Exploration Of Visual Attention Analysis And Optimization Algorithms In Packaging Design

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In today's highly competitive market, consumer decisions are increasingly shaped by evolving preferences and the rapid recognition of brands. To meet these demands, this study proposed an innovative approach that integrates visual attention analysis with advanced optimization algorithms to enhance packaging efficiency and consumer engagement. A comprehensive packaging visual attention and engagement dataset was developed, encompassing design attributes, attention metrics, emotional responses, engagement measures, and performance indicators. During preprocessing, all package images were resized and normalized to ensure uniformity. Convolutional Neural Networks (CNNs) were employed for feature extraction, enabling the identification of critical design elements such as layout, color palette, typography, and branding components.To further improve design optimization, the U-Net Driven Multi-Objective Cuckoo Search Tuned Efficient Fire Hawk Optimizer (UN-MOCS-EFHO) approach was implemented. This method combined the strengths of U-Net for segmentation, MOCS for multi-objective optimization, and EFHO for efficient convergence. Visual saliency was defined as the ability of specific design elements-such as color, contrast, or layout harmony-to capture consumer attention, while emotional resonance referred to how design structure influenced consumer perception and brand recall. By jointly modeling these factors, the proposed method optimized layout parameters and aesthetic features to achieve maximum consumer appeal.Experimental results demonstrated that the UN-MOCS-EFHO model outperformed other approaches, achieving superior performance with 99.995% accuracy, 98.5% precision, 97.4% recall, and 98.8% F1-score. This research established a data-driven, intelligent design framework that leverages algorithmic modeling to create personalized, visually engaging, and emotionally resonant packaging aligned with contemporary market trends.

Keywords: Visual Attention Analysis, Packaging Design Optimization, Emotional Perception, UNet Driven Multi-Objective Cuckoo Search Tuned Efficient Fire Hawk Optimizer (UN-MOCSEFHO), layout parameters

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1. Introduction

Attention may lie in the essence of sight and in the inception of brand recall, quality perceptions, and buying behaviour witnessed in consumers. The emotional state of the customers and their visual attention to the products announce very loudly how important the design characteristics are in their decision-making process. Visual attention metrics reveal the duration of fixations, the sequence of gazes, and heatmaps. Also, they indicate the specific areas on the package that attract the most customers. Since it detects the designs that evoke favourable emotional reactions such as happiness or trust, emotional analysis is also significant in this context. Consequently, if the two components are combined, users can evaluate the impact of the packaging through the increased engagement rates, improved recall, and higher sales conversions. Strategies that would be more customer-friendly and market-oriented at the same time, resulting in customer gratification and buying behaviour, which can be quantified as improvements.

The physical aspects of a package, such as color, shape, size, and font, significantly contribute to the attraction of visual attention. Moreover, the emotional connections formed between the customer and the brand are strengthened through greater visual exposure [1]. Besides its main functions of safeguarding and extending the life of the product, food packaging also has a psychological impact on consumers and thus has value.

The roles of protection and consumer influence, which are considered two sides of the same coin, interact in modern packaging design in a very dynamic manner. The protective function of packaging serves to maintain the product's quality, prevent any health risks, and keep the product within the legal limits of environmentally friendly packaging and labelling. On the other hand, the consumer influence aspect is in complete agreement with marketing goals as it is realized through such ways as aesthetic appeal, emotional engagement, and brand communication. In the case of tight competition, product packaging designers make use of these two roles: they opt for strong, environmentally friendly packaging materials that protect the product, and at the same time, they use the attractive layouts, colours, and textures that not only draw the eye but also meet the changing consumer's demand for quality, responsibility, and authenticity.

Consumer influence and protection, functions that cohere very well with one another, are in fact very dynamic in their interaction when it comes to contemporary packaging design. The protective function of packaging not only makes the product lawfully packaged and labelled as eco-friendly but also maintains its quality and prevents any health hazards. On the other hand, the consumer influence aspect is in perfect tune with marketing goals, as it is realized through brand communication, emotional binding, and visual attractiveness. In scenarios where competition is intense, the packaging designers of the products take into account the looks and safety of the customers at the same time. They creatively put together attractive forms, colors, and textures with tough, environmentally friendly materials that assure the safety of the product. The mentioned design characteristics not only attract customers, but they also mirror the demands of the current packaging regarding liveliness, transparency, and superiority.

The packaging that has commercial significance gives a lot of signals through the visual and verbal channels. It is not just the protection of its contents that highlights its importance, but rather its influence on consumers. The product's benefits are mentioned, but the buyer's perception is determined by the visual elements such as color, images, and overall look [2]. Packaging design is a creative way of using materials like metal, glass, paper, or plastic to make a container that will provide safety, utility, and beauty, thus attracting attention and increasing sales [3].

Packaging and its accompanying informational and visual elements are commonly used in terms of marketing as a method for presenting the product as maintainable or healthy, as sustainability and health become increasingly important. There is a void in research to understand the impact that packaging can have on consumer perceptions [4]. Creative packaging plays an impactful role in business outcomes and consumer behavior by generating awareness, recognition, purchase, and brand selection. Creative packaging creates less environmental impact and generates more sales than ugly packaging, which repels involvement [5].

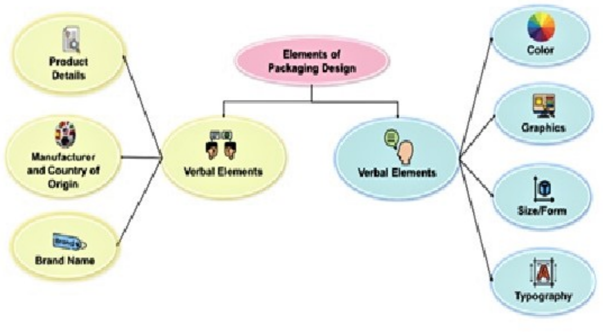

Fig. 1. The elements of packaging design

To promote environmentally friendly products, manufacturers are using sustainable production practices and employing green communication techniques in labeling and advertising. However, some businesses overstate their environmental benefits to deceive customers about their environmental policies or product advantages. This false practice is called "greenwashing" [6]. "Greenwashing" refers to making deceptive environmental claims about products or product packaging that is accomplished to give the impression of being ecologically friendly or socially responsible. In this study, the proposed UN-MOCS-EFHO framework will assist with the identification or prevention of eco-deceptive claims by evaluating packaging visual conditions and package emotional cues about sustainability. The framework would verify that design elements reflect sustainability and service sustainability (e.g., colors and visuals of eco-consciousness, material reference for eco-friendliness, ecofriendly assembly and disassembly indications (not further or deceivingly suggesting meaning to the consumer), color coding or reference to recyclable solutions, and so forth). The intention is to ensure disclosure and to prevent eco-deceptive implications about environmental or place-related messages in the package design. Packaging contributes to waste generation, prompting consumers to seek environmentally friendly options like green packaging. Ignoring this component may underestimate its significance [7]. When a new product is introduced, a date or tired pack is revitalized, a product is repositioned, the target market is altered, packaging cost reductions are necessary, legal or regulatory requirements necessitate it, or new packaging technology becomes available, marketers and the food industry can be involved in designing or redesigning food packs [8]. Food and beverage package visual design is evolving, blending scientific communication methods with intuitive techniques, utilizing cross-modal correspondences to convey brand connections and product meaning [9]. Packaging is a major communication tool from the perspective of marketing professionals and academics, along with its classic use in logistics and distribution. Being a tool that is physically easier to access during the buying and consumption process than other communication means, it plays an important role in drawing attention, forming good expectations, elevating the entire consumption experience, and encouraging the purchase behaviour [10].

The goal of the research is to improve the effectiveness of package design by combining optimization methods with visual attention analysis. More precisely, the objective of this study is to improve package design based on the analysis of visual attention patterns. The model can determine the design aspects that are able to attract and hold the most attention effectively by means of knowing the consumer's focus on a package in terms of color, layout balance, typeface, or logo position. Through the visual attention analysis applied to the optimization algorithms, companies can create packaging that is not only visually and functionally pleasing but also in sync with the marketing practices of today that prioritize the customer's engagement and emotional connection. This method assists the companies in packaging solutions, allowing the system to explore multiple design possibilities while still quickly reaching a point of convergence. The global optimum search in the design area is not only prolonged but also sharpened through the EFHO (Efficient Fire Hawks Optimizer) algorithm with the incorporation of the extra Phasor Operator and dimension learning-based hunting tactics. Owing to the substantial differences in processing time, flexibility, and accuracy of results, the latter then prevails over the former, making it a more robust tool than the already existing ones, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), to cope with the intricate and very variable nature of packaging design.

- The investigation suggests the UN-MOCS-EFHO, which ingeniously syndicates emotional mapping and visual saliency to optimize packaging characteristics for make and customer interaction.
- The UN-MOCS-EFHO model combines U-Net segmentation, multi-objective optimization, and emotional resonance mapping, while previous models often depended on AI or deep learning. Therefore, the integrated approach of the UN-MOCS-EFHO denotes a radical new theory in packaging design optimization by improving the design layout and aesthetic balance and, at the same time, optimizing for customer emotional connection.
- Clustering represents reaction and feelings, U-Net gets structure, MOCS keeps exploration balance, EFHO adjusts the optimization for visual attraction and emotional impact of packaging, saliency models indicate the areas of consumer attention, and CNNs take out package components.
- The performance of UN-MOCS-EFHO over the traditional methods based on experimental data is remarkable, as it leads to a significant enhancement of layout accuracy and quality. The method appears to be good at generating customer-oriented and effective packaging design solutions.

2. Materials and methods

The research was focused on the 3M Visual Attention Software (3M-VAS), an AI-based tool that was developed through eye-tracking data and aimed at determining visual attention patterns in relation to architectural forms [11]. Alexander, through the comparison of real and modified images of geometric patterns and structures, was able to bring forward the differences in the fields of attention, fixation points, and design coherence, thus backing his theory of geometrical order. The study [12] mapped the customers' visual experiences in retail situations in order to enhance the marketing strategies. The eye-tracking combined with the virtual reality (VR) was the method used to get the gaze behaviour and the emotional responses of the 46 subjects. Then, the parameters were calculated as per the total time looking, the count of fixations, and the pupil's diameter.

The research examined how different aspects of packaging design influence consumer selection in the snack food market. To assess the main features, a questionnaire grounded on the Decision-making Trial and Evaluation Laboratory (DEMATEL) was conducted with 25 design experts and 121 students [13]. The five elements that were most often noticed included color, shape, picture, line, and letters. Most significant factors; although technology and materials were important, the image had the biggest impact. The authors of the article intended to show the interplay between children's eating habits and packaging image activities [14]. The investigation took into consideration textual claims, visual communication, and packaging features as the customer impression determinants. The poll has shown that adults are tempted to swallow more calories by false health claims, whereas packaging often attracts children the most.

The research was aimed at longevity of emotions in visual communication design, which can lead to longer product life and be more environmentally friendly [15]. Emotional perception in packaging design is a significant factor in the development of a good brand-consumer relationship.

The emotional attachments influence the loyalty to a brand, the interaction with it, and whether it gets the consumer's money or not, all this thanks to the evocation of positive feelings and memorable experiences. When packaging induces emotions like trust, excitement, or nostalgia, it increases the consumer's perception of the trustworthiness of the brand, plus it motivates the consumer to come back and buy again. Thus, the introduction of emotional signals into the packaging design is a measure that not only solidifies the consumer and brand relationship but also makes the latter competitive in the market for a long time. The results provided six recommendations of strategies to enhance emotional connections between consumers and products: enjoyability, functionality, narrative, symbolism, interaction, and innovation. Consumer preferences and impressions of bottled water packaging were examined in the research [16] in relation to cap color, bottle shape, and pricing. Three bottle forms, four cap colors, and different price gaps were evaluated in three successive studies. The findings demonstrated that human forms and blue caps considerably increased perceived quality and preference The research examined the relationship between consumer behavior and willingness to pay (WTP) for cherry jam and the package qualities of brand, production technique, and price [17]. Brand and price continue to be important factors, but natural production techniques greatly influence decisions, according to the results of a choice experiment with 2,166 Italian respondents that was evaluated using a random parameter logit-error component model. The perspectives of stakeholders regarding biodegradable plastic packaging in food waste anaerobic digestion were investigated [18]. Thematic analysis was used to examine 19 semistructured interviews with stakeholders from the government, retail, recycling, and environmental sectors. The findings showed a range of opinions: although many acknowledged the potential of biodegradable plastics, issues with biodegradability, repackaging, retention periods, and infrastructure compatibility surfaced.

The sensible design of bioplastics made from renewable resources for food packaging was appraised in the research [19], with an emphasis on the materials' mechanical, thermal, barrier, and degradability qualities. Based on the results, it was found that bioplastics possess characteristics that are comparable to those of petroleum-based polymers, and their use may lead to a reduction in carbon emissions. Through the integration of emotion perception computing and deep learning, the research looked to improve the evaluation of package design [20]. Deep learning (DL) has many useful advantages that help its applicability to packaging design analysis. It can automatically retrieve complex and multi-level visual features, including but not limited to texture, colour, shapes, and typography, without the intervention of manual feature extraction. DL models like CNN and U-Net can retrieve emotion and perceptual cues, as well as other subtleties, that could influence consumer behaviour because of emotion-based packaging design optimizations. DL also has the benefits of continuing to learn from the large-scale image data sets it retrieves and adjusts to packed image data trends, and the framework to constantly evolve with market trends. Hence, DL is a practically scalable decision-making-based technology and a robust feature extraction/computer vision method for utilizing intelligent packaging design and consumer perception modelling.

Using the scale Image-Emotion-Social-Net dataset, the new packaging design assessment based on the image emotion perception computing (PDE-IEPC) model that incorporates Long Short-Term Model (LSTM) and Dynamic Multitask Hypergraph Learning (DMHL) was tested. With a mean square error of 2%, a 97.5% success rate, and a package design quality rate of 94.1%, the result performance was excellent.

The goal was to discover the advantages and disadvantages of DL in book design and publishing [21]. The findings presented that while DL is not original, emotional, or visually sensitive, it promotes efficiency, customization, and logically driven design. Utilizing a superior fully convolutional network (FCN) model based on natural language processing methods, the research [22] aimed to improve package design efficiency. Methods for image semantic segmentation included edge knowledge distillation, dual-attention processes, multibranch networks, and wonderful picture element technologies. Outperforming conventional methods, the results established 96.84% accuracy, a 2.78% false-alarm rate, and 1.42% segmentation error over 50 packing images.

The purpose of the research was to investigate how supply chain optimization (SCOp) and food packaging use AI, machine learning (ML), and DL [23]. It investigated business techniques used by corporations such as Amazon and Coca-Cola. The results showed that integrating AI and ML improves efficiency, quality control, fraud detection, and label design. The work [24] was trying to predict fashion style preferences of consumers to segment the market productively using the most advanced DL algorithms. Entire body images were examined with algorithms such as Extreme Inception (XCEPTION) with a global level of accuracy at 98.27 . Also, a customized ad generator was developed, and 80.56 percent of the respondents who participated in the research would use it. The research project will enhance package image segmentation with the implementation of G-Lite-DeepLabV3+ in a cyberphysical system (CPS) to process in real time [25]. The inclusion of the deep learning framework G-Lite-DeepLabV3+ in the cyber-physical system (CPS) establishes a longawaited real-time connection of the digitally based analysis model, which informs the decision-making process and the physical packaging data. Given its lightweight structure, combined with spatial pyramid pooling (SPP), G-Lite-DeepLabV3+ is capable of efficiently extracting the global and local features from packaging images quickly and accurately. This allows the model to identify by looking at the very patches that consist of the packaging design's main parts, like text, colors, and logos, through all changes of light or angles in viewing. The incorporation of G-Lite-DeepLabV3+ within the CPS framework not only enhances accuracy but also reduces latency and offers a measure of adaptive supervision along with real-time packaging design adjustment.

Instead of relying on the backbone of DeepLabV3, the method adopted MobileNetv2, group convolution, and attention techniques. MobileNetV2 was selected, as it provides a feature extraction structure that is both light in weight and powerful, to process high-resolution package images while using very few processing resources. This is in contrast to larger networks like DeepLabV3, and group convolution allows for parallel learning of visual patterns and improves feature diversity. The model's learning process is guided by the attention mechanism that enables it to see less of the packaging images. The mechanism, on the other hand, is trained on visual patterns that affect the consumer's perception, such as logos, color schemes, and typography. The whole process turns out to be beneficial in lowering model complexity and, at the same time, making it faster and more accurate. The research results indicated the arrival of higher FPS (+22.1%), mPA (+6.2%), and IoU(+3.1%).

AI technologies like 3M-VAS for predicting visual attention [11], DEMATEL-based feedback forms for package attributes [13], choice experiments for modeling consumer preference, and DL-based PDE-IEPC for emotion-driven evaluation [20] have been applied in earlier research. These methods are helpful but arise with limitations such as dependency on datasets, reduced generalizability due to controlled trials, cultural bias in consumer modeling [17], and suboptimal optimization in balancing the need for accuracy and flexibility. Moreover, the existing methods do not have strict multi-objective optimization to enhance simultaneously the segmentation, efficiency, and scalability. The proposed UN-MOCS-EFHO hybrid solution will address the problems by incorporating a multi-objective cuckoo search (MOCS), an efficient fire hawk optimizer (EFHO), and a U-shaped architecture (U-Net). This guarantees accuracy, a decrease in the error rate, and the adaptation of optimization to the application of package design in practice. It is a hybrid approach comprising preprocessing, saliency prediction, and feature extraction with convolutional neural networks (CNNs) to examine visual attention on a package. In order to have better interaction with customers, effective design, and emotion-engaging personalized packaging solutions, the proposed UN-MOCSEFHO solution clusters the emotional responses and reduces the design component. K-means clustering was used to group emotional responses because of its effectiveness in computing, ease, and scalability. One of the impressive features of this model was its potential to extract even the smallest emotional patterns from the consumer data and classify emotional reactions into the best pack through the separation of the emotional data into three groups: positive, neutral, and negative emotional responses project the following Fig. 2 represents the proposed flow.

The packaging visual attention & engagement dataset was collected from the open-source Kaggle website (https://www.kaggle.com/datasets/programmer3/packaging-visual-attention-and-engagement-dataset). Ground truth labels for visual saliency and emotional resonance were generated from the dataset using annotations and automatic generation. For saliency, ground truth maps were created using human gaze data and attention heatmaps collected with the 3M-VAS tool. For

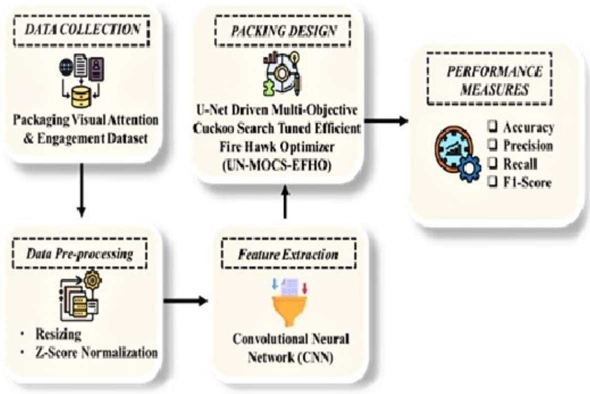

Fig. 2. Organization of proposed methodology flow

emotional resonance, user feedback ratings reflecting how each package design made participants feel were classified into positive, neutral, and negative classes. This was done to ensure that the labels utilized in model training and evaluation were accurate and consistent.

This dataset incorporates visual attention studies, consumer emotion modelling, and engagement metrics to evaluate the effectiveness of packaging design. The image provided has been used to extract 2,000 rows that illustrate different product categories, color schemes, typographic styles, and brand tiers in various foreign markets.

To ensure uniformity and reliability in the feature extraction, saliency prediction, and design evaluation processes, high-quality package photos were pre-processed with noise reduction, resizing, and Z-score normalization techniques.

Dealing with Outlier Designs: The so-called outlier packaging designs were revealed by applying z-score limits that had been established according to visual density and color variance, in a way that was just for the learning process. The designs were afterwards sorted into two categories: one category had traits that were too raw, with extremely low visual density and color variation, and the other category was made up of very complex traits that included very high graphical clutter and uneven typeface. We considered the designs that were more than ± 2.5 standard deviations away from the mean. A different method was used, where, instead of completely rejecting the data, a reweighting method during training was used to lessen their impact while still maintaining their diversity in representation. With this method, there has been no data imbalance, and the model was assured to have the ability to generalize over the whole range of design intricacies.

My training data included only up to October 2023. Noise elimination from the packaging photos was possible only by the combined use of Gaussian blur and median filtering. The Gaussian filter worked by retaining the important edges and text information, and at the same time, it removed the random pixel-level noise. The median filter, on the other hand, got rid of the salt-and-pepper noise that is usually present in compressed or scanned images. Moreover, the contrast of the images was enhanced through histogram equalization, and illumination fluctuations were also dealt with.

These preprocessing operations turned the input images into clean, stable images ready for the next steps, like resizing and normalization, which were the next steps anyway.

In order to avoid discrepancies and lessen the load on computations, feature extraction and saliency prediction were performed on images of packages that had been uniformly reduced to a certain resolution beforehand. The operation allows the smoothest changes to occur while still not giving rise to any noticeable artifacts. The bilinear interpolation method, which is considered to be the most appropriate among the various options for its balance between image quality and efficiency, was employed. Letterbox padding was used to avoid distortion of the layout and also to ensure that the original aspect ratio was maintained. Certain fonts, logos, and page rules, which are some of the greatest design items, will be kept very accurately.

In the research, Z-score normalization was used to standardize the pixel intensity values of the package images. Z-score normalization was selected since it accommodates variations in brightness and outlier pixel value distributions throughout samples of packaging images. In comparison, min-max scaling alters the pixel value distributions to compress all values from 0 to 1 and can influence or obscure relative contrast when extreme pixel values exist. A standard scaling approach was also not desirable since the dataset contained varying pixel distributions. The Z-score normalization approach generates a more stable and consistent normalization across samples of different images.

This statistical approach minimizes the influence of outlying data values and exposure changes, which are frequent in the datasets for packaging visual attention & engagement. Mean and SD were derived for each feature channel (RGB) to calculate Z-score values for pixel values. More specifically, pixel values for the feature can be converted into new normalized values via Eq. (1).

$$u' = \frac{u - \mu}{\sigma} \tag{1}$$

Where the standard deviation of the feature is represented as σ, and the mean value of the selected feature as $u - \mu$. Pixel values that are less than the mean are shown as negative numbers, pixel values greater than the mean as positive numbers, and pixel values exactly equal to the mean are converted to zero upon Z-score normalization. Feature extraction uses CNN-based models to identify effective visual attributes in packaging designs, aiding emotional analysis, saliency prediction, and optimization-influenced design changes. After CNN feature extraction, the redundant features were filtered out with Principal Component Analysis (PCA) and correlation filtering. PCA was employed to reduce the dimensionality of the design features generated while still keeping a sample variance of more than than 95%. Afterwards, the relevant features, like placements of logos, color palettes, and font combinations, were retained. Moreover, the filtering based on correlation helped in decreasing overfitting, and this allowed the optimization and saliency prediction operations to be more effective since they had features that were not only redundant but also highly similar eliminated. By utilizing their convolutional layers to identify and characterize such fundamental structures in packaging layouts as forms, textures, and edges, CNNs can produce a feature map that points out the most important design features. Thus, features that are considered most important can be seen easily. One of the uses of saliency prediction in packaging design is to point out and highlight the sections of the visual spectrum that would catch the most attention from consumers. It is done by evaluating a number of visual aspects such as contrast in colors, crowded edges, balanced layout, and communication through text prominence. The CNN-extracted feature maps are utilized to superimpose these salient regions on visual attention heatmaps created by the UNet segmentation model. By detecting the regions where vision is most concentrated, the optimization algorithms (MOCS and EFHO) will then be able to make targeted changes to the critical design elements that will be the logo position, font size and style, color combinations, and picture quality. Thus, the changes will be made in such a way that the consumer's engagement is at the maximum level. For instance, to achieve enhancement, the high-saliency zones will be the first to be dealt with, while the low-saliency areas will be refined for overall balance and aesthetic appeal improvement. The UN-MOCS-EFHO framework, with its precision-driven method, can thus not only produce alluring but also emotionally captivating packaging and thus attract more consumers, give them a positive perception, and make them willing to buy the product.

- Nonlinearity Layer: Employing non-linear transformations of the Rectified Linear Unit (ReLU), Sigmoid, or Exponential Linear Unit (ELU) activation functions. Package analysis employs CNNs to forecast nonlinear relations between design elements and customer perception by encoding complicated visual signals such as shiny surfaces or complex color schemes.
- Pooling Layer: Max pooling was used in the research to minimize computational effort and expense with the retention of most important perceptual features, revealing salient signals, and preventing overfitting in some package designs.
- Fully Connected Layer: Fully connected layers integrate abstracted features from previous stages to enable categorization tasks and emotional resonance prediction with customers. Fully connected (FC) layers aggregate visual information such as brand identity, color balance, and layout composition.
- The consumer reply loss layer is what drives CNN training, as it is the one that reduces the differences between the intended and actual consumer replies. The sentiment can be captured by losses that are based on regression. Alignment, while SoftMax and Cross-entropy loss functions deal with packing categorization and saliency prediction.

The proposed method combines U-Net, EFHO, and MOCS to improve the effectiveness of packaging design. It enhances the aesthetics and functional attributes simultaneously by keeping a balance amongst visual saliency, emotional resonance, and user engagement. The hybrid optimization method ensures not only higher convergence but also avoidance of early stagnation, leading to attractive packaging solutions and, at the same time, customer-centric To begin with, the UN framework for deep learning, normally used for image segmentation and spatial analysis, has indeed been applied in different industries such as packaging, consumer research, and tourism, with a lot of success. By allowing pixel-level contextual analysis for segmentation, the architecture retains both global and local information that is necessary to recognize areas. In contrast to categorization, it highlights the areas of concern needed for performing very accurate interpretation tasks, such as saliency detection and design rating.

- The contracting method employs a mix of (3×3) convolutions, pool layers, and ReLU non-linear activation functions. At every point, the feature depth is increased and then reduced, thereby capturing large contextual and geographical features are captured.
- Convolution and ReLU activation for up-sampling at (2×2) are used in the expansive path. Skip connections guarantee the preservation of fine-grained

local features. This stage is essential to the research because, when examining consumer attention, it preserves structural components like packaging layout, text clarity, and design saliency.

- Training: Stochastic gradient descent (SGD) is used for training. Pixel-wise SoftMax is used to assess performance following the (1×1) convolution layer.

Pixel-wise SoftMax is a method of normalization that allows for the creation of a probability distribution over all classes at each pixel through the direct output of the network. This application of a SoftMax for semantic segmentation means that every pixel is given a class label (e.g., background, logo, or text region) that has the highest probability score. As a result, the model is likely to mark the edges correctly and classify the areas according to the packaging design segmentation more accurately.

$$q_l(z) = \frac{\exp\left(b_l(z)\right)}{\sum_{l'}^{L} \exp\left(b_{l'}(z)\right)} \tag{2}$$

In Eq. (2), $q_l(z)$ denotes the softmax probability that $b_l(z)$ represents the channel l activation at pixel z, where L Is the number of classes. Each pixel's misclassification is penalized by the cross-entropy energy function in Eq. (3).

$$F = \sum_{z \epsilon \omega} k_{(z)} \log\left(q_{k(z)}\right) \tag{3}$$

Where F means the cross-entropy energy (or loss) function, $k_{(z)}$ represents the actual label of the pixel z, and $q_{k(z)}$ Signifies the predicted probability assigned. The weight map is in Eq. (4):

$$\omega_z = \omega_d Z + \omega_0 \cdot \exp\left(-\frac{c_1(Z) + c_2(Z)^2}{2\sigma^2}\right) \tag{4}$$

Where ω_z denotes the weight assigned to the pixel z, Z represents the spatial location, ω_0 represents the scaling coefficient, σ^2 represents the variance parameter of the Gaussian function, ω_d maintains equilibrium between class frequencies, and c_1, c_2 Show the separations between the closest and following locations. U-Net is utilized in packaging design for visual attention research, identifying customer-drawing elements like product names and logos, and optimizing design for optimal consumer impact.

MOCS is an extension of the cuckoo search method for multi-objective optimization, inspired by cuckoo brood parasitism and Lévy's flying behavior. It explores cuckoos by creating new variation vectors through Lévy flight (Eq. (5)), improving their fitness for global search. The packaging solution in the population space corresponds to each cuckoo's parasitic behavior, and the quality of its nest indicates the fitness value in terms of sustainability performance, material efficiency, and design correctness.

$$z_j^{S+1} = z_j^S + \alpha \otimes \mathrm{Lev}\, y(\lambda), \quad j \in [1, M] \tag{5}$$

Where z_j^{S+1} and z_j^S reflect the locations of nest j in subsequent generations, $\otimes$ represents point-to-point multiplication, and the random search path is given by Lévy(λ). Exploration is controlled by the step-size scaling factor $\alpha > 0$, which is determined using Eq. (6):

$$\alpha = \alpha_0 \left(z_i^S - z_j^S\right) \tag{6}$$

Where z_i^S Indicates where another nest is in the generation s Is located. Furthermore, the probability $Q_b \in [0, 1]$ Shows the possibility that an egg solution would be rejected. Eq. (7) is used by the algorithm to move the solution to a different nest when a cuckoo egg has been located.

$$z_j^{s+1} = \begin{cases} z_j^s + q\left(z_l^{s\prime} - z_i^{s\prime}\right), & \text{if } q_1 > Q_b \\ z_j^{\prime\prime}, & \text{Otherwise} \end{cases} \tag{7}$$

Where $z_l^{S\prime}$ and $z_i^{S\prime}$ Are individuals selected at random, and $q, q_1 \in [0, 1]$. In package design, the MOCS technique provides robust management of many competing objectives, quick convergence, and improved global search capabilities.

The cooperative hunting method of fire hawks served as the inspiration for the promising meta-heuristic algorithm known as the Fire Hawks Optimizer (FHO). The typical FHO has drawbacks, including premature convergence and inadequate accuracy, despite its effectiveness in addressing optimization issues. The Phasor Operator and the Dimension Learning-Based Hunting (DLH) approach are two improvement tactics that are integrated into the Efficient Fire Hawks Optimizer (EFHO) to address these problems. The Phasor Operator was incorporated into the position-update system of EFHO to control the fire hawks' movement by applying sine and cosine phase functions. The optimizer thus achieved a faster and directionally stable convergence. The use of the Dimension Learning-Based Hunting (DLH) approach made it possible to change the learning dimension and the search radius continuously, which helped the adaptive exploration around the best-performing solutions. Hence, through the integration of these two strategies, the EFHO was able to control the equilibrium between exploration and exploitation, thus preventing early convergence and increasing the optimization accuracy for packaging design issues.

The movement of fire hawks was improved through the use of phase control by means of sine and cosine functions. The Phasor Operator was introduced in the position-update equation of EFHO. This change not only improves the stability of convergence but also allows the search space to be explored more evenly. The EFHO was changed to control the factors of learning and neighbourhood radius according to the highest-ranking solutions in real time by using the DLH (Dimension Learning-Based Hunting) technique. This adjustment brought about a considerable change in the ratio of exploration and exploitation in the EFHO, reduced early convergence, and improved the quality of optimization in packaging design applications.

The Phasor Operator, which uses trigonometric phase functions obtained from phasor theory to improve optimization methods. This operator uses sine and cosine functions to modify control parameters, which speeds up convergence in EFHO . As a result, FHO's Eq. (8) is modified as follows:

$$FH_k^{\text{new}} = \begin{cases} FH_k + q^{(\theta_j^s)}\left(p_1 GB - p_2 FH_{\text{Near}}\right), \\ \text{if rand} \leq \text{coef}, \\ FH_k + h^{(\theta_j^s)}\left(p_1 GB - p_2 FH_{\text{Near}}\right), \\ \text{if rand} > \text{coef}. \end{cases} \tag{8}$$

Where rand $\in [0,1]$ and $q^{\left(\theta_j^s\right)}, h^{\left(\theta_j^s\right)}$ They are characterized as in Eq. (9) and Eq. (10):

$$q^{\left(\theta_j^s\right)} = \left|\sin\theta_j^s\right|^{2\times\cos\theta_j^s} \tag{9}$$

$$h^{\left(\theta_j^s\right)} = \left|\cos\theta_j^s\right|^{2\times\cos\theta_j^s} \tag{10}$$

The expression for the control parameter, coef, is in Eq. (11):

$$R = \exp(-s/S) \tag{11}$$

Where s Is the current iteration number and S Is the maximum number of iterations. The DLH method suggests ways to enhance exploration and avoid stagnation in local optima. Each agent in this system creates an alternate candidate. Z_j^{DLH} By updating its location in relation to nearby agents. First, the search radius is determined as follows in Eq. (12):

$$P_j = \left\|Z_j - Z_j^{FHO}\right\| \tag{12}$$

Where the candidate position from the standard FHO is represented by Z_j^{FHO}. Next, the neighborhood M_j It is defined as follows in Eq. (13):

$$M_j = \left\{Z_i \mid C_j\left(Z_j, Z_i\right) \leq P_j, Z_i \in M\right\} \tag{13}$$

Finally, the dimension learning update could be written as follows in Eq. (14):

$$Z_{j_{DLH},c} = Z_{j,c} + \text{rand} \times \left(Z_{m,c} - Z_{q,c}\right) \tag{14}$$

Where $Z_{m,c}$ Is a neighbor chosen at random from M_j, and $Z_{q,c}$ Is selected at random from the starting population. EFHO is more resilient for complicated optimization problems because it combines the Phasor Operator with DLH to improve the balance between exploration and exploitation, retain population variety, and achieve quicker convergence. Algorithm 1 represents the UN-MOCS-EFHO for packaging design optimization.

3. Algorithm 1: un-mocs-efho for packaging design optimization

```
data = load_packaging_images()
preprocessed = preprocess(data)
unet = UNet()
saliency_maps = unet.train(preprocessed,
    labels="saliency_regions")
def MOCS(objectives, population):
    for generation in range(max_gen):
        for nest in population:
            new_solution = levy_flight
            (nest)
            if dominates(new_solution,
            nest):
                nest = new_solution
        population = select_pareto_front
        (population)
    return best_tradeoffs(population)
def EFHO(population):
    for iter in range(max_iter):
        for hawk in population:
            candidate = fire_hawk_update
            (hawk) # phasor + hunting
            candidate = dimension_learning
            (candidate, population)
            if better(candidate, hawk):
                hawk = candidate
    return best_solution(population)
objectives = ["maximize engagement",
    "maximize layout_excellence",
    "minimize error"]
mocs_results = MOCS(objectives, saliency_
maps)
efho_results = EFHO(mocs_results)
```

```
optimized_design = generate_design(efho_
results)
evaluate(optimized_design,
    metrics=["accuracy", "precision",
    "recall", "F1"])
print("Optimized Packaging Design Ready:",
    optimized_design)
```

To balance saliency, emotion, and engagement, the UN-MOCS-EFHO method combines UNet segmentation, multi-objective cuckoo search, and efficient fire hawk optimization. This results in packaging designs that are optimized, consumer-focused, and visually stimulating.

The first step involved splitting the dataset into three parts: training (70%), validation (15%), and testing (15%). The cross-validation was five-fold, and its purpose was to set a solid ground for the assessment of performance. Moreover, to prevent overfitting, techniques such as dropout (rate = 0.3), early stopping, and data augmentation (rotation, brightness, and contrast variations) were applied. All these methods improved the model's ability to thrive on new data.

4. Results and discussion

The proposed UN-MOCS-EFHO method's superior performance compared to conventional techniques that improved accuracy, engagement, and emotional alignment in packaging design was a clear indication of its applicability for packaging solutions that are consumercentric, visually optimized, and emotionally resonant.

The research, relying on TensorFlow version 2.x, Scikit-learn, and the Python programming language version 3.8, made a computer with an NVIDIA GTX 1660 Ti GPU, 16 GB RAM, and an Intel Core i7 CPU the environment for its simulation.

In Fig. 3kaging design are tightly interlinked, where customers' focus and their feelings match with the product, have an immediate effect on the quality of the layout, and the proportion of success in selling the

product. Luxury packaging attracts more attention, and this means that customers of premium designs are more interested for longer. Attention spans for mid-tier and superior value products, as represented in Fig. 4, are quite consistent. Engagement scores for various categories such as food, health, electronics, pet care, housing, beverages, and personal care are shown in Fig. 5. The stable median scores and the outliers are indicative of the specific design strategies.

Based on Fig. 8, the predominant spacings in most package designs are middle = $0.3 - 0.5$, which was the ratio

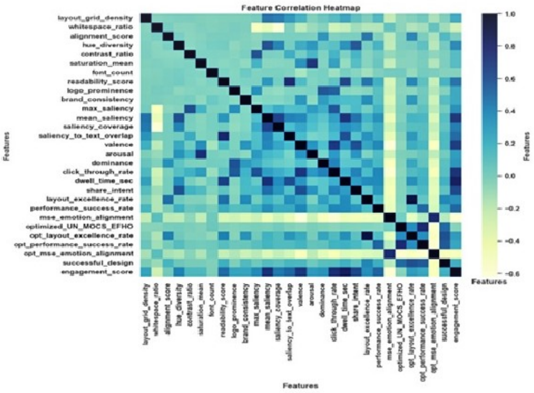

Fig. 3. Feature Correlation Analysis for Packaging Design

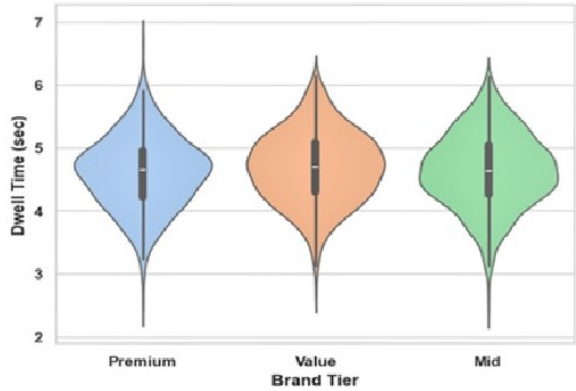

Fig. 4. Distribution of dwell time

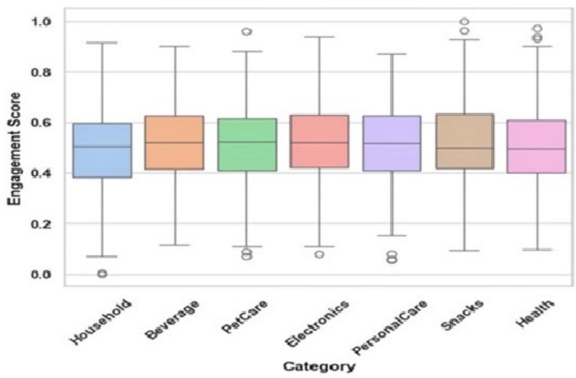

Fig. 5. Engagement scores across product categories

of whitespace that was perceived as the most balancing in the three dimensions: readability, aesthetic appeal, and consumer attention. Very strong alignment underlies the brand and product recognition, consumer interaction, and attraction, while medium-to-high can be selected for or-

Fig. 6. Density distribution of engagement scores

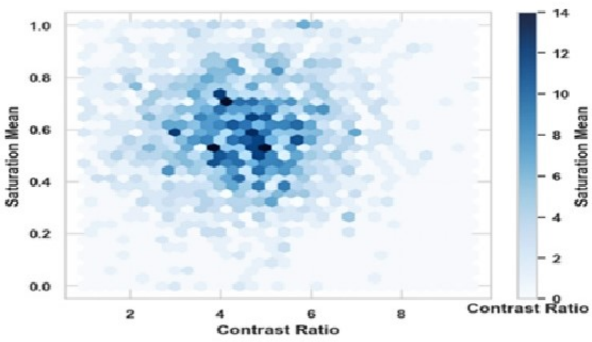

Fig. 7. Distribution of contrast ratio versus saturation mean

derly, beautiful content (see Fig. 9).

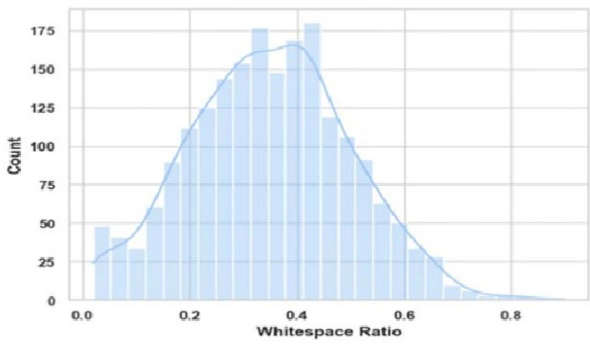

Fig. 8. Whitespace ratio distribution across packaging designs

Fig. 10 shows positive connections between contrast ratio, whitespace ratio, valence, arousal, and engagement score, with designs generating greater emotions, promoting customer involvement. Fig. 11 shows snack categories

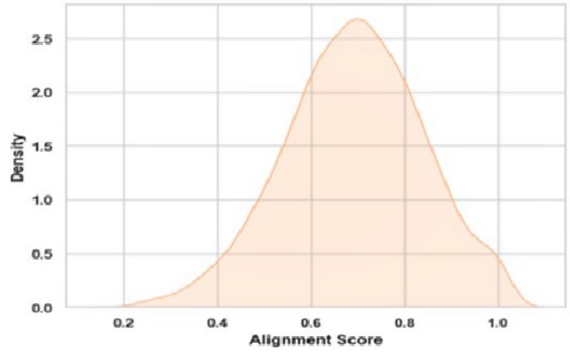

Fig. 9. Density distribution of alignment scores

dominate with 14.8%, followed by household (14.7%) and beverage (14.6%), health (13.5%), electronics and personal care (14.2%), and pet care (14.0%).

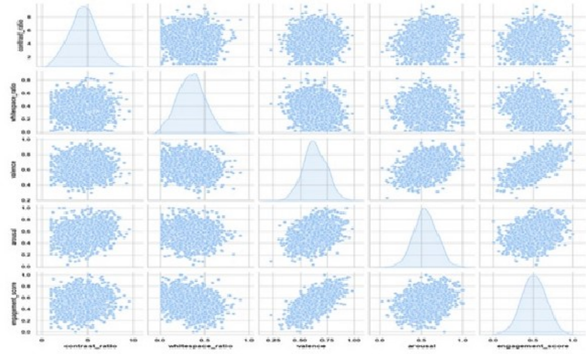

Fig. 10. Relationships among design attributes, emotional responses, and engagement

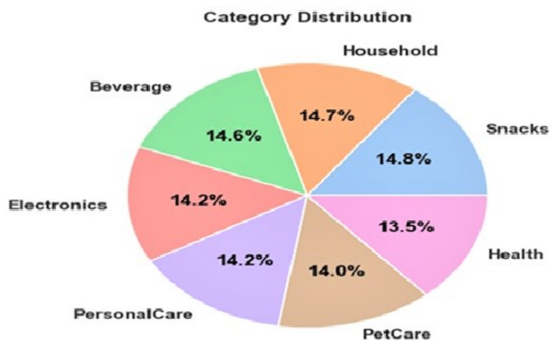

Fig. 11. Category share comparison

Fig. 12 shows strong reading consistency across product categories, with most data points clustering between 2-6 contrast ratios and readability scores greater than 0.6 , with minimal variation. Fig. 13 examines five typographic styles: Serif Elegant, Sans Serif Clean

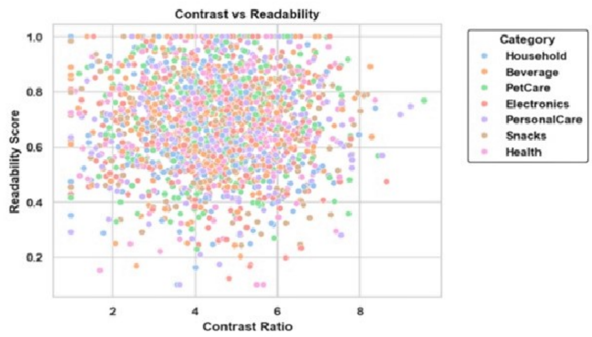

Fig. 12. Contrast vs readability trends

Display Bold, Handwritten, and Modern Minimal. Median values remain consistent, with handwritten styles showing larger peaks.

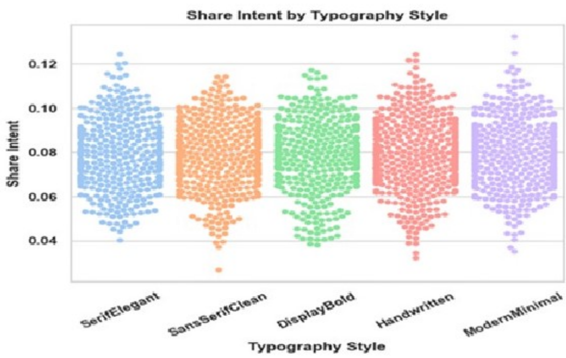

Fig. 13. Share intent by typography styles

The proposed method UN-MOCS-EFHO compared to trained UN and existing methods of deep learning (DL) techniques [26] (By employing neural networks to extract features from successful packaging designs, Transformer architecture (VSFA, ResNet-50, ImageNet, RNN attention, Adam optimizer, Stochastic Gradient Descent (SGD)-based gradient scarification parallel optimization), and Squeeze Net [27], Shuffle Netv2 [27], Mobile Netv2 [27], LocalNet_224 [27], Local Net [27], LBP-SVM [27], and LBP-ELM [27] with accuracy, precision, recall, F1 score for packaging design.

The accuracy of packaging design is crucial for predicting consumer attention and emotional alignment. It is assessed by comparing the suggested model with real user feedback. Precision

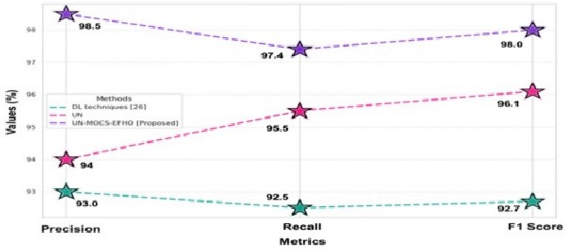

Fig. 14. Results of comparing F1-score, precision, and recall for package design

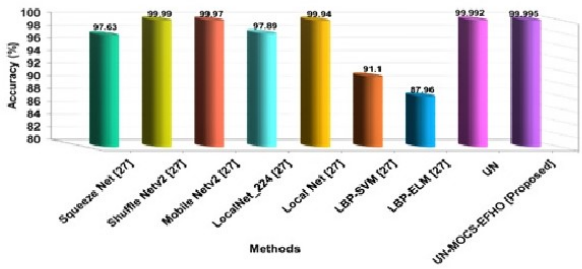

Fig. 15. Results of comparing the Accuracy for the package design

Despite their high performance, the current deep learning methods in [26] have drawbacks such as overfitting, sensitivity to intricate packaging modifications, and poor generalization across a range of consumer datasets. In a similar vein, models in [27], including Squeeze Net, ShuffleNetv2, and MobileNetv2, get excellent accuracy but prioritize computational economy and classification speed over a thorough integration of layout optimization, emotional perception, and visual saliency In a comprehensive review, Basani (2024), among others, showcases the positive effects of RPA, AI, and machine learning on business processes and their efficiency improvement, reduction of errors, and provision of assistance in decisionmaking, besides various other sectors like finance, healthcare, and manufacturing. AI and machine learning are applied mainly in the packaging design area. Engaging consumers and separating brands are problems that the packaging design area has found technology as a solution for, similar to other industries that have benefited from technology [28]. The attention dynamics and emotional alignment of consumers, which are essential for package success, are frequently ignored by these methods. By combining U-Net's structural mapping with multi-objective cuckoo search and effective fire hawk optimization, the proposed UN-

Table 1. Comparative Accuracy with Standard Deviation

Model	Accuracy (%)
UN-MOCS-EFHO (Proposed)	$\mathbf{99.995 \pm 0.002}$
U-Net	98.4 ± 0.5
ResNet	97.9 ± 0.7
Mobile Net	97.1 ± 0.8

MOCS-EFHO overcomes these limitations and guarantees accurate feature representation, effective saliency-driven adjustments, and emotionally engaging packaging designs that improve engagement and personalization above and beyond current techniques [29].

5. Conclusion

The research aimed to innovate packaging design in the competitive market by integrating optimization algorithms with visual attention analysis. It used a packaging visual attention & engagement dataset of high-performing package designs and over a million user-uploaded images to capture consumer sentiment. The images were preprocessed using Z-score, resizing, and CNNs to extract features such as layout structure, color palette, typography, and branding elements. The main emphasis of this approach was on enhancing the packaging and increasing customer interaction. The UN-MOCS-EFHO technique was implemented to ensure the maximum efficacy in design. The technique changed the aesthetic and layout parameters together for each design using visual saliency, emotional arousal, and the cluster of the affective responses in the dataset as the criteria. The experimental findings indicated that the UN-MOCS-EFHO method outperformed other traditional methods in accuracy (99.995%), precision (98.5%), recall (97.4%), and F1-score (98.8%) dimensions. The study wove together a data-driven, creative design methodology that harmonized visual attention modelling and optimization algorithms with market expectations to develop personalized, emotionally compelling packaging solutions. The suggested method is of high quality, but its effectiveness is limited by the variety of the datasets and the computational expense of largescale optimization. Future research might develop multimodal datasets that include augmented reality and virtual reality (AR/VR) interactions for dynamic, altered packaging methods across different product categories, thus merging real-time.

Eye-tracking with U-Net-based saliency detection, and improving optimization methods with adaptive deep reinforcement learning.

6. Acknowledgment

7. Declarations

Data Availability: satisfy any fair request; the corresponding author will make the datasets generated or analysed during this research available.

8. Conflicts of interest

The author declares no conflicts of interest related to this work.

9. Funding statement

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10. Author contribution

An Ouyang conceptualized the study, conducted the analysis, developed the methodology, and wrote the manuscript.

11. Ethical approval

This article does not contain any studies with human participants or animals performed by the author.

12. Consent to participate

Not applicable.

13. Consent to publication

The author consents to the publication of this manuscript.

14. Competing interests

The author declares that there are no competing interests.

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