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# Product Appearance Aesthetics in Industrial Design Based on Variational Onsager Neural Network Optimized with Osprey Optimization Algorithm



**Abstract:** - Aesthetics are significant because they may elicit emotions, induce feelings of pleasure or desire, and convey an item's perceived worth and desirability. A well-designed and visually appealing product might stick apart in a competitive market and capture the interest of customers. In contrast, a badly constructed product may be disregarded or considered as inferior quality, regardless of its real functioning. In this manuscript, Product Appearance Aesthetics in Industrial Design Based on Variational Onsager Neural Network Optimized with Osprey Optimization Algorithm (PAAID-VONN-OOA) is proposed. The input image is collected from the Product Design Aesthetic Database. Then the images are pre-processing using Master-Slave Adaptive Notch Filter (MSANF) to remove the noise. The pre-processed image is given into the Variational Onsager Neural Networks which is used for Product Appearance Aesthetics in Industrial Design. In general, the Variational Onsager Neural Network does not express adapting optimization techniques to determine ideal parameters to assure precise prediction. Therefore, it is proposed to utilize the Osprey Optimization Algorithm enhancement Variational Onsager Neural Network for Product Appearance Aesthetics in Industrial Design. The proposed PAAID-VONN-OPA method is implemented on python. Then, the performance of proposed technique is compared with other existing techniques. The proposed technique attains 16.28%, 30.78% and 25.29% higher accuracy, 29.13%, 18.47%, and 31.69% higher precision, 28.96%, 33.21% and 23.89% higher specificity comparing with the existing methods such as An Aesthetic Measurement Approach for Evaluating Product Appearance Design (PAAID-ETT) Research on Modern Book Packaging Design under Aesthetic Evaluation Based on Deep Learning Model (PAAID-SVM), and Evaluation and Design Method for Product Form Aesthetics Based on Deep Learning (PAAID-DCNN).

**Keywords:** Master-Slave Adaptive Notch Filter, Osprey Optimization Algorithm, Product Appearance Aesthetics in Industrial Design, Product Design Aesthetic Database, Variational Onsager Neural Network.

## I. INTRODUCTION

China's creative economy has developed over the past 30 years from a modest beginning to a pillar industry, supporting the nation's overall growth as well as its industrial and economic transformation [1]. Local cultural and creative sectors are experiencing uncoordinated growth, with a focus on number rather than quality [2]. China's artistic sector has become a key driver of economic growth as it undergoes a third upgrade in consumer architecture [3]. Consumers are shifting their focus from material to spiritual and cultural life, resulting in increased spending on culture and higher standards of beauty [4]. Cultural and creative items have a significant role in society and are growing as a source of cultural consumers. Increasingly, young people prioritise aesthetically in their daily lives [5]. Consumers respect their cultural heritage and seek out items that reflect it [6]. Developing cultural and creative tourist goods transforms conventional travel assets, improving their economic benefits and attractiveness in market places [7]. This is a key factor in promoting local culture and developing the tourist industry, as each location has unique qualities [8]. Natural cultural differences may partially compensate for a lack of inventiveness and regional growth in China's artistic and creative sectors [9, 10]. Cultural heritage encompasses the mental and bodily contributions of the local population to the long-term social and historical growth of an entire nation or region [11]. It is constantly enhanced established and enhanced [12]. Regional social, economic, and cultural developments are correlated with one other, according to scientific as well as technical advancements, basic beliefs [13]. Manufacturers are increasingly using regional cultural themes to create creative tourism designs in China and beyond. Cultural power that is soft is a key factor in worldwide rivalry and may boost a country's cultural confidence and feeling of identity [14]. The state and administration prioritise the education, inheritance, growth of China's cultural legacy, which has significant artistic assets and contributes to national culture [15]. The state is promoting cultural independence and providing financial assistance for the preservation, promotion, and innovation of traditional culture, history, and goods [16-17]. Numerous online market places have emerged as the result of the internet's explosive growth, allowing for convenient product searches without leaving the house [18]. Art galleries and financial benefits have witnessed success in China's cultural and creative product sector, but there is still room for improvement [19]. The expansion of the product industry and design is uneven across places, and architectural operate falls short of *international* standards [20].

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Numerous products are still in the infancy stages of development, with single types and homogenous shapes that ignore their distinctive qualities and cultural significance. The rapid growth of innovative items and peripheral markets may explain why consumers are prepared to pay high prices for popular products. Having something is preferable than not feeling embarrassed. It's challenging to entice people to buy, and without diffusion, it's hard to sustain the cultural worth of creativity. The disadvantages in the existing work motivate us to carry out this research work.

The major contributions of this proposed method are abridged below:

- The Product Appearance Aesthetics in Industrial Design Based on Variational Onsager Neural Network Optimized using Osprey Optimization Algorithm (PAAID-VONN-OPA) is proposed.
- The input image is collected from the Product Design Aesthetic Database. Then the images are pre-processed using Master-Slave Adaptive Notch Filter (MSANF). The MSANF filter is used to remove the noise.
- Variational Onsager Neural Network is used to design the Product Appearance Aesthetics in Industrial.
- The VONN does not express adapting optimization methods to determine optimal parameters to assure precise design. Therefore, it is proposed to utilize the Osprey Optimization Algorithm.
- The proposed approach is compared to existing techniques like PAAID-ETT, PAAID-SVM, and PAAID-DCNN respectively.

## II. RELATED WORK

Numerous research studies were suggested in the literatures were depend on Product Appearance Aesthetics in Industrial Design; few of them were reviewed here,

Zhu and Han [21] have presented cultural product appearance design based on improved multi objective optimization method. The presented paper suggests a multi objective optimisation method that uses the VGG model to investigate and develop the look, colour coordination, and aesthetics of cultural and creative items. The research aims to revive traditional Chinese culture via innovative design of products, providing fresh ideas for modern themes. To better serve people, product design should consider their unique demands and do extensive research on functionality and visuals. It provides high accuracy and low precision. Here, using an enhanced multi objective optimisation technique and the visual geometry group method to create looks, colour coordination, and aesthetics for culturally and artistic items. The research aims to revive traditional Chinese culture via innovative design of products, providing new concepts for sophisticated themes. It provides high f1-score and low sensitivity.

Li [22] have suggested a research on deep learning-based modern book packaging design under aesthetic evaluation. Here, the AdaBoost and SVR approaches are among the machine learning techniques used in the work. It offers the concepts and comprehensive implementation methods for the SVR regression and AdaBoost classification algorithms, together with the AdaBoost categorization along SVR regression assessment indices. Through packaging and design, physical book production embodies the creativity, uniqueness, professionalism, appeal and vitality of books in the age of electronic data. It provides high sensitivity and low f1-score.

Zhou et al. [23] have suggested a deep learning-based evaluation as well as design approach for product form aesthetics. Assessing thresholds served as the foundation for the building of a deep convolutional neural network for categorization. The network was optimized by batch normalization and other techniques, producing good classification effects. An adversarial neural network was employed for the product form's aesthetic design based on this research. A vehicle's front face was sketched in shape, and the recommended evaluation was carried out. It provides high specificity and low accuracy.

Gong et al. [24] have presented functional nanomaterial' use in industrial design concepts and aesthetic art. The presented study covers the electrical spinning process and offers a method for analyzing and investigating the application of aesthetic art, or the idea of industrial design, through the use of active nanotechnology. The presented study explores the problems with the industrial design notion depend on aesthetics. The expansion of industrial design and associated aspects are therefore highlighted in this article. Industrial design is planning and assessing the usage of functional nanomaterials. It provides greater accuracy and less precision.

Yan et al. [25] have presented an application of virtual reality technology in visual optimization of product appearance design. The suggested paper employed a survey analytic approach to extract trustworthy data from the study's findings after investigating the professional roles of designers, operators, as well as product planners in associated organizations. Furthermore, it conducted research and assessments on consumers of all ages to

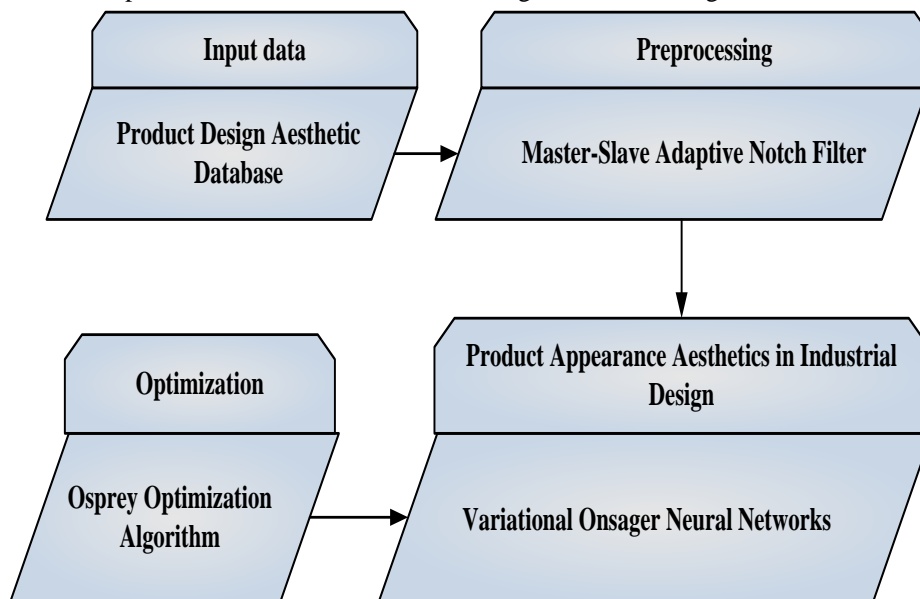
ascertain the distinct functional needs of wearables for age groups, as well as to contrast and evaluate the benefits and drawbacks of various kinds of smart wearables in terms of presenting. It provides high specificity and low sensitivity.

Yu [26] have presented a model for applying the industrial design-based user experience gene extraction technique. With a focus on expression structure, application research advancement, and critical technology research, the article offers a thorough overview of the present status and product design DNA research trajectory domestically and internationally. The law of DNA generation and derivation; investigate consumers' perceptions of product design DNA; and understand the relationship between manufacturing and market design DNA. It provides high accuracy and low f1-score.

Liang [27] have presented an assessment of the aesthetic merit of artificial intelligence-based digital culture and creative output. In order to improve back propagation (BP) networks for assessing the aesthetic worth of digital cultural and creative objects, this article proposes using neural networks. Initially the BP network's fundamental idea, structural elements, learning algorithm, and operational flow were examined. Then, a visual quality rating model for digital cultural and creative items was created using the BP networking. It provides high precision and low specificity.

### III. PROPOSED METHODOLOGY

The Product Appearance Aesthetics in Industrial Design Based on Variational Onsager Neural Network Optimized using Osprey Optimization Algorithm (PAAID-VONN-OOA) is depicted in this section. The proposed PAAID-VONN-OOA for Product Appearance Aesthetics in Industrial Design System is shown in Figure 1. It contains four stages like data acquisition, preprocessing, aesthetic measurement and optimization. Thus the detailed description about PAAID-VONN-OOA is given below in Figure 1,



**Figure 1:** Block diagram for proposed PAAID-VONN-OOA model for Product Appearance Aesthetics in Industrial Design

#### A. Data acquisition

Input image taken from Product Design Aesthetic Database [28]. The original collection included 11,507 product design photos. After deleting undesirable, weakened, and duplicate photos 10,003 high quality images of product design submissions from Equipment Product Design Competition. It has 4,990 samples in the qualifying class (medium aesthetic level), 8,35 samples in the awarded class (high aesthetic level), and 4,178 samples in the stopped class (poor aesthetic level).

#### B. Pre-processing using Master-Slave Adaptive Notch Filter

In this step, image pre-processing using Master-Slave Adaptive Notch Filter (MSANF) [29] is discussed. The suggested MSANF has the aim to eliminate the noise in the image. Master-Slave Adaptive Notch Filters (MSANF) has been recognised as a type of variable notch filter that utilises an adaptive algorithm to alter the notch frequency in real time. Reduce any noise or undesired artefacts in the image produced by low lighting, sensor quality, or other variables. It is recognised that aesthetic adaptation is crucial Master-Slave ANF to acquire exact design outcomes. Frequency adaptation given in equation (1),

$$\dot{\hat{\rho}} = -\frac{\ell}{2\aleph} y_1 (\ddot{y}_1 + \hat{\rho}^2 y_1) \tag{1}$$

Where,  $\hat{\rho}$  represents the size of image,  $\ell$  represents the total image in the input image,  $\aleph$  represents the response speed of filter,  $y_1$  represents the unknown noise in image,  $\ddot{y}_1$  represents the filter parameter. The rating based sinusoidal vector is useful for removing the noise present in the input images. The sinusoidal vector is given in equation (2),

$$y_1 = -\frac{C}{\rho_1} \sin(\rho_1 f + \phi_1) \tag{2}$$

Where,  $C$  represents the input images,  $\rho_1$  represents the sigma points,  $f$  represents the specific hormones,  $\phi_1$  represents the numerical values in input images. The mathematical calculation of the steady state is given in equation (3),

$$y_1^2 = \frac{C^2}{2\rho_1^2} (1 + \sin(2(\rho_1 f + \phi_1))) \tag{3}$$

Normalisation entails reducing the pixel values of a picture to a certain range. Normalisation variables define the normalisation range and procedure. The periodic orbit is close it is given in equation (4),

$$\dot{\hat{\rho}} = -\frac{\ell}{2\aleph\rho_1} [C^2(\hat{\rho} - \rho_1) + C^2(\hat{\rho} - \rho_1)\sin(2(\rho_1 f + \phi_1))] \tag{4}$$

Where,  $\hat{\rho}$  signifies pixel value, while at lower speeds, it will be gradual. This causes issues with the tuning of  $\ell$ . Histogram equalisation is a technique for increasing the contrast of a picture by dispersing pixel values. The variables determine the intensity mapping or thresholding used to equalise the histogram. The threshold adaptation algorithm is given in equation (5),

$$\dot{\hat{\rho}} = -\ell \left( \hat{\rho} - \sqrt{\dot{y}_{1\gamma}^2 + \dot{y}_{1\phi}^2} / \sqrt{y_{1\gamma}^2 + y_{1\phi}^2} \right) \tag{5}$$

Where,  $\dot{y}_{1\gamma}^2$  represents the state variable,  $\dot{y}_{1\phi}^2$  represents the  $\gamma$  axis variables,  $y_{1\gamma}^2$  and  $y_{1\phi}^2$  represents the estimated fundamental waves of the  $\gamma$   $\phi$ -axis. The fundamental waves of the axis are orthogonal; the noise removal is given in equation (6),

$$\begin{cases} \ddot{y}_{1\gamma} + \hat{\rho}^2 y_{1\gamma} = 2\aleph \hat{\rho} \kappa_\gamma(f) \\ \ddot{y}_{2\gamma} + (2\hat{\rho})^2 y_{2\gamma} = 2\aleph \hat{\rho} \kappa_\gamma(f) \end{cases} \tag{6}$$

Where,  $\ddot{y}_{1\gamma}$  represents the second state variable,  $\ddot{y}_{2\gamma}$  represents the third state variable  $\gamma$  axis variables. Thus the noise was removed from the input image by using the Master-Slave Adaptive Notch Filter method. The pre-processed image fed into the Product Appearance Aesthetics in Industrial Design.

### C. Product Appearance Aesthetics in Industrial Design using Variational Onsager Neural Networks

In this section, the Product Appearance Aesthetics in Industrial Design using Variational Onsager Neural Networks (VONN) [30] is discussed. VONN can automatically produce fresh concepts that meet particular aesthetic requirements. By training the network on an image of current visually appealing designs, it learns to develop new designs that match the required aesthetics. Here, the generic trainable architecture which uses spatiotemporal image of the state as well as process variables, and boundary image, if relevant is described for learning the dissipation potential and free energy densities for a specific process. The hidden layer general architecture is given in equation (7),

$$x_{j+1} = h_j(Q_j x_j + a_j), \quad j = 0, \dots, l, \tag{7}$$

Where,  $x_{j+1}$  represents the hidden layer,  $h_j$  and  $Q_j$  represents the learnable parameters,  $x_j$  and represents the vectors,  $a_j$  represents the bias vector and  $l$  represents the variable. The activation function is deduced from an indefinitely differentiable common activation function. The free energy participate in the evolution is given in equation (8),

$$t(k) = t * [\tilde{t}(k) - \tilde{t}(0)] \tag{8}$$

Where,  $t(k)$  represents free density and  $\tilde{t}$  represents the logistic function of the image,  $k$  represents the reference pixels for the Product Appearance and  $t *$  represents the characteristic scale of  $t(k)$ . In the presence of viscoelasticity, for example, the stresses are predicted to be zero at the zero value of the strain and viscous strain. The free product aesthetics in industrial design density is given in equation (9),

$$t(\mathcal{G}, \mathcal{G}^c) = t * \left[ \tilde{t}(\mathcal{G}, \mathcal{G}^c) - \tilde{t}(0,0) - \frac{\Phi \tilde{t}}{\Phi \mathcal{G}} ; \mathcal{G} \right] \tag{9}$$

Where,  $\mathcal{G}$  represents the value of strain for the product appearance,  $\mathcal{G}^c$  represents the value of the viscous strain,  $\Phi$  represents the original input image. The dissipation potential density is needed to fulfill the product appearance. So, the network is combined with “passthrough” layers that connects the input layer with units is given in equation (10),

$$x_{j+1} = h_j \left( Q_j^x x_j + Q_j^\infty \tilde{q} + a_j \right) \quad i = 0, \dots, l \tag{10}$$

Where,  $Q_j^x$  represents the weight matrices for aesthetics,  $q$  represents the normalized input,  $a_j$  represents the bias vector and  $x$  represents the non-negative weights of the image. The convexity of the sum of convex functions and convexity composition of a convex function and a convex as well as non-decreasing function lead to the natural condition for  $h_j$ . The network architecture is expressed in eqn (11),

$$y_{j+1} = h_j^y \left( Q_j^{ty} y_j + a_j^{ty} \right) \quad j = 0, 1, \dots, l - 1 \tag{11}$$

Where,  $y_{j+1}$  represents the vector of activation values,  $a_j^{ty}$  represents bias vector and  $Q_j^{ty}$  represents weight matrix in the image and  $Q$  represents the function of  $\tilde{Q}$  is given in equation (12),

$$Q = \begin{cases} \tilde{Q} + \exp(-\epsilon), & \tilde{Q} \geq 0 \\ \exp(\tilde{Q} - \epsilon), & \tilde{Q} < 0 \end{cases} \tag{12}$$

Where,  $Q$  represents the function,  $\epsilon$  represents the positive constant,  $\exp(-\epsilon)$  represents experimental constant in the variance of the image and  $\tilde{Q}$  parameter of the neural network for product appearance aesthetic in industrial design. The dissipation potential density is used in combination with the thermodynamic circumstances and the rescaling of the VONN output is given in equation (13),

$$\wp(k, q) = \wp * \left[ \tilde{\wp}(k, q) - \wp(k, p) - \frac{\Phi \tilde{\wp}}{\wp q} . q \right] \tag{13}$$

Where,  $\wp$  represents the potential density,  $q$  represents the normalized input,  $\wp *$  represents the characteristic scale. The combination of the characteristics is obtained from the Onsager’s Variational principle is given in equation (14),

$$\begin{aligned} B_l S(\varpi) &= 0, & l &= 1, \dots, m_{PDEs} \\ A_l S(\varpi) &= g(\hat{\varpi}), & l &= 1, \dots, m_{VZs} \end{aligned} \tag{14}$$

Where,  $A$  and  $B$  represents the operators,  $S$  denotes the size of image,  $\varpi$  signifies combination of  $\hat{\varpi}$  and  $g$  denotes dissimilarity in the images. The loss function is given in equation (15),

$$\hbar_{PDEs}^l = \frac{fv(L)}{fv(L_{ll})}, \quad l = 1, \dots, m_{PDEs} \tag{15}$$

Where,  $fv$  represents the trace of a matrix of contrast,  $L_{ll}$  represents the matrix block and  $m_{PDEs}$  the future parameter. The matrix model is given in equation (16),

$$\hbar_{VZs}^l = \frac{fv(L)}{fv(L_e)} \quad \text{with } k = l + m_{PDEs}, \quad l = 1, \dots, m_{VZs}, \tag{16}$$

Where,  $L_e$  represents the diagonal matrix and  $m_{VZs}$  represents the vector parameter. The calculation of weight  $\hbar_{VZs}^l$  and  $\hbar_{PDEs}^l$  only needs the trace for matrix blocks in the diagonal for the product appearance. The homogeneity is given in equation (17),

$$fv(Q) = \sum_{l=1}^{m_{PDES} + m_{VZS}} fv(L_{ll}) \tag{17}$$

Where,  $fv(Q)$  represent the homogeneity in the image. The expressions is easily generalized in the event like the dependence for the product appearance aesthetics in industrial design using the products. Finally, the Variational Onsager Neural Networks for the product appearance aesthetics in industrial design has been done. Due to its convenience, pertinence and artificial intelligence-based optimization technique is used in the Variational Onsager Neural Networks. The OOA is used to enhance the VONN optimal parameter  $L_e$  and  $S$ . Here, OOA is utilized for tuning the weight and bias parameter of VONN.

*D. Optimization using Osprey Optimization Algorithm*

The weight parameter  $L_e$  and  $S$  of VONN is optimized using the OOA [31] is discussed. The Osprey Optimisation Algorithm is intended to efficiently search for optimum solutions across a broad search space. It uses a combination of local and global search strategies to swiftly and effectively navigate the search space. The algorithm is capable of dealing with large-scale communication networks with a large number of subcarriers and users.

*1) Stepwise Procedure OF OOA*

Here, step by step process is defined to obtain optimal value of VONN based on OOA. Initially, OOA makes the equally distributed population to enhance the VONN paramater. The best solution is promoted using OOA algorithm and related flowchart is illustrated in Figure 2.

**Step 1: Initialization**

In the OOA population, each osprey selects values for the issue variables according to its position within the search space. Every osprey represents a potential solution to the problem through mathematical modelling. The OOA population is made of ospreys and a matrix is used to model themis expressed in equation (18),

$$V = \begin{bmatrix} V_1 \\ \vdots \\ V_k \\ \vdots \\ V_M \end{bmatrix}_{M \times n} = \begin{bmatrix} V_{1,1} & \dots & V_{1,l} & \dots & V_{1,n} \\ \dots & \dots & \dots & \dots & \dots \\ V_{k,1} & \dots & V_{k,l} & \dots & V_{k,n} \\ \dots & \dots & \dots & \dots & \dots \\ V_{M,1} & \dots & V_{M,l} & \dots & V_{M,n} \end{bmatrix}_{M \times n} \tag{18}$$

Where,  $J$  denotes population matrix of osprey locations,  $J_k$  signifies  $k^{th}$  osprey,  $J_{k,l}$  denotes  $l^{th}$  dimension,  $M$  implies number of ospreys, and  $n$  denotes number of problem variables. The ospreys position in search space is randomly initialized at the beginning of OOA implementation is given in equation (19),

$$j_{k,l} = sa_l + e_{k,l} \bullet (ca_l - sa_l), \quad k = 1,2,\dots, M, l = 1,2,\dots, n, \tag{19}$$

Here,  $e_{k,l}$  represents signals, and  $ca_l$  &  $sa_l$  signifies lower, upper bounds of  $l^{th}$  problem variable. Because every osprey represents a possible solution for issue, the objective function may be assessed.

**Step 2: Random generation**

The input parameters are created randomly after initialization. The ideal fitness values chosen depend on clear hyper parameter condition.

**Step 3: Fitness Function Estimation**

The random solution is created from initialized evaluations. Fitness function is assessed using parameter optimization value for optimizing weight parameter  $L_e$  and  $S$  of the network. It is expressed in eqn (20),

$$Fitness\ function = [L_e \ \& \ S] \tag{20}$$

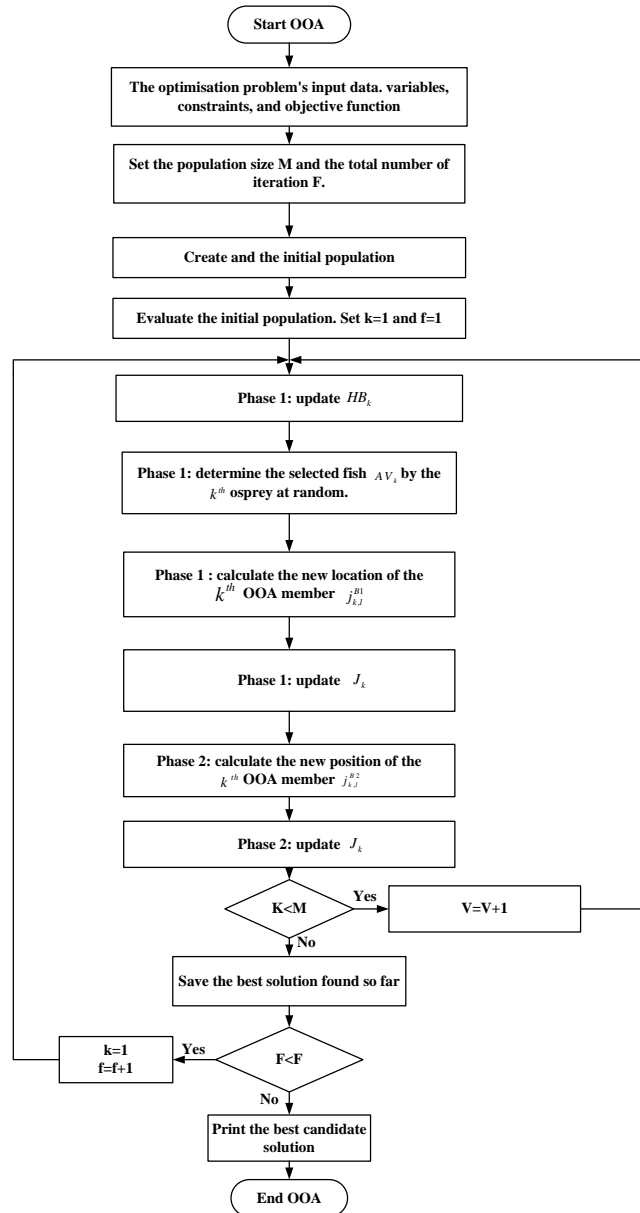


Figure 2: Flowchart of OOA for optimizing VONN parameter

**Step 4: Position Identification and Hunting (Exploration)**

Strong hunters, ospreys have keen vision that helps them find fish below. Once they've located the fish, they seek beneath it. A simulation of ospreys' natural behaviour serves as the foundation for OOA's initial population update stage. By simulating the osprey's attack on fish, the location of the osprey in the search space is significantly altered, which improves OOA's capability to explore and identify the ideal site while avoiding local optima. Underwater fishes are considered in OOA design for each osprey's position in search space with greater objective function value. Each osprey's fish set is configured as given in equation (21),

$$HB_k = \{J_l \mid l \in \{1, 2, \dots, M\} \wedge H_l < H_k\} \cup \{J_{best}\} \tag{21}$$

Where,  $HB_k$  signifies set of fish positions for the  $k^{th}$  osprey,  $J_{best}$  indicates ideal candidate solution for reducing the PAPR. The osprey strikes these fish at random after detecting its location. A novel location for relevant osprey is determined depend upon the simulation of osprey's movement towards the fish is given in eqn (22),

$$j_{k,l}^{B1} = j_{k,l} + e_{k,l} \cdot (AV_{k,l} - Q_{k,l} \cdot j_{k,l}) \tag{22}$$

Where,  $j_{k,l}^{B1}$  is its  $l^{th}$  dimension,  $AV_{k,l}$  is its  $l^{th}$  dimension,  $AV_k$  is the fish selected for  $k^{th}$  osprey,  $e_{k,l}$  signifies the random number, and  $Q_{k,l}$  represents the random number from the set. The new location replaces the osprey's prior position if it improves the goal function value is given in equation (23),

$$J_k = \begin{cases} J_k^{B1}, H_k^{B1} < H_k; \\ J_k, \text{ else,} \end{cases} \quad (23)$$

Where,  $J_k^{B1}$  denotes new place of  $k^{th}$  osprey based on exploration of OOA, and  $H_k^{B1}$  denotes objective function value.

**Step 5:** Carrying the fish to suitable location (Exploitation)

The osprey transfers the fish to a suitable (and safe) spot to eat. A simulation of osprey behaviour serves as the foundation for the second stage of OOA population updating process. The osprey's position in the search space is slightly altered by the fish carrying models, which leads to an increase in the OOA's ability to exploit the local search and convergence towards better solutions close to identify solutions. The OOA structure first determines a fresh, random position for every population member as a "appropriate position to consume fish" to mimic the natural activity of ospreys is given in equation (24)& (25),

$$j_{k,l}^{B2} = j_{k,l} + \frac{sa_l + e_{k,l} \cdot (ca_l - sa_l)}{f}, k = 1, 2, \dots, M, l = 1, 2, \dots, n, f = 1, 2, \dots, F \quad (24)$$

$$j_{k,l}^{B2} = \begin{cases} j_{k,l}^{B2}, sa_l \leq j_{k,l}^{B2} \leq ca_l; \\ sa_l, j_{k,l}^{B2} < sa_l; \end{cases} \quad (25)$$

Where,  $j_{k,l}^{B2}$  denotes  $l^{th}$  dimension,  $e_{k,l}$  signifies the random numbers,  $f$  indicates algorithm's iteration counter, and  $F$  represents total iterations. The Osprey finishes its trips and creates sequences as solutions in each iteration. The proposed novel location replaces the previous location of the equivalent osprey and increases the goal function value is given in eqn (26),

$$J_k = \begin{cases} J_k^{B2}, H_k^{B2} < H_k; \\ J_k, \text{ else,} \end{cases} \quad (26)$$

Where,  $J_k^{B2}$  denotes novel position of  $k^{th}$  osprey based on exploitation stage of OOA and  $H_k^{B2}$  represents its objective function value. An osprey moves across the graph looking for the best combination of parameters until the number of visited nodes meets the stopping threshold.

**Step 6:** Termination Condition

With the aid of OOA, the weight parameter value  $L_e$  and  $S$  from the Variational Onsager Neural Networks are optimized using OOA, will repeat iteratively step 3 until halting criteria  $V = V + 1$  is satisfied. Then, the PAAID-VONN-OOA method effectively done the Product Appearance Aesthetics in Industrial Design with high accuracy.

#### IV. RESULT WITH DISCUSSION

The experimental results of the proposed technique are discussed. The ARM Cortex A53 (Broadcom BCM2387) quad-core processor using 64-bit CPU operating at 1.2GHz speed and RAM 1 GB is included in its main specifications. The proposed PAAID-VONN-OOA method is applied by using Python using mentioned performance metrics. The acquired outcomes of the proposed technique are analyzed to existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN techniques.

##### A. Performance measures

The performance of the proposed technique is examined using performance metrics like accuracy, specificity, precision, sensitivity, f1-score.

- True Positives (TP): The number of positive Product Appearance Aesthetics in Industrial Design correctly done to positive.
- True Negatives (TN): The number of negative Product Appearance Aesthetics in Industrial Design correctly done to negative.
- False Positives (FP): The number of negative Product Appearance Aesthetics in Industrial Design incorrectly done to positive.
- False Negatives (FN): The number of positive Product Appearance Aesthetics in Industrial Design incorrectly done to negative.



1) Accuracy

The proportion of exact authentication with total predictions made for a dataset. It is measured through the equation (27),

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{27}$$

2) Precision

Precision is a metric which quantifies the count of correct positive prediction made. It is scaled using eqn (28),

$$precision = \frac{TP}{(TP + FP)} \tag{28}$$

3) Sensitivity

Sensitivity is a metrics that calculates the predictions made by correct number of positive forecasts made by total positive predictions. It is measured by equation (29),

$$Sensitivity = \frac{TP}{TP + FN} \tag{29}$$

4) Specificity

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (30),

$$Specificity = \frac{TN}{TN + FP} \tag{30}$$

5) F1-Score

F1-score combines the precision and Specificity into a single value, providing a balance between these two important metrics. It is computed in eqn (31),

$$F1\ Score = \frac{TP}{\left( TP + \frac{1}{2}[FP + FN] \right)} \tag{31}$$

B. Performance Analysis

Figure 3 to 7 determines stimulation results of PAAID-VONN-OOA proposed method. Then, the proposed VONN-AHA-BA-TPI is compared to existing PAAID-ETT [21], PAAID-SVM [22], and PAAID-DCNN [23] techniques respectively.

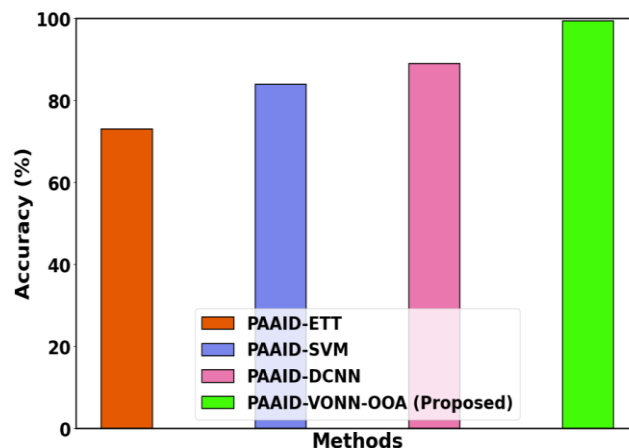


Figure 3: Accuracy analysis

Figure 3 shows accuracy analysis. Here, PAAID-VONN-OOA attains 16.28%, 30.78% and 25.29% higher accuracy comparing to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN techniques respectively.

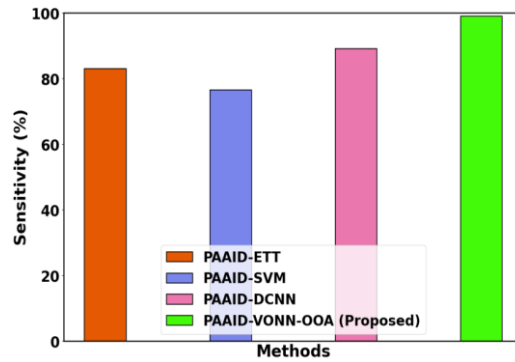


Figure 4: Performance analysis of Sensitivity

Figure 4 shows sensitivity analysis. Here, PAAID-VONN-OOA attains 31.47%, 23.12% and 19.89% higher sensitivity comparing to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN respectively.

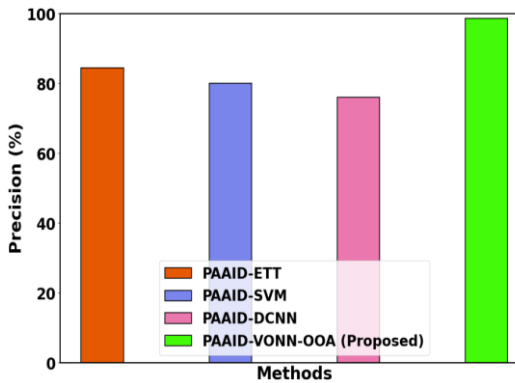


Figure 5: Performance analysis of precision

Figure 5 shows precision analysis. Here, PAAID-VONN-OOA attains 29.13%, 18.47%, and 31.69% higher precision comparing to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN respectively.

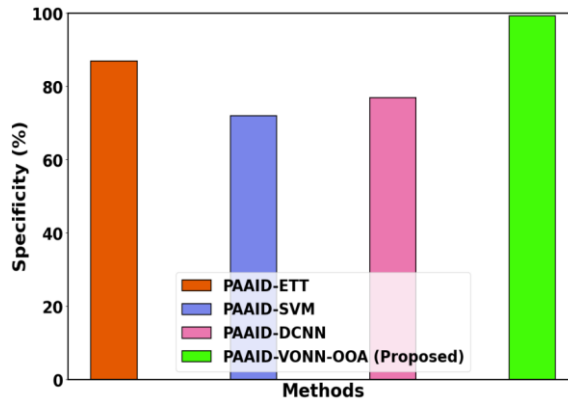


Figure 6: Performance analysis of specificity

Figure 6 shows specificity analysis. Here, PAAID-VONN-OOA attains 28.96%, 33.21% and 23.89% higher specificity comparing to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN respectively.

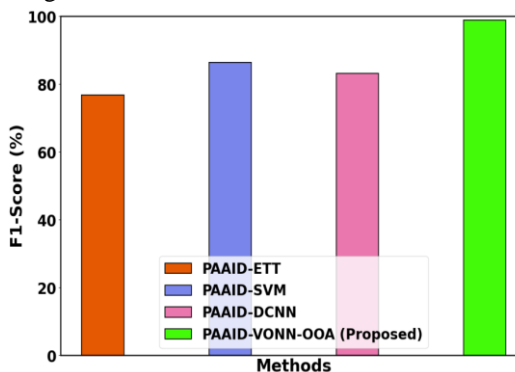


Figure 7: Performance analysis of F1-score

Figure 7 shows F1-score analysis. Here, PAAID-VONN-OOA attains 24.58%, 26.36%, and 18.56% higher F1-score comparing to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN respectively.

### C. Discussion

In this work, PAAID-VONN-OOA model for Product Appearance Aesthetics in Industrial Design is discussed. This work contributes to the development of ideas and methods for designing Product Appearance Aesthetics in Industrial, with possible applications. The appearance focuses on cultural value. The extensive study is needed to enhance the aesthetics of artistic and cultural objects. Wages and components contributed 35.7% and 9.3%, respectively. The views of customers of Product Appearance Aesthetics value are unreliable, and several factors might impact assessment findings. The empirical evaluation of proposed VONN-AHA-BA-TPI method is highlighted through a range of evaluation metrics, including accuracy, specificity, sensitivity, Precision, and F1-score. Presenting a comparison of the 99.5% accuracy, 99.3% precision, 99.2% sensitivity, 99.4% specificity, 99.42% F1-score achieved by the proposed technique to that of PAAID-ETT, PAAID-SVM, and PAAID-DCNN. It concludes that the proposed PAAID-VONN-OOA method is better than existing models for Product Appearance Aesthetics in Industrial Design.

## V. CONCLUSION

The Product Appearance Aesthetics in Industrial Design Based on Variational Onsager Neural Network Optimized with Osprey Optimization Algorithm (PAAID-VONN-OOA) is successfully implemented. This study's initial experiment selects individuals based on their aesthetic level using an emotional measuring exam. This serves as the basis for subsequent tests on product psychological design. It evaluates one's appearance using an established index system. The performance of the proposed PAAID-VONN-OOA method approach contains 31.47%, 23.12% and 19.89% higher sensitivity; 24.58%, 26.36%, and 18.56% higher f1-score when analyzed to the existing PAAID-ETT, PAAID-SVM, and PAAID-DCNN methods b27% respectively.

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