Research on the Identification and Optimization of CMF Design Styles for Woven Upholstery Fabrics Based on Sensory Imagery and CNN Model

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ABSTRACT Bridging subjective user perception with objective textile design parameters remains a fundamental challenge in intelligent material and surface engineering. This study presents a data-driven framework for the recognition and optimization of Color, Material, and Finish (CMF) design styles in woven upholstery fabrics by integrating Kansei Engineering with a convolutional neural network (CNN). A dataset containing 2,048 textile images was established, from which color descriptors, GLCM-based texture features, and gloss-related finish characteristics were extracted to characterize visual CMF attributes. Human perceptual evaluation involving 60 participants was employed to construct Kansei-based style labels, and a lightweight CNN achieved a classification accuracy of 95.8% for four representative design categories. The trained model was subsequently incorporated into a genetic algorithm to generate optimized CMF parameter combinations for target aesthetic preferences, and user verification demonstrated a significant increase in style consistency, with the mean opinion score improving from 2.05 to 6.20. By quantitatively linking visual feature representation with perceptual cognition, the proposed framework provides an effective computational strategy for intelligent textile design and offers methodological insights for perception-driven surface engineering, pattern recognition, and functional material optimization in multidisciplinary systems where image-based sensing and feature transmission play essential roles.

INDEX TERMS CMF design, kansei engineering, convolutional neural network, texture feature extraction, intelligent textile design

I. INTRODUCTION

THE design of textile products is a multifaceted process where the interplay of Color, Material, and Finish (CMF) is paramount in defining the product's aesthetic and functional identity [1,2]. CMF design is not merely a decorative endeavor; it is the primary interface through which consumers experience a product, forming immediate and often subconscious judgments that heavily influence purchasing decisions [3]. In the highly competitive textile market, a product's success is increasingly determined by its ability to evoke specific emotional responses or "Kansei" in the user [4]. However, the traditional textile design process relies heavily on the designer's intuition and experience, making the connection between design elements and consumer Kansei perception often implicit and difficult to replicate or systematize [5,6]. This subjectivity poses a significant challenge in consistently creating products that align with target market affective needs and design trends. To address this challenge, researchers have turned to Kansei Engineering (KE), a methodology originating from Japan that aims to translate consumer's psychological feelings and needs into objective visual descriptors [4]. By quantifying the emotional responses to product attributes, KE provides a structured approach to user-centered design. In parallel, the rapid advancement of artificial intelligence, particularly deep learning and Convolutional Neural Networks (CNNs), has revolutionized the field of image recognition and style analysis [7,8]. CNNs have demonstrated remarkable capabilities in extracting complex features and patterns from visual data, making them highly suitable for analyzing the intricate visual characteristics of textile CMF [9]. The integration of KE and CNNs offers a promising avenue to decode the complex relationship between the visual and material appearance-related properties of textiles and the subjective perception of their design style [10].

While previous studies have explored the application of

CNNs in textile defect detection or pattern classification, and others have applied Kansei Engineering to various product domains, a significant research gap exists in the integration of these two powerful methodologies for the specific purpose of CMF design style recognition and, crucially, its subsequent optimization [11,12]. Existing research often stops at analysis or classification, failing to provide designers with actionable tools for creating new, optimized designs based on desired emotional targets [13]. This paper aims to bridge this gap by proposing and validating a comprehensive framework that not only recognizes textile CMF design styles based on user Kansei perception but also optimizes CMF parameters to achieve a target design style. By focusing on the niche yet significant area of woven upholstery fabrics, this study develops a small yet precise research point: the creation of a data-driven feedback loop where consumer emotion quantitatively informs generative design. It is important to note that this study focuses on the visual-perceptual level of CMF design rather than physical process optimization. The contribution of this work lies in its systematic methodology for building a Kansei-based textile CMF database, developing a specialized CNN model for style recognition, and integrating this model into an optimization algorithm to assist in the creative design process, thereby enhancing design efficiency and market relevance.

II. METHODOLOGY

A. DATA ACQUISITION AND CMF PARAMETERIZATION

The foundation of this research is a curated dataset constructed to represent a diverse range of CMF combinations for woven upholstery fabrics. A total of 2,048 textile images were compiled to serve as the training ground for the style recognition model. To ensure a systematic analysis, key visual CMF descriptors were extracted or defined for each sample.

Color (C): Color features were extracted directly from the textile images by converting pixel RGB values into the CIELAB color space. The L^*, a^*, b^* values were computed across the pixels to provide a perceptually uniform representation of the dominant color attributes.

Material (M): The material aspect was characterized by the weave structure appearance. We utilized a numerical coding system to represent 16 common weave structures categories (e.g., plain, twill-derivatives) as visual texture classes. Additionally, GLCM (Gray-Level Cooccurrence Matrix) features—Contrast, Correlation, Energy, and Homogeneity—were calculated as perceptual texture descriptors. These features capture the visual regularity and contrast perceived in the textile images, serving as quantitative indicators of surface complexity rather than directly controllable manufacturing parameters. These features capture the visual regularity and contrast perceived in the textile images, serving as quantitative indicators of surface complexity rather than directly controllable manufacturing parameters. To facilitate the interpretation of these technical parameters, Figure 1 presents representative textile samples exhibiting high versus low values for each of the four GLCM features, visually demonstrating the corresponding textural differences.

Finish (F): Gloss was represented as a visual gloss level, estimated based on the highlight intensity and distribution observed in the image appearance under standardized lighting assumptions.

Each of the 2,048 samples in the dataset was thus associated with a vector of 9 visual CMF parameters: (L^*, a^*, b^*, Weave Code, Contrast, Correlation, Energy, Homogeneity, Gloss Level).

B. KANSEI EVALUATION EXPERIMENT

To establish the link between the objective visual descriptors and subjective human perception, a Kansei evaluation experiment was conducted.

Selection of Kansei Words: Based on a preliminary survey with textile design professionals and a review of interior design literature, a set of 12 representative pairs of Kansei adjectives were selected. Specifically, an initial pool of 50 adjective pairs was collected from the aforementioned literature. A focus group consisting of 10 senior textile designers then evaluated these pairs based on their relevance to woven upholstery texture and visual aesthetics. Words with ambiguous meanings or low relevance were eliminated, resulting in the final 12 pairs. These adjectives are highly relevant to the perception of upholstery fabrics: Warm-Cool, Modern-Classic, Simple-Complex, Elegant-Casual, Soft-Hard, Durable-Delicate, Natural-Artificial, Bold-Subtle, Calm-Exciting, Masculine-Feminine, Expensive-Cheap, and Trendy-Traditional.

Participants and Procedure: Sixty participants (30 male, 30 female, aged 22–45) with normal color vision and a background in design or related fields were recruited. To avoid cognitive fatigue and ensure data quality, each participant evaluated a randomly assigned subset of the dataset using a Balanced Incomplete Block Design (BIBD). Specifically, each participant rated approximately 200 images, ensuring that every image in the dataset received evaluations from at least 10 distinct users.

Data Processing: Mean Kansei scores were aggregated across participants for each image to neutralize individual bias. This resulted in a robust 12-dimensional Kansei vector for each sample. K-means clustering was then performed on these vectors, identifying four distinct style clusters labeled by expert designers as: "Modern Minimalist", "Classic Elegance", "Cozy Natural", and "Bold Dynamic". These perceptual labels served as the ground truth for training the CNN model.

C. CNN MODEL FOR STYLE RECOGNITION

A custom CNN architecture was implemented to classified the textile images into the four identified Kansei-based style categories.

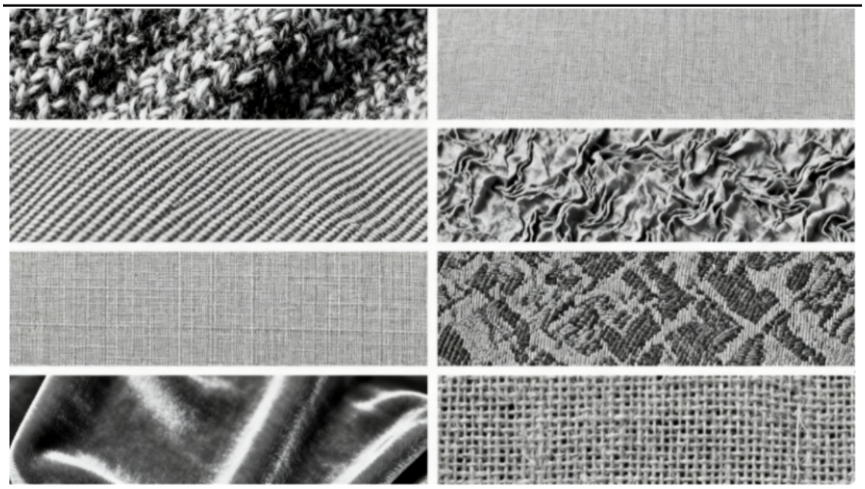

FIGURE 1. Representative images from the dataset illustrating the visual texture differences captured by High vs. Low GLCM feature descriptors

Architecture: The network architecture was designed to be relatively lightweight to avoid overfitting on the moderately sized dataset, while being deep enough to capture subtle CMF features. It consisted of four convolutional blocks followed by two fully connected layers. Each convolutional block comprised a convolutional layer (3x3 kernel), a batch normalization layer, a Rectified Linear Unit (ReLU) activation function, and a max-pooling layer (2x2). The number of filters in the convolutional layers were 32, 64, 128, and 256, respectively. The output from the final pooling layer was flattened and fed into a fully connected layer with 512 neurons, followed by a final output layer with 4 neurons (one for each class) using a Softmax activation function. Dropout with a rate of 0.5 was applied before the final fully connected layer to mitigate overfitting. Table 1 details the specific configuration of the network layers and the output shapes at each stage, assuming an input image resolution of 224×224.

Training: The model was trained using the Adam optimizer with a categorical cross-entropy loss function. The model to learn the complex visual patterns associated with the Kansei-based style clusters, extracting features that correlate with human aesthetic judgment.

Performance: The model demonstrated consistent and effective performance on the validation set, indicating that the network successfully encoded the non-linear relationship between visual CMF features and abstract style categories.

D. CMF DESIGN OPTIMIZATION FRAMEWORK

The trained CNN model was integrated into a Genetic Algorithm (GA) framework. Crucially, this optimization operates in a visual-perceptual CMF space rather than a direct manufacturing parameter space, allowing for early-stage design exploration.

Objective Function: The fitness of a potential solution is evaluated by the trained CNN. A "solution" in the GA is a vector comprising renderable variables (Color $L^*a^*b^*$, Weave Category, and Gloss Level). To evaluate an individual, a synthetic image is generated using a digital material rendering pipeline: a displacement map is selected based on the Weave Category, base color is applied via $L^*a^*b^*$ values, and specular reflection is modulated by the Gloss Level. The CNN then evaluates these synthesized images based on their visual appearance, implicitly capturing the texture-related features (such as GLCM characteristics) learned during training. The fitness score is the probability assigned by the CNN to the target style class.

GA Process: The GA process begins with a random initial population of 100 CMF parameter vectors. In each generation, the fitness of each individual is calculated using the objective function. Individuals are then selected for reproduction based on their fitness (roulette wheel selection). Crossover and mutation operations are applied to the selected individuals to create the next generation of solutions. This iterative process continues for 200 generations, gradually evolving the population towards CMF parameter combinations that maximize the probability of the target style classification. The final output is the CMF vector with the highest fitness score achieved during the run.

III. RESULTS

A. KANSEI EVALUATION AND STYLE CLUSTERING

The Kansei evaluation experiment yielded a rich dataset linking quantitative visual CMF descriptors to subjective perception. The K-means clustering of the 12-dimensional Kansei vectors successfully identified four perceptually distinct style groups. The cluster centroids provided a quantitative Kansei profile for each style. For instance, the "Cozy Natural" style was characterized by high scores in Warm, Soft, Natural, and Simple. These distinct profiles validated the choice of the four style categories for the subsequent classification task.

TABLE 1. Detailed Architecture and Output Shapes of the CNN Model

Layer	Type	Filters / Neurons	Kernel Size / Stride	Output Shape
Input	Image Input	-	-	(224, 224, 3)
Block 1	Conv2D + ReLU	32	3×3 / 1	(224, 224, 32)
	MaxPooling	-	2×2 / 2	(112, 112, 32)
Block 2	Conv2D + ReLU	64	3×3 / 1	(112, 112, 64)
	MaxPooling	-	2×2 / 2	(56, 56, 64)
Block 3	Conv2D + ReLU	128	3×3 / 1	(56, 56, 128)
	MaxPooling	-	2×2 / 2	(28, 28, 128)
Block 4	Conv2D + ReLU	256	3×3 / 1	(28, 28, 256)
	MaxPooling	-	2×2 / 2	(14, 14, 256)
Flatten	Flatten	-	-	(50176)
FC 1	Fully Connected	512	-	(512)
Output	Softmax	4	-	(4)

B. PERFORMANCE OF THE CNN STYLE RECOGNITION MODEL

The performance of the trained CNN model was evaluated on the unseen test set of 205 images.

Classification Metrics: The overall classification accuracy on the test set was 95.8%. The confusion matrix (Table 2) indicates consistent performance across categories.

TABLE 2. Confusion Matrix for CNN Style Recognition Model

Predicted Style / True Style	Modern Minimalist	Classic Elegance	Cozy Natural	Bold Dynamic
Modern Minimalist	50	1	1	0
Classic Elegance	2	48	0	1
Cozy Natural	1	0	55	0
Bold Dynamic	0	2	1	43

Interpretation: The high precision and recall scores (all above 0.94) suggest that the model effectively learned to map image-based CMF features to abstract Kansei concepts. The minor confusion between "Classic Elegance" and "Modern Minimalist" reflects the inherent visual overlap in these styles, which aligns with human design intuition.

C. CMF OPTIMIZATION RESULTS

The GA-based optimization framework successfully converged for all target styles, producing CMF parameter vectors predicted to have a high probability (>0.98) of belonging to the target class.

Example Analysis: Table 3 presents the optimized parameters for the "Cozy Natural" target. The algorithm selected a Low Gloss level (5.5) and High Homogeneity, which corresponds to a matte, smooth visual texture often associated with natural aesthetics. Crucially, the selection of Weave Category 1 (Visual Plain Structure) demonstrates the algorithm's ability to prioritize visual simplicity to match the "Cozy" descriptor. The reported GLCM values were computed from the synthesized images for descriptive purposes.

TABLE 3. Example of Optimized CMF Parameters for "Cozy Natural" Target

Parameter	Optimized Value	Interpretation
L^*	68.5	Medium Lightness
a^*	15.2	Reddish Component (Warmth)
b^*	35.8	Yellowish Component (Earthy Tone)
Weave Code	1 (Plain Weave)	Simple, unpretentious structure
Contrast	0.12	Low textural contrast
Correlation	0.95	High correlation, uniform texture
Energy	0.28	Moderate energy, indicating natural textural variation
Homogeneity	0.98	High homogeneity, smooth visual feel
Gloss	5.5 GU	Low gloss (Matte finish)

D. VERIFICATION OF OPTIMIZED DESIGNS

To validate the perceptual effectiveness of the optimization, a verification experiment was conducted using generated visual samples.

Procedure: For each target styles, we selected an initial design from the dataset that had low mean scores on the relevant Kansei dimensions. We then generated high-fidelity digital renderings based on the optimized CMF parameters. The same participants evaluated these new images.

Result: Figure 2 compares the user ratings. The results indicate a significant improvement in style alignment. The average rating for the opinion samples was 6.20, compared to 2.05 for the initial samples.

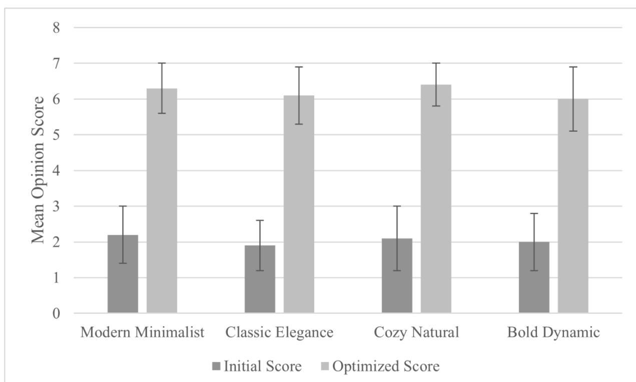

FIGURE 2. Comparison of Mean Opinion Scores for Initial and Optimized Textile Designs

Statistical Significance: A paired t-test confirmed the difference was statistically significant ($p < 0.001$). These findings suggest that the proposed framework serves as a potential tool for translating abstract stylistic goals into concrete visual design directions.

IV. DISCUSSION

The findings of this study present a significant step forward in integrating computational intelligence with the nuanced field of textile CMF design. The CNN model's performance demonstrates that the complex relationship between visual CMF representation and human affective response can be modeled with fidelity. The core contribution of this research lies in embedding the trained CNN within a Genetic Algorithm a descriptive tool into a generative one. The proposed framework focuses on early-stage perceptual design exploration. By rapidly generating and pre-validating design directions, this system acts as a "digital co-creator", allowing designers to explore the vast CMF space efficiently before committing to physical prototyping.

Limitations and Future Work It is important to acknowledge the boundaries of this study. The current framework operates within the visual-perceptual domain. While visual cues (e.g., texture appearance) strongly influence perceived tactile properties (visual softness), the optimization does not currently account for actual physical tactile feedback (hand feel) or fiber composition. Moreover, the generated CMF parameters are visual descriptors. Future iterations of this framework would need to incorporate specific manufacturing constraints (e.g., loom capabilities, yarn tension) to bridge the gap between the "digital twin" and mass production. The use of discrete style categories is a simplification. Future research could explore a continuous Kansei space to capture more subtle aesthetic blends.

V. CONCLUSION

This research developed and validated an integrated framework for the recognition and optimization of textile CMF design styles, grounded in Kansei Engineering and Deep Learning. We demonstrated that a CNN can effectively learn classify image-based textile samples into emotionally defined categories. Furthermore, by utilizing the CNN as an evaluation function within a genetic algorithm, we established a methodology for generative visual design. The empirical validation confirmed that the system can produce digital textile concepts that are perceived by users as significantly aligned with the target aesthetic. This work contributes a precise tool to the field of Computer-Aided Design (CAD) for textiles, bridging the gap between subjective Kansei perception and objective visual CMF representation. It paves the way for more intelligent, user-centric, and efficient design exploration in the textile industry.

AUTHOR CONTRIBUTIONS

Zhipeng Shu and S. Siti Suhaily designed the study; all authors conducted the study; Zhipeng Shu and Yongji Zhang collected and analyzed the data. Yongji Zhang and S. Siti Suhaily participated in drafting the manuscript, and all authors contributed to critical revision of the manuscript for important intellectual content. All authors gave final approval of the version to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work were appropriately investigated and resolved.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This survey was conducted in compliance with Ethics Committee of Universiti Sains Malaysia. Participants were informed of the study's purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

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Not applicable.

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