ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

Multifaceted Applications of New Media Technology in Visual Design for Advertising Packaging: A Deep Learning and Reinforcement-Based Approach

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SUMMARY: *Packaging design has become a central element of consumer choice and brand recognition, which are now more affected by artificial intelligence (AI) and new media technology. With increasing demands in complexity and personalization of design, intelligent systems provide new approaches to automate, create and optimize visual packaging. The proposed study will develop a multi-model AI system to improve advertisement packaging via classification, creative system generation, object detection, and optimization of design through improved deep learning methods. The framework combines four approaches: the Convolutional Neural Networks (CNNs) that classify the visual elements of design, Generative Adversarial Networks (GANs) that create the new packaging designs, YOLO that can detect objects in real-time, and Reinforcement Learning (RL) that can optimize the package design in terms of color and logo size. Normalization, PCA and clustering were applied to preprocess ADS16 and additional designs. The models were assessed based on accuracy, F1-score, FID, IS, mAP, and reward trajectory in order to measure functional and aesthetic performance. The suggested multi-model is an effective combination of AI and design intelligence. Specifically, reinforcement learning offers the most promising prospects of developing customized, data-reinforced packaging solutions in accordance with the new media and advertising objectives.*

KEYWORDS: *Packaging design; Reinforcement learning; Deep learning; Generative adversarial networks; YOLO; Visual optimization*

1 Introduction

In a more and more crowded market, packaging looks may serve as the decisive factor to the consumer population buying products [1]. That explains why, as a recent study conducted by Ipsos revealed 72 percent of American consumers claim that the design of packaging of a specific product usually affects their buying decision, making the role of packaging as a major touchpoint in the customer journey even more important now. This understanding is consistent with the information that packaging does not only have an influence on a brand recognition, but also motivates new buying behavior especially when the products are positioned in busy digital or physical spaces. Also, 67 percent of the respondents said that use of packaging design could have direct impact on their overall perception of the quality of brand which by implication indicates that visual features such as color, typography and structure has increasing strategic role in influencing consumer trust and attractiveness.

Traditionally, the guide of packaging design has been based on artistic talent and marketing instinct. However, the development of artificial intelligence (AI) and new media technologies

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https://doi.org/10.65102/is20261074 Published: 10 June, 2026

has created an explosive packaging design explosion [2]. As the Rebellion Group explores, although AI is not a new tool to automate design, it is gradually becoming a collaborative accomplice to create. The designers are using AI models to scale their packaging idea tests and generative iteration of package ideas driven by the data-based aesthetics of the design. This enabled more interactive and adaptive design workflow with the integration of machine learning models such as CNNs, GANs, and reinforcement learning algorithms. These technologies make real-time prototyping, predictive modelling of consumer behavior, and customized packages in terms of user profiles possible. Such applications of AI not only bring about a shift in the linear, human-led design.

Despite the extensive literature on the use of AI in marketing and/or product design, to the best of which I am aware at this time, no single study addresses the development of fully integrated deep learning, generative models, object detection, and adaptive learning techniques into a unified framework for packaging design [3]. While Jain et al.'s recent research provides evidence of the feasibility of applying AI to determine product aesthetics, the majority of the existing research still relies on a single model deployment, although visual design attributes can be classified and predicted using machine learning, they are not tightly linked to the optimization mechanisms that can determine the most effective combinations of design attributes over time, including reinforcement learning. This fragmentation arises from the need for an integrated research model that would interface classification, generation, detection, and optimization in a loop to create visually appealing and market-oriented packaging.

The goal of this work is to fill this gap by proposing a multi-layered AI framework that uses the ability of CNNs to classify visual design features, the GAN to generate new packaging aesthetics, YOLOv5 for detecting key visual elements such as logos, characters or focal image, and RL to optimize combinations of packaging variables like colour palette, typography size, logo placement. The datasets to be used in the study will be ADS16 and other open-source design datasets that exhibit real-world packaging scenarios. These are understood to be combined to produce not only designs that are 'creatively' (rather than strategically) sound but also leverage data (as well as behaviours such as predicated engagement or likelihood to purchase), thereby being strategic, backed by data, and tested. It provides a new direction for packaging innovation by applying the principles of this novel integrative approach inspired by related work in cognitive systems [4].

This research is significant in the academic as well as practical domains. The results will be practical knowledge to marketers on the way AI can provide a physical form of the abstract elements of branding into implicit designs and present what consumers desire. Designer study demonstrates that AI is applicable as an augmentation tool instead of a substitution of prototypes to help to offer fixes, suggestions, and visual analysis and stop ideation. Ranjan et al. work suggests that a blend of AI and human creativity results in smoother and more effective and emotionally and psychologically oriented designs [5]. Moreover, the project is also a new case study on the AI research community regarding cross-domain machine learning, in which object-detection and reinforcement algorithms can be applied to an uninvolved sector of the creative packaging design.

The framework also remarks on the current issues in the field of sustainability in packaging and personalizing. The other frontier is that the models access what is visualized to be a function of the demographic or psychographic data so that a new sense of customer engagement with personalized packaging can be taken. Primarily, reinforcement learning allows the model and experiment with design decision-making of thousands of hypothetical cases to achieve success based on the optimal prediction of cumulative reward.

2 Literature Review

2.1 Visual Design Principles in Advertising Packaging

Design concepts are critical in forming out consumer perceptions, brand associations and buying decisions. The combination of visual characteristics such as colour, graphics, logo, typography and layout have a strong impact on purchase intention, particularly with low involvement products such as tea bags. Their research was done in Malaysia based on orthogonal type of experimental design where 14 prototypes of packaging were developed and tested by 490 consumers. They used SPSS and Mplus as methods of data analysis to show how the experience with a brand mediates the impact of these visual elements. Colour harmony and layout balance were mostly crucial elements, which prove the idea that the consumers make decisions not only rationally but also visually and emotionally. Their study of over 1,300 participants emphasized the fact that the lesser the visuals you have the lower the number of ingredients you communicate; this makes the food item appear healthier. Such facts confirm the symbolic aesthetics theory indicating that simplicity in itself is a communicative means in packaging [6]. Nevertheless, they were also able to state explicitly that there were some boundary conditions, in which store brands and indulgence goals undermine this effect, showing that minimalist strategies should be contextualized.

To continue the list of those, focusing on attention and engagement, the researchers resorted to Tobii Pro tools and noted that the longest fixation time and engagement score were produced by designs related to character and bold illustration and brand visibility. This observation reinforces the hypothesis that the use of visual storytelling elements, i.e., the use of characters and symbols, contributes to better emotional appeal and recall. Markedly, there was a bias in preferences to cultural familiarity because the foreign participants were attracted to design that was globally familiar. In contrast, [7] applied the Theory of Planned Behavior (TPB) in a Chinese context to examine how packaging design affects consumer intentions to buy nearly expired food products. For example, structural equation modelling of 426 participant survey data from the instructions of visual interface revealed that their visual design significantly affected perceived behavioral control, especially when cues of trust are present in labels. Verbal cues did not have as much sway, but visuals helped lay customers' minds at ease that the product they're buying is safe, and doing so can overrule negative temporary associations. These contrasting studies highlight that design effectiveness may vary by product type and consumer context; that is, product type and consumer context may raise or reduce program effectiveness.

The theories of graphic design were conceptualized and integrated into practical packaging. The research, which is based on 450 design practitioners in 6 phases of the graphic design process, confirmed that the use and knowledge of graphic design theories like balance, emphasis and rhythm affect to what degree packaging is perceived to be attractive [8]. The study then emphasized the programmable matter in commercial applications beyond trial and error efforts. [9] also filled a gap between previous research in that they use design and marketing lenses in their multi-level analysis rather than visual elements on a stand-alone basis, as have other studies. Their structural model showed that even small changes in graphic type or colour harmony as small as in the perception of a brand and buy behaviour. Under these circumstances, it is evident that empirical methodologies and theoretical basis are necessary to understand consumer responses to packaging. Some scholars would favour minimalism. As a result, a crucial balance of simplicity and stimulus (implied complexity and resulting stimulus) emerges to suggest that a design that works might depend on a balance between market, culture, and category, and a particular combination will have winners and losers.

2.2 Applications of Deep Learning in Visual Perception

Deep learning technologies have increasingly transformed how visual elements are perceived and interpreted in packaging and advertising. Based on their study, they compared conventional object detection datasets to the dataset used for goods-on-shelf scenarios. They concluded that detecting small targets and observing objects under occlusion is challenging. The authors used deep learning-based target detection models (CNN) to propose optimized dataset creation and enhancement techniques for recognition accuracy. Based on their analysis, they emphasized developing new datasets that are dimensioned for shelf packaging and the increasing ability of CNN architectures for scalable package identification. Nevertheless, there are challenges like overfitting, the absence of packaging data at high resolutions, and design subjectivity. This coincides with related issues that have remained in the field of computer vision to date, where performance is sensitive to dataset generalization and contextual change. According to that, deep learning for exploding detection and recognition automates the process. Still, the lack of interpretability of CNN models can be a barrier to commercial deployment and user trust.

To determine how AI tools like deepfakes and GANs radically change the production of advertising visuals, they investigated. They built on existing global campaign cases and contemplated the ethical issue around the use of AI for image manipulation. Indeed, the article doesn't offer empirical data, but it provides conceptual analysis toward understanding how AI is increasingly generating and less and less analyzing Vis Media. This is a change from using CNNs as analytic tools to generative agents that can carry out style transfer, aesthetic augmentation, and personalization. However, an aspect that introduces ethical challenges when deploying AI in this application is its potential to present misleading visual content. [10] used a YOLOv8 framework for logo detection and packaging logo saliency prediction in a way that introduced a novel brand attention-scoring model. Their study combined logo detection with transformer-based saliency map generation using the FoodLogoDet-1500 and LogoDet-3K datasets. It turned out that deep learning integrated with cognitive models, such as attention mapping, can yield a complete picture of who consumers focus on. They validated their model against psychophysical data and proposed several new hypotheses for logo placement, visual orientation, and humans on packaging methodologically. This deep learning research tackles visual reasoning and classifies the problem several steps beyond simple classification tasks. Meanwhile, although their framework performs well, its dependence on large labelled datasets and high-end computational resources makes it unsuitable for a small firm or developing market. [11] also did with visual advertising, they investigated AI on facial recognition and biometry. They conducted their pilot study by capturing emotional reactions to video advertisements using Amazon Rekognition. Their research is no longer packaging-specific but demonstrates how deep learning can predict consumer engagement based on emotional cues. Instead, they propose the integration of emotion analytics as a part of iteration and, thus, a more dynamic and feedback-driven process. Still, the existing AI applications that utilize pre-trained facial models rely on generalised models among cultures and diverse audiences, which points to a downside currently overlooked in the AI applications.

In a related domain, [12] have done a systematic review of the application of deep learning in food processing, including problems like visual inspection tasks such as grading and impurity detection. While not regarding direct advertising design, the study supports the more general conclusion that deep learning performs well in the segmentation and recognition of images. They pointed out the problems of unsound models and the need for real-time processing systems in an industrial setting, a situation similar to that of packaging design, where speedy visual decisions are necessary. Despite being in healthcare, [13] also affirmed that deep learning obtained higher accuracies than traditional machine learning on image-based classification tasks by providing superior features. However, their approach to diabetic retinopathy detection does recognize the potential risk of overfitting and data inefficiency due to limited/datasets or unbalanced datasets — which are problems equally relevant in visual packaging research.

2.3 Generative Models in Creative Design

Generative Adversarial Networks (GANs) have emerged as transformative tools in the creative design process, enabling machines to produce novel, aesthetically rich content across various domains. By disentangling shape and texture features, the model aimed to replicate human-inspired design principles. Evaluated through a combination of automatic metrics and human experiments, the results indicated that 61% of generated images were perceived as human-created, showcasing the power of GANs in both novelty and likability. According to this empirical evidence, generative models can learn the core principles of artistic design if sufficiently good loss functions and architectural tuning are used. However, the authors recognised the difficulty in standardizing evaluation metrics as they were subjective.

The study was conducted at ICANN. The adversarial network used in the study used spatial feature fusion to produce a plausible structure in the generated outputs while being inspired by nature. Their qualitative and quantitative assessments confirmed that DesignGAN could generate functionally and visually acceptable outputs. However, the paper also pointed out the drawbacks of dramatically controlling design outcomes, which are strongly dependent on training data. These results indicate that GANs are helpful and creative ideation tools yet do not yet exhibit well-defined controls that designers may need to aim for specific projects.

Generative AI application in the creative industries like art, advertising, and entertainment was described. However, the review pointed out how GANs, VAEs, and transformers have sped up prototyping and iteration. These tools now automate layout generation and personalize and are widely popular in advertising. However, Alabi observed that although generative AI is widely exploited, authorship and creative ownership of generative AI are still up in the air [14]. On the WikiArt dataset, conditioning in artistic styles could produce human creativity more closely than their experiments. However, they found that DCGANs merely make copies of training data, which they critiqued as being lacking in original and concept development.

Additional advancements are seen in the work of [15], who proposed a GA-SAGAN model for simulating and recommending styles for handmade artworks. Using genetic algorithms to optimize self-attention modules, their study achieved superior precision and recall over traditional GANs, demonstrating the model's ability to produce diverse, high-fidelity designs. The results of their experiments were high inception scores and SSIM values, and professional artists assessed the generated work with high ratings in visual and artistic value. Though these studies confirm the usefulness of GANs in creative production, they also cast doubt on how human curation assists in the filtering, direction, and contextualization of production since full autonomous design generation is still unable to capture subtle intent or thematic where ableness.

2.4 Object Detection in Product Packaging

Object detection is now a fundamental technology in product packaging analysis, especially to recognize logos, labels, icons and other elements of a brand. [16] made a comparative study where they compared YOLOv3, Faster R-CNN, and SSD in terms of real-time pill recognition in a medical facility. On the basis of a specialized set of pill photographs, the scientists researched the model performance in terms of mean average precision (mAP) and speed. Whereas, Faster R-CNN got the best accuracy at 87.69, YOLOv3 had trained under real-time performance, with the speed of detection more than eight times faster than Faster R-CNN. On the contrary, SSD performed poorly by both measures. These results emphasize the trade-off between speed and precision in detection, particularly, to the packaging component, where high-speed analysis may be highly required in a dynamic setup like in a pharmacy or a store. Nevertheless, analysis of their results also concluded that there were challenges in identifying problematic samples, and as a consequence, object complexity, occlusion and small-scale logos pose a challenge towards the strength of object detectors.

To further develop the domain application, [17] analyzed the same three models of the cloud, which are: YOLO, Faster R-CNN, and SSD, in cloud detection, as it is a task similar to small object recognition in packaging. His analysis revealed that YOLO was not sufficient at the detection of targets that were very similar to each other, and this may be compared to differentiating almost identical packages of the product. The reason was the object detection speed in which the accuracy motivated models are essential as opposed to other situations where object detection rates are not crucial, and also to adapt this type of object detection algorithms to suit the needs by the industry.

2.5 Reinforcement Learning in Design Decision-Making

Reinforcement Learning (RL) has become an attractive framework of adaptive and data-driven design-making in the fields. [18] gave a background about the topic of RL and its origins to dynamic programming and optimal control. His book distinguishes between precise dynamic programming algorithms and coarse techniques such as Q-learning and policy iteration which make it possible to solve multistage decision problems that are computationally intractible. He pointed out that RL gives a mediating factor between AI and control theory with algorithms that can adapt dynamically to experience despite stochastic or partially known environments. Model-free RL is especially useful because of its robust ability to be flexible, particularly in design applications where the objective function is complex and the user requires real-time feedback of the ongoing solutions. Nonetheless, the book also found practical challenges in reward specification and convergence reliability and proposed a balance between a theoretical rigor and a sense of design.

This suggests that RL can also be applied to flexibility design in strategic decision-making problems like network optimization or adaptive manufacturing, as [19] have proposed an RL framework for flexibility design. They emphasized noisy exploration and variance reduction techniques to achieve a better solution quality than classical heuristics. The results of the simulated case studies found that RL could repeat such reconfiguration dynamically to adapt to escalating uncertainty and evolving user demands of systems. However, they cautioned that RL's success is highly sensitive to appropriate exploration strategies coupled with strong environmental modelling.

To approach autonomous driving decision-making with uncertainties, [20] proposed a Bayesian RL method that can estimate uncertainties. They showed that with randomized prior function training, they could train an ensemble of neural networks, which resulted in assessing the confidence level of their own decisions, a necessary feature in design contexts where incorrect decisions may result in severe user dissatisfaction. Uncertainty in decisions can also bring up more user trust and safety in design systems. Still, the model was brittle regarding out-of-distribution data, thus calling the generalization on RL into question.

3 Methodology

3.1 Dataset Overview

Due to the extensive collection of over 3,000 ad images by different categories such as product, service, and social ads on the ADS16 dataset, the ADS16 dataset was adopted as the primary dataset of this study. Moreover, we provide a dataset that is particularly suited for the analysis of visual packaging design because it contains various advertisement styles, brand representations, and layouts, which are all essential input elements for training deep learning models in classification, detection, and generative design tasks. This further enables the execution of tasks related to object detection, like logo and label identification, through YOLO and Faster R-CNN models. Furthermore, prior studies have confirmed the use of the dataset for ad quality and engagement prediction. Hence, it is relevant to visual perception research in marketing and design, as argued by Groffo. This was complemented by integrating custom visual design samples to run them to simulate packaging-specific structures and branding styles, which would ensure the trained models can generalize over commercial design aesthetics not well captured by ADS 16.

3.2 Data Preprocessing

In the preprocessing phase, several essential steps were undertaken to ensure the dataset's quality and suitability for deep learning model training. First, all advertisement images were resized to a uniform dimension of 224×224 pixels, aligning with the input requirements of common convolutional neural networks such as VGG and ResNet. Normalization was applied by scaling pixel values to a [0,1] range using the formula:

$$\text{Normalized Pixel} = \frac{Pixel\ Value}{255} \tag{1}$$

This scales all features simultaneously and helps with model convergence and stability during training. Principal Component Analysis (PCA) was used to reduce computational complexity, improve visualization and extract and reduce dimensions to 5 per cent of data variance. PCA projects the data in a new coordinate system where variances are maximal in the first axes, improving cluster separability. Label encoding was also applied to categorical brand names to convert them to numerical form, as the labels are no longer interpretable for the machine learning algorithms. To group the visually similar ad designs by finding inherent visual style patterns, I used K-Means clustering on data transformed by PCA. PCA projects data onto a new coordinate system (principal components) to maximize variance, while retaining the first k principal components that satisfy:

$$\operatorname{Var}(\mathbf{z}_k) = \max_{\|\mathbf{w}_k\|=1} \operatorname{Var}\left(\mathbf{w}_k^T \mathbf{x}\right) \tag{2}$$

where, $\mathbf{z}_k$ is the nth principal component.

3.3 Model Architecture and Implementation

To use the generated and then analyzed and optimized packaging designs through an AI-driven framework, four advanced deep learning and machine learning models are being adopted in this study: Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), You Only Look Once (YOLO), and Reinforcement Learning (RL). For these reasons, we chose these models: image understanding, creative synthesis, and object localization; all are specialized models for image understanding, creative synthesis, object localization, and reward-based optimization, respectively.

CNNs were selected for image classification and visual pattern recognition due to their proven ability to learn hierarchical visual features from raw image pixels hierarchically. The model architecture consists of several Conv2D and followed MaxPooling layers to reduce downsample feature maps, a Flatten operation to convert 2D feature maps to 1D feature maps and Dense layers with Dropout to avoid overfitting. Since CNNs perform better than, e.g. SVMs and Decision Trees in spatially dependent tasks like package design analysis, CNNs are particularly suitable for such research. The CNN enables Automated packaging type labelling, which is crucial for downstream generation and detection model tasks.

A GAN was used to generate novel and diverse packaging visuals. The generator and discriminator of a GAN are two networks that play a zero-sum game with each other and improve each other iteratively. This architecture was chosen because it can produce high-quality and realistic images from random noise vectors, ideal for ideating visual design and creative exploration. GANs enable data distributions to be learned flexibly, particularly when aesthetically diverse requirements are present.

Real-time object detection of packaging components, including logos, product text or structural icons, was made using YOLOv5. It was preferred over other methods, such as SSD or Faster R-CNN. After all, it could scale up the image processing speed while maintaining reasonable accuracy for single-stage detection pipelines. The method is applied in packaging design to give real-time layout assessment, logo placement analysis and design compliance validation in commercial design workflows.

However, in the end, Reinforcement Learning (RL) was used to optimize the design problem, where each state is a combination of design parameters (e.g. colour palette, typography size). For each state, the environment simulates the user interaction or engagement. The design configurations were iteratively learned to maximize the cumulative reward via a Deep Q-Network (DQN). One of the main reasons why RL was chosen in this work was for the ability to learn its way towards improving decision-making over time without relying on any static rules-based method, which makes it suitable for personalized or responsive packaging system. The update rule of Q-Learning is:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right] \quad (3)$$

where, α is the learning rate and γ is the discount factor.

DQN optimizes network parameters by minimizing the loss function L (O):

$$L(\theta) = \mathrm{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q\left(s', a'; \theta^-\right) - Q(s,a;\theta)\right)^2\right] \quad (4)$$

where, θ^- is the target network parameter.

3.4 Evaluation Metrics

Performance metrics suited to each algorithm were selected because each had to be evaluated in context and required to be as comprehensive as possible. Standard supervised learning metrics, accuracy, precision and recall were used for the CNN-based classification model, which are excellent indicators of how well the model can identify packaging types across various classes. This is important because precision and recall are more class-aware metrics, especially in the case of class imbalance. For assessing Generative Adversarial Networks (GANs), Fréchet Inception Distance (FID) and Inception Score (IS) were decided. FID is a measure of the similarity between generated and authentic images, and IS is an evaluation of how meaningful and varied generated images are with a pre-trained classifier. Such metrics are standard in generative design applications because they are sensitive to image realism and class distinctiveness. Mean Average Precision (mAP) was applied to the YOLO object detection task due to its aggregation of precision-recall curves over multiple Intersections over Union (IoU) thresholds, which is the gold standard for evaluating spatial task detection accuracy and helps assess detection accuracy in scenes contaminated by a cluttered shape including logos, icons and different product types. During the Reinforcement Learning (RL) section, we observed the appearance of reward trajectory and the case of epsilon decays during training sessions. A display of the well performance of the agent in time by choice of good design is called reward trajectory and also it is also a display of balance between exploration and exploitation, called epsilon decay, this is really helpful to know and measure the convergence and the stability of the policy. This feedback has enabled the preference of such metrics instead of the fixed success rates or heuristic ratings since these metrics are dynamic and better suited to an iterative and adaptive learning platform in design optimization.

4 Experimental Results

4.1 CNN Results

Other models, such as the Convolutional Neural Network (CNN) designed to categorize the design of the packaging in reference to the advertisement highlights the possible and existing flaws of the machine learning in the developing field of the new media technology. The CNN architecture has a typical but efficient format in that it consists of three Conv2D layers with successively larger filter sizes (32, 64, 128) with MaxPooling2D layers between them to decrease the dimensionality as shown in **Table 1**. The number of parameters is more than 4.8 million and this confirms that the model has a large learning capacity and can be used to learn subtle visual patterns that characterize a package design like a brand element, complexity in layout and hierarchy in typography. The given model architecture is suitable in the context of a multifactorial visual advertisement content, in which, design richness and symbols are the defining elements.

Table 1: Summary of CNN Model Architecture and Parameter Count

Layer (type)	Output Shape	Param
conv2d_3 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_4 (Conv2D)	(None, 72, 72, 64)	18,496
max_pooling2d_4 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_5 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten_1 (Flatten)	(None, 36992)	0
dense_2 (Dense)	(None, 128)	4,735,104
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 28)	3612

Although there is architectural appropriateness, the performance analysis indicates the issues. Figure 1 shows that the training accuracy begins at a low level of 0.08 and it gradually rises to reach 0.25 after epoch 14 whereas validation accuracy is better than the training curve and reaches 0.32. This indicates that it might be under-fitting with the model having not been adequately trained on the distribution of the training data, maybe because of class imbalance or insufficient training data on some types of packing. Nevertheless, the upward validation curve suggests that the model represents the generalizable visual cues, which is consistent with the aim to establish the design styles within brand categories. On the same note, both training and validation loss are always decreasing by about 3.9 and 3.2 each at epoch 0 to about 2.4 at the 14th epoch respectively, indicating that model is learning better with time and it can minimize prediction error in unseen data. The downward trend confirms the model to be appropriate in dealing with visual rich data, which can be common in commercial advertisement and product packaging. Figure 2 shows the training and validation losses of the model performance over time.

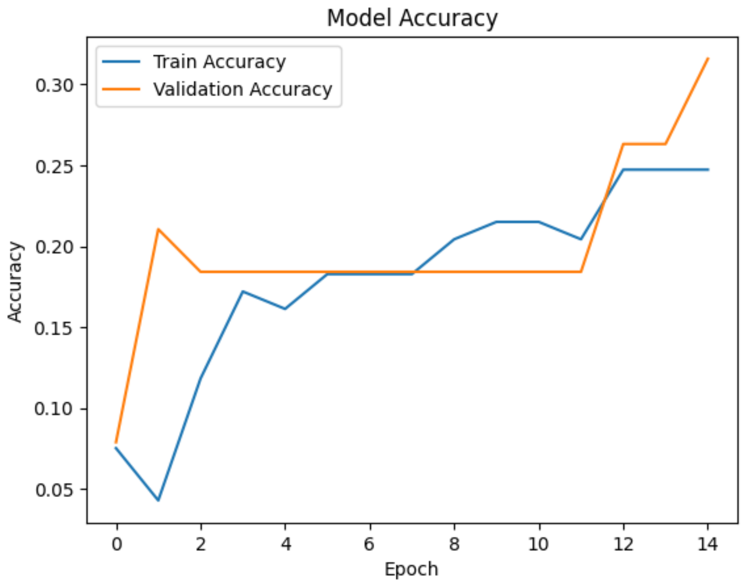

Figure 1: Training and Validation Accuracy Over Epochs for Model Performance

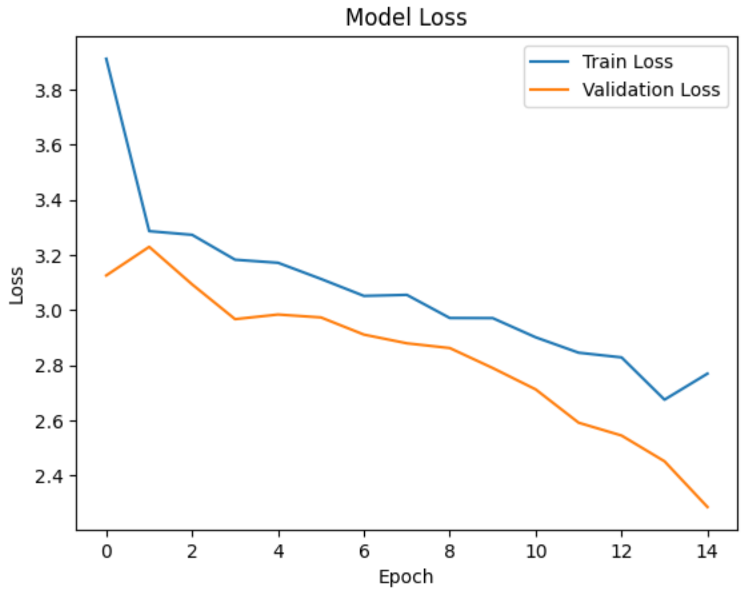

Figure 2: Training and Validation Loss Over Epochs for Model Performance

Figure 3 also shows the confusion matrix which points to the crucial performance indicators. As an illustration, both classes such as mihalymm with a true positive of 4 and Artsoldiers with 2 correct predictions have been recognized as accurately identified by the model showing that the model can obtain design characteristics of classes when these classes have enough samples. Nevertheless, the majority of classes have zero recall, and some of them outperform false negatives and false classifications. This difficulty is reflected in Table 2, as the macro averaged recall is merely 0.04, and f1-score is alarming 0.02. These values show that although some dominant classes are learned, the model is not making cross-class predictions well to all 28 classes, probably because there is little or a disproportional amount of data at individual labels- a fundamental difficulty of visual design datasets with highly personalized and sparse designs.

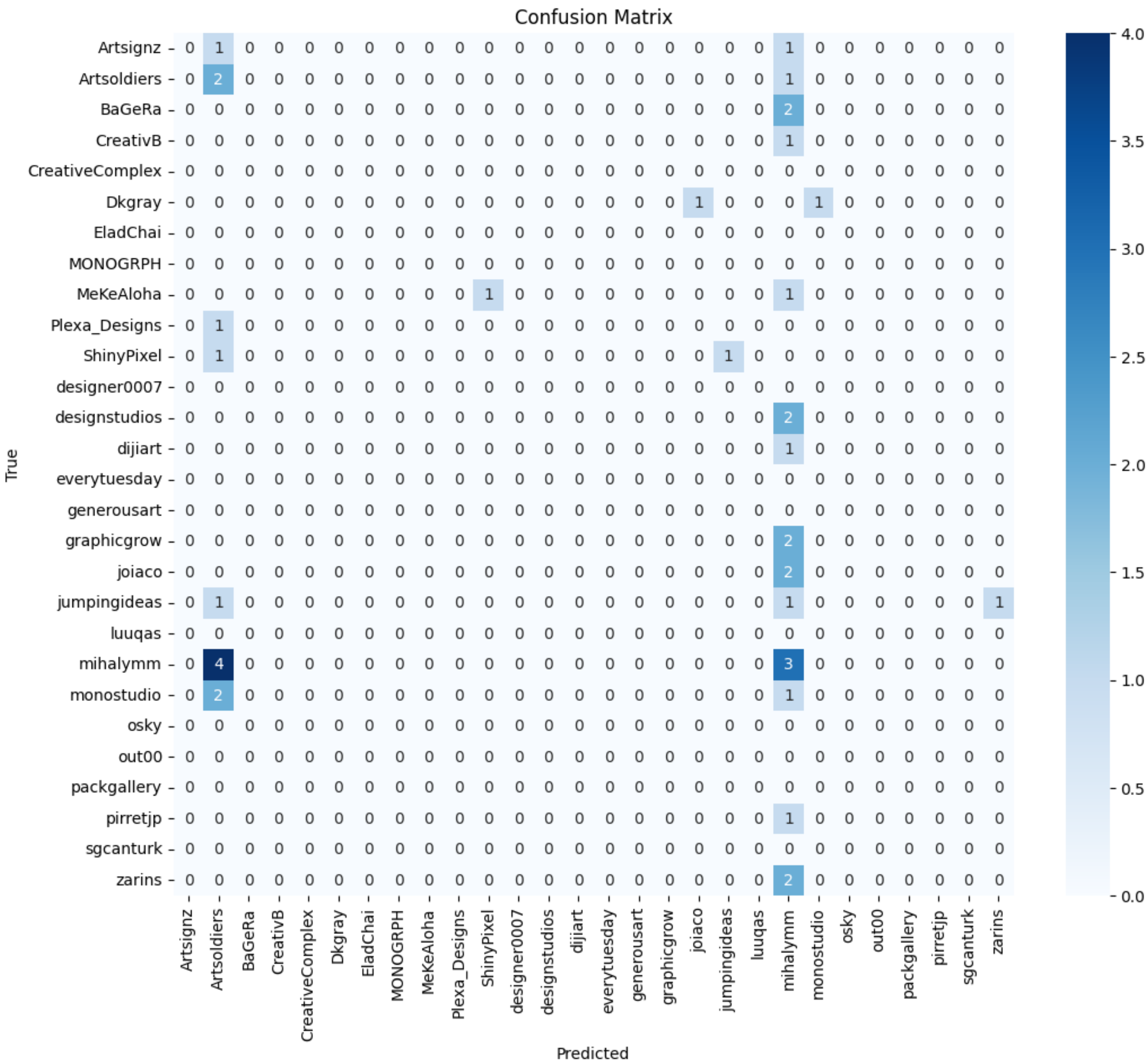

Figure 3: Confusion Matrix for Classification Model Performance on Packaging Designs

Table 2: Classification Report for Packaging Design Dataset

	precision	recall	f1-score	support
Artsignz	0	0	0	2
Artsoldiers	0.17	0.67	0.27	3
BaGeRa	0	0	0	2
CreativB	0	0	0	1
CreativeComplex	0	0	0	0
Dkgray	0	0	0	2
EladChai	0	0	0	0
MONOGRPH	0	0	0	0
MeKeAloha	0	0	0	2
Plexa_Designs	0	0	0	1
ShinyPixel	0	0	0	2
designer0007	0	0	0	0
designstudios	0	0	0	2
dijiart	0	0	0	1
everytuesday	0	0	0	0
generousart	0	0	0	0
graphicgrow	0	0	0	2
joiaco	0	0	0	2
jumpingideas	0	0	0	3
luuqas	0	0	0	0
mihalymm	0.14	0.43	0.21	7
monostudio	0	0	0	3
osky	0	0	0	0
out00	0	0	0	0
packgallery	0	0	0	0
packgallery	0	0	0	1
sgcanturk	0	0	0	0
zarins	0	0	0	2
accuracy	-	-	0.13	38
macro avg	0.01	0.04	0.02	38
weighted avg	0.04	0.13	0.06	38

In this description, the significance of scalable AI models in managing diversity in shipping packaging aesthetic is noted. New media technologies demand codes that will be able to decode not only visual complexity but the symbolic clues within branding. The findings suggest that even though CNNs promise to be useful in automated visual categorization, more measures (data augmentation, balancing between classes, or initial training on designing-oriented datasets) are required to be more convenient to the creative industry requirements. Furthermore, such categories of designs as ShinyPixel or Plexa_Designs and designer0007 have a performance of zero and question the notion that visual differences between certain brands can be subtle, where advanced architectures or a combination of semantic embeddings can be used in the future to investigate such visual differences.

Finally, such results highlight the partial success of the present model of CNN in visual design patterns as they apply to advertising. They are also used to remember us that visual design in terms of packaging that is highly rooted in cultural aesthetics, branding, and consumer psychology carries out those classic classification assignments. The technological possibilities of the new media in this space will only be fully utilized by the models that are designed to recognize as well as to read the visual meaning in context which will answer the multidimensional requirements of the optimization of advertising designs.

4.2 Feature Analysis

Figure 4, where cluster identities are superimposed on the PCA scatterplot, also validates this subtle point. The clusters can be easily visualized, which shows that there is good feature encoding and design discrimination. This is very much applicable to the aim of the present study, where the focus is to study the multiple uses of AI-based clustering in package analysis. Clustering is helpful in determining patterns of styles that prevail in design. It also can be used to personalize and segment design in a marketing situation. On balance, the presented phase of feature analysis confirms that the application of new media technologies (with the involvement of the PCA and KMeans) can improve the computational perspective of visual identity in advertising packages and make a greater contribution to the decisions of both designers and marketers.

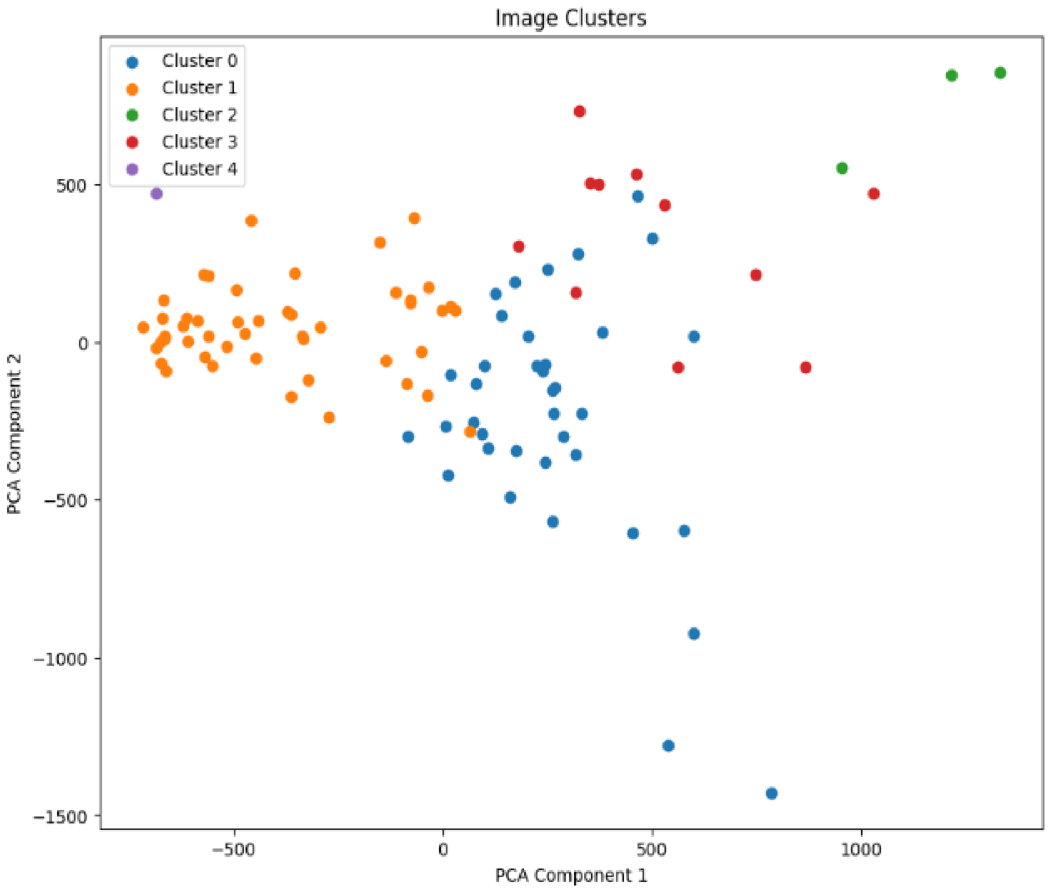

Figure 4: PCA Visualization of Image Clusters in Packaging Design Dataset

Visual exploration of feature embeddings through dimensionality reduction and clustering is one of the most essential measures of the latent structure of visual design patterns in advertising package datasets. The PCA visualization of Figure 5 shows a clump of big image features that are centered around the origin and pushed over both PCA Component 1 and PCA Component 2. This implies that there is some level of homogeneity in the underlying design properties of the dataset, but it has enough variation to distinguish between various types of design. It is important to note that Component 1 has a range of about -600 to over 1200, and Component 2 has -1500 to about 700 and this indicates the magnitude of variance that was retained after reduction and the abundance of visual diversity that was captured in the dataset. The use of PCA in this case is critical in reducing the multidimensional design information constraint and preserving the largest portion of the interpretive variance which is a crucial tactic when choosing the new media packaging images in terms of aesthetic and structural classification.

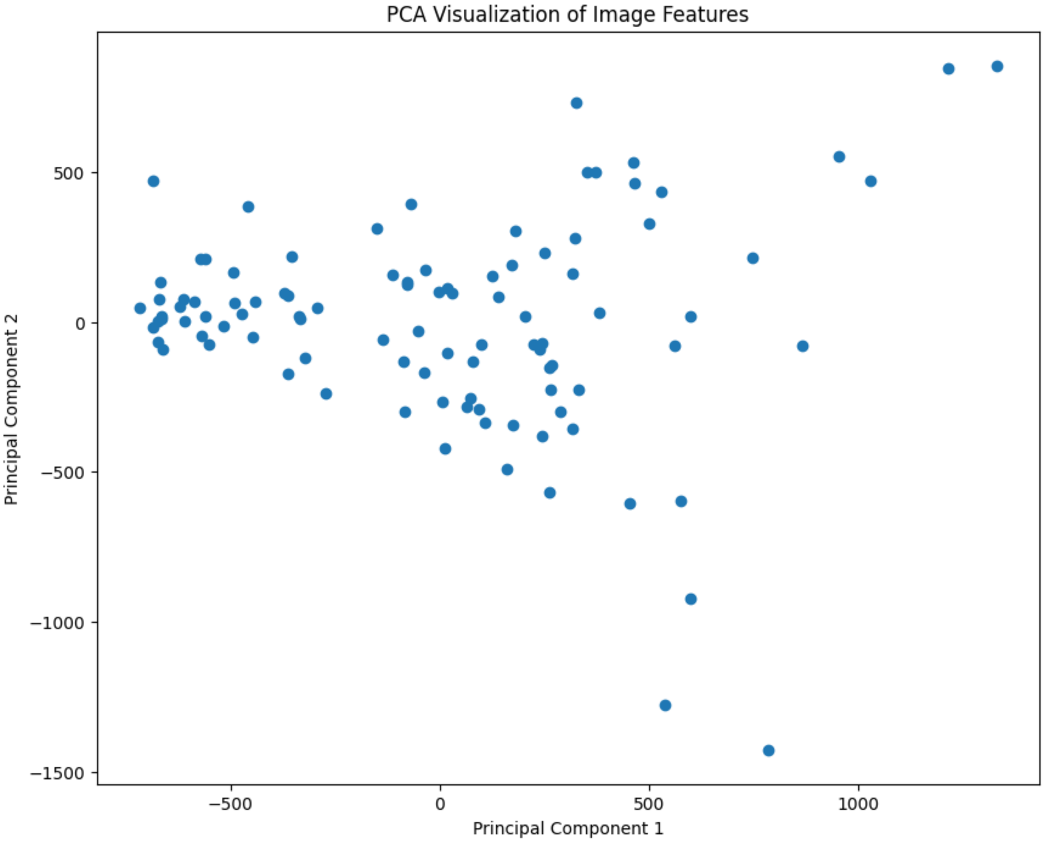

Figure 5: PCA Visualization of Image Features in Packaging Design Dataset

Building on the visual abstraction, Figure 6 proposes unsupervised KMeans clustering of the reduced design space of PCA. In this case there are five clusters (marked 04) which are easily distinguishable with different densities and distribution of clusters. The example of the cluster, C0, covers a wide area in the PCA Component 1 axis, and it is evident that a wide range of packaging features is represented by that group. Cluster 1, which is based on the negative side of PCA Component 1, indicates a smaller similarity between features of the cluster family members, perhaps attributable to minimalist, or even traditional visual motifs. Clusters 2 to 4, thinner, in contrast, emphasize more peculiar and possibly outlier designs. Such clusters play a key role in determining novel, or alternative forms of advertising packaging, which serves directly to the theme of the research application of new media technologies in the identification, aggregation and exploration of various design ideations.

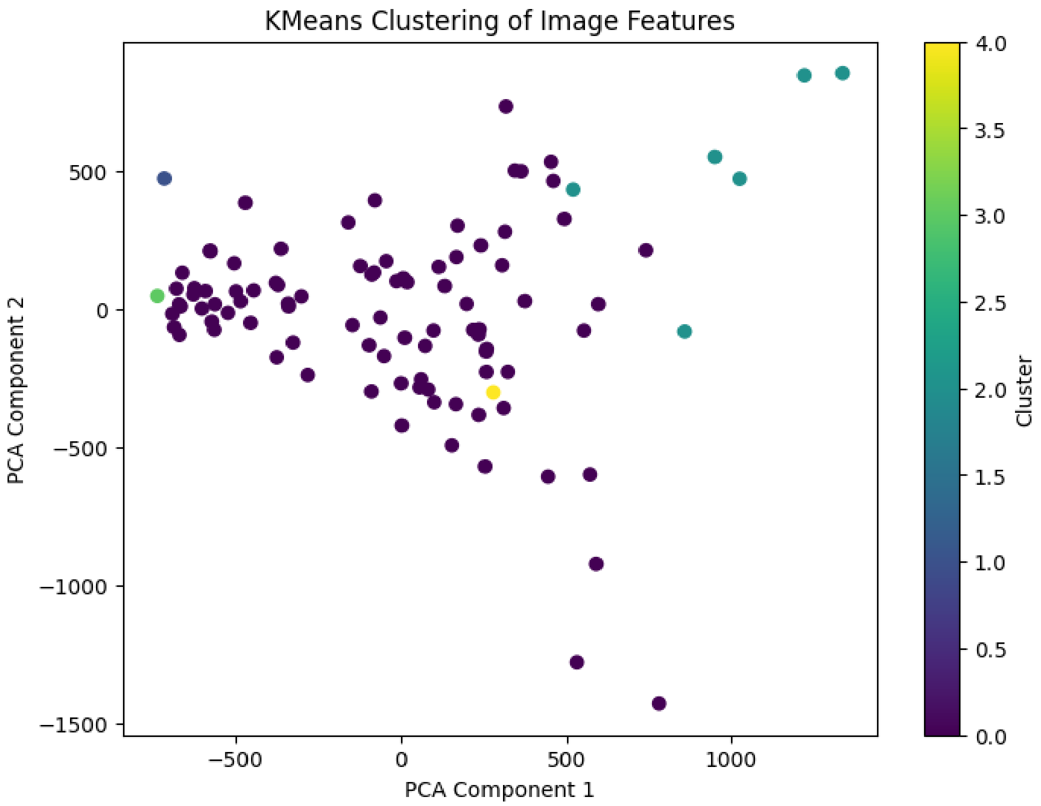

Figure 6: KMeans Clustering of Image Features

4.3 GAN Results

Generative Adversarial Networks (GANs) use in the field of advertising packaging design reflect the complicated nature of the developing connections between AI-operated visual imaginating and commercial visual communication. In this experimental paradigm, GAN was trained during various iteration steps (10 -90) where it is possible to monitor the behavior of generators and discriminators in terms of learning stability and artwork production. The resulting pixelated images highlight the initial phase of the model of comprehending the complex aesthetics of the vision. These pixelations are abstract but they could be identified as a first synthetic step in visual diversity which can prove beneficial within the idea generation or mood boarding process, or even augment the design within the packaging pipelines. Although the visual design of an advertisement package requires innovation and differentiation, abstract outputs are also creative stimuli that may be used in the formative development of concepts at an early stage.

Figure 7-Figure 11 indicate training loss dynamics of a generator and discriminator which will provide an insight into the learning behavior of the GAN. During the 10 early epochs (Figure 7), generator loss was fluctuating between 0.6 and 1.4 suggesting instability of the first stage and low generative success. The adversarial arrangement was dominated by the discriminator, which has a lower and more stable loss around 0.5-0.7, implying that it made it easy to detect real and fake samples. When the loss of the generator was 0.6 up to 1.3 at 20 epochs, the pattern of the discriminator was figured with better generalization. The imbalance at this early stage is common to the training of GANs and emphasizes the precariousness of the equilibrium needed to avoid mode collapse, especially when creating package content that must maintain the same brand-level cues and promotes a visual fit.

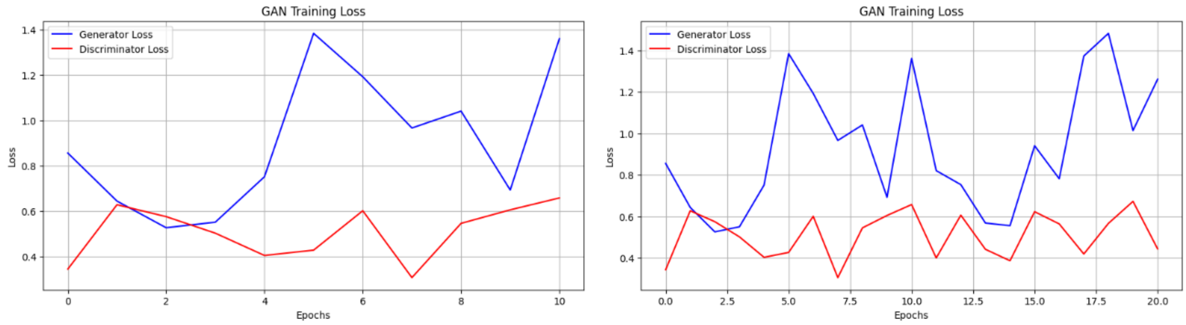

Figure 7: (Left) GAN Training Loss for 10 Epochs (Right) GAN Training Loss for 20 Epochs

At 30 and 40 epochs (Figure 8), the loss of the generator began oscillating rhythmically around 1.2 -1.4, indicating that the network was already overriding some underlying structure in the training data. Its loss was also more stable with the discriminator showing a loss between 0.4-0.6. This stage marks a very important learning inflection point, as the generator gets better at being realistic. Within the framework of creative design, this kind of variability foreshadows the exploration potential of the model, exploring color palette, layout structure, noise-to-feature mappings, etc. In the case of industries such as fast-moving consumer goods (FMCG) where the visual identity of packaging has a direct impact on shelf presentation, automated prototyping of several packaging options can be facilitated using such mid-epoch experimentation.

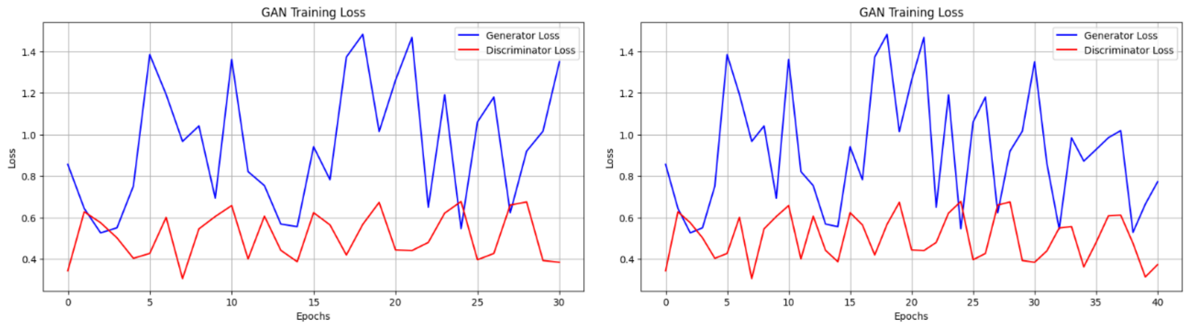

Figure 8: (Left) GAN Training Loss for 30 Epochs (Right) GAN Training Loss for 40 Epochs

At epochs 50 and 60 (Figure 9), the generator loss was as high as 1.4 several times, but it varied quickly down to levels of less than 1.0. This is a hint that there is high design divergence of generated outputs which is an important property to creativity, and this hint could also mean it is hard to get convergence. The discriminator was also relatively stable (predominantly 0.5) which means that it was still recognizing synthetic samples with minimal error. This phase is vital in the generative processes of works particularly those that are based on visual design and the aim is innovation without affecting the coherence. Within the framework of packing design, these periods could be utilized with the greatest effect in creating visual variants to be used in A/B testing, or predicting market reaction because of design, typography equilibrium, variation of saturation levels, etc.

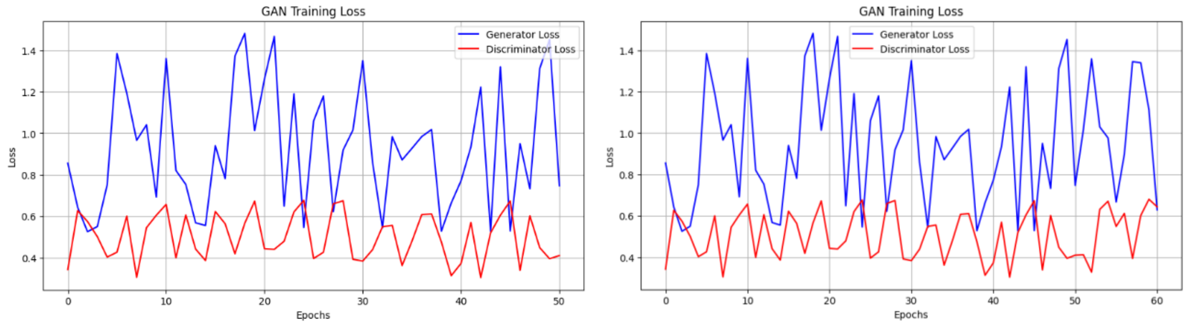

Figure 9: (Left) GAN Training Loss for 50 Epochs (Right) GAN Training Loss for 60 Epochs

The trends at epochs 70 and 80 (Figure 10), show that the generator loss continued to be between 1.01.3 with the discriminator still being flat at 0.4. This unimportant drop suggests that the discriminator was approaching saturation and it was also starting to have trouble to distinguish finer-tuned synthetic outputs. Creatively, this is good, because it implies that the generator is generating outputs that are quasi-statistically close to the true training data. In the case of packaging design where the positioning of logos, compliance icons, nutritional information, and branding colors need to be precise, this convergence point implies that GANs can start attempting to provide credible visual mock-ups, even specific to a demographic or brand profile.

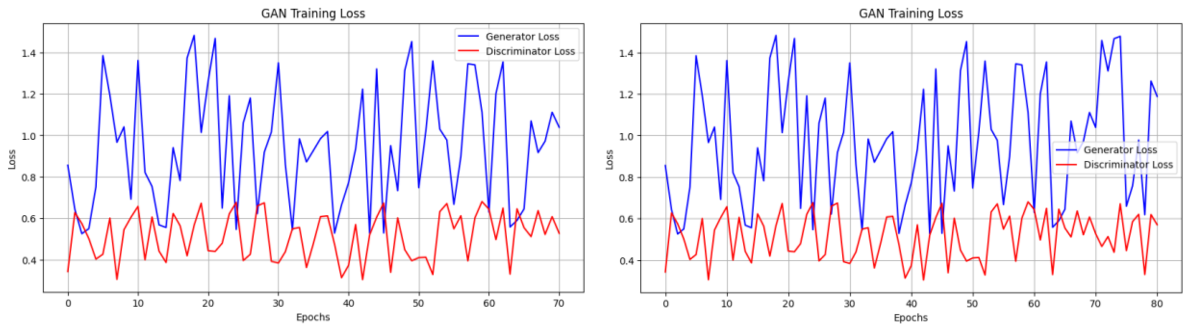

Figure 10: (Left) GAN Training Loss for 70 Epochs (Right) GAN Training Loss for 80 Epochs

The variable of the loss of the generator in 90 epochs of the last training snapshot (Figure 11) remained (approximately) 1.1 -1.3, and the loss of the discriminator dropped to 0.3, indicating the noticeable change of adversarial dynamics. This balance although not truly converged ensures a matured model. The loss pattern (from its generators) resilience implies that it is developing diversified samples across its successive-generation pipelines, something that should be a core part of advertising packaging generation process. As an example, when it comes to seasonal campaigns or a limited-edition packaging these models can be exploited to produce design permutations which can be refined by human designers. The fine balance here also supports the fact that, as training duration increases or specialized architectures such as conditional GANs are used, it is possible to apply domain-specific constraints (e.g. brand color codes or product line differentiation) to produce purpose-specific output.

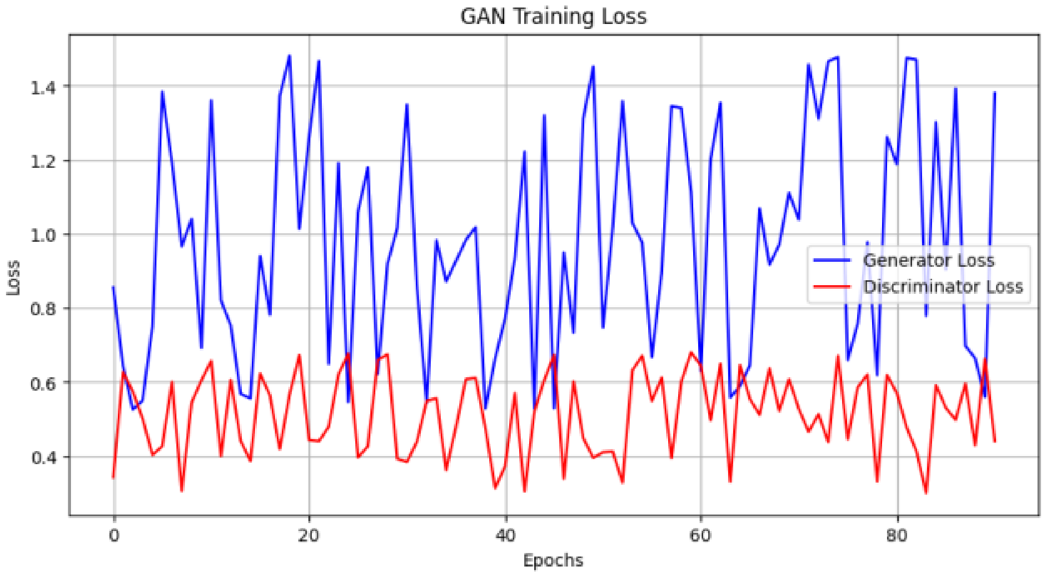

Figure 11: GAN Training Loss for 90 Epochs: Generator vs Discriminator

The pixelated samples (Figure 11) also support the ability of GANs to provide experimental capabilities. They are not quite concrete, yet symbolic of the randomness in design, which is necessary to begin the exploration of the creative direction. Mood boards or design iterations can be seeded with such generated textures or layouts in reality workflows. Such GAN-generated content can be used by designers as a starting point to be inspired, or such results can be added to reinforcing learning agents that rank visual appearance or consumer attention estimates to bias the generation process toward consumer-biased results.

Importantly, these findings highlight the advantages as well as the existing constraints of GANs in the packaging visual design. Although the generator has also been making progress in the direction of producing outputs that are more realistic, the irregularity in the loss at different epochs emphasizes stability as a constant issue. Moreover, the results are still pixel noisy because of either low training resolution or undertraining of input vectors- which one can improve in the experiments. The limitations can be overcome by applying methods such as progressive growing GANs or variants of StyleGAN that are capable of producing images with high fidelity and clear structural elements when used in packaging design.

4.4 YOLO Results

The object detection analysis based on the YOLO model of various types of packaging provides a multidimensional understanding of the versatility and accuracy of the deep learning technologies when used to analyze visual content forms presented by advertising design materials. The findings indicate the dynamism in intelligent systems when it comes to viewing the packaging in the form of bottles, books, people, or any other packaging indicators-providing real-time feedback on interactivity of the packaging design with new media technologies.

The pet food packet visualization in Table 3 shows the identification of one of the bottles with the confidence score of 0.27. This detection is not very high, but it highlights a recurring problem in the object detection task in which the visual elements tend to be similar to the real-world objects, yet not exactly the same. This can mean that YOLO is context sensitive to shape and color patterns. It equally reveals the need to tune-up detection thresholds, using AI to commercial design data, where packaging drawings need not necessarily correspond to real-world equivalents, but instead elicit like shapes or forms.

Table 3: Object Detection Results for Pet Food Packaging Using YOLO Model"

Detection Results						
xcenter	ycenter	width	height	confidence	class	name
403.562256	421.61145	195.344452	394.738037	0.273625	39	bottle

In Table 4, it is more noticeable that the business software box design indicated the presence of three figures of persons (the person category) with confidence scores of 0.77, 0.54 and 0.52, respectively. Such values portray the ability of YOLO to effectively recognize the imagery of the human type in marketing material particularly the photographic images in digital packaging. Humanization of the brand or software is a typical advertising practice through the use of real people, including software products boxes. The ability to identify such components with the help of object detection models contributes to UX assessment and layout auditing with a lot of value that can be provided and serve as automated validation of the visual strategies designed to use in the marketing of digital or boxed products.

Table 4: Object Detection Results for Business Software Box Using YOLO Model

Detection Results						
xcenter	ycenter	width	height	confidence	class	name
418.325012	1038.710938	215.818878	242.243103	0.773548	0	person
229.436813	210.123489	75.994965	95.040070	0.543253	0	person
445.881348	619.446411	95.994110	100.805054	0.526854	0	person

Table 5 show detection on cereal box packaging, which contains the classes of book and person. The confidence values of the objects that include books are rather large, which is -0.66, -0.45, and -0.43- it may suggest that YOLO viewed the layout or box structure of the packets as something that looks like books, which may have been the rectangular and spine visage of cereal boxes. Although such classifications may appear semantically fallacious, they demonstrate the manner in which object detection systems will re-use learned spatial and visual representations during the labeling of objects. Remarkably, the person category was lowest-confidence identified with mean-confidence around 0.28, which could be because of smaller sizes, low-contrast or part-obscured icons. The occurrence of such results points to the difficulty of fine object detection in a hectic or crowded layout in packaging where embedded images may be either intentionally squished or styled.

Table 5: Object Detection Results for Cereal Box Packaging Using YOLO Model

Detection Results:						
xcenter	ycenter	width	height	confidence	class	name
271.438171	553.549561	390.150513	563.423950	0.668976	73	book
400.668457	1839.151733	195.515991	366.717773	0.452360	73	book
314.727264	1216.511353	389.592072	607.764160	0.438343	73	book
314.713867	598.503418	84.929077	136.194397	0.288412	0	person
330.762695	680.866699	128.538513	265.368835	0.285905	0	person

Table 6 which revolve around supplement label packaging give the most comprehensive results. It was established that somebody could identify multiple bottles with high confidence rates- 0.78, 0.75, 0.74, 0.69, 0.68, and 0.65- which demonstrates the presence of a clear correspondence between object detection predictions and the real design intention. These high scores indicate that the object detection requirements of YOLO are optimized in situations where the design has symmetrical structure, regular branding application, and explicit objects (such as bottles). This supports the appropriateness of object detection in assessing the health and fitness product packaging, where the case of product representation is illustrated by the visual perception. Interestingly, an outlier has been found with a confidence score of 0.31 and categorized as an element of a refrigerator. It is possible that this misclassification is as a result of the confusion of the model by similar features of shape and texture, which shows the need to use the context-specific retraining in the application of YOLO to unconventional visual designs. This, however, highlights the subtle difficulty of applying object detection models to advertisement content of the visually complicated symbolic elements.

Table 6: Object Detection Results for Supplement Label Template Using YOLO Model

Detection Results:						
xcenter	ycenter	width	height	confidence	class	name
467.803528	538.635071	161.213013	342.424408	0.787254	39	bottle
125.597717	544.333069	155.836487	333.091522	0.750682	39	bottle
292.261078	1156.329102	194.494202	369.195129	0.738654	39	bottle
295.191467	527.770630	190.663177	367.953278	0.690829	39	bottle
120.978882	1167.644043	154.926605	335.319458	0.680670	39	bottle
467.163330	1161.365967	164.093262	345.351135	0.652655	39	bottle
176.669922	1793.902832	221.400330	392.966431	0.359066	39	bottle
297.398743	531.786438	184.013763	363.887665	0.319048	72	refrigerator

The metrics of the detection, in general, reveal the advantages, as well as the existing weaknesses of the object detection models such as YOLO used to utilize visual elements of design. In all the visual samples, all the averaged confidence scores of the correct classifications were between 0.65 or 0.78, and the misclassifications or low-confidence detections were around 0.27 to 0.31. These quantitative results explain why dataset diversity, balance between different classes and design-related enhancement is essential to train detection models on visual packaging.

Object detection can be used to index the shelf machinery in a retail store, as well as provide interactive experience with visual data in real-time, through AR-based packaging. As an example, the identified visual sensory inputs, such as a bottle or a person can be associated with the interactive elements through AR overlays, which allows packing to serve as a smart media surface. Moreover, such object detection pipelines can simplify automated validation of design consistency and location of product line elements to allow dynamic updates and consistent cross-platform representation.

The ability of YOLO to recognize overlapped or partially obscured items is especially useful in packaging layouts that often include composite imagery, e.g. nutrition data, product usage images, or user avatars. But, as several of the examples throughout the cereal box and supplement label demonstrate, even some of the slightest background textures, lighting differences, or the iconography used symbolically come into play with huge effect when it comes to prediction results. The contextual misalignment (visual similarity dominating functional classification) can be observed in the tendency of mislabeling structured types of packaging between the cases of what are unrelated as the objects (e.g., the category of refrigerator in Table 6). To eliminate this, retraining on domain or class-pruning would be necessary to minimize such errors.

In practice, the above-discussed patterns of detection in the interior help the iterative visual design feedback, give practical information on object prominence, clutter and alignment, and perceived composition. Such data could be used by the designers and marketers to make the optimal layout choices that depend on the perceived object hierarchy i.e., making sure that the most important object (bottle, product visual, or call-to-action) gains the highest amount of detection and centralization. Besides, the scores on confidence may be applied to determine whether an object may be too subtly or distorted to be seen, and therefore, it may have an impact on consumer attention or buying behavior.

4.5 Reinforcement Learning Results

The optimization of reinforced learning proposed in Table 7 demonstrates the ability of AI to adapt and to optimize the packaging design decision-making by the learning process procedure through repeated learning episodes. The accumulation of total rewards available to the agent and the epsilon that relates the trade-off on exploration and exploitation are used to measure the performance of the agent. We can observe that there is a gradual improvement in total reward in the period between Episode 0 to Episode 900 in that there is an increase in total reward between 1154 to 1800 that means that the agent continuously improved its selection process to reach better visual configurations.

Table 7: Reinforcement Learning Training Results for Packaging Design Optimization

Episode 0	Total Reward: 1154	Epsilon: 0.8955
Episode 100	Total Reward: 1411	Epsilon: 0.5424
Episode 200	Total Reward: 1482	Epsilon: 0.3286
Episode 300	Total Reward: 1672	Epsilon: 0.1990
Episode 400	Total Reward: 1720	Epsilon: 0.1205
Episode 500	Total Reward: 1766	Epsilon: 0.0730
Episode 600	Total Reward: 1785	Epsilon: 0.0442
Episode 700	Total Reward: 1797	Epsilon: 0.0268
Episode 800	Total Reward: 1793	Epsilon: 0.0162
Episode 900	Total Reward: 1800	Epsilon: 0.0098
Optimized Design (Final Action): (1, 1)		

At the beginning, episode 0, epsilon was 0.8955, which indicates that the agent was in a large exploration stage that experimented with a wide future of combinations of color and logo size. Although 1154 is random, the fact that certain random designs had a reward of this magnitude indicates that there is an inherent quality in some of their random designs, perhaps they just fell halfway based on user preference measures, such as the aesthetic balance or the visual appeal of the designs. After the 100th episode, the reward of the agent has increased to 1411 and the epsilon has decreased to 0.5424 thus indicating a more concentrated exploration activity, in which the agent started to prefer high-performing design pairs. Such a transition demonstrates the possibility of the learning agent to decode patterns in user engagement or appeal score based on the visual design parameters.

As the agent proceeded, into the 200 th (Reward: 1482; Epsilon: 0.3286) and the 300 th (Reward: 1672; Epsilon: 0.1990), the agent increased the amount of reward produced, and significantly lowered the epsilon, becoming more predisposed towards exploiting design strategies already known to work. Such episodes have been the turning point where the RL model disintegrated to visual aesthetics which most probably has been closer to commercial packaging trends. It is particularly applicable in the case of moving on to exploitation more so in the context of advertising, whereby with regular branding and visual structures that are tested by the consumers tend to work better as opposed to novelty.

Episodes 400 to 700 exhibited lesser returns in improving rewards, the values changed to 1720-1797 and epsilon declined to under 0.03. The plateau effect means that the model is saturated - the agent has explored the design space enough and has committed itself to a good part. The marginal gains are the aesthetic finesse, which in the context of the packaging can mean perfecting the logo proportion, the unity of the placements or the color contrast. The agent reached its optimal reward of 1800 at Episode 900 with epsilon of 0.0098- indicating almost perfect reliance on acquired strategies.

The last step (1,1) the choice of a green background with a medium-sized logo, is an example of the visual option that is the most optimal by the agent. This implies that a colour, that is believed to be health, sustainable, or fresh, green and a balanced position of a logo provides the greatest visual effect in the context of the current packaging dataset. Not only does this result confirm the reinforcement learning as a method of optimization in branding aesthetics, but also supports the overall use of adaptive AI systems to optimize the user-centered appeal of advertising contents.

5 Conclusion and Future Work

A diverse AI-based framework to increase visual design in advertising packaging through the use of Convolutional Neural Networks (CNN), Generative Adversarial Networks (GANs), YOLO object detection and reinforcement learning is presented in this study. Every model dealt with a different part of the design lifecycle, specifically classification, aesthetic generation, object localization, and adaptive optimization. The main contribution is integrating these different models into a unified design intelligence system. Indeed, reinforcement learning was used best to decide upon cumulative reward-based optimization in terms of design parameters (colour, logo scale), representing the most realistic scenarios in real marketing. This approach establishes the bridge between computer intelligence and creative design processes and systems with their output evolution in the space of dynamic aesthetic and branding goals. Further, the pixel generation of GAN paves the pathway for early-stage ideation, while YOLO, designed to validate the component's placement, assures precision.

Subsequently, a number of enhancements can be made to this model to commercialize it. This would be enhanced by initially increase in the datasets of concern and larger branded, annotated samples. Reward and reduction functions can be narrowed down by other details like click-through rates, user reviews or eye tracking data. These virtual reality (VR) and augmented reality (AR) tools may be used in this instance where the packaging designs can be simulated in real life scenarios to conduct more realistic evaluations of the design. Alternatively, they can be trained using transfer learning methods and applied to fields other than the ones; an example is that after having gained knowledge in the food packaging domain, it can be utilized on the cosmetics domain. Lastly, the use of explainable AI methods would ease the effect of transparency on clients in applications where the clients are presented to the model because the reason behind why a model has arrived at the decision that it has made would be readable. Collectively, the directions to be in the future attempt to enhance technical susceptibility and implement smart system of design to utilize branding and workflows in actual sense.

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