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Research article

Analyzing the packaging design evaluation based on image emotion perception computing

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ABSTRACT

Nowadays, a wide variety of labels of items are widely available, and human consumption is increasingly tailored to meet their individual needs. So, many businesses are starting to focus on improving the functionality of modern packaging. Sensorial paradigms and emotional reactions could change during the user-product interaction lifecycle. The designer's emotional imagination and past experiences are the backbone of conventional product package design, which has limitations due to unmanageable content and an absence of professional advice—the majority of previous research on emotional image analysis aimed to forecast the most common viewer emotions. Since the feelings a picture evokes are quite individual and vary from viewer to viewer, this overarching feeling isn't always enough for practical uses. The research presented an approach to packaging design evaluation based on image emotion perception computing (PDE-IEPC), which combines emotion perception technology with a deep LSTM (Long short-term model), resulting in an immersive and dynamic experience for the human senses. Emotion Perception Computing's Dynamic Multi-task Hypergraph Learning (DMHL) approach considers graphical data, social context, spatial evolution, and location, among other criteria, to evaluate packaging designs efficiently based on their emotional impact. Image-Emotion-Social-Net is a large dataset used to evaluate multidimensional and categorical attitude representation. The dataset is sourced from Flickr and contains over 1 million images presented by over 9000 users. Personalized emotion categorization is an area where research on this dataset shows that the suggested strategy outperforms many modern techniques. The experimental results show that the proposed method achieves a high packaging design quality rate of 94.1 %, a performance success rate of 97.5 %, and a mean square error rate of 2 % compared to other existing methods.

1. Introduction

Packaging design is essentially the transfer of visual symbols. It has practical and logical qualities, making it an effective tool for advertising products and improving their visual appeal. Images can evoke various emotions and convey complex meanings [1]. Predicting the most common viewer emotions has been the primary focus of previous research on emotive perception analysis [2]. Since the feelings a picture evokes are quite individual and vary from viewer to viewer, this overarching feeling isn't always enough for practical uses [3]. Emotional perception and subjective evaluation are the primary obstacles to advancing picture emotion analysis.

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Multimedia approaches are gaining popularity and exhibiting diverse growth [4]. One of the most effective ways to advertise a product is its packaging. Packaging design has emerged as an increasingly essential product marketing technique due to customers' increasingly open views of purchasing and the relentless desire for material wealth [5]. Hence, it is crucial to incorporate visual communication technologies into product packaging design. Visual communication directly and effectively transmits visual information, establishing consumers' initial perception of the product [6].

Previous studies mostly focused on predicting the most common emotions for a diverse audience, without considering subjective evaluations, to find characteristics that better express emotions and bridge the emotional divide [7]. Since the emotions a picture evokes are personal and varied owing to the impact of viewers' social, educational, and cultural backgrounds, it is typically more practical to forecast individualized emotion [8]. For individualized emotion prediction, conventional methods based on prevailing emotions might not be applicable in this case. The prediction of individual emotional perceptions has made very little headway thus far [9]. Packaging design is an integral part of the marketing mix, completely reflecting the brand theory, product attributes, and customer behaviour and satisfying the impulse to buy. Thus, the art and science of packaging design work together to make products' packaging more secure and aesthetically pleasing [10]. Designing packaging involves more than aesthetics or a general concept of "creativity"; it is an integrated expression of several disciplines, including but not limited to science, art, material science, economics, psychology, and the market [11]. Designing the structure, contents, and outside of a package are the three main components of packaging design. The three elements above should naturally combine to form a great packaging design [12]. The three must naturally come together to realize the full potential of packaging design; it incorporates art and technology and draws on related disciplines in each area [13]. A new subfield of computer vision called computable image aesthetics has developed in response to this trend toward agreement. Successful human-computer interaction relies on accurate predictions of users' aesthetic experiences with image interactive systems based on calculations and evaluations of image aesthetics [14]. This, in turn, aids designers in judging and obtaining aesthetic expressions that align with users' psychological feelings. This paper presents LSTM and hypergraph learning algorithms, which may learn to anticipate several users' emotions simultaneously by integrating visual, aural, textual, and emotional data for a fuller picture of emotional situations. An expansion of a basic graph, a hypergraph allows hyperedges to connect more than two vertices. This approach lays the groundwork for using a deep learning methodology to simulate how a human eye perceives images; this enhances the model's ability to identify emotions and predict their range to determine whether it is feasible to use computer-aesthetically evaluated images to assist designers in their jobs [15].

To identify the emotions conveyed by people engaging with package designs, IEPC algorithms may examine photos of such designs. Knowing if the package makes people happy, excited, or trusted might be helpful, whereas negative feelings like bewilderment or dissatisfaction can be more easily identified. The IEPC method may determine the most popular package designs by studying the emotional reactions of buyers to various designs. Designing packaging that appeals to customers' emotions may be guided by this knowledge.

The main contributions of the article include.

(1) The research used emotion perception technology and a Deep LSTM model to create an immersive and dynamic sensory experience for Packaging Design Evaluation Based on Image Emotion Perception Computing (PDE-IEPC).
(2) Emotion Perception Computing's Dynamic Multi-task Hypergraph Learning (DMHL) method addresses picture emotion perception variables such as graphical data, social context, spatial evolution, and location for efficient packaging design evaluation.
(3) Investigating dimensionality and categorical attitude representation, the work used the Image-Emotion-Social-Net huge Flickr dataset, which contains more than 1 million photographs contributed by more than 9000 users.
(4) The dataset suggests a personalized emotion categorization strategy that outperforms several modern methods.

Here are the additional sections of the paper: Section 2 will explore the literature pertinent to this topic. More details about the proposed model are provided in Section 3. The fourth section details and compares the experiment's findings. Outline the next steps and concluding thoughts in Section 5.

2. Literature survey

2.1. Emotion detection using ensemble machine learning models

Yang et al. [16] employed Affectiva, Amazon Rekognition, Baidu Research, Face++, and Microsoft Azure as part of a two-experiment comparison of their effectiveness in detecting emotions. As a first step, the algorithms' effectiveness in classifying photos from three distinct, extensively standardized face expression databases. The findings suggest that academics and developers might incorporate commercial face emotion recognition technologies. Nayak et al. [17] present a three-stage human-computer interaction (3s-HCI) method for perceiving emotions and suggesting entertainment through multimodal time-lapse infrared video sequencing. First, use the Faster R–CNN structure to identify the mouth, pupils, and nose. The Multiple Instances Learning (MIL) approach monitors the facial ROIs in this thermal clip. Using temperature records and competing classification algorithms, we found that our proposed methodology reliably produced better results. The small sample size limits the ability to draw broad conclusions about human emotion, a major limitation of the research. Kamble et al. [18] proposed Five classical ML (CML) and five EML algorithms that use ensemble learning to recognize EEG emotions. Nine emotions are available from the public DREAMER database for ML-based system training. This research started with a discrete wavelet transform to divide EEG data into theta, alpha, beta, and gamma bands.

The EML-based tagging method had the most extensive F1, kappa, and AUC values, with 95.81 % arousal and 95.53 % valence accuracy. EML algorithms outperform CML for multiclass emotion recognition. Zhou et al. [19] proposed an automated face emotion detection and cursor tracking (AFED-CR) approach. Participants completed cad assignments alone or in pairs. Logistic research showed significant patterns tying emotions to CAD occurrences and that particular CAD software designer behaviours enhance specific emotions. These findings support the well-established links between designer happiness, creativity, efficiency, and other outcomes that engineering managers and designers increasingly value in virtual collaborative situations. The limits of this tool for future research about biased face analysis algorithms sample size was too small to include people from this community. Clark et al. [20] proposed a study on how product-generated or product-associated (PG or PA) emotions affect milk packaging customer acceptance and purchase intent. Participants then used individual products for 30 s and had AFEA examine their facial expressions for implicit PG feelings. The CATA questionnaire measured explicit PG emotions. Time series analysis of AFEA data demonstrated significant differences in emotion intensity.

2.2. Packaging design using emotion detection models

Mao et al. [21] developed an expansive empirical investigation on emotion recognition and prompt-based sentiment analysis that delves into the biases of large-scale pre-trained language model (PLM) technology towards emotional computing, piqued curiosity about prompt-based classification applications like emotion recognition and ultimately led to the development of this technology. Pandiangan et al. [22] examine the relationship between the packaging design and the likelihood that online shoppers will return to Politeknik IT&B Medan. This study's sample consists of 47 learners from the Faculty of Business Administration at Politeknik IT&B Medan, drawn from the second and fourth semesters of the academic year. The data analysis approach uses packaging design, responsible for 64.1 % of the total variation, influencing consumers' propensity to rebuy a product, while numerous other factors contribute. Cascini et al. [23] explore the possibilities of an innovative augmented reality system that utilizes projections to assist in creating design depictions that might be used in collaborative design sessions. The new technology's ability to support joint design sessions is evaluated through qualitative feedback and performance metrics. The ideas generated by projection-based AR sessions are more creative and of higher quality than those caused by conventional or handheld AR sessions. Using convenience sampling, Yang et al. [24] selected 54 students from a packaging design class. After that, we split them into 12 different groups based on their level of creativity. This empirical study examined how incorporating design thinking into a packaging design course affects students' flow state and confidence in their creative abilities. The results showed that design thinking increased students' self-efficacy and feelings of creative flow, even for students who often lacked creativity. Amanullah, M. et al. [25] analyse the CNN-based predictions with an Optimistic Method for detecting phishing attacks using multi-centric feature extraction that relies solely on URL functions to quickly and reliably find phishing websites and explore structured databases. To implement anti-phishing measures, professionals must first identify phishing URLs using the URL Behavioural Rectifier (U-BR) and then utilize behavioural principles to extract their unique traits. The suggested method uses writing embedding techniques to transform URLs into conventional size scales, uses the CNN model to segregate features at different levels, and then categorizes the features as risk. Shitharth S. et al. [26] described Rapid Probabilistic Correlated Optimization (RPCO) and Block Correlated Neural Network (BCNN) techniques for Attack Detection and Classification in SCADA Systems. The best characteristics are then chosen using the RPCO process, which calculates the probability of particles and their matching scores. When classifying the predicted label, the BCNN approach is used, with the kernel function and feature points used to calculate the relevance score. To further demonstrate the suggested attack detection system's superiority, the acquired results are contrasted with the RPCO-BCNN technique.

Based on the analysis, there are some issues in the 3s-HCI, PLM, and AFED-CR such as quality packaging, less emotion analysis and mean square error rate. Iterative attempts to enhance package designs may be aided by IEPC's continual analysis of emotional reactions. Packaging designs may be quickly optimized with real-time feedback on the emotional effect of design modifications. Consumers' levels of pleasure or irritation with package designs may be identified using IEPC's usability analysis. With this data, designers can better optimize packaging for functionality and comfort.

3. System methodology

The paper proposes that the design thinking process be highly esteemed to address consumer demands and societal complexity. Businesses and non-profits have extensively used it to address societal and economic issues. In the last decade, design thinking has gained popularity among academics as a paradigm that can offer fresh approaches to tackling problems in extremely complicated social and environmental contexts. Training *trans*-disciplinary teams is a good fit for design thinking. Beginning with an emotional analysis, design teams emphasize the connections between subjects and end users. The process starts with problem understanding, continues with problem inspiration, creativity, and execution, and concludes with implementation. By quantifying customers' emotional reactions to package designs, IEPC may augment conventional market research approaches. Better knowledge of customer preferences and behaviours may be achieved using this data, which can lead to better package design choices. The IEPC can back iterative design improvement attempts by continually monitoring emotional reactions to package designs. Iterative optimization of package designs is made possible by designers receiving real-time input on the emotional effect of design modifications. Better, more audience-resonant packaging designs may result from integrating IEPC into the assessment process for package designs. This is because it can provide important information about customer preferences and emotions.

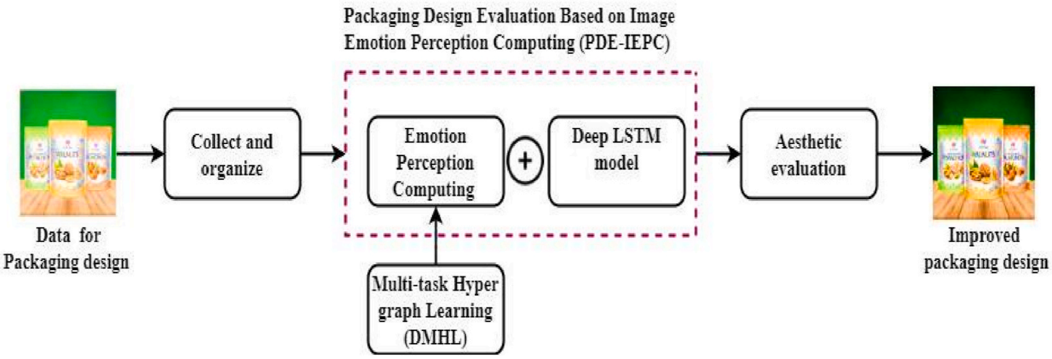

Fig. 1. Overview of Packaging Designs using Picture Emotion Perception Computing.

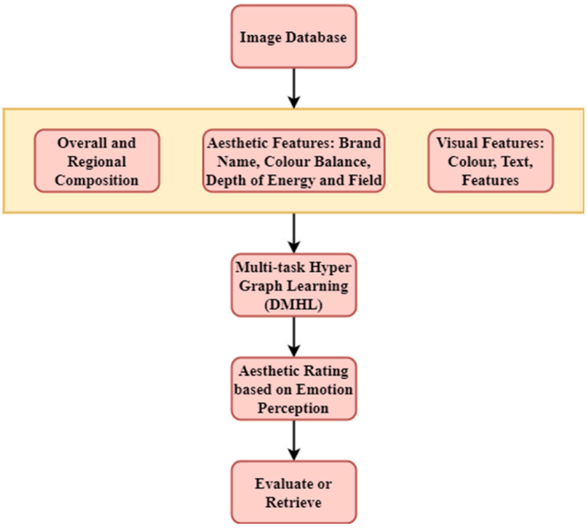

Fig. 2. Product design evaluation.

3.1. Overview of PDE-IEPC

In evaluating packaging designs using picture emotion perception computing (PDE-IEPC), this study introduces a fresh perspective on packaging design that uses state-of-the-art technology integration in Fig. 1. The research presents an immersive and reactive packaging design approach that takes consumers on a multisensory trip by neatly combining emotion recognition technology with the advanced Deep LSTM model. With Augmented Reality (AR) technology, an organization's concept can be created in a virtual world for consumers to explore. Meanwhile, the Dynamic Multi-task Hypergraph Learning (DMHL) approach and other emotion identification technologies are crucial for the real-time evaluation of customers' emotional responses to the tea package and virtual reality experience. With this feedback mechanism, the PDE-IEPC model may adapt to the customer's emotional state by continuously processing and evaluating various sensory inputs.

A revolutionary feature of the PDE-IEPC framework is its ability to integrate and interpret data from multiple sensory modalities simultaneously. It paves the way for the immediate identification of user emotions, which shape the development of virtual reality experience. For instance, the immersive virtual reality experience can react to a customer's enthusiasm or interest by showing them where the idea came from or giving them a hands-on manufacturing process experience. It is quite probable that the Deep LSTM model incorporates features from three essential techniques:

Augmented reality: Through AR technology, users can construct interactive, three-dimensional worlds. Consumers can engage with completely immersive three-dimensional settings made possible by this innovation. As a whole, packaging aims to make packing boxes and packaging materials more versatile. Using virtual modelling language, which augmented reality brings to packaging design, makes it easy to calculate the inside area of packaging, improving packaging comfort. The outcome of the packaging design is achieved by first setting the image of the outside packaging and commodities information with a combination of the packaging's interior data. Then, using AR technology for lighting and rendering, the virtual look of the packaging is generated.

Emotion perception computing: The packaging design should prominently feature the data and beneficial characteristics of the

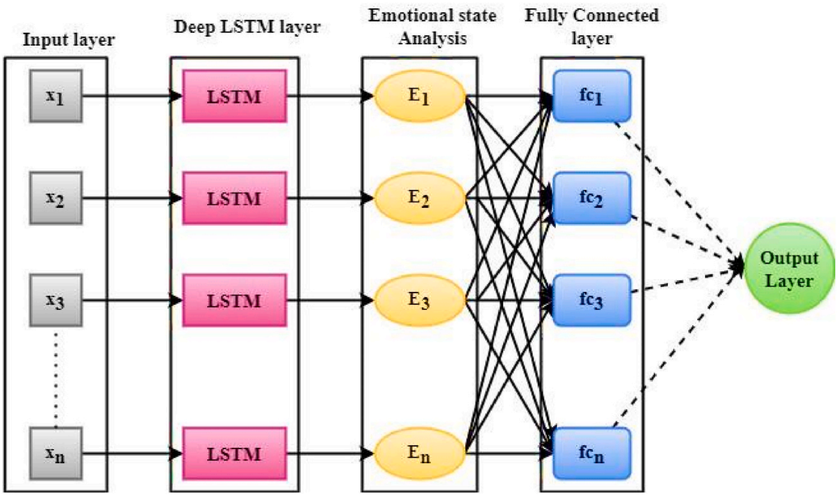

Fig. 3. Deep LSTM model for emotion recognition.

products. The utilization of detectors such as microphones and cameras in emotion perception technology enables the identification and examination of human emotions. By analyzing an individual's gaze, vocal accent, or other biological information, these sensors can accurately identify an individual's emotional state concerning packaging design. Extensive research into dynamic multi-task hypergraph learning (DMHL) methods has yielded promising results in computer vision and imaging applications, including the ability to model complex subject-wise relationships easily and have enough flexibility to handle missing data from perception-based multimodal imaging.

Deep LSTM model: A recurrent neural network that can process sequential input is the LSTM network. Deep LSTM refers to utilizing numerous LSTM layers, allowing complex information sequences to be processed. In the context of package design, the Deep Emotional Intelligence LSTM could be programmed to handle and evaluate the behavioural data retrieved from the sensation detection system. Fig. 2 shows the product evaluation for the improved package design based on emotion perception computing. Product evaluation for computerized design typically relies on professional creative design of visual aspects at different levels of abstraction, as well as compositional and high-level aesthetic features. An early researcher suggested a connection between computer vision features and picture aesthetics; using criteria like colour matching and contrast, techniques like long short-term memory (LSTM) and hypergraph learning to divide images into high and low aesthetics.

One possible use of emotional perception computing is to dynamically modify the augmented reality experience based on dynamic data processed in real time by emotion recognition sensors. Considering an individual panel with a random selection of 1000 residents to complete the survey. Fifty individuals took part in the first trial and sixty in the second. By showing the product's history or preparation procedure dynamically and energetically, the DMHL teach the AR system to deliver a livelier and engaging virtual emotional experience. However, if the user's mood is calm, the packaging design experience could change to a more peaceful one. To make the immersion in virtual reality more engaging and memorable for customers, the DMHL model is crucial in dynamically adapting it to trigger specific emotional responses based on the package design. It results in a more memorable package design that attracts customers.

The five steps of each experiment were as follows.

- selecting the product at the marketplace
- unwrapping the packaging
- cooking the food
- consuming it
- Making another purchase.

Subjects were led step-by-step through the experiment, and participant feedback was incorporated into each of the five phases by having them assess the product's performance. Initially, the participant stood in a virtual storefront before a set of shelves displaying 26 different commercially available varieties of dehydrated vegetable items. There were five samples for every packet. Similar glossy packaging featured big images of the veggie product and other graphic components. The second trial used two prototype packaging, each with a unique tactile feel and matte surface. The first, P1, had bold, visually appealing images of the vegetable product, reminiscent of the two advertising packages; the second, P2, had more subdued visuals. Identical to B1, both prototypes were food-related and featured a comparable brand. The participant was instructed to investigate one of the two samples in case fail to choose the target product (P1 and P2) from the shelves. During the supermarket product selection process, the participant ranked the importance of each of the five dynamic perceptions sight, sound, smell, texture, and taste. Use of scorn, admiration, discontent, contentment, uncomfortable surprise, delightful surprise, rejection, enticement, boredom, interest, melancholy, and joy were all emotions that were employed. Originally developed to gauge emotional reactions to visual appearances, these feelings are now utilized to evaluate the enhancement of package design. It has been demonstrated that these emotions are pertinent for characterizing emotional reactions to products. A combined analysis of the AR experiment data was performed.

3.2. Deep LSTM model

Fig. 3 shows a highly developed framework for analyzing and responding to customer emotions in the context of packaging design, which incorporates emotion recognition with the Deep LSTM model. It consists of an input layer, LSTM layer, emotional state analysis, fully connected layer and output layer. The basic idea is to dynamically impact the packaging design by integrating emotion detection data from the shop into the deep LSTM; the exact equations may differ based on the particular implementation. Equation (1) is one alternative way that the emotion recognition component takes sensor data and uses it to calculate an emotional assessment.

$$ES = f(x1, x2 \ldots xn) \tag{1}$$

Physiological sensors, analysis of the customer's facial expressions and voice tones, and other data sources (x1–xn) determine the customer's emotional state (E1-En). The "f" function takes all of these parameters into account. It returns an emotional score that represents the customer's level of emotional intensity and maybe even the exact nature of their feeling. The deep LSTM model updates its decision-making process based on this emotional score and other multidimensional inputs, including visual and aural data. This secret setting encapsulates the model's perception of the present emotional state of shoppers about packaging in stores. For example, the Deep LSTM could modify the augmented reality information to deliver a more engaging and lively audio and visual experience if the Emotion Score suggests that the user is experiencing excitement. On the other hand, if emotion recognition indicates a desire to relax, the deep LSTM will turn the virtual space into an intelligent package design. By continuously evaluating and reacting to the consumer's emotional state, emotion detection with LSTM creates an evolving feedback mechanism within the packaging design.

The objective is to create stunning, attention-grabbing packaging that resonates with consumers emotionally, allowing us to give them a one-of-a-kind, personalized experience.

Here, the LSTM model is required to handle a variety of multimodal inputs, including emotional data and visual and aural data. Internal gates, cell state, and hidden state are all factors in equations (2)–(4) that control how LSTM operates.

$$Input\ gate = \sigma(w_i * H(t-1) + E_i) \tag{2}$$

$$Hidden\ state = o_t * \tanh\ (state\ update) \tag{3}$$

$$output\ date = (w_o * H(t-1) + E_o) \tag{4}$$

It is possible to change the LSTM equations by adding the emotion score from the emotion detection component as a further input characteristic to the LSTM model. This tweaked LSTM operation incorporates the Emotion Score into the input sequence, allowing the deep LSTM to adjust for improved packaging structure dynamically. Using deep LSTM for emotional perception in the design sector is a huge step toward providing better customer service. This cutting-edge approach generates a captivating and emotionally engaging tea packaging trip by integrating sensory inputs, including visual, aural, and emotional data. In this case, LSTM's principal goal is to dynamically interpret these multimodal inputs and adjust the packaging design according to the customer's emotional state. This part uses consumer-facing sensors or technology that picks up on their emotional signals. Facial recognition systems, voice analysis, and other physiological sensors are all examples of what might be considered sensors. The functioning of this component yields an emotional score that reflects the customer's current emotional state.

3.3. Emotion perception computing

A complex undertaking that skilfully integrates state-of-the-art technology to elevate the customer experience, DMHL incorporates the Deep LSTM model into industry packaging design in tandem with emotion perception computing. This cutting-edge model enhances the design process by providing an interactive experience sensitive to the user's feelings. This integration allows the designing experience to adjust dynamically to the user's emotional state. For instance, the PDE-IEPC can tell the AR system to make the visual and auditory design more lively and engaging if the emotional score shows enthusiasm. Integrating emotional recognition into the PDE-IEPC paradigm is a game-changer for the designing sector in improving customer satisfaction. Fig. 2 shows the results of a hypergraph learning analysis of quantitative data (sensory modality significance evaluations and targeted product emotional ratings) to determine what adjustments to make to the product packaging design to increase sales.

3.4. Dynamic multi-task hypergraph learning (DMHL) approach

A hypergraph is a special kind of graph that accounts for the high-order link that exists when three or more vertices share an attribute by allowing an edge, called a hyperedge, to connect more than two vertices. In a hypergraph H = (X, Y, Z), the vertex set is X = $x_1, x_2, \ldots x_n$, while the hyperedge set is Y = $y_1, y_2, \ldots y_m$. Representing the hypergraph H as an incidence matrix, $I \in r_{n \times m}$ since every hyperedge $edge_j$ ($1 \leq j \leq m$) in the graph has multiple vertexes X_i($1 \leq i \leq n$).In H, every element in Equation (5)

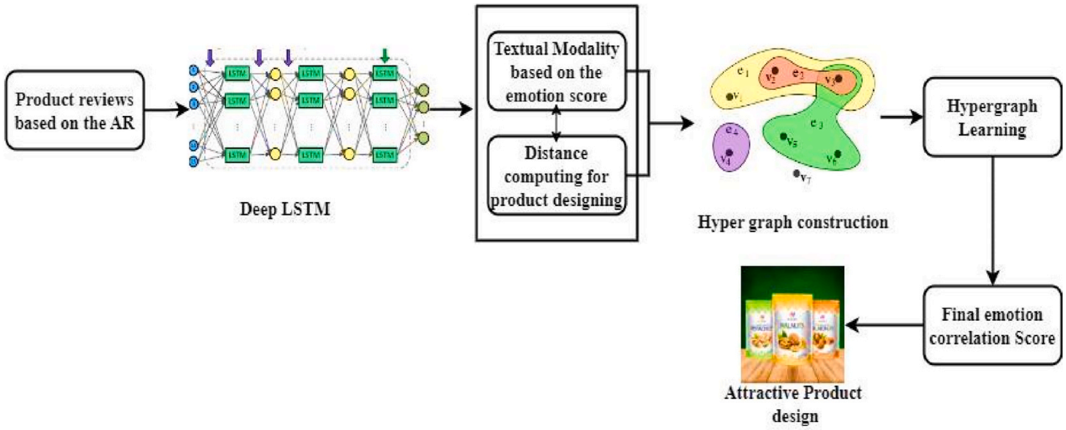

Fig. 4. Dynamic Multi-task Hypergraph Learning (DMHL) approach.

$$I(X_i, Y_j) = \begin{cases} 1 & X_i = edge_j \\ 0 & X_i \neq edge_j \end{cases} \tag{5}$$

The Stochastic kernel technique determines the positive weight w (edgej) for each hyperedge (edgej), shown in Equation (6). $d(x_i x_k)^2$ represents the Euclidean distance, σ average distance between all the vertices.

$$w\left(edge_j\right) = \sum_{x_i, x_k} exp\left(\frac{d(x_i x_k)^2}{\sigma^2}\right) \tag{6}$$

The subsequent calculation in Equation (7) that the degree $\Delta edge_j$ of a hyperedge, ej is equal to the number of vertices that are part of this hyperedge.

$$\Delta edge_j = \sum_{i=1}^{n} I(X_i, Y_j) \tag{7}$$

Fig. 4 shows the suggested Dynamic Multi-task Hypergraph Learning (DMHL) method for assessing the aesthetics of brand packaging from the multiple features of data and emotions. Before fine-tuning it on the target human expression in the shop's datasets, the deep LSTM was trained on a face-recognizing dataset to forecast emotion labels accurately. After removing the classification layers, the node values of the final hidden layer were normalized exponentially. Each of these hidden units contends that it represents a crucial face feature for emotion categorization and stores unique conceptual knowledge; the normalized figure that each node produces may be seen as the likelihood that the sample being processed possesses the related attribute. For the effective emotion of the images, there has been extensive research on both minimal and high-level vision tasks. An essential but difficult aspect of these activities is the intricate data correlation underlying the vision data. From an aesthetic standpoint, for instance, picture pixels or patches constitute the image's elements, and these bits and pieces stand in for the image's semantic content. Multiple views, point clouds, voxels, and meshes are common approaches to depicting three-dimensional objects. The precarious connections between these things are heightened in this context. There are too many intricate relationships between different three-dimensional objects for a simple graph to depict adequately.

By restructuring the textual modality recognition of emotions task as a hypergraph partitioned problem, in which face photographs serve as the vertex and calculate visual features serve as the hyperedges, we may leverage produced attributes in the second stage. The second step was to structure the emotion detection job as a hypergraph partitioning issue. Here, images were utilized as vertices and calculated visual characteristics were used as hyperedges. It allowed us to make use of the created attributes. According to the definition, a hypergraph is a graph where an edge can have more than two vertices based on distance computing. It accounts for the high-order connection where three or more vertex share the same feature.

- Create the image's underlying correlation by connecting each picture patch with a collection of hyperedges, using each patch as a node in a hypergraph.
- The distance-based hypergraph generation method is employed at this point, which entails selecting a patch's centroid and linking its hyperedges to its neighbours in the feature space.
- Hypergraph nodes can represent any real-world item in three dimensions in this scenario. An item is selected to act as the centroid of the feature space for each iteration, and hyperedge connections are made between it and its closest neighbours.
- The process restarts once each element in this feature space has its centroid selected once. With this method, it may take advantage of any feature—or set of features—by itself. The incidence matrices V1, V2, …, and Vm allow us to build many hypergraphs that display relationships differently.

Table 1
Emotion Analysis based on PDE-IEPC.

Time Step	Emotion Score	Anticipated Emotion
2.5	0.93	Happiness
5	0.52	Relaxation
7.5	0.61	Surprise
10	0.84	Joy
15	0.45	sad
17.5	0.93	Happiness
20	0.32	Sad

The connection defies description by standard pairwise graphs, where an edge only connects two nodes. Because the first-stage attributes contain numerous photos, a hypergraph better describes the connection among the expressions seen in the images. When building hyperedges, the previous method relied on local clusters calculated from manually constructed low-level characteristics. Further ways in which deep LSTM's acquired attributes differ are the semantic characteristics, which picture annotators previously defined. In such a setting, the complex relationship between these objects becomes much more so. A simple graph cannot represent the complex interrelationships between individual image pixels or patches, much alone between various three-dimensional objects. Using each picture patch as a node in a hypergraph, simulate the image's underlying correlation by creating a set of hyperedges that link the patches together. When this happens, we can use the distance-based hypergraph generation technique, which involves picking a centroid for each patch and connecting its hyperedges to its feature space neighbours. Based on the evaluation results, designers can assess their work and adjust their strategy for creating better designs. Images, point clouds, and other multimodal data are present in computer vision. Next, the approach divides the initial image's aesthetic quality into excellent and poor categories. Images with an average score of 3 or higher have "acceptable" aesthetic quality, while those with an average score below 3 have "low" aesthetic value. Evaluation of the packaging's ability to communicate the brand's identity and message can be aided by IEPC. It guarantees that the packaging will evoke the intended feelings and impressions. Hypergraph learning allows DMHL to grasp complex interrelationships among design aspects, customer comments, market tendencies, and brand goals. With DMHL, a more all-encompassing method of evaluating packaging designs may be achieved, allowing for more thorough analysis and better decisions. Designing packaging that evokes the right feelings while serving practical purposes and furthering a brand's goals is possible when the DMHL framework is used with other design criteria.

4. Experiment results

The proposed method utilized the Flicker image dataset in sentence-based image description; the Flickr30k dataset has established itself as a gold standard. kaggle.com/datasets/hsankesara/flickr-image-dataset [27]. This study introduces Flickr30k Entities, an enhancement to Flickr30k′s 158k captions that adds 244k reference chains to connect image-wide references of the same entities, along with 276k bounding boxes annotated by hand. They allow us to establish a new standard for entity-mention localization in images. They provide a robust foundation for this job that integrates picture-text embeddings, common object detectors, a colour classifier, and a preference for bigger items in object selection. While our basic model is equally accurate as more complicated state-of-the-art models, we demonstrate that its benefits on image-sentence retrieval and other tasks cannot be transferred to these new approaches, highlighting their limits and the need for more study.

4.1. Emotion analysis based on PDE-IEPC

Deep LSTM with DMHL is a ground-breaking framework that revolutionizes the field of package construction by efficiently handling data sequences with several modalities. This distinctive model, which incorporates LSTM units and the ability to integrate information from various sources such as text, images, audio, and more, can tackle complex tasks that require a full understanding of multimodal input. The PDE-IEPC excels in various domains like language processing and dynamic virtual environments, signalling the advent of a thrilling new era of immersion and participative technology. PDE-IEPC can revolutionize awareness, manufacturing, and engagement with information by harnessing the potential of simultaneous multimodal input. It surpasses the limitations of conventional machine learning. This initial section provides a glimpse into the efficient capabilities of PDE-IEPC and establishes the foundation for exploring its potential applications and ramifications. The Emotion Score in Table 1, which varies between 0.30 and 1, represents the model's assessment of the strength of emotions during a specific time interval. The Predicted Emotion refers to the classification assigned by the model to determine the emotional state of the information being provided at each time step.

4.2. Packaging design quality evaluation rate

The utilization of Image Emotion Perception computing in packaging design is highly significant. The significance of hues and patterns in package design and the implementation strategy of these aspects have been discussed earlier. The designer must incorporate cultural connotations into the product's packaging design using artistic visual symbols or language to enhance the effectiveness of information transfer. Typically, individuals select design images or symbols in two dimensions as graphic symbols, which differ from conventional visual symbols. Designers must recognize that regardless of the visual design or colours utilized, ensure that it is easily

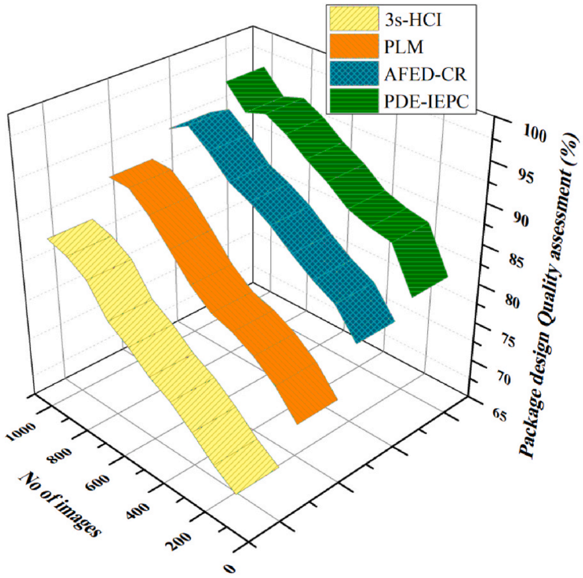

Fig. 5. Packaging design Quality evaluation rate.

Table 2
Performance comparison of the proposed model.

Method	Accuracy
RCNN + DTW	89.8 ± 2.2 %
LSTM + CNN	87.8 ± 1.3 %
LSTM + SVM	90.5 ± 0.9 %
D-CNN + R–CNN Softmax	94.8 ± 1.5 %
Deep LSTM + DMHL	**97.5 ± 2.5 %**

understandable for average consumers. The fundamental components of packaging design are colour, graphics, and text. The utilization of deep LSTM with DMHL for image product evaluation distribution has been discovered to assist designers and organizations. The proposed method is evaluated against the 3s-HCI, AFED-CR, and PLM models to assess its effectiveness in improving packaging design quality. Based on picture analysis, IEPC algorithms can identify and categorize the emotions conveyed by package designs. Emotions including happiness, enthusiasm, trust, surprise, and dissatisfaction may be detected by IEPC using visual clues such as colour schemes, facial expressions, and body language. Emotional response-based quantitative examination of package design impressions is now possible with IEPC. Fig. 5 shows the package design quality assessment.

4.3. Performance comparison of the proposed model

Performing pre-training on the model was the first step in training the deep LSTM. During the pre-training phase, the identified faces from flicker images are limited to frontal views. Cut a thousand images into ten non-subject-dependent subsets for more accurate adjustment and hypergraph learning. The categorization can be done after this division is completed according to the instructions. The pre-trained LSTM model was fine-tuned on each occasion using the images from the training set. The optimizing outcomes were improved through the use of data augmentation methodologies. The model attained an astounding average performance success rate of 97.5 % during the tenfold experiment. Eight different variants are employed in each trial when learning hypergraphs. The final realized expression was decided by picking the one with the most significant predicted score among eight other emotions. Using the same deep LSTM modelling Table 2, the hypergraph learning technique outperforms LSTM + SVM by 0.9 % and D-CNN + R–CNN Softmax by 1.5 %. Collect a set of graphic designs and the emotional labels that go with them. This data collection should include pictures of graphic designs and labels describing the feelings those designs make people feel. Surveys, user studies, and crowdsourcing can help gather these labels. For picture classification jobs, select a CNN architecture that works well. Popular models include VGG, ResNet, and Inception for feature extraction from photos. By analysing the model's predictions, Determine the role of various graphic design components in generating particular human emotions. Resize the photos to a uniform scale, normalize the pixel values, and employ data augmentation techniques to boost the dataset's diversity as part of the preprocessing step. Random rotations, flips, zooms, and shifts are data augmentation approaches that can improve CNN generalizability to unknown data and architectural component variations. Verify the improved designs by gathering input from the intended users or doing user testing. It is important to gather feedback from people to make sure the design elements successfully evoke the desired emotions. Graphic designs that are both engaging and

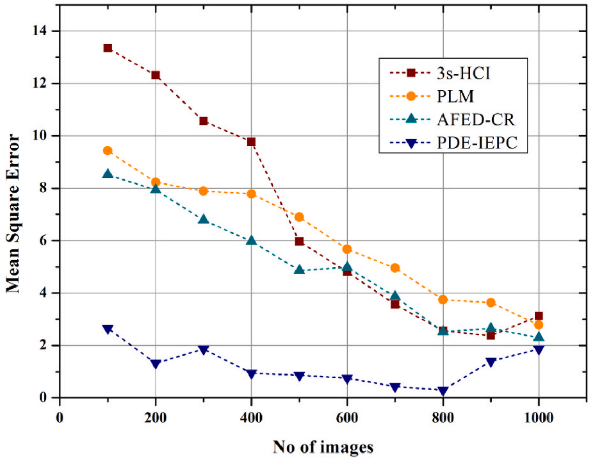

Fig. 6. Mean square error.

effective are the result of incorporating convolutional neural networks (CNNs) into the iterative design process.

Constantly add new instances of packaging designs and the corresponding emotional expressions to the datasets used to train CNN models. To keep up with the ever-changing world of graphic design, the model may be updated with new data as trends and consumer preferences come and go. Apply transfer learning methods to update pre-trained convolutional neural network (CNN) models with fresh packaging-specific data. The algorithm can swiftly adapt to new emotional expressions in packaging design with minimal training data by utilizing knowledge from past assignments or domains.

Emotional categorization accuracy is a measure of how well IEPC algorithms perform. It assesses the IEPC model's ability to identify and categorize emotions communicated by package designs based on visual clues. According to its high accuracy rate, the IEPC model accurately predicts how people will feel about certain package designs. Typical IEPC model mistakes, including conflations between comparable emotional categories or misclassifications may be better understood by examining the confusion matrix. Insight into these mistakes may direct improvement and refining of the model, leading to better performance.

4.4. Mean square error

According to an analysis of the anticipated emotion labels, incorrect categorization frequently happened within comparable emotion perception. It is possible to calculate the difference between the expected and actual values of hypergraph learning the mean squared error by using Equation (8)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{8}$$

As shown in Equation (8), where n is the number of test images, x_i is the real value of the emotion score and y_i denotes the estimated values. The major goal of IEPC models in package design is to reduce prediction errors via enhancing model precision, feature characterization, data integrity, and ensemble tactics. Through these strategies, IEPC may make a meaningful contribution to improving the assessment of package design and maximizing emotional impact. Fig. 6 shows the mean square error rate.

A higher Precision number means better results for emotion classification, while a lower MSE value means better results for emotion perception. Using deep LSTM with DMHL to distribute image product evaluations is helpful for both designers and companies. The recommended model is compared to the 3s-HCI, AFED-CR, and PLM models to ascertain the enhanced packaging design quality and decreased mistake rate. The efficiency of packaging in communicating the brand's identity and message can be evaluated using IEPC. The packaging is guaranteed to evoke the desired feelings and thoughts when done. Using hypergraph learning techniques allows DMHL to grasp the complex interrelationships of many design aspects, customer comments, market tendencies, and brand goals. With DMHL's ability to provide a more holistic approach to evaluating packaging designs, comprehensive analysis and decision-making are made easier. Designers can optimize packaging designs to accomplish functional needs and brand goals while also appealing to consumers' emotions by integrating considerations of emotional perception with other design criteria within the DMHL framework.

5. Conclusion

The primary focus of earlier studies on emotional picture analysis was predicting the most prevalent emotions in viewers. This general impression isn't often sufficient for practical purposes because the emotions elicited by a picture are very subjective and differ from viewer to viewer. To provide an interactive and engaging experience for the senses, the researchers proposed a method for evaluating packaging designs called PDE-IEPC, which combines emotion perception technology with a Deep LSTM (Long Short term model). Emotion Perception Computing's Dynamic Multi-task Hypergraph Learning (DMHL) approach considers graphical data, social context, spatial evolution, location, and other variables that impact picture emotion perceptions to evaluate packaging designs efficiently. Image-Emotion-Social-Net is a large dataset used to evaluate multidimensional and categorical attitude representation. The dataset is sourced from Flickr and contains over 1 million images presented by over 9000 users. Comparing the suggested approach to 3s-HCI, AFED-CR, and PLM models to determine how effectively it improves packaging design quality and reduces errors. The experimental results show that the proposed method achieves a high packaging design quality rate of 94.1 %, a performance success rate of 97.5 %, and a lower mean square error rate of 2 % compared to other existing methods. From eight emotions, choose the learned expression with the greatest predicted score. Using the same deep LSTM model, hypergraph learning beats LSTM + SVM and D-CNN + R–CNN Softmax in Table 2 by 0.9 % and 1.5 %, respectively. For future use with both intra- and inter-modal communications, a hierarchy-based hypergraph neural network using the current hypergraph network as a foundation is planned.

CRediT authorship contribution statement

Shang kui Yang: Writing – review & editing, Writing – original draft. **Won jun Chung:** Writing – review & editing, Writing – original draft. **Fan Yang:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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