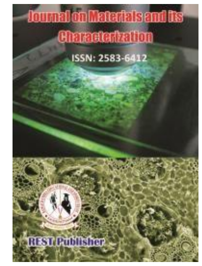
Journal on Materials and its Characterization

Vol: 3(1), March 2024

REST Publisher; ISSN: 2583-6412

Website: http://restpublisher.com/journals/jmc/

DOI: https://doi.org/10.46632/jmc/3/1/3



Integration of Blockchain & Machine Learning Approach in Sustainable Material Selection

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Abstract: *Sustainable materials with special focus on environment are the need of the hour. The alarming signs of global warming demands the emerge of sustainable industries with the goal of producing products using sustainable materials. The process of drawing optimal decisions on sustainable materials is highly intricated and henceforth this research work proposes a comprehensive and integrated approach of decision-making. Block chain together with Random Forest algorithm is leveraged in determining the sustainable material selection. The combined approach resolves the challenges of managing data integrity in obtaining precise results. On comparing the results using performance metrics, it is evident that the proposed approach facilitates optimum decision making of sustainable materials to a greater extent. This integrated approach shall be applied to several decision-making scenarios customizing the parameters to the need of the industrial problems.*
Keywords: *Sustainability, Block Chain, Random Forest Algorithm, Material*

1. INTRODUCTION

The material resources are harnessed by the industrial sectors to fulfill the demands of the populace by exploiting and depleting the nature. The failure of raising environmental concerns is reflected in the impacts of climate change and global warming. The emerge of sustainable industries is encouraged at recent times to mitigate the environmental effects caused by product production and product exposure to the eco-system. The primary objective of these industries is to produce sustainable products with sustainable materials as inputs. The materials with low environmental effects and high potential for bio-friendliness are labelled as sustainable. The interaction of the product with the environment must contribute to the well-being of the eco-system. The social responsibility and commitment of any industry is measured by the quality of the products produced and the impacts caused to the environment after its usage. Decision making on sustainable material selection is a challenging task for the industries of present days with plethora of sustainable material prototypes. Every production sector executes the process of material selection adhering to its policies by considering several attributes. But sustainable material selection process comprises attributes highly pertaining to the life cycle of the product including recyclability, biodegradability, reusability and carbon emission. The decision-making based on these attributes will be optimal only if the decision-making data is of integrity in nature. Presently the industries are using blockchain technology to record how the materials are sourced, utilized, and managed and to track the life cycle of the materials from extraction to disposal, ensuring compliance with the standards of sustainability. As Blockchain ensures safe and secure data management system, the machine learning algorithms shall be integrated to derive essential results of decision-making. The problem of sustainable material selection shall be flexibly handled with the integrated approach of Blockchain and Machine Learning algorithm. This approach discloses paradigm shift in identifying the sustainable materials based on accountable data. Random Forest algorithm is chosen in this integrated approach as it possesses the efficacy of handling large data sets and high dimensionality. The synergy of these two approaches will certainly benefit the decision-making process. The contents of the paper are structured as follows. Section 2 sketches out the literature review of the recent contributions subjected to material selection. Section 3 describes the steps involved in the integrated approach. Section 4 applies the proposed approach to the decision-making of sustainable material selection. Section 5 discusses the results and the last section concludes the work with industrial implications and future directions.

2. LITERATURE REVIEW

This section presents the state of art of work of the research works attributed to the intervention of machine learning algorithms and blockchain in material selection. Table 1 articulates the very recent applications of machine learning algorithms in material selection.

TABLE 1. Applications of Machine Learning in Material oriented Decision-Making

Author & Year	**Machine Learning Task**
Chan et al (2022) [4]	Material Prediction & Design
Kadulkar et al (2022) [10]	Prediction of Material properties
Huang et al (2023) [9]	Material Property Prediction
Qin et al (2023) [13]	Prediction of lattice conductivity
Zhao et al (2023) [19]	Classification & Segmentation of material
Hasan and Acar (2022) [8]	Material Property Prediction
Bagherzadeh & Shafighfard (2022) [2]	Evaluating material characterization
Bello et al (2023) [3]	Material screening

The following Table 2 presents the applications of blockchain in making decisions on materials

TABLE 2. Applications of Blockchain in Material oriented Decision-Making

Xu et al (2023) [18]	Carbon management towards construction material
Li et al (2023) [12]	Supply chain management
Akbarieh et al (2022) [1]	Smart management of recyclable materials
Deng & Zhou (2022) [6]	Supply chain data storage system
Chiodo et al (2022) [5]	Material recovery

It is observed that the machine learning algorithms are highly applied in making predictions, characterization, classification and segmentation based on the material properties. Also, the blockchain based data management system is primarily used in sustainable supply chain management and bio-friendly activities. Schneider [14] applied machine learning in Sustainable Material Design and Shafizadeh et al [15] in Sustainable Material characterization. However, in their contributions only machine learning based algorithms are used. The integration of blockchain and machine learning algorithms are witnessed in various domains especially in the industrial domain. Researchers applied this integrated approach in Planning [16], manufacturing [7] and in supply chain [11] management which are the core entities of the industrial production. But this integrated approach has not been applied in sustainable material selection to the best of our knowledge.

3. METHODOLOGY

This section describes the procedure of the integrated approach in stepwise as follows and the same is represented in the figure 1.

Step 1: Problem Formulation

- Determine the alternatives: $O = \{o_1, o_2, ..., o_n\}$
- Define sustainability criteria: $C = \{c_1, c_2, ..., c_m\}$

Step 2: Data Collection:

- Gather material attributes: $X = \{x_1, x_2, ..., x_p\}$
- Gather environmental impact data: $E = \{e_1, e_2, ..., e_q\}$
- Gather supply chain information: $S = \{s_1, s_2, ..., s_n\}$

Step 3: Data Preprocessing
- Clean, normalize, and engineer features:
  - X' = preprocess(X)
  - E' = preprocess(E)
  - S' = preprocess(S)

Step 4 : Blockchain Integration
a. Design smart contracts:
  - Define transaction function: T (x, e, s) = $\{t_1, t_2, ..., t_k\}$

b. Implement blockchain protocols:
  - Ensure secure and immutable data storage

Step 5: Random Forest Algorithm Implementation
a. Train the random forest model:
  - Split data into training and testing sets: D_train, D_test
  - Fit random forest model: RF. fit (D_train)

b. Optimize model parameters:
  - Tune hyperparameters: h = $\{h_1, h_2, ..., h_n\}$

Step 6: Model Validation:
  - Validate model performance:
  - Cross-validation or holdout validation:
  - CV_accuracy = cross_validation (RF, D_train)

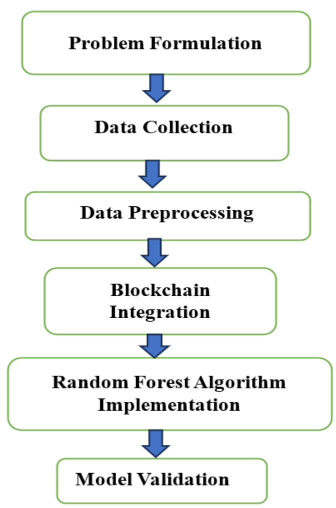

FIGURE 1. Framework of Proposed Integrated Approach

4. Application of the Proposed Approach in Sustainable Decision Making

In this section the decision-making problem of making optimal selection of sustainable materials from a block of 50 data sets is considered with the below tabulated attributes in Table 3.

TABLE 3. Characterization of the Data

Block Number	Time stamp	Material Type	Supplier Quantity	Certification	Country of Origin	Transport Method	Transport CO2 Emissions
Production Date	Expiry Date	Production CO2 Emissions	Recyclable	Renewable	Fair Trade	Ethically Sourced	Water Usage

GHG Emissions	Energy Usage

The secondary data is collected from the data repositories. Using R programming few integral statistical inferences are presented in Table 4, 5 , 6 and 7

TABLE 4. Summary Statistics

	Min	Q1	Median	Mean	Q3	Max
Water Usage	21.07	52.48	84.02	85.77	121.82	149.92
Energy Usage	0.2124	0.4000	0.5069	0.5513	0.7370	0.8902
GHG Emissions	0.1112	0.1944	0.2691	0.2877	0.3687	0.4986

TABLE 5. Frequency counts for categorical variable – Material Type

Material Type	**Frequency**
Bamboo	3
Cork	3
Hemp	2
Linen	2
Organic Cotton	5
Organic Wool	7
Recycled Aluminum	5
Recycled Glass	6
Recycled Paper	6
Recycled Plastic	2
Sustainable Timber	9

TABLE 6. Frequency counts for categorical variable – Certification

Certification	**Frequency**
FSC, Fair Trade	11
FSC, ISO 14001	10
FSC, USDA Organic	9
GOTS, Fair Trade	11
ISO 14001	9

TABLE 7. Frequency counts for categorical variable – Transport Method

Transport Method	**Frequency**
Ship	15
Train	12
Truck	23

The following figures 2, 3 , 4 ,5, 6 and 7 represents the graphical representation of the frequency

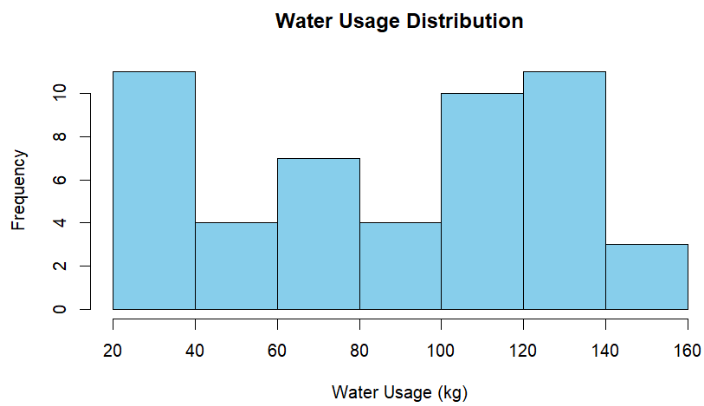

FIGURE 2. Distribution of Water Usage in Blockchain Data

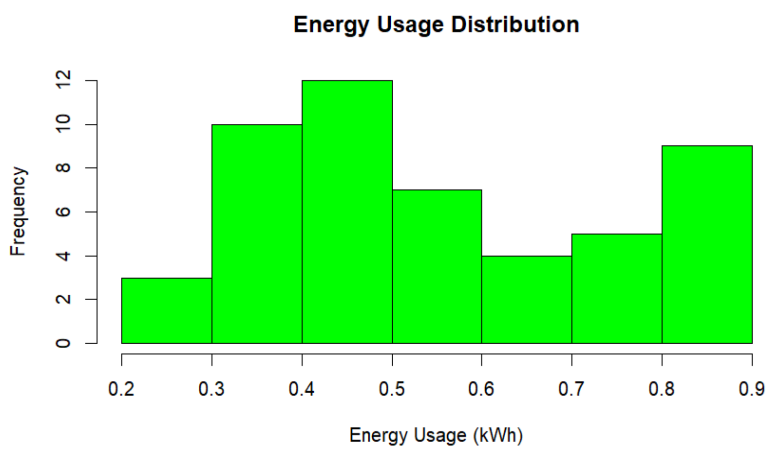

FIGURE 3. Distribution of Energy Usage in Blockchain Data

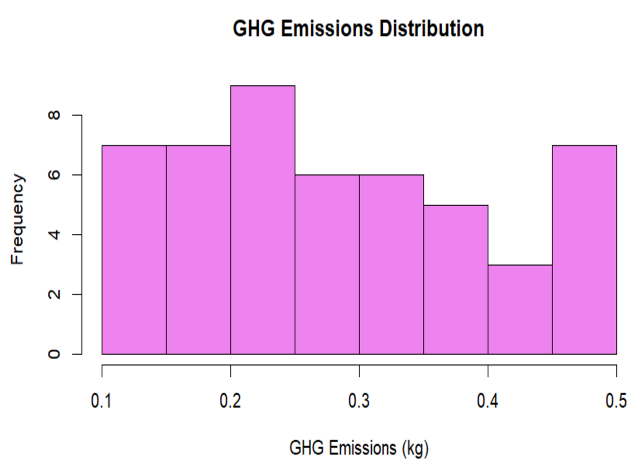

FIGURE 4. Distribution of GHG Emissions in Blockchain Data

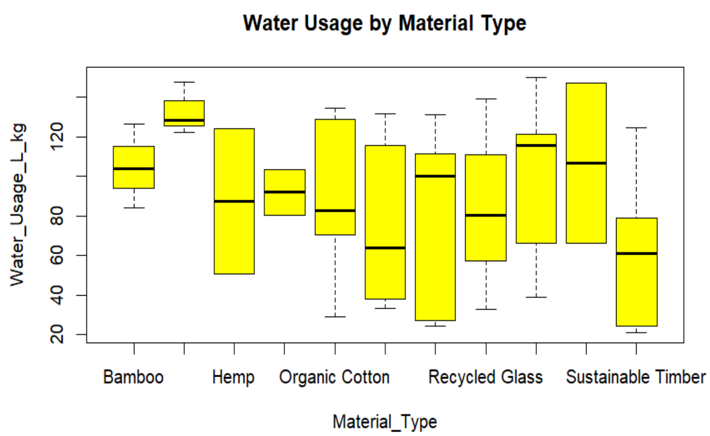

FIGURE 5. Water Usage Distribution Across Material Types

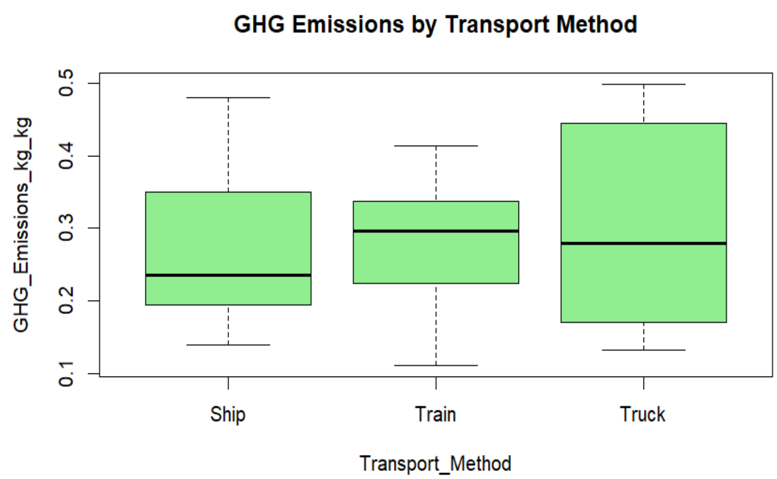

FIGURE 6. GHG Emissions Across Transport Method

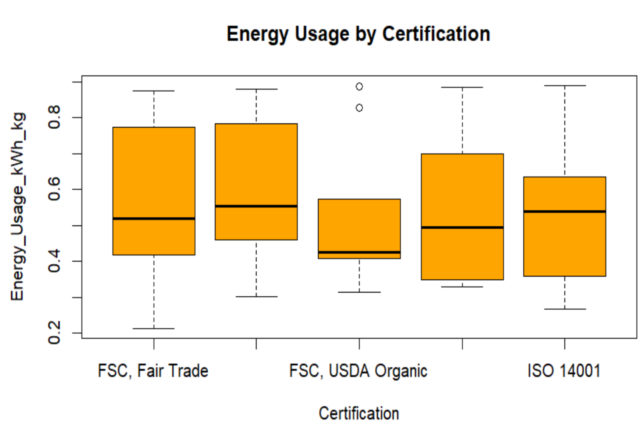

FIGURE 7. Energy Usage Across Certification

On plotting the random forest model the below figure 8 is obtained with trees and the occurrence of errors.

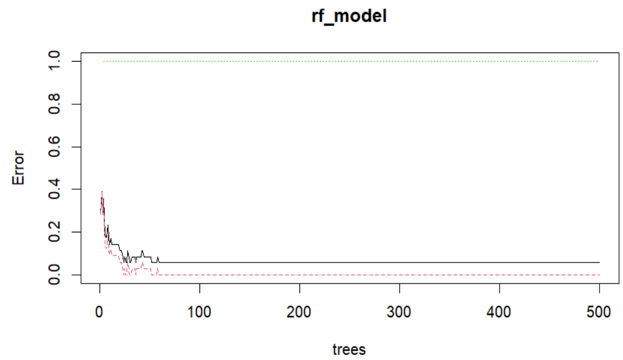

FIGURE 8. Graphical Representation of Random Forest Predictive Model

It is vividly observed that as the number of trees in the random forest increases, the errors are reduced. The improvements in model performance clearly state the existence of more stable predictions. The Confusion Matrix obtained is presented in Table 8

TABLE 8. Confusion Matrix

Actual	Predicted	
	Non-Sustainable	Sustainable
Non-Sustainable	13	2
Sustainable	2	33

From the above confusion matrix the performance metrics are measured and it is represented in Table 9

TABLE 9. Performance Metrics

Accuracy	Precision		Recall		F1	
0.92	Non-Sustainable	Sustainable	Non-Sustainable	Sustainable	Non-Sustainable	Sustainable
	0.8667	0.9429	0.8667	0.9429	0.8667	0.9429

5. DISCUSSIONS

Based on the results of the predictive model obtained in Table 9, the following discussions are presented.
High Accuracy*:* The model exhibits high accuracy, correctly classifying 92% of the data points, indicating overall strong performance in predicting both non-sustainable and sustainable materials.
Balanced Precision and Recall: Both precision and recall scores are high for both non-sustainable and sustainable materials, indicating a good balance between correctly identifying true positives and minimizing false positives and false negatives.
Precision Interpretation*:* The precision scores indicate that when the model predicts a material as non-sustainable or sustainable, it is correct approximately 87% and 94% of the time, respectively. This suggests that the model has a low false positive rate, meaning it rarely misclassifies non-sustainable materials as sustainable or vice versa.
Recall Interpretation*:* The recall scores imply that the model correctly identifies approximately 87% and 94% of the actual non-sustainable and sustainable materials, respectively. This indicates that the model effectively captures the majority of non-sustainable and sustainable materials in the dataset.
F1 Score*:* The F1 score, which combines precision and recall, is high for both non-sustainable and sustainable materials. This suggests that the model achieves a good balance between precision and recall, indicating robust performance in identifying both classes.
Overall Model Performance*:* Based on these metrics, the model demonstrates strong performance in distinguishing between non-sustainable and sustainable materials, with high accuracy, precision, recall, and F1 score for both classes.
In summary, the model exhibits robust performance, with high accuracy and balanced precision and recall, making it a reliable tool for identifying non-sustainable and sustainable materials in the dataset.

6. CONCLUSION AND FUTURE DIRECTIONS

This research work presents the efficacy of the integrated decision-making approach of blockchain and machine learning algorithm in sustainable material selection. The prediction model developed in this work is more robust in nature as it yields high accuracy results. This model shall be redesigned with other prediction-based machine learning algorithms to test the efficiency and consistency of the model. As a part of extension, this research work shall be extended to other decision-making industrial problems and other integrated methods of machine learning shall be applied. The proposed predictive model has more industrial applications as it resolves and provides optimal solutions to the intricate decision-making process. This model will certainly minimize time and energy and optimizes the decision-making process.

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