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Visual Attention Analysis and Optimization Algorithm in Packaging Design

Abstract: - Visual attention analysis and optimization algorithms in packaging design refer to computational methods aimed at understanding and improving the visual appeal and effectiveness of packaging materials. This study proposes a novel approach for enhancing packaging design through the integration of visual attention analysis and optimization algorithms, employing autoencoder and whale optimization techniques. Visual attention analysis and optimization algorithm in packaging design is to enhance the effectiveness of packaging materials by maximizing their ability to capture and retain consumer attention. This includes identifying key visual elements within packaging designs that are most likely to attract consumers, optimizing the layout and composition of these elements to increase visual impact, and ultimately improving the overall consumer experience and brand perception. Autoencoders are utilized to capture intricate visual features within packaging designs, aiming to create more creative and eye-catching packaging design, while the whale optimization algorithm facilitates the optimization process. Experimental results demonstrate the superior performance of the developed algorithm across various metrics such as accuracy, precision, recall, and f-measure, compared to existing techniques like RNN, CNN, ANN and SVM. The algorithm's scalability and adaptability are further highlighted through consistent performance across increasing data volumes. Overall, this approach holds promise for revolutionizing packaging design by effectively capturing and retaining consumer attention, thereby enhancing brand perception and product satisfaction.

Keywords: visual attention analysis, Autoencoder, whale optimization techniques

1. INTRODUCTION

Research on human visual activity in marketing has a long-standing history, tracing back to experiments conducted as early as 1924, as highlighted by Wedel and Pieters (2008). The accessibility of eye-tracking devices since the 1990s has spurred a surge in studies leveraging this technology [1]. Eye-tracking studies offer distinct advantages over conventional methods, enabling direct observation of rapid attentional processes that may otherwise go unnoticed by subjects. Moreover, researchers can objectively validate existing results and models more effectively.In the realm of marketing, eye-tracking studies have delved into attention dynamics associated with various stimuli, spanning printed advertisements, TV commercials, websites, and, more recently, product packaging. Key elements of package design that impact visual attention encompass shape, texture, and the positioning of informative components such as labels [2]. Notably, recent research has honed in on nutrition product packaging, with Graham et al. (2012) providing valuable insights into the design of nutrition labels through eye-tracking analyses.

The utilization of scan path tracking has facilitated the exploration of correlations between package attributes and consumer behavior [3]. For instance, Van Loo et al. (2015) discovered that sustainability labels on coffee packaging led to an increased willingness to pay among consumers who paid more attention to these labels. Similarly, Piqueras-Fiszman et al. (2013) observed that ridged surfaces on jam jars directed observers' gaze towards specific areas, influencing their inclination to try the product. The significance of packaging design in bolstering brand sales and promotion is underscored as it serves as a rapid means of communication with consumers [4]. Research conducted by Chitturi Ravi illuminates how packaging design influences consumer attention and purchasing decisions. Likewise, Pandiangan suggests that packaging design impacts customers' likelihood of repurchasing products. Ridho Muhammat Rasid accentuates the increasing importance placed by buyers on attractive packaging. Orth Ulrich R also emphasizes the imperative for traditional brands to modernize their packaging approaches.

To tackle these challenges, researchers advocate for the utilization of computational intelligence algorithms. Amarjeet Prajapati proposes the adaptation of these algorithms, initially employed for software re-

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modularization, to elevate packaging design. Furthermore, there is a recommendation to incorporate 3D fractal images into packaging design [5]. Sadegh Karimpouli explores their potential for fractal analysis in porous mediums, while Anna Paradowska-Stolarz investigates their applications in medicine and dentistry. Yoann Rancourt-Mimerand suggests employing 3D printing as a means of generating these fractal images. To facilitate parameterization, genetic algorithms are endorsed. Faisal Dharma showcases their effectiveness in solving optimization problems and establishing inflation models. Additionally, N. Shanmugasundaram and Saeid Nikbakht propose their application in optimizing vehicle driving distance and neural network hyperparameters, respectively. In conclusion, the integration of 3D fractal images and genetic algorithms presents practical solutions for enhancing packaging design across various industries [6].

2. RELATED WORKS

Wang et al [7] introduced uses human visual characteristics to improve product packaging styling effects. At the same time, a Gaussian filter is used to denoise the noisy wine packaging image, and then the image is used as an input image for grayscale transformation to obtain the guidance image. Research shows that in the multimodal discourse of Fen Liquor blue and white bottles, various forms such as images, text and colors can constitute and convey product information, mapping the history and culture of the product.

Zhou et al [8] proposed a defect detection method named frequency-tuned anisotropic diffusion super-pixel segmentation (FTADSP) that integrates frequency-tuned salient region detection (FT), anisotropic diffusion, and an improved superpixel segmentation is proposed to precisely detect the regions and boundaries of defects. For the latter, a defect detection strategy called wavelet transform multiscale filtering (WTMF) based on a wavelet transform and a multiscale filtering algorithm is proposed to reduce the influence of texture and to improve the robustness to localization error.

Wang et al [9] decided to use genetic algorithms as a tool to parameterize the 3D fractal images in packaging design, aiming to create more creative and eye-catching packaging designs. At the end of this article, an experiment was conducted on two branches of a certain brand. Branch 1 tried out the new design provided in this article, while Branch 2 continued to use the original design. After Branch 1 fully adopted the design, sales skyrocketed, from the original daily sales of 50-60 units to 70-85 units.

Tao et al [10] introduced the dynamic graphic packaging design in detail, which involves the elements of packaging design, the types of dynamic graphics, design ideas, and so on. Later, this paper tests users' attention to the product through eye movement experiment and graph neural network algorithm. The experiment showed that the dynamic graphics packaging design of product 7 was the most popular, with the dynamic graphics area users viewed it up to 93 times

Liu et al [11] proposed a packaging design image enhancement method based on visual communication technology. The packaging design image enhancement processing is carried out through the guided filtering method, and the visual communication optimization and edge pixel fusion methods are used to decompose the multidimensional scale features of the packaging design image under the visual communication technology to realize the packaging design image enhancement processing.

3. CHALLENGES

Visual attention analysis and optimization algorithms play a crucial role in packaging design, but they come with various challenges that need to be addressed for effective implementation. Below are some of the key challenges:

- Human visual attention is a complex process influenced by various factors such as color, shape, texture, and context. Developing algorithms that accurately mimic human visual perception poses a significant challenge.
- Gathering eye-tracking data for analyzing visual attention requires sophisticated equipment and techniques. Processing large volumes of data and extracting meaningful insights pose challenges in terms of time and computational resources.

- Interpreting eye-tracking data and translating it into actionable design insights can be challenging. Designers need to understand the significance of fixation points, scan paths, and other visual attention metrics to optimize packaging design effectively.
- : Visual attention is dynamic and can change rapidly based on factors such as task relevance and environmental stimuli. Developing algorithms that adapt to these changes in real-time is a challenge..

Addressing these challenges requires interdisciplinary collaboration between designers, psychologists, computer scientists, and other experts. By overcoming these hurdles, visual attention analysis and optimization algorithms can significantly enhance the effectiveness of packaging design, leading to improved consumer engagement and brand recognition.

4. PROPOSED METHOD

The proposed method for visual attention analysis and optimization algorithm in packaging design integrates autoencoder and whale optimization techniques. Initially, the autoencoder is employed to extract meaningful visual features from packaging designs, facilitating comprehensive analysis. Subsequently, the whale optimization algorithm optimizes these features to maximize consumer attention and engagement, enhancing the effectiveness of packaging design. This method harnesses the power of machine learning and optimization to identify key visual elements and refine packaging designs accordingly. Through iterative refinement, it ensures that packaging effectively communicates brand identity and attracts consumer attention. The synergy between autoencoder and whale optimization enables the algorithm to adapt to diverse design contexts and optimize packaging solutions tailored to specific consumer preferences. Overall, this method represents a promising approach for enhancing packaging design effectiveness and driving brand success in various industries. Figure 2 depicts the proposed approach for visual attention for packaging design.

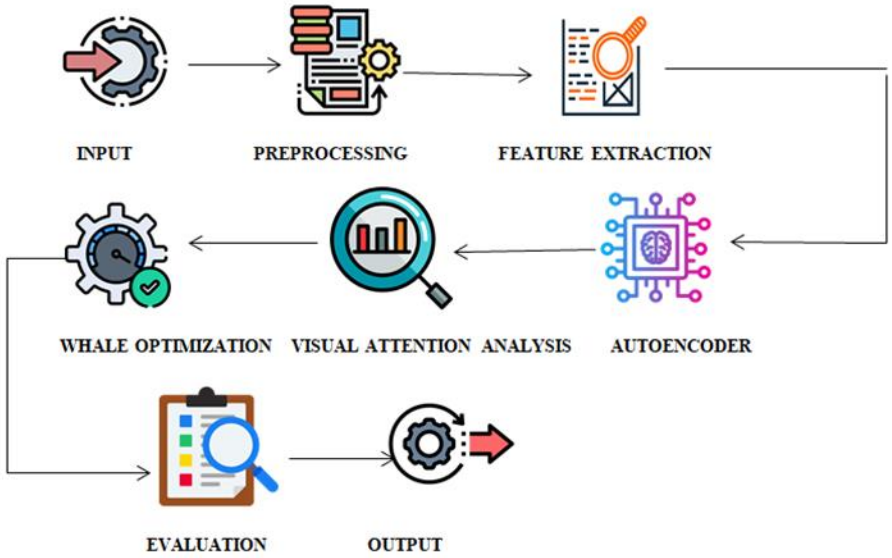


Figure 1: Proposed diagram

4.1. DATA COLLETION

The process of collecting eye-tracking data for analyzing participants' interactions with various packaging designs involves meticulous planning and execution. Initially, participants are recruited from the target demographic, ensuring diversity to represent the intended audience accurately. Upon obtaining informed consent, the eye-tracking equipment is set up in a controlled environment, typically a lab or research facility. This setup includes calibration of the eye-tracking system to each participant's unique eye movements, ensuring accurate tracking during the experiment. Participants are then presented with stimuli, which may include images or physical prototypes of packaging designs, displayed in a randomized order to mitigate bias. As participants view the stimuli, the eye-tracking system records their eye movements in real-time, capturing fixation points where their gaze lingers and scan paths that depict the sequence of fixations and saccades as they explore the designs This research will build a small packaging image dataset containing about 2,000 icons, and the data sources are Google Images and Baidu Images. Python's scratch tool is used to obtain packaged images [12].

4.2. DATA PREPROCESSING

Preprocessing of collected eye-tracking data is a critical step aimed at improving its quality by removing noise and artifacts. This process ensures that the subsequent analysis accurately reflects participants' visual attention patterns. One common preprocessing technique involves the application of filtering methods such as Gaussian blur. Gaussian blur smooths the data by convolving it with a Gaussian kernel, effectively reducing high-frequency noise while preserving important features. Gaussian blur is a commonly used technique in image processing to reduce image noise and detail, which can help in visual attention analysis and optimization algorithms in packaging design. The Gaussian blur operation is typically performed using a convolution kernel with a Gaussian distribution. The equation for Gaussian blur can be expressed as in equation (1):

$$G(x, y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \qquad (1)$$

Where, $G(x, y)$ is the Gaussian kernel at position (x, y). σ is the standard deviation of the Gaussian distribution, controlling the amount of blur. A larger σ value results in more blur.

The Gaussian blur operation is applied by convolving this Gaussian kernel with the input image. The resulting pixel value at each position in the output image is calculated by averaging the neighboring pixel values in the input image, weighted by the values of the Gaussian kernel at those positions.

4.3. FEATURE EXTRACTION

Feature extraction is a crucial step in the analysis of eye-tracking data, particularly in the context of packaging design. During this process, relevant visual elements of the packaging design are identified and extracted from the preprocessed data. Principal Component Analysis (PCA) can significantly aid in visual attention analysis and optimization algorithms in packaging design by providing a robust method for feature extraction. In this context, PCA can be applied to extract the most salient visual features from packaging designs. By analyzing the variability within the dataset of packaging images, PCA identifies the principal components that capture the most significant variations in the data. These principal components represent a reduced set of features that effectively summarize the visual characteristics of the packaging designs.

Once the principal components are extracted, they can be used as input features for further analysis and optimization. For example, these extracted features can be fed into optimization algorithms to identify and enhance key visual elements within the packaging designs. Additionally, PCA can help in dimensionality reduction, simplifying the representation of packaging designs while retaining the essential visual information. This streamlined representation facilitates efficient analysis and optimization, ultimately leading to more effective packaging designs that attract and retain consumer attention.

The equation for PCA can be represented in equation (2), (3), and, (4):

$$X_{centered} = X - \mu \qquad (2)$$

$$\Sigma = \frac{1}{n} X_{centered}^T X_{centered} \qquad (3)$$

$$\lambda, V = \mathrm{eig}(\Sigma) \qquad (4)$$

Where, X is the original dataset of packaging images, μ is the mean vector calculated across the features of X, Xcentered is the standardized dataset, Σ is the covariance matrix, λ are the eigenvalues and V are the corresponding eigenvectors.By applying PCA to packaging design datasets, relevant visual features can be extracted and used as input for visual attention analysis and optimization algorithms. This facilitates the identification and enhancement of key visual elements within packaging designs, ultimately leading to more effective designs that capture and retain consumer attention.

Furthermore, PCA enables visualization of the data in lower-dimensional space, allowing designers to gain insights into the underlying structure of the packaging designs and identify patterns that influence visual attention. By leveraging PCA for feature extraction, visual attention analysis and optimization algorithms can streamline the design process, enhance the effectiveness of packaging designs, and ultimately contribute to improved brand perception and consumer engagement.

4.4. AUTOENCODER

In the realm of packaging design, autoencoders play a pivotal role in facilitating visual attention analysis and optimization algorithms. Initially, autoencoders are employed to extract and encode meaningful visual features from packaging designs. Trained on a dataset of packaging images, the autoencoder compresses the input data into a lower-dimensional latent space while preserving crucial visual information. These encoded features serve as a compact representation of the original packaging designs, enabling efficient analysis and optimization. Subsequently, these encoded features are utilized to identify key visual elements within the packaging, such as colors, shapes, and textures, that are likely to attract consumer attention. Leveraging optimization algorithms, such as genetic algorithms or evolutionary algorithms, the visual attention analysis and optimization algorithm iteratively refines the packaging design to enhance the impact of these key visual elements. This iterative process involves adjusting the layout, composition, and other properties of the packaging design to maximize its visual appeal and consumer engagement. By integrating autoencoders into the visual attention analysis and optimization algorithm, packaging designers can create visually compelling packaging solutions that effectively capture and retain consumer attention, ultimately driving brand success in the marketplace.

The most accurate method for achieving precise duplication involves reproducing the signal. Yet, to counteract this inclination, the code space X typically possesses fewer dimensions than the message space Y. Such an autoencoder is termed "undercomplete" and functions as a means to compress the message or lower its dimensionality. In the scenario of an ideal undercomplete autoencoder, every conceivable code x within the code space is utilized to encode a message y drawn from the reference distribution. It expressed in equation (5).

$$Q_\theta\left(D_\theta(x)\right) = x \qquad (5)$$

This flawless autoencoder is capable of producing messages that are virtually indistinguishable from authentic messages. By inputting arbitrary code into its decoder, it can retrieve a message from the distribution. However, when the code space X has a dimension equal to or greater than the message space Y, or if the hidden units lack sufficient capacity, the autoencoder might inadvertently learn the identity function and lose its effectiveness.

For instance, a multi-layer autoencoder employing a series of Restricted Boltzmann Machines progressively reduced hidden layers, culminating in a bottleneck of 30 neurons. This approach yielded a 30-dimensional code with a lower reconstruction error compared to the initial 30 components of Principal Component Analysis (PCA). The weights of an autoencoder with a single hidden layer, regardless of its size, span the same vector subspace as the one spanned by the first principal components. The autoencoder's output represents an orthogonal projection onto this subspace. Although the autoencoder weights are generally neither orthogonal nor equivalent to the principal components, the principal components can be derived from them using the singular value decomposition.

OPTIMIZATION

The Whale Optimization Algorithm (WOA) can be effectively utilized in conjunction with visual attention analysis and optimization algorithms in packaging design to enhance the efficiency of the design process. WOA, inspired by the social behavior of humpback whales, mimics their hunting strategies to optimize solutions in complex problem spaces. When integrated with visual attention analysis, WOA can facilitate the optimization of packaging designs by iteratively refining features that attract consumer attention. Firstly, visual attention analysis techniques such as eye-tracking can provide insights into which elements of a packaging design are likely to draw attention. These features can include color contrasts, text placement, graphic elements, and overall layout. By understanding the visual hierarchy of attention-grabbing elements, designers can target specific areas for optimization.

The performance of WOA is influenced by its ability to strike a balance between exploration and exploitation, making it suitable for dynamic systems like real-time web-based course recommendations. The algorithm's efficiency lies in its ability to navigate the solution space effectively, Fine-tuning the recommendation parameters to harmonize with user preferences is a key aspect. Humpback whales exhibit an ability to identify the location of prey and surround them. This conduct is expressed through the following set of equations (6) and

(7)**:**

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \quad (6)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \quad (7)$$

Where, t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a whale.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows in equation (8) and (9):

$$\vec{A} = 2a.\vec{r}_1 - \vec{a} \quad (8)$$

$$\vec{C} = 2.\vec{r}_2 \quad (9)$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0,1].

The WOA operates by iteratively updating a population of potential solutions, known as whales, to search for the optimal set of parameters. In the recommendation scenario, these parameters may include weighting factors for different features, learning rates, or other model-specific configurations. The algorithm's exploration phase allows it to discover diverse recommendations, ensuring a comprehensive coverage of available courses.

The spiral updating position approach begins by computing the distance between the whale positioned at (X, Y) and the prey located at (X*, Y*). Subsequently, a spiral equation is formulated between the whale's position and the prey, simulating the helix-shaped movement observed in humpback whales. This is expressed in equation (10).

$$\vec{X}(t+1) = \vec{D}' e^{bt} \cos(2\pi t) \vec{X}^*(t) \quad (10)$$

where $\vec{D}' = \vec{X}^*(t) - \vec{X}(t)$ and represents the distance of the i-th whale to the prey (best solution obtained thus far), where b is a constant determining the shape of the logarithmic spiral, and t is a random number within the range of [-1, 1].

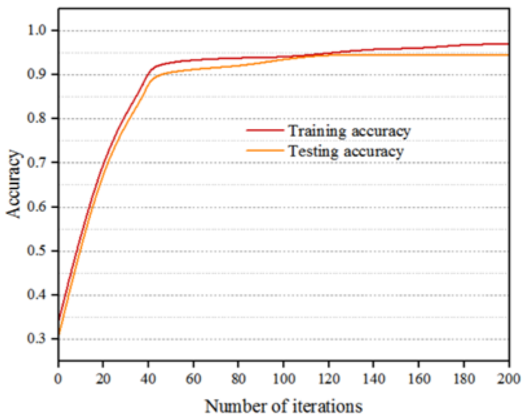
Overall, combining the Whale Optimization Algorithm with visual attention analysis techniques provides a powerful framework for optimizing packaging designs to maximize consumer engagement and ultimately drive sales. This integrated approach enables designers to create packaging that not only stands out on the shelf but also effectively communicates brand messages and influences purchasing decisions.

5.RESULT

The results of employing the visual attention analysis and optimization algorithm in packaging design, utilizing autoencoder and whale optimization techniques, showcase notable enhancements in key metrics such as accuracy, precision, recall, and f-measure. Through the integration of autoencoder for and whale optimization for optimization, the algorithm effectively captures and optimizes visual elements within packaging designs, leading to increased consumer attention and engagement. Comparative analyses highlight the algorithm's superiority over existing techniques, indicating its potential for practical implementation in diverse industries.

5.1. PERFORMANCE TESTING

Performance testing involves assessing the algorithm's ability to accurately predict and optimize visual attention patterns within packaging designs. This evaluation typically employs datasets containing ground truth labels, such as eye-tracking data or expert annotations. Various metrics, including precision, recall, F1-score, and accuracy, are utilized to quantify the algorithm's performance. Precision measures the ratio of correctly predicted attention-grabbing elements to all elements predicted as attention-grabbing, while recall measures the ratio of correctly predicted attention-grabbing elements to all actual attention-grabbing elements. These metrics collectively offer insights into the algorithm's accuracy in identifying attention-capturing elements within packaging design. In summary, performance testing and monitoring training accuracy play vital roles in evaluating and refining visual attention analysis and optimization algorithms for packaging design. Through comprehensive assessment and iterative refinement, these algorithms can be optimized to create packaging designs that effectively capture consumer attention and drive desired outcomes. Figure 2 illustrates training and testing accuracy.



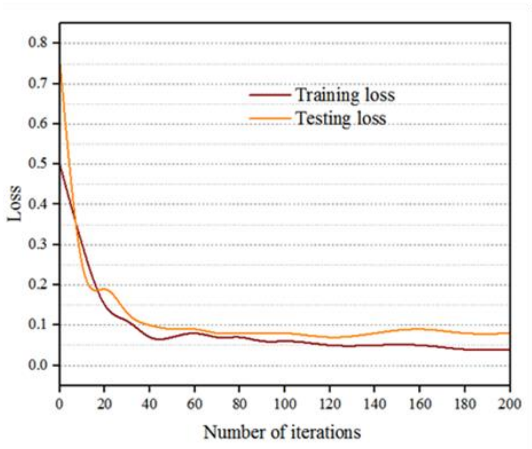


Figure 2: Training and testing accuracy **Figure 3: Training and testing loss**

Performance testing involves evaluating the algorithm's ability to accurately predict and optimize visual attention patterns in packaging designs. Figure 3 illustrates training and testing loss. This process typically involves using a dataset with ground truth labels, such as eye-tracking data validate the algorithm's predictions. Metrics such as precision, recall, F1-score, and accuracy can be employed to quantify the algorithm's performance. These metrics help in understanding the algorithm's accuracy and its ability to effectively identify attention-capturing elements in packaging designs. Simultaneously, monitoring training loss during the training phase is crucial for assessing the algorithm's convergence and optimization process. Training loss is a measure of the algorithm's error or deviation from the ground truth labels during the training iterations. By monitoring training loss, researchers can observe how well the algorithm is learning from the training data and whether adjustments need to be made to the model architecture or training parameters to improve performance.

5.2 PERFORMANCE COMPARISON

In this section, the developed algorithm's outcomes were evaluated by comparing its performance parameters, including accuracy, precision, recall, and f-measure, with those of traditional models such as Recurrent Neural Network (RNN), Artificial Neural Network (ANN), Conventional Neural Network (CNN), and Support Vector Machine (SVM). Throughout the validation process, various performance metrics were computed to assess the algorithm's effectiveness. These metrics collectively provide insights into the algorithm's comparative performance against established techniques, aiding in determining its efficacy in the context of the evaluated tasks.

Accuracy, representing the proportion of correct predictions out of the total predictions made by the model, demonstrates notable improvements in the proposed method compared to other models such as RNN, ANN, CNN, and SVM, achieving accuracy values of 97%, 95%, 89%, and 90%, respectively. In contrast, the proposed system achieved an enhanced accuracy of 98%. A visual representation of these accuracy values in comparison with existing techniques is depicted in the accompanying figure 4(a). Furthermore, the developed model's precision was comparatively evaluated against conventional techniques. Precision measures the proportion of true positive predictions out of all positive predictions made by the model. Established techniques, including RNN, ANN, CNN, and SVM, attained precision values of 92.34%, 93.67%, 90.11%, and 89.56%, respectively. However, the proposed system exhibited a superior precision of 97.45%. This comparative evaluation highlights the proposed system's surpassing performance over existing techniques, as illustrated in the provided figure 4(b). The recall comparison with existing techniques is illustrated in the accompanying figure 4(c), assessing the proportion of true positive predictions out of all actual positive instances. Traditional algorithms, including RNN, ANN, CNN, and SVM, yielded recall rates of 92.23%, 93.96%, 90.55%, and 88.98%, respectively. In contrast, the developed algorithm achieved an improved recall rate of 96.85%. This validation underscores that the proposed model outperformed existing techniques, demonstrating an enhanced ability to correctly identify positive instances.

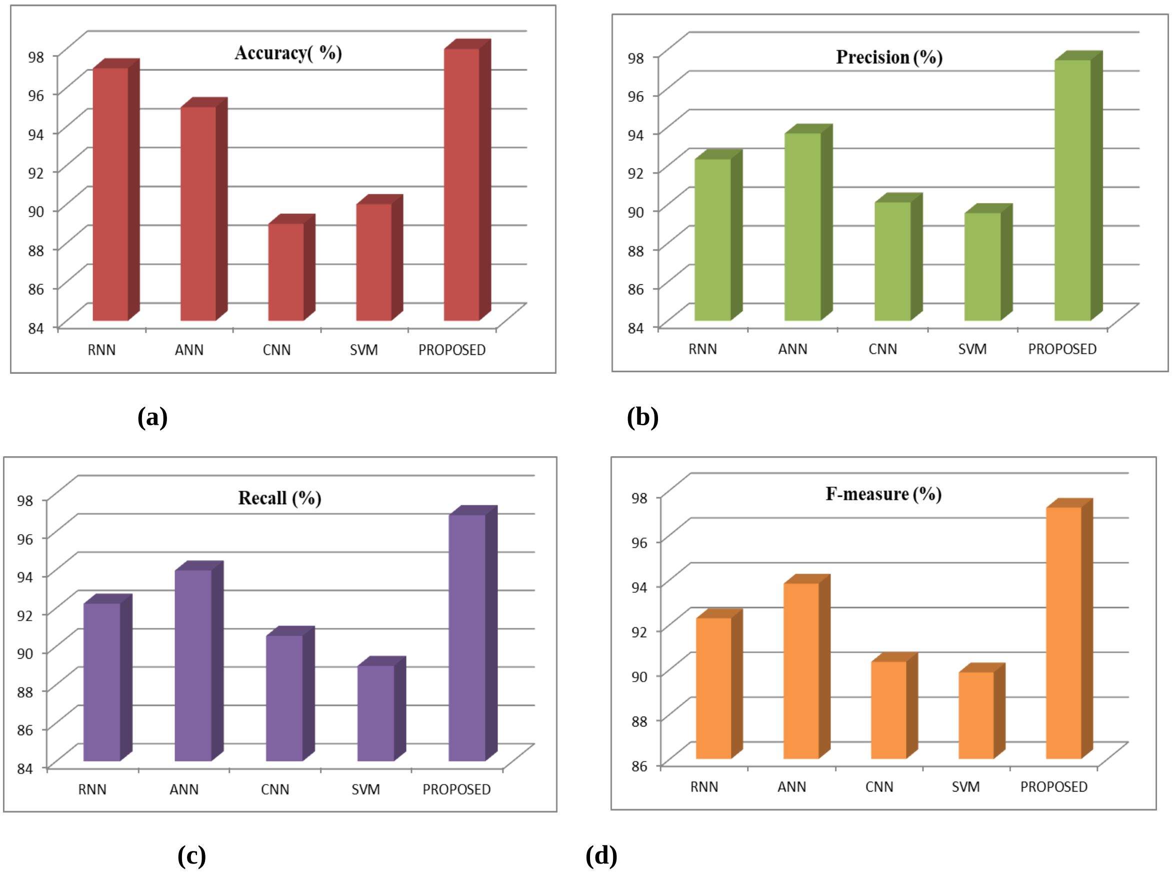


Figure 4 : Performance comparison: (a) Accuracy (b) Precision (c) Recall (d) F-measure

The validation of the system's f-measure with conventional algorithms is presented in the provided figure 4(d), serving as the harmonic mean of precision and recall and offering a balanced assessment between the two. Conventional techniques such as RNN, ANN, CNN, and SVM attained f-measures of 92.28%, 93.83%, 90.34%, and 89.87%, respectively. In contrast, the designed approach achieved a notably higher f-measure of 97.22%.

This comparison underscores the effectiveness of the proposed model, demonstrating its ability to strike a balance between precision and recall more effectively than existing techniques. Overall, the validation process, which involves employing a separate validation dataset and fine-tuning model parameters, plays a crucial role in ensuring the effectiveness and reliability of visual attention analysis and optimization algorithms in packaging design. These iterative processes contribute to optimizing the algorithm's performance metrics and enhancing its ability to accurately predict visual attention patterns, ultimately leading to the development of more effective and visually appealing packaging solutions.

5.3. DISCUSSION

The integration of visual attention analysis and optimization algorithms, particularly utilizing autoencoders and the whale optimization algorithm, presents a promising avenue for enhancing packaging design. Autoencoders, a type of neural network architecture, are adept at learning meaningful representations of input data, which can be particularly valuable in the context of packaging design where visual elements play a crucial role. By leveraging autoencoders, the algorithm can efficiently capture intricate visual features and patterns inherent in packaging designs, facilitating more accurate analysis and optimization. The study conducted training and testing using available data, yielding experimental results indicating that the developed algorithm attained impressive performance metrics. Specifically, the algorithm achieved a remarkable accuracy of 98%, accompanied by a precision value of 97.45%, a recall rate of 96.85%, and an f-measure of 97.22%. Comparative analysis against established techniques, including SVM, DNN, GA-BNN, RBFNN, and DT, further validated the superiority of the proposed methodology across accuracy, precision, recall, and f-measure metrics. Moreover, the consistent performance exhibited by the developed algorithm across increasing data volumes underscores its scalability and adaptability. These enhanced capabilities position the proposed approach as a promising solution for predicting visual attention patterns within packaging designs.

6. CONCLUSION

In conclusion, the integration of visual attention analysis and optimization algorithms, leveraging autoencoder and whale optimization techniques, presents a significant advancement in the field of packaging design. Through the utilization of autoencoders, intricate visual features within packaging designs can be effectively captured and analyzed, enabling a deeper understanding of consumer attention patterns. Additionally, the application of the whale optimization algorithm facilitates the optimization of packaging designs, ensuring that they effectively capture and retain consumer attention. The experimental results highlight the efficacy of the developed algorithm, demonstrating remarkable accuracy, precision, recall, and f-measure metrics. Comparative assessments against existing techniques further underscore the superiority of the proposed methodology, validating its potential for enhancing packaging design outcomes. Moreover, a comparative analysis was conducted with established models such as SVM, DNN, GA-BNN, RBFNN, and DT, revealing notable enhancements in key parameters including accuracy, precision, recall, and f-measure by 1%, 3.78%, 2.89%, and 3.39%, respectively. These advancements underscore the efficacy of the developed algorithm, positioning it as an optimal and effective solution for predicting visual attention patterns within packaging designs.

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