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Article

Research on the design of biomimetic cultural and creative products driven by mechanical force

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Abstract: The incorporation of biomimetic ideas into product design has emerged as a viable strategy for increasing creativity and utility in cultural and creative products. This study focuses on the design of a household appliance, especially a cultural one, by substituting standard materials with novel alternatives powered by mechanical forces. The objective of this research is to provide a thorough framework for assessing the quality of the newly constructed home appliance by utilizing a unique technique called Adaptable Pelican optimization fine-tuned Gradient boosting machine (APO-GBM). We apply powerful machine learning techniques to predict product quality by identifying essential features like design quality, durability, and user satisfaction. The results show that the application of mechanical forces increases the vessels' functional efficiency and durability in addition to improving their appearance. The hybrid model is highly accurate in forecasting product quality, opening the path for future advances in biomimetic design. The study's findings highlight the possibility of combining mechanical forces with biomimetic concepts to produce unique, cultural, and creative products. This information may be very helpful to manufacturers and designers who want to improve the sustainability and quality of their products.

Keywords: biomimetic; creative products; product design; product quality; materials; mechanical forces

1. Introduction

The clearer biomimetic or biomimicry approaches and techniques that make biological information understandable and applicable to challenges in design and engineering are becoming more and more necessary as cultural designers and engineers turn more and more to nature as a source of similar solutions. A diverse variety of professions, experts in materials science, biology, engineering, architecture, and product and industrial design, are part of the biomimicry practitioner community [1]. Biomimetic architecture is one of these multidisciplinary approaches to sustainable design that adheres to a set of principles rather than stylistic codes. As opposed to merely drawing inspiration from nature for the aesthetic elements of built form, biomimetic architecture seeks to use nature to solve energy-saving and functional design issues [2]. A unique biomimetic architecture comprising crystalline prisms or platelets, needles, columns, or rods encapsulated in an organic matrix is credited with giving bio composites the remarkable mechanical properties that set them apart from conventional engineering materials [3]. Environmental concerns were the original driving force behind cultural design for sustainability, but it has since expanded to include social, economic, and environmental aspects of production in addition to moral and ideological considerations. It also moved from being a general clean production method to a product-focused approach [4]. The activity of creating objects, systems, or materials via a design that draws inspiration from live things or their interactions.

More transparent biomimicry approaches and methodologies are needed to make biological knowledge more comprehensible and useful for design and engineering problems since designers and engineers rely more and more on nature for comparable information [5]. A variety of frameworks for infrastructure sustainability are gaining traction globally and signify a first step in addressing the environmental and social effects of infrastructure development and operation on a global scale [6]. The prominence of sustainability strategies, plans, and rating systems in infrastructure projects has raised awareness of the triple-bottom-line sustainability implications that occur throughout the asset duration [7]. Mechanical characterization of biological materials is a difficult process due to their great heterogeneity. Among the most difficult problems in solid mechanics is computational contact mechanics [8]. The benefits of mechanical energy are its infinite supply and ability to be transformed into other types of energy. The equipment that provides users with the benefits of mechanical energy might wear out and require expensive repairs, which is a drawback of mechanical energy [9,10].

The objective of the study to develop a comprehensive framework for assessing the quality of Biomimetic cultural and creative products, specifically household is appliances. The study investigates Adaptable Pelican optimization fine-tuned Gradient boosting machine (APO-GBM) the impact of mechanical forces on product design, functionality, durability, and user satisfaction, enhancing sustainability and creativity.

Contributions of the study

1) The study advances the understanding that the biomimetic principle enhances creativity and functionality in product design, specifically in cultural and creative household appliances. By mimicking natural processes and structures, a designer creates more innovative and effective products.
2) The research highlights new potential for improving product quality, by substituting standard materials with novel alternatives that are driven by mechanical forces. The approach leads to more sustainable and efficient designs, promoting environmental consciousness in product development.
3) The introduction of the adaptable pelican optimization finetuned gradient boosting machine (APO-GBM) provides a robust framework for evaluating product quality. The innovative method not only enhances the accuracy of quality predictions but also identifies crucial features such as design quality, durability, and user satisfaction, making it a valuable tool for manufacturers and designers.
4) The findings demonstrate that the incorporation of mechanical forces not only improves the aesthetic appeal of the product but also significantly enhances its functional efficiency and durability.

The research follows the organization, section 2 presents the related work of biomimetic cultural and creative products driven utilized Machine Learning (ML) algorithm. Section 3 demonstrates the proposed method including dataset, data-preprocessing, feature extraction, and classification. Section 4 presents the experimental setup, comparative research, and study discussion. Section 5 finally concluded the research.

2. Related work

To create bionics that could be printed in three dimensions using a machine learning (ML) approach and a model system that employs natural biomaterials [11]. It illustrates that in comparison to natural collagen (NC), atelocollagen (AC) has favorable physical qualities for printing. The weakly elastic, temperature-responsive structure of AC gel generated a soft, cream-like architecture with low yield stress, in contrast to the strongly cross-linked, temperature-responsive, irreversible behavior of NC gel, which caused brittleness and high yield stress.

Innovative interdisciplinary processes that connect engineers, architects, material scientists, and manufacturers could provide different approaches to more lightweight, environmentally friendly architectural applications [12]. A lightweight construction with optimum cross-sections and good performance was achieved by the use of Natural Fiber-Reinforced Polymer Composites (NFRP) derived from plants, also known as Bio composites.

It emphasizes the use of useful guidelines and deep learning (DL) integration into 3D bio-printing technology [13]. It discusses how DL could be used in a variety of 3D bio-printing processes, including image segmentation and processing, optimization of printing parameters, in-situ correction, and enhancement of the tissue maturation process.

A presentation of the promises and claims made by practitioners of biomimicry can be found on the Biomimicry Global Network (BGN) homepage [14]. The suppositions and needs of these promises are evaluated in light of the most recent literature. The results highlight the need for a certain ethos and a respectful interaction with nature to go hand in hand with the technological efforts of biomimicry for the technique to fulfill its promised potential.

It looks at factory organization lessons that are transformed into the bio-inspired idea of reconfigurable colonic architecture. The use of genetic regulatory networks in the biological cell cycle is then discussed [15]. While complexities would be difficult to execute in an industrial environment on Mars, standard electrical engineering design captures much of the spirit of biological circuitry, with a focus on feed-forward and feedback loops to incorporate resilience.

It provides an overview of the state and development of ML applications from several perspectives, including material design, in situ monitoring and control, scaffold performance evaluation, and parameter optimization in the fabrication model [16]. Outlining the problems that now need to be solved and possible solutions might lead to the development of a generic framework that digitally combines scaffold design, bio-printing, and performance assessment.

It concentrates on how different engineering system designs might enhance biomimetics more effectively. A section highlighting the kinds of natural systems that might aid in better design could be included. In addition, a specific study of several biomimetics application fields such as architecture, biomedicine, and aerospace was provided [17].

In contrast to traditional biomaterials or synthetic materials, biomimetic scaffolds derived from natural biomaterials can provide cells with an extensive range of biochemical and biophysical stimuli that replicate the extracellular matrix (ECM) inherent in biology [18]. The study presents a summary of the current developments in biomimetic natural biomaterials (BNBMs), encompassing advancements in production, functioning, possible uses, and upcoming obstacles.

It provides a Bidirectional encoder representation from the transformers (BERT) model that is bidirectional and enabled by connected biological techniques to aid in biomimetic design, enhance design efficiency, and enrich the biomimetic information [19]. As part of the database, it takes the biological strategies and dimensional data out of nature. Finding a biological strategy is aided by the language expression model BERT. Based on the examination of linked biological strategies, Bio Design provides quantitative findings for biomimetic methods.

In digital and artificial learning environments, it may be beneficial to apply biomimetic learning design concepts, such as personal difference, implicit support, interaction and integration, developmental discontinuity, and adaptability [20]. The objectives of this strategy are to combine implicit and explicit learning, facilitate self-regulation, and customize and adjust learning experiences.

Research gap

The research on designing Biomimetic cultural and creative products driven by mechanical force faces several real-time challenges. One significant problem is the integration of Biomimetic principles into the design process, it necessitates a profound comprehension of both natural systems and the particular cultural settings in which the items are used. Additionally, identifying and selecting suitable novel materials that effectively harness mechanical forces while ensuring sustainability presents a complexity in material science and engineering. Furthermore, developing an adaptable framework for assessing product quality using advanced ML techniques, such as APO-GBM, necessitates a robust dataset and the precise extraction of relevant features.

3. Proposed method

The studies of innovative designs of household appliances, with a particular focus on vessels, by replacing traditional materials with novel alternatives that are powered are mechanical forces. The primary objective is to develop a comprehensive framework for evaluating the quality of these newly constructed vessels. To achieve this, the research employs a cutting-edge approach using the adaptable pelican optimization fine-tuned gradient boosting machine (APO-GBM).

3.1. Material preparation

Using natural inspiration to create innovative goods and find solutions to challenging human problems is known as biomimetic design. Through an analysis of biological systems' structures, materials, and processes, designers can create solutions that are effective, long-lasting, and visually appealing. Biomimetic techniques have the potential to improve usefulness, durability, and energy efficiency in several sectors, including materials science, architecture, and product design. In the end, this design concept encourages sustainable innovation by advancing a healthy coexistence of technology and the natural environment. The research presents of galvanized steel cot a bed frame made from steel that has undergone a galvanization process, it includes applying a layer of zinc to the steel to improve the furniture it houses, both indoors and outdoors, including cots. The mild steel cot iron such as mild steel is mostly made of carbon. With a multitude of general-purpose applications, it is one of the most extensively used types of steel. Differences in carbon content across mild steel grades result in improved strength at the price of ductility. Three layers of electroplated mild steel, coated with layers of nickel, copper, and chromium, serve as the disk for the experiment. **Figure 1** shows the product structure of (a) mild steel cot, and (b) galvanized steel cot. **Table 1** shows the features of galvanized steel cots and mild steel cots.

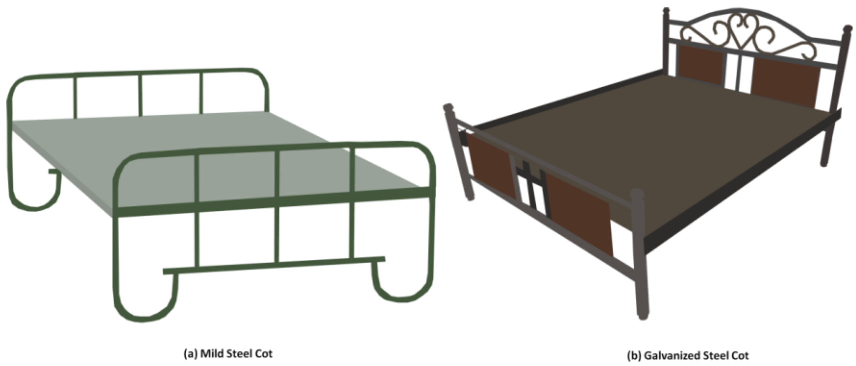

Figure 1. Framework of creative products, **(a)** mild steel cot, **(b)** galvanized steel cot.

Table 1. Features of galvanized steel cot and mild steel cot.

Feature	Galvanized Steel Cot	Mild Steel Cot
Properties	Corrosion-resistant	Malleable
	Durable	Ductile
	Low maintenance	High tensile strength
	Strong	Good weldability
	Lightweight	Low cost
Components	Frame (steel pipes)	The frame (solid steel or tubes)
	Slats (supporting bed)	Slats (supporting bed)
	Legs (stability)	Legs (stability)
	Coating (zinc layer)	No additional coating

Table 1. (*Continued*).

Feature	Galvanized Steel Cot	Mild Steel Cot
Applications	Residential furniture	Construction (beams, bars)
	Outdoor settings	Automotive parts
	Institutional use	Furniture (beds, cots)
	Camping and travel	Machinery
Advantages	Long-lasting	Cost-effective
	Minimal maintenance	Versatile in fabrication
	Aesthetic appeal	Readily available
	Versatile usage	Strong and durable

3.2. Mechanical force

A biomimetic cultural and creative product configuration changes as a result of direct interaction between two items, producing a mechanical force. When it comes to traveling across a medium, mechanical forces need a physical link, whereas natural forces, including gravity, electromagnetic, and strong and weak nuclear forces, are through space. The principle behind the design of a galvanized steel cot lies in the innovative substitution of conventional materials with novel alternatives, utilizing mechanical forces to enhance functionality and sustainability. Galvanized steel, known for its corrosion resistance and durability, serves as a robust framework that not only meets structural requirements but also offers an aesthetic appeal. By integrating mechanical systems that harness natural forces, such as springs or tension mechanisms, the cot provides improved comfort and support, promoting ergonomic benefits. The approach reflects a blend of traditional craftsmanship and modern engineering, resulting in a household appliance that is both culturally relevant and technologically advanced. The forces influence the design, stability, and performance of the cot. The primary mechanical forces involved, such as tension, compression, shear, bending torsion, and weight.

Tension refers to the pulling forces experienced by the components of the cot, particularly in the frame and slats when weight is applied. It helps maintain the integrity of the structure, ensuring that components do not separate or deform under load. The process of applying balanced inward forces to a material or structure to shrink it in one or more dimensions is called compression. **Figure 2** shows the structure of mechanical force.

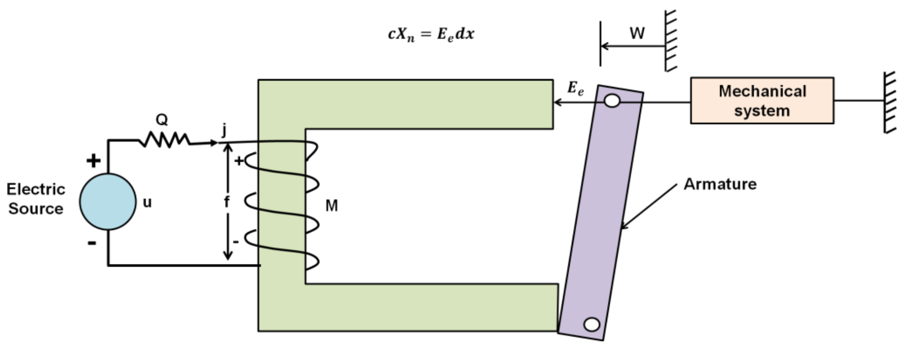

Figure 2. Framework of mechanical force.

where, σ tensile stress F is the force applied, and A cross-sectional area of the material, as shown in Equations (1) and (2).

$$\sigma = F/A \tag{1}$$

$$dW_m = F_f dx \tag{2}$$

The change in field configuration, shown by dx, draws this energy out of the field, as shown in Equation (3).

$$F_f dx = id\lambda - dW_f \tag{3}$$

It is observed that $F_f dx$ represents the gross mechanical output, of which mechanical friction is expected to create a portion, as following Equations (4)–(7).

$$cX_e = c(j\lambda) - X'_e(j,w) = jc\lambda + \lambda cj - \left(\frac{\partial X'_e}{\partial j} cj + \frac{\partial X'_e}{\partial w} dx\right) \tag{4}$$

$$E_e dx = \left(\frac{\partial X'_e}{\partial j} - \lambda\right) cj + \frac{\partial X'_e}{\partial w} dx \tag{5}$$

$$\frac{\partial X'_e}{\partial j} - \lambda = 0 \tag{6}$$

$$E_e = \frac{\partial X'_e(j,w)}{\partial w} \tag{7}$$

where e is an independent variable, the mechanical force produced statement is applicable, as following Equation (8).

$$cX_e = \frac{\partial X_e}{\partial \lambda} \partial\lambda + \frac{\partial X_e}{\partial \lambda} d \tag{8}$$

3.3. Quality prediction using adaptable pelican optimization fine-tuned gradient boosting machine (APO-GBM)

The Biomimetic cultural and creative products utilize mechanical inspired by nature. The adaptable pelican optimization (APO) fine-tuned with a gradient boosting machine (GBM) enhances design efficiency, enabling innovative solutions that mimic biological systems. The approach fosters sustainable creativity, merging technology with nature-inspired principles for optimized product development.

3.3.1. Gradient boosting machine (GBM)

A sophisticated supervised algorithm that is well-known on Kaggle ML contests with its advantages of good efficiency and adequate flexibility. GBM loss function includes an extra regularization term for the biomimetic cultural and creative products function, it prevents over-fitting and smoothest the final learning weights. The loss function is further optimized by using gradient estimates of the initial and second orders. Furthermore, GBM provides row and column collection to address this problem and allows regular words to be inserted to avoid over-fitting. Since it is supplied, model exploration is finished more rapidly, and parallel processing guarantees quicker learning. The GBM framework is explained in brief in the next paragraphs. The total of each tree's prediction score $e_l(W_j)$ is the predicted output $\hat{z}_j$ of the GBM tree representation, as following Equation (9).

$$\hat{z}_j = \sum_{l=1}^{l} e_l\left(W_j\right), e_l \in \Gamma \tag{9}$$

When the sample $j's$ characteristics are represented byW_j, regression tree space is denoted by Γ and the quantity of regression trees by l. There is a quality prediction score $e_l(W_j)$, often referred to as leaf weight, for every leaf node j in a given dataset. The most fundamental statement for ML issues is to predict product quality functions. Increasing the boost continues until the reduction of the product functions reaches a limit. The collection of functions that the model approximates is defined by Equation (10) and thus determines the regularized objective function.

$$\phi = \sum_{j=1}^{m} k, (z_j, \hat{z}_j) + \gamma^S + \frac{1}{2}\lambda \sum_{i-1}^{S} \omega_i^2 \tag{10}$$

The amount of data samples is m, and the training loss function, $\sum_{j=1}^{m} k(z_j, \hat{z}_j)$, represents how well the model matches the training set of data. The regularization term $\gamma^S + \frac{1}{2}\lambda \sum_{i-1}^{S} \omega_i^2$ is employed to penalize the complexity of the model. In additive learning processes, every tree is constructed sequentially. Every new tree is added with the knowledge of its predecessors, and refreshes the forecast values' residuals. Therefore, $\hat{z}_j^{(l-1)}$ has already been included in the outcomes of all the trees' iterations. As a result, $\hat{z}_j^{(l)}$ represents$\hat{z}_j^{(l-1)} + e_l(w_j)$ for the l^{th} iteration, and the objective function $\Phi_{(l)}$ is expressed as follows in Equation (11).

$$\Phi_{(l)} = \sum_{j=1}^{m} k\left(z_j, \hat{z}_j^{(l-1)} + e_l(w_j)\right) + \gamma^S + \frac{1}{2}\lambda \sum_{i-1}^{S} \omega_i^2 \tag{11}$$

It employs the second-order Taylor expansion given by Equation (12) to efficiently estimate the goal for the first-term loss training function.

$$\Phi_{(l)} \simeq \sum_{j=1}^{m} k\left[z_j, \hat{z}_j^{(l-1)} + h_j e_l(w_j) + \frac{1}{2} g_j e_l^2(w_j)\right] + \gamma^S + \frac{1}{2}\lambda \sum_{i-1}^{S} \omega_i^2 \tag{12}$$

where $h_j = \partial_{\hat{z}^{(l-1)}} k\left(z_j, \hat{z}_j^{(l-1)}\right)$ and $g_j = \partial^2_{\hat{z}^{(l-1)}} k\left(z_j, \widehat{z}_j^{(l-1)}\right)$ are the loss function's initial and second request gradient statistics, respectively. The following Equation (13) approximate goal is obtained in step l once the constant terms are eliminated.

$$\Phi_{(l)} \simeq \sum_{j=1}^{m} \left[h_j e_l(w_j) + \frac{1}{2} g_j e_l^2(w_j)\right] + \gamma^S + \frac{1}{2}\lambda \sum_{i-1}^{S} \omega_i^2 \tag{13}$$

The process is represented as $\sum_{j=1}^{m} e_l(w) = \sum_{i=1}^{S} \omega_i$ recast as follows Equation (14). A mapping function for the leaf index that converts an instance to a leaf I and a vector of scores expressed in leaves constructs the tree.

$$\Phi_{(l)} = \sum_{j=1}^{m}\left[\left(\sum_{j\in J_i} h_j\right)\omega_j + \frac{1}{2}\left(\sum_{j\in J_i} g_j + \lambda\right)\omega_i^2\right] + \gamma S \tag{14}$$

Simple quadratic programming is used to solve for the extreme value of $\Phi_{(l)}^*$ and the ideal leaf weight ratings for every leaf node ω_i^* in a given tree structure, as shown in Equations (15) and (16).

$$\omega_i^* = -\frac{\left(\sum_{j\in J_i} h_j\right)}{\left(\sum_{j\in J_i} g_j\right) + \lambda} \tag{15}$$

$$\Phi_{(l)}^* = -\frac{1}{2}\sum_{i=1}^{S}\frac{\left(\sum_{j\in J_i} h_j\right)^2}{\left(\sum_{j\in J_i} g_j\right) + \lambda} + \gamma S \tag{16}$$

An established structural scoring function for determining if a given leaf score vector is appropriate is found in Equation (16). A smaller number is preferred since it more closely matches the facts. A greedy strategy is devised for practical applications to find the optimal tree structure while avoiding an infinite number of different tree topologies. **Table 2** shows the hyperparameters of GBM.

Table 2. Hyperparameters of GBM.

Hyperparameter	**Value**
Learning Rate	Typically between 0.01 to 0.3
Number of Trees (l)	Depends on the dataset; often set between 100 to 1000
Regularization Parameter (λ)	Usually between 0 to 1
Complexity Cost (γ)	Usually set to a small value, e.g., 0.01
Max Depth of Trees	Commonly set between 3 to 10
Minimum Child Weight	Often set between 1 to 10
Subsample Ratio	Typically between 0.5 to 1.0
Column Sampling Ratio	Usually set between 0.5 to 1.0
Early Stopping Rounds	Typically set between 10 to 50
Boosting Type	‘gbtree’ is common for tree-based models

3.3.2. Adaptable pelican optimization (APO)

A method for swarm intelligence called the APO is developed by studying the hunting process of pelicans, a species that exhibits accurate hunting behavior in nature. As members of the family of giant swimming birds, pelicans are found worldwide in warm seas. Pelicans are adept swimmers and flyers with extremely keen eyes. The fish swimming in the water cannot avoid the pelicans’ watchful eyes, not even when they are soaring high in the air. When pelican flocks come across fish, they arrange themselves in a semicircle or a straight line to outflank the fish and guide them toward the shallows. The fish then become their meal, independent of the water that has already been collected, as they open their beaks and swim forward. It swallows the tasty fish for a satisfying meal after closing their lips and contracting their throat sacs to expel the water. APO replicates the way pelicans forage. It is capable of doing both local and worldwide searches and finding the best possible answer within the search parameters. This method has several potential applications in solving various optimization issues. The following is a mathematical representation of the algorithm.

Initialize the population.

The APO algorithm is based on a population-centric methodology, whereby pelicans are considered the constituent members of the population. A potential solution is represented by each pelican. Consider that there are M pelicans in N, an N-dimensional space. An $M \times N$ matrix, called matrix P, represents the locations of the M pelicans as follows in Equation (17).

$$O = \begin{bmatrix} O_1 \\ \vdots \\ O_j \\ \vdots \\ O_M \end{bmatrix}_{M\times N} = \begin{bmatrix} o_{1,1} & \cdots & o_{1,i} & \cdots & o_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ o_{j,1} & \cdots & o_{j,i} & \cdots & o_{j,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ o_{M,1} & \cdots & o_{M,i} & \cdots & o_{M,n} \end{bmatrix}_{M\times N} \quad j = 1,2,\dots,M, \quad i = 1,2,\dots,N \tag{17}$$

where $o_{j,i}$ is the pelican's location in the i^{th} dimension on the j^{th}visit. Given that the pelican's site is initially dispersed randomly, $o_{j,i}$ is started arbitrarily inside the lower and higher bounds of the prey hunting range for the pelican at index j in the i^{th} dimension, as shown by Equation (18).

$$o_{j,i} = min_i + q \times (max_i - min_i), \qquad j = 1,2,\dots,M, \qquad i = 1,2,\dots,N \tag{18}$$

These are the pelican's prey-hunting range at index j in the i^{th} dimension, with min_i and max_i serving as its minimal and maximum borders, respectively, and q denoting a randomly generated value inside the range$(0, 1)$.

Predict product quality function.

By considering the vector consisting of potential solutions, the quality prediction function of the APO technique is determined. Each pelican's location functions as follows Equation (19).

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_J) \\ \vdots \\ E(W_M) \end{bmatrix}_{N\times 1} \quad , j = 1,2,\dots M \tag{19}$$

where $E$the objective is function vector and E_j is predicting product quality for the j^{th} desirable result.

Find and capture prey.

Pelicans hunt for and locate prey high in the sky during this phase, after which they go toward the prey's location. The pelican's ability to search is improved by the dispersion of prey in the search space. Equations (20) and (21) represents the pelican's location update during this period.

$$o_{j,i}^{b} = \begin{cases} o_{j,i} + q \times \left(g_i - Q \times o_{j,i}\right), & E_g < E_j; \\ o_{j,i} + q \times \left(o_{j,i} - g_i\right), & E_g \geq E_j; \end{cases} \tag{20}$$

$$O_j = \begin{cases} o_j^b, E_j^b < E_j \\ o_j^b, E_j^b \geq E_j \end{cases} \tag{21}$$

where, $o_{j,i}^b$ represents the updated location of the j^{th} pelican in the i^{th} dimension, and q is a random number with a value of either $1\ or\ 2$. The number of related objective functions is E_g, and the prey's position in the i^{th} dimension is represented by g_i. The i^{th} pelican's most recent global position is o_j^b, and its objective function is E_j^b.

Execute the prey's predation.

The purpose of this stage is for the pelican to force the prey inside the locked region to migrate toward shallow water by extending its wings over the water's surface. This allows the fish to ascend and easily enter the pelican's throat sac. The pelicans are capable of catching more fish by using this predation strategy. The stage involves the following Equations (22) and (23):

$$o_{j,i}^a = o_{j,i} + D \times (1 - \frac{s}{S}) \times (2 \times q - 1) \times o_{j,i} \tag{22}$$

$$o_j = \begin{cases} o_j^a, E_j^a < E_j \\ o_j E_j^a \geq E_j \end{cases} \tag{23}$$

where, $o_{j,i}^a$ is the pelican's updated site at index j in the i dimension, as established in step 4; $D = 0.2$ is a constant; and $D \cdot (1 - \frac{s}{S})$ represents the pelican members' neighborhood radius. The variables s and S represent the current iteration number and the maximum limit of iterations, respectively. The quality prediction function of E_j^a is dependent on the location of the j^{th} pelican, and E_j^a is its most recent global position at the current step. **Figure 3** shows the flow structure of APO. Algorithm 1 shows the quality prediction model APO-GBM.

Algorithm 1 Adaptable Pelican optimization finetuned Gradient boosting machine (APO-GBM)

```
Input: APO − GBM parameters
Output: Quality prediction
Step 1: Initialize parameters
Step 2: Initialize population (pelicans)
forj from 1 to M:
fori from 1 to N:
o[j][i] = min_i + random(0, 1) ∗ (max_i − min_i)
Step 3: Evaluate the initial objective function for each pelican
forj from 1 to M:
E[j] = PredictQuality(o[j])
Step 4: Main optimization loop
For iteration from 1 to S:
Step 5: Find and capture prey
For j from 1 to M:
If E[g] < E[j]:
 else:
E[j] = PredictQuality(o[j])
 Step 6: Execute predation
forj from 1 to M:
o[j] = o[j] + D ∗ (1 − iteration/S) ∗ (2 ∗ random() − 1) ∗ o[j]
```

Algorithm 1 (*Continued*)

```
21:  E[j] = PredictQuality(o[j])
22:  Step 7: Identify an effective solution
23:  best_index = argmin(E)
24:  best_solution = o[best_index]
25:  return
```

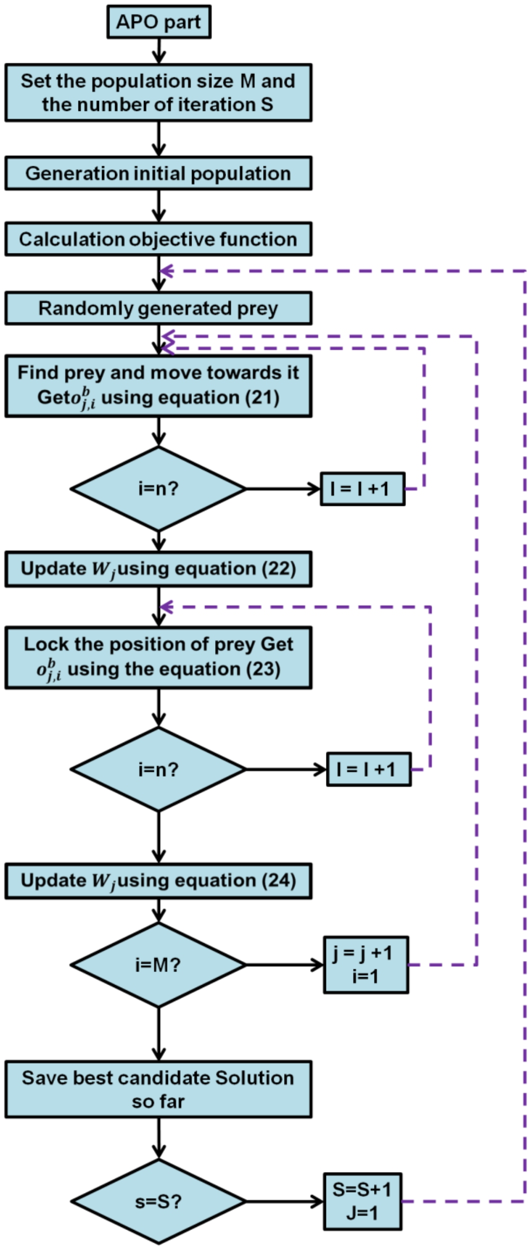

Figure 3. Flow structure of APO.

4. Result and discussion

The design of biomimetic cultural and creative products driven by mechanical forces, the experimental setup involved a series of controlled experiments simulating various mechanical forces to evaluate their effects on product design. The study highlighted the significance of integrating biomimetic principles, demonstrating that nature's solutions inform and improve the creative design process. The findings suggest that leveraging mechanical force in biomimetic designs leads to innovative cultural products.

4.1. Experimental setup

The research includes a demonstration of the Linux operating system with 64GB of memory utilized to ensure efficient processing and memory management for large information. Python 3.7 served as the primary programming language, and Core i7 CPU, 16GB of RAM, and 4G-GT (NVIDIA) with GPU-740 m. providing a flexible environment for evaluating various ML techniques.

4.2. Comparative analysis

Several assessment metrics are used to evaluate the model, including the ones for design quality, durability, user happiness, corrosion resistance, maintenance requirements, weight, cost-effectiveness, comfort level, aesthetic appeal, and sustainability which are mentioned in the methods section. Furthermore, the APO-GBM results of the proposed model are compared with those of other ML techniques. The quality prediction of the machine learning model is measured in **Table 3**, and the assessment metrics of the outcomes are described in **Table 4**.

Table 3. Comparative of quality prediction model APO-GBM.

Feature	Mild steel cot Scale (1–10)	Galvanized Steel Cot Scale (1–10)
Design quality	7	9
Durability	5	8
Weight	8	6
Corrosion resistance	2	9
Maintenance needs	6	3

Table 4. Analysis of the proposed APO-GBM method.

Feature	Mild steel cot Scale (1–10)	Galvanized Steel Cot Scale (1–10)
Cost-effectiveness	8	7
Comfort level	6	8
Aesthetic appeal	7	9
Sustainability	5	8
User satisfaction	6	9

Design quality and durability: The cot is constructed and designed to meet user needs, including functionality and usability. The process of determining a design's quality, which might include its attractiveness, efficacy, and usability, is called design evaluation. It is an essential step in the design process that may aid in issue identification, insight generation, and solution validation. Testing for durability is the process of determining if a product can endure the circumstances of its intended use over an extended period. It is a means of gauging a product's durability and resilience against abrasion, exhaustion, and external variables.

Figure 4 shows the design quality and durability evaluation of the proposed approach. The cot is constructed and designed to meet user needs, including functionality and usability. The proposed method APO-GBM, design quality of mild steel cot (7), galvanized steel cot (9), and durability offered mild steel cot (5), galvanized steel cot (8), galvanized steel cot performance effectively.

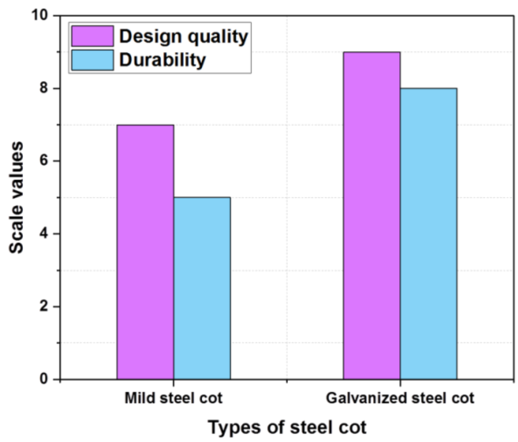

Figure 4. Comparative analysis of design quality and durability.

Corrosion resistance and User satisfaction: The capacity of a substance to resist degradation in corrosive settings is known as corrosion resistance. It is typically assessed by tracking the material's weight loss from corrosion over time. The degree of satisfaction with a product or service indicates that it satisfies the needs and expectations of the user. It is employed to assess the design, performance, usability, functionality, and support of a product.

Figure 5 shows the comparative analysis of Corrosion resistance and user satisfaction with quality prediction. The overall weight of the cot impacts portability and ease of handling, and resist degradation is environmental factors, particularly moisture. In the proposed method APO-GBM offered, user satisfaction is higher for galvanized steel (9) compared to mild steel (6). Additionally, galvanized steel exhibits significantly better corrosion resistance (9) than mild steel (2), highlighting its durability and suitability for various environments.

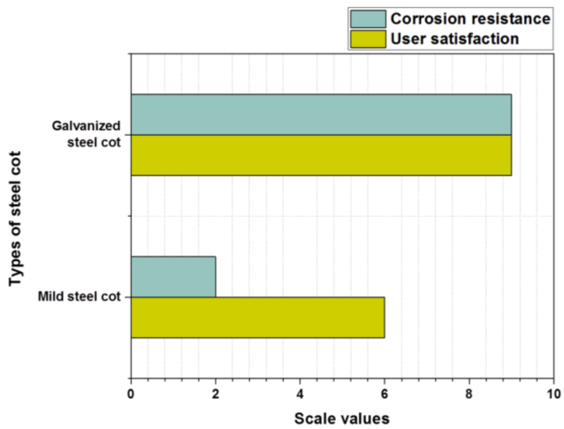

Figure 5. Corrosion resistance of user satisfaction.

Maintenance needs and Weight: A methodical approach to deciding on the kind and quantity of maintenance that each asset needs. Unexpected downtimes may be expensive, particularly for manufacturing and other asset-intensive companies. The weight of the product is a significant factor, particularly in applications where portability is essential. A lighter product enhances usability and marketability, making it more attractive to consumers.

Figure 6 shows the maintenance needs and weight of the proposed APO-GBM method. The frequency and type of maintenance required to keep the cot in good condition. It reflects that satisfied users are with the cot based on their experience and expectations. The proposed method demonstrates mild steel cots require more maintenance (6) than galvanized steel cots (3) for susceptibility to rust and wear. In terms of weight, mold steel cots are heavier (8) compared to galvanized steel cots (6), making them less portable but potentially more stable.

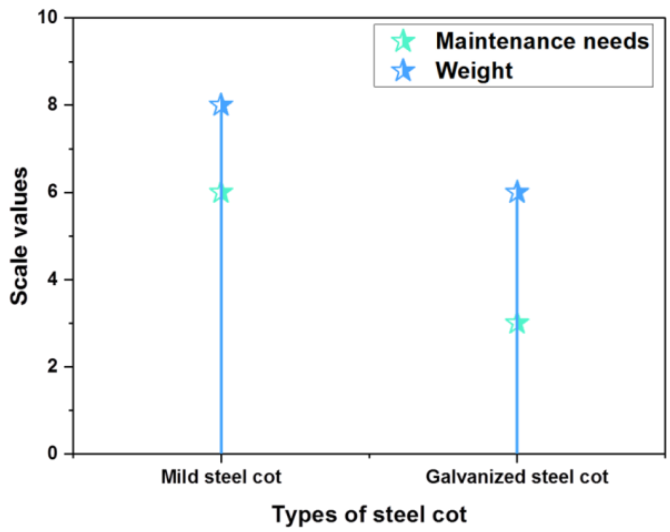

Figure 6. Comparative performance of maintenance needs and weight.

Cost-effectiveness and Comfort level: The metric evaluates the balance is the product's cost and the value it provides. A product that is affordable while maintaining high quality and performance is more likely to succeed in the market. Comfort is particularly relevant in products that interact directly with users. The metric measures how comfortable the product is to use, considering factors like ergonomics and tactile experience.

Figure 7 shows a comparative analysis of the comfort level and cost-effectiveness of the quality prediction model APO-GBM. The cost is users, taking into account the design and materials used. The comfort level and cost-effectiveness of the quality prediction model APO-GBM for two types of cots, mild steel and galvanized steel. Mild steel cots score higher in cost-effectiveness (8) while galvanized steel cots excel in comfort level (8), respectively.

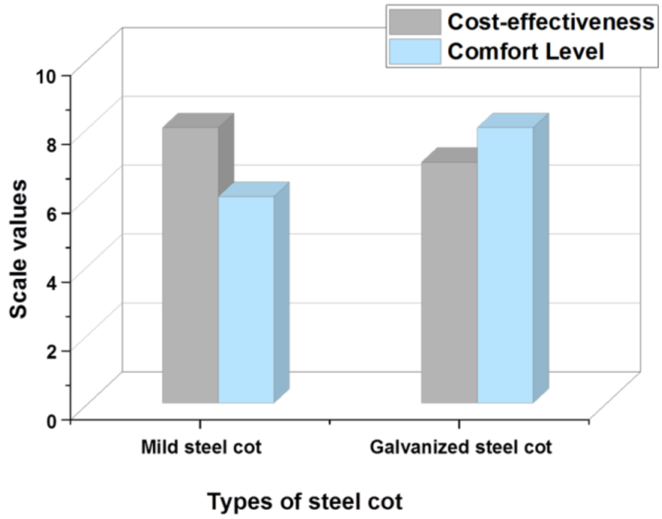

Figure 7. Analysis of comfort level and cost-effectiveness.

Aesthetic appeal and sustainability: Aesthetic appeal looks at the visual attractiveness of the product. Biomimetic designs often mimic forms and patterns, potentially increasing consumer interest and desirability. Sustainability evaluates the environmental impact of the product, including the materials used and energy consumed during production and usage. Biomimetic designs that are sustainable appeal to environmentally conscious consumers and contribute positively to brand image.

Figure 8 shows the comparative analysis of the sustainability and aesthetic appeal of the proposed method. The environmental impact of the cot, including materials used and end-of-life recyclability, and visual attractiveness of the cot, including design finish. The proposed method APO-GBM achieved, mild steel cots score (7) in aesthetic appeal and (5) in sustainability, while galvanized steel cots score higher, with 9 in aesthetic appeal and 8 in sustainability, indicating a better overall performance.

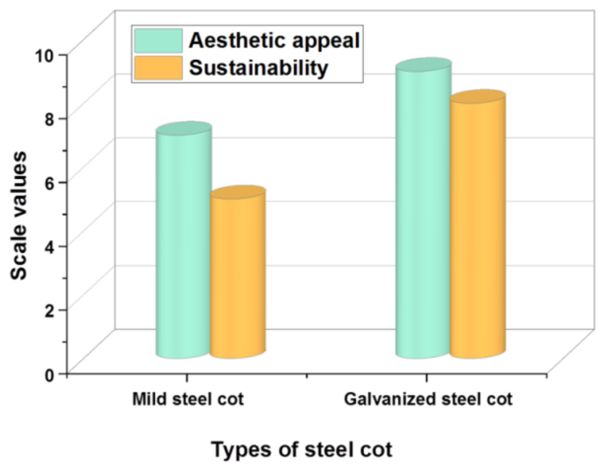

Figure 8. Comparative analysis of sustainability and aesthetic appeal.

With a concentration on the functionality of cots made of mild steel and galvanized steel, **Table 5** shows the validity and reliability analysis for several metrics assessed using the APO-GBM approach. The validity evaluation shows how well each metric represents user preferences and product performance, while the reliability coefficients show the measurements' internal consistency. Lower reliability and validity scores point to areas that might need more research, while higher numbers indicate that the suggested technique efficiently satisfies user needs.

Table 5. Reliability and validity assessment.

Features	**Mild steel cot score**	**Galvanized steel cot score**	**Reliability coefficient (α)**	**Validity assessment**
Design quality	7	9	0.85	High
Durability	5	8	0.82	High
Corrosion resistance	2	9	0.88	Very High
Maintenance needs	6	3	0.75	Moderate
Weight	8	6	0.70	Moderate
Cost-effectiveness	8	7	0.65	Lower
Comfort level	6	8	0.80	High
Aesthetic appeal	7	9	0.86	High
Sustainability	5	8	0.81	High
User satisfaction	6	9	0.87	Very High

4.3. Study discussion

The method highlights its performance against various metrics related to the quality prediction of costs made from mild and galvanized steel. The study analysis incorporates key assessment parameters such as design quality, durability, corrosion resistance, maintenance needs, weight, cost-effectiveness, comfort level, aesthetic appeal, user satisfaction, and sustainability, revealing a comprehensive understanding of how different materials meet user needs. In terms of design quality and durability, the analysis indicates that galvanized steel cots outperform mild steel cots, scoring 9 and 7 for design quality with 8 and 5 for durability. Design quality is essential as it encompasses not only aesthetic appeal but also functionality and usability. The higher score for galvanized steel suggests its significant design to user expectations, potentially leading to enhanced usability and overall satisfaction.

The analysis of cost-effectiveness and comfort level reveals a nuanced trade-off. Mild steel cots score higher in cost-effectiveness (8) due to potentially lower initial costs, while galvanized steel cots excel in comfort level (8). This suggests that while mild steel is more affordable upfront, galvanized steel offers greater user comfort, which I particularly important in products intended for direct user interaction.

The metrics for aesthetic appeal and sustainability are effective galvanized steel cots, which score 9 in aesthetic appeal and 8 in sustainability compared to mild steel scores of 7 and 5. The higher aesthetic appeal of galvanized steel significantly influences consumer preference, especially in a market increasingly focused on environmentally sustainable practices. The sustainability metric addresses the environmental impact of materials used and the potential for recycling, which is becoming an essential criterion for modern consumers. The comparative analysis demonstrates the APO-GBM model's effectiveness in evaluating diverse aspects of cost quality, emphasizing the advantages of galvanized steel over mild steel across several critical metrics. The study highlights the necessity of considering multiple factors in product design and material selection to user expectations effectively. By integrating ML techniques like APO-GBM, manufacturers optimize their products for performance, satisfaction, and sustainability, aligning with contemporary consumer values.

5. Conclusion

The study shows that biomimetic cultural and creative items can be evaluated with the suggested APO-GBM approach, especially when comparing mild steel and galvanized steel cots. Strong internal consistency is indicated by the dependability coefficients, which range from 0.65 for cost-effectiveness to 0.88 for corrosion resistance. The efficacy of the method is demonstrated by the validity assessments, which show that both design quality (mild steel: 7, galvanized steel: 9) and user happiness (mild steel: 6, galvanized steel: 9) are in good agreement with user expectations. Additionally, galvanized steel performed better than mild steel in several crucial areas, including sustainability (galvanized steel: 5, mild steel: 5) and durability (mild steel: 5, galvanized steel: 8). The results make a strong case for the use of mechanical forces in product design since they produce creative solutions that consumers find appealing. Overall, the APO-GBM approach not only satisfies validity and reliability standards but also improves the creative design process by utilizing natural insights. To improve upon these results, more research on different aspects of product appraisal should be conducted.

Limitations and future research

The focus on a single category of household appliances is limiting the generalizability of the findings to other product categories. Additionally, the use of specific mechanical forces is not universally applied to all biomimetic designs, necessitating further exploration of diverse mechanical systems. Future research could expand the scope by investigating a wider range of cultural and creative products, integrating more complex biomimetic principles, and exploring the long-term performance and sustainability of these designs in real-world applications.

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