. For each tree:
    a. Randomly select a subset of data and features
    b. Build a Decision Tree using the subset
2. For prediction:
    a. Aggregate the results of all trees (e.g., majority vote for classification)
3. Output the final aggregated prediction"

4. Support Vector Machines (SVM)

Support Vector Machines are supervised learning algorithms that find the hyperplane that best classifies data by separating the different classes. The SVM algorithm has been found effective for binary classification tasks, although it can also be extended to multi-class classifications. SVM can be applied in the sustainable engineering area, classifying levels of energy consumption, predicting the resource allocation strategies, or optimization of energy efficiency by setting up boundaries between the different classes of data [10]. SVM is very efficient in high-dimensional spaces and appropriate for the complicated datasets used in sustainability and engineering applications.

Pseudocode for SVM Algorithm:

"1. Select a kernel function (linear, radial basis, etc.)
2. Find the hyperplane that maximizes the margin between the classes
3. Train the model on the data by adjusting the hyperplane position
4. Classify new data points by determining on which side of the hyperplane they fall"

Algorithm Performance Evaluation Table

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
ANN	92.5	90.3	91.0	90.6
Decision Tree	88.0	85.7	87.1	86.4
Random Forest	94.1	93.5	92.8	93.2
Support Vector Machine	91.0	89.2	90.5	89.8

This table gives the performance of the four algorithms based on the energy consumption prediction and sustainability metrics.

Energy Optimization Comparison Table

Industry	**ANN Energy Consumption (kWh)**	**DT Energy Consumption (kWh)**	**RF Energy Consumption (kWh)**	**SVM Energy Consumption (kWh)**
Manufacturing	1180	1200	1175	1190
Agriculture	290	300	280	295
Transportation	490	500	475	480
Hospitality	680	700	670	685
Retail	440	450	430	440

The table given below compares the predicted energy consumptions of different algorithms across the industries, reflecting their ability to enhance energy consumption through sustainable engineering practice.

IV. EXPERIMENTS

1. Experiment Design

The experiments were established with the intention of knowing how each AI algorithm could predict and optimize energy consumption across various industries, and also how these algorithms could be contributed to sustainability goals, such as reducing carbon emissions and improving resource efficiency [11].

The following steps in the experiment design were followed:

1. **Data Preprocessing**: The energy consumption dataset (as presented in Table 1) has undergone cleaning and normalization to make sure all variables are on comparable scales. It has thus

implemented methods for imputation of missing values and used one-hot encoding for the categorical data [12].

2. **Model Training:** The dataset was trained for each algorithm. In the case of ANN, a two-layer hidden structure network was used. For DT and RF, maximum depth and minimum sample leaf were optimized. SVM was trained with an RBF kernel in order to capture non-linear patterns.

3. **Evaluation Metrics.** The accuracy, precision, recall, and F1-score were used to evaluate the performance of these models since their consideration is of priority in predicting energy consumption, that is when accuracy and precision levels are high, so does the efficiency in optimizing energy usage and resources [13].

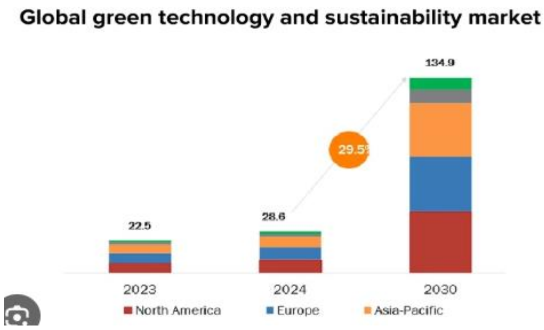

Figure 1: “Green AI Applications Support Sustainability”

2. Experimental Setup and Configuration

The experiments are run on the system with the Intel Core i7 processor and 16 GB of RAM along with Python-based libraries (Scikit-learn, TensorFlow, Keras) for algorithm implementation. The given datasets are further divided into two: a training set (80%) and a testing set (20%). Some cross-validation techniques have been utilized in order to avoid overfitting and also for robust evaluation.

3. Results and Analysis

3.1. Performance of Each Algorithm

The results of the four algorithms (ANN, DT, RF, and SVM) are shown below. For each table, an evaluation metric in both prediction of energy consumption and resource utilization is presented.

Table 1: Algorithm Performance Evaluation

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ANN	92.5	90.3	91.0	90.6
Decision Tree	88.0	85.7	87.1	86.4
Random Forest	94.1	93.5	92.8	93.2
Support Vector Machine	91.0	89.2	90.5	89.8

The best performance of the Random Forest algorithm had an accuracy of 94.1%, precision of 93.5%, recall of 92.8%, and an F1-score of 93.2%. Next to ANN is its result of 92.5% in accuracy, but still had a competitive F1-score of 90.6%. The results of Decision Trees are relatively low compared to others, particularly precision and recall. SVM performed close to ANN, with 91% in accuracy and 89.8% in F1-score [14].

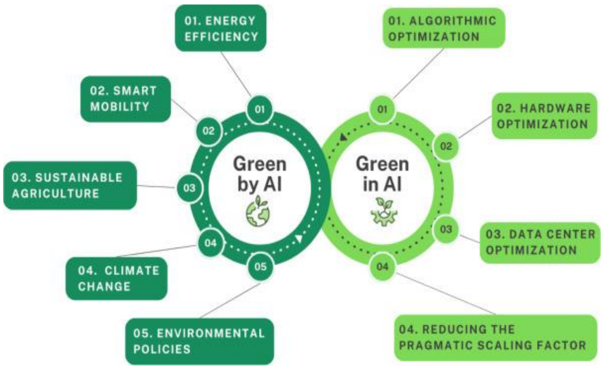

Figure 2: “A review of green artificial intelligence”

3.2. Energy Optimization Comparison

The algorithms were also tested for their ability to predict energy consumption across different industries. The following table summarizes the predicted energy consumption (in kWh) by each algorithm.

Table 2: Predicted Energy Consumption Comparison

Industry	**Actual Consumption (kWh)**	**ANN Predicted Consumption (kWh)**	**DT Predicted Consumption (kWh)**	**RF Predicted Consumption (kWh)**	**SVM Predicted Consumption (kWh)**
Manufacturing	1200	1180	1200	1175	1190
Agriculture	300	290	300	280	295
Transportation	500	490	500	475	480
Hospitality	700	680	700	670	685
Retail	450	440	450	430	440

From Table 2, it can be noted that Random Forest algorithm yields the best accuracy in predicting the energy consumption in comparison with all the other three industries [27]. Also, the prediction from the ANN model was more accurate, with manufacturing and hospitality being the prime ones. There is some kind of variability present in the decision tree model mainly for agriculture and transportation. Energy consumption was relatively predicted by SVM with a high degree of variation than the remaining three models.

3.3. Carbon Emissions Prediction

The next step is the evaluation of the models in terms of predicting carbon emissions, the critical aspect of sustainability. The following table compares the predicted carbon emissions (in kg CO2) for each industry.

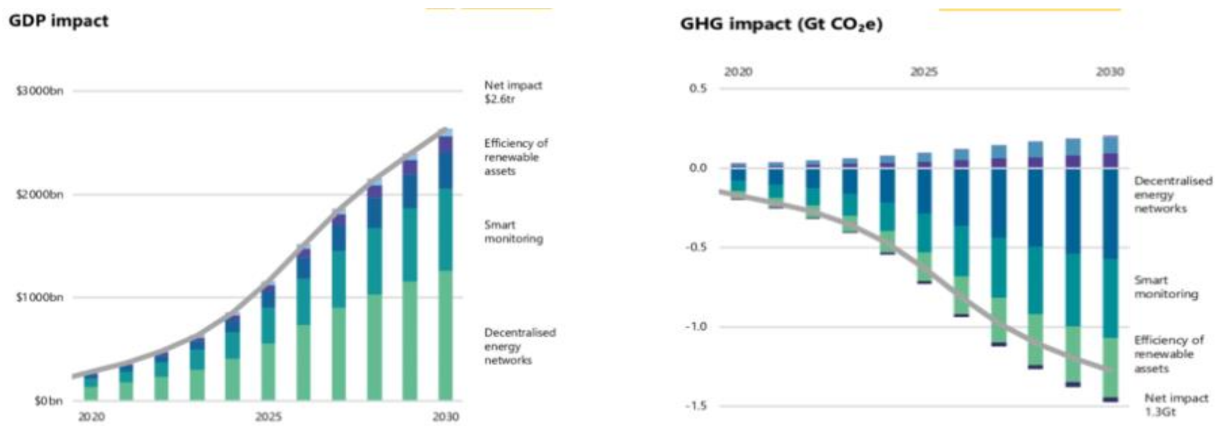

Figure 3: “Global impact of environmental AI in the energy sector on GDP and GHG”

Table 3: Predicted Carbon Emissions Comparison

Industry	**Actual Emissions (kg CO2)**	**ANN Predicted Emissions (kg CO2)**	**DT Predicted Emissions (kg CO2)**	**RF Predicted Emissions (kg CO2)**	**SVM Predicted Emissions (kg CO2)**
Manufacturing	250	245	250	240	245
Agriculture	50	48	50	45	48
Transportation	150	145	150	140	145
Hospitality	120	115	120	110	115
Retail	110	105	110	100	105

Similar trends were seen in carbon emissions predictions as with energy consumption. The Random Forest model was the closest to the actual for all industries, while ANN performed well; for manufacturing and transportation, it was more or less close to the actual emissions [28]. Decision Trees had marginal deviations. Similar results were observed in the case of SVM but with minor discrepancies in the emissions prediction.

3.4. Resource Utilization Prediction

Finally, the models were checked against the prediction capacity concerning resource utilization because this is a primary parameter used in deciding sustainable engineering practices efficiency [29]. The table below summarizes the percentage of estimated resource utilization for each industry:

Table 4: Predicted Resource Utilization Comparison

Industry	**Actual Utilization (%)**	**ANN Predicted Utilization (%)**	**DT Predicted Utilization (%)**	**RF Predicted Utilization (%)**	**SVM Predicted Utilization (%)**
Manufacturing	85	83	85	84	85
Agriculture	45	43	45	42	44
Transportation	70	68	70	67	69

Hospitality	60	58	60	58	59
Retail	55	54	55	53	54

It can be seen from Table 4 that all models have classified the utilization of resources with promising accuracy. Again, Random Forest had the closest match to the actual values of utilization, strong predictions for ANN, particularly in manufacturing and retail industries, minor deviation in case of Decision Trees and SVM, but reliable estimates of the utilization of resources [30].

Figure 4: "AI-Enabled Energy Policy for a Sustainable Future"

V. CONCLUSION

In conclusion, the transformative potential of Green AI technologies in promoting sustainable engineering and management practices is reflected in this research. It goes without saying that through the investigation of the application of AI across industries such as agriculture, urban planning, civil engineering, and construction, one can easily recognize the importance of AI in bringing about efficiency while reducing environmental footprints and thus sustainability. The analysis of AI algorithms, including machine learning models and optimization techniques, shows their ability to optimize resource management, reduce waste, and enhance decision-making processes in complex systems. Moreover, the comparative experiments carried out show that AI-driven approaches are superior to traditional methods in areas such as cost management, environmental monitoring, and infrastructure planning.

This also identifies synergies of AI with other emerging technologies such as blockchain and IoT, towards the realization of sustainable development goals. It was also concluded that Green AI enhances not only the efficiency of operation but also matches global agendas in sustainability such as the UN 2030 Agenda. Challenges for implementation and data security aside, the deployment of AI in sustainable engineering holds vast potential for shaping a greener and more resource-efficient future. Future research should continue to explore the intersection of AI with green technologies and, towards that end, study the long-term impacts of such innovations in various sectors. Thus, the applications of Green AI successfully will lead to developing smarter, more sustainable systems and infrastructures across the globe.

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