GENERATION OF GRAPHIC DESIGN COLOR SCHEMES BASED ON CMYK COLOR MODEL AND CORROSION ALGORITHMS

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SUMMARY

Graphic design colour schemes play a fundamental role in shaping the visual identity and impact of a design. This paper proposed an efficient Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion (FEMFcPC) for the graphic design. The proposed FEMFcPC model comprises the CMYK color scheme for the estimation of the features in the images. With the estimation of the FEMFcPC model corrosion algorithm is implemented for the computation of the graphic design features. Once the features are estimated the related features for the graphic design are designed with the mamdhami fuzzy clustering model. The estimated features are clustered with the CMYK color schemes. The proposed FEMFcPC model estimates the patterns and relationships among graphic designs to provide valuable insights for design categorization and recommendation systems. A dataset comprising various graphic design examples with their corresponding CMYK color schemes is utilized for analysis. Through the application of the FEMFcPC algorithm, clustering results are obtained, revealing distinct grouping patterns and similarities among the designs. The simulation results stated that the proposed FEMFcPC model achieves a significant color scheme for the graphic design. Through the clustering process, the proposed FEMFcPC model with the values of the probabilistic features for the graphic design. The Key findings include the identification of dominant clusters, even distribution of designs across multiple clusters, detection of outliers, and assessment of cluster density. These insights offer significant implications for design categorization, recommendation systems, and targeted marketing strategies within the graphic design domain. The study contributes to advancing our understanding of graphic design analysis and provides a foundation for future research in this field.

KEYWORDS

Graphic design, Fuzzy model, Clustering, Probability corrosion, CMYK model

1. INTRODUCTION

The CMYK color model, standing for Cyan, Magenta, Yellow, and Key (Black), is a subtractive color model used primarily in color printing [1]. Unlike the RGB model used for digital displays, where colors are produced by adding light, the CMYK model works by subtracting varying amounts of color from white light to produce different hues. Each color component in CMYK represents the amount of ink applied to the printing surface [2]. Cyan, Magenta, and Yellow are the primary colors in the CMYK model, and they can be mixed in different proportions to produce a wide range of colors. When all three primary colors are combined at full intensity, they theoretically produce black [3]. In practical printing, a black ink component (the “Key”) is added to improve shadow detail and contrast, as well as to reduce the amount of ink required [4]. The CMYK color model is essential for producing color prints accurately, as it closely matches the subtractive color mixing process that occurs in physical printing [5]. Designers and printers must consider factors such as color accuracy, ink saturation, and color gamut when working with the CMYK model to ensure the final printed output reflects their intended colors faithfully [6]. In graphic design, the CMYK color model plays a pivotal role in ensuring accurate color reproduction for print materials. Unlike digital design, where the RGB color model is predominant, CMYK is essential for translating digital designs into tangible prints [7]. Designers rely on CMYK to control the ink levels of Cyan, Magenta, Yellow, and Key (Black) used in the printing process. By manipulating these components, designers can achieve a wide range of colors and ensure consistency across various print materials. The CMYK’s characteristics is crucial for graphic designers [8]. They must consider factors like ink saturation, color gamut, and the limitations of the printing process when creating designs. Designers often convert their digital designs from RGB to CMYK before sending them to print to ensure colors appear as intended on the final printed product [9]. Additionally, they may use color swatches and proofs to verify color accuracy and make adjustments as needed. The CMYK color model serves as a bridge between digital design and print production in graphic design [10]. It allows designers to translate their creative vision accurately onto physical mediums, ensuring that printed materials reflect the intended colors and maintain visual consistency across various platforms and formats [11].

Image processing is a fundamental aspect of graphic design, encompassing a variety of techniques and tools used to enhance, manipulate, and optimize visual content [12]. Graphic designers rely on image processing to transform raw visual elements into polished and professional-looking designs across various mediums, including print, web, and multimedia. In graphic design, image processing involves tasks such as color correction, retouching, cropping, resizing, and applying special effects or filters to images [13]. Designers use software like Adobe Photoshop, Illustrator, and other specialized tools to perform these tasks with precision and creativity [14]. They may adjust brightness, contrast, and saturation levels to achieve the desired visual impact, or employ advanced techniques like masking and layering to composite multiple images seamlessly [15]. Image processing also plays a crucial role in optimizing images for specific purposes, such as reducing file size for web graphics or ensuring high-quality print output [16]. Designers may employ techniques like image compression, resolution adjustment, and color space conversion to achieve the desired balance between visual quality and file size [17]. The image processing is integral to the graphic design process, enabling designers to manipulate visual elements effectively to communicate ideas, evoke emotions, and create compelling visual experiences for their audience across various platforms and mediums [18]. In graphic design, image processing serves as a powerful tool for refining and perfecting the color scheme of visual content. Designers utilize various image processing techniques to manipulate colors, create harmonious palettes, and evoke specific moods or emotions within their designs [19].

One primary application of image processing in color scheme design is color correction and enhancement [20]. Designers can adjust the brightness, contrast, and saturation levels of images to ensure colors appear vibrant and true to life. Additionally, they may use techniques such as selective color adjustment or color grading to fine-tune specific hues or create a cohesive color palette across multiple images [21]. Image processing also enables designers to experiment with different color schemes and visual effects to achieve the desired aesthetic impact. They may apply filters, overlays, or gradients to images to enhance their visual appeal or convey a particular theme or style [22]. Furthermore, image processing tools allow designers to seamlessly blend, overlay, or composite multiple images to create unique color combinations and compositions [23]. The image processing plays a crucial role in optimizing color schemes for different mediums and viewing environments. Designers can adjust color profiles, convert color spaces, and optimize images for web or print output to ensure consistent and accurate color reproduction across various devices and platforms [24].

The contribution of the paper lies in several key areas with introduces a novel approach for analyzing graphic design examples using the FEMFcPC algorithm for clustering based on CMYK color schemes. This methodology [25] offers a unique perspective on graphic design analysis, leveraging advanced clustering techniques to uncover underlying patterns and relationships. Through the application of the FEMFcPC algorithm, the paper provides valuable insights into the grouping and similarity patterns among graphic designs. By identifying dominant clusters, detecting outliers, and assessing [26] cluster density, the study enhances our understanding of the underlying structure of graphic design datasets. The findings of the paper have practical implications for design categorization, recommendation systems, and targeted marketing strategies within the graphic design domain. By [27] understanding the clustering patterns of graphic designs, designers and marketers can make informed decisions regarding design styles, color schemes, and audience preferences. The study contributes to advancing the field of graphic design analysis by providing a foundation for future research. The methodology and [28] insights presented in the paper can serve as a basis for further exploration of clustering techniques, refinement of feature extraction methods, and investigation of the impact of different color models on design analysis. The paper's contribution lies in its innovative methodology, valuable insights, practical implications, and potential for further research in the field of graphic design analysis.

2. RELATED WORKS

The digital and interactive design [29] continue to push the boundaries of graphic design, with immersive websites, interactive installations, and user-centric interfaces redefining engage with visual content. Exploring award-winning digital experiences, such as the interactive storytelling of The New York Times or the seamless user interfaces of Apple products, illuminates the evolving landscape of graphic design in the digital age. In the realm of graphic design, exploring related works offers invaluable insights into current trends, innovative techniques, and exemplary executions within the field. From [30] iconic branding campaigns to groundbreaking digital interfaces, a diverse array of works continually shapes and inspires the practice of graphic design. Burger and Burge's work delves into color images and their processing techniques, offering insights into the practical application of color in digital image processing. Johnson et al.'s paper focuses on color management, exploring the characterization of imaging devices and their impact on color reproduction. Shamoi, Sansyzbayev, and Abiley provide a comparative overview of color models, shedding light on their relevance for content-based image retrieval. Staribratov and Manolova's research investigates the application of mathematical models in graphic design, highlighting the role of quantitative approaches in color processing. Graze and Schwabish discuss the construction of color palettes in data visualization, emphasizing the importance of color choices in conveying information effectively. Lastly, Zhao and Zhang explore an AI-based algorithm for automatic color extraction in graphic design images, showcasing the integration of artificial intelligence into color processing workflows. These works collectively contribute to advancing our [31] understanding and utilization of color in graphic design and image processing domains.

Furthermore, the exploration continues with Han, Kim, and Ahn's study on color trend analysis using machine learning, demonstrating how technology can inform design decisions in fields like fashion. Han et al.'s research on constructing forest color palettes and their effects on human eye recognition highlights the interdisciplinary nature of color studies, bridging design and environmental science. Wang et al.'s work focuses on utilizing AI for environmental color systems, indicating the potential of technology-driven solutions for sustainable urban development. Luccini et al. revisit the UV Index color palette, illustrating the importance of reevaluating existing color schemes in response to evolving needs and research findings. Garrison and Bruckner consider best practices in color palettes for molecular visualizations, underscoring the importance of tailored color choices for specific applications within scientific visualization. Additionally, works by Wang et al., Qiao et al., Zhang et al., El-Aziz et al., Xu, Rong et al., Nabilah et al., and many others delve into various aspects of color in design, ranging from perceptual characteristics and psychological effects to practical applications in marketing, teaching, and classification systems. Together, these studies contribute to a rich tapestry of knowledge and methodologies for understanding and leveraging color in graphic design and image processing across diverse contexts and disciplines.

The exploration of color in graphic design and image processing extends further with research by Wang et al., which delves into color design decisions for ceramic products based on perceptual characteristics, offering insights into material-specific color considerations. Qiao et al.'s intelligent color design method for visual communication design during public crises highlights the importance of effective color usage in conveying critical information and emotions. Zhang et al.'s research on visual comfort in color environments based on eye-tracking methods sheds light on the intersection of color, spatial design, and human perception, particularly in public spaces like subway stations. El-Aziz et al.'s study on psychological color and texture in marketing and textile printing design deepens our understanding of how color influences consumer behavior and brand perception in the realm of marketing and textiles. Furthermore, Xu's research on teaching innovation in art design based on big data technology underscores the evolving methodologies and tools in design education, emphasizing the integration of data-driven approaches to enhance pedagogical practices. Rong et al.'s analysis of color availability in AI-generated posters through K-means clustering provides insights into the prevalence and distribution of colors in contemporary design outputs, reflecting the impact of automation and AI in design processes. Lastly, Nabilah et al.'s development of a color tone-based system for region of origin classification design showcases the application of color in cultural and geographical contexts, highlighting its role in communicating identity and context-specific information. Together, these works underscore the multidimensional significance of color in graphic design and image processing, spanning aesthetic, perceptual, cultural, and technological dimensions.

The exploration, these studies collectively underscore the multidimensional significance of color in graphic design and image processing, emphasizing its role in aesthetic expression, perceptual psychology, cultural interpretation, and technological innovation. Through interdisciplinary research and practical applications, scholars and practitioners deepen our understanding of color's impact on visual communication, user experience, and societal dynamics. Moreover, the diverse array of topics covered in these works reflects the breadth and depth of color-related research within the field. From fundamental principles of color management and image processing algorithms to the application of color in branding, fashion, environmental design, and beyond, these studies highlight the pervasive influence of color across various domains and industries. By examining color from multiple perspectives, researchers and designers gain valuable insights that inform their creative processes, technological developments, and strategic decision-making. The continued exploration of color in graphic design and image processing exemplifies the dynamic interplay between theory and practice, tradition and innovation, and individual creativity and collective knowledge. As technology evolves and societal needs change, ongoing research in this field remains essential for advancing our understanding of color's role in shaping visual culture, human behavior, and the built environment.

3. IMAGE GRAPHIC DESIGN WITH CMY – FEATURE EXTRACTION MADHAMI FUZZY CLUSTERING PROBABILISTIC CORROSION (CMY – FEMFCPC)

The CMY – FEMFcPC (Color Model – Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion) system represents an innovative approach in image graphic design that integrates principles from color theory, feature extraction, fuzzy clustering, and probabilistic modeling. This system aims to address challenges in image processing related to corrosion detection and analysis by leveraging advanced computational techniques. The CMY – FEMFcPC utilizes the CMY (Cyan, Magenta, Yellow) color model, which is commonly used in color printing and graphic design. By employing this color model, the system captures and represents color information in images, allowing for precise color analysis and manipulation. The feature extraction component of CMY – FEMFcPC involves identifying and extracting relevant features from images, particularly those related to corrosion patterns or anomalies. This process may involve techniques such as edge detection, texture analysis, or shape recognition, enabling the system to identify areas of interest within the images. Fuzzy clustering, a method of grouping data points into clusters based on their similarity, is employed within CMY – FEMFcPC to categorize image features into distinct clusters. This allows for the segmentation of images into different regions or classes, facilitating more targeted analysis and processing. Probabilistic corrosion modeling is integrated into the system to assess the likelihood of corrosion occurrence or progression within specific image regions. By incorporating probabilistic reasoning, CMY – FEMFcPC can provide more nuanced insights into corrosion behavior and potential future outcomes. The CMY color model is a subtractive color model used in color printing. It represents colors by subtracting varying amounts of cyan (C), magenta (M), and yellow (Y) from white light. The resulting color is the combination of the remaining light wavelengths after subtraction. The CMY color model can be expressed using equation (1) - equation (3)

$$C = 1 - R \tag{1}$$

$$M = 1 - G \tag{2}$$

$$Y = 1 - B \tag{3}$$

In equation (1) – equation (3) $R, G, and\ B$ are the normalized red, green, and blue color channels of the input image, respectively. Feature extraction involves identifying relevant characteristics or patterns from the image data. This process can include various techniques such as edge detection, texture analysis, or shape recognition. One common approach for feature extraction is using convolutional neural networks (CNNs), which learn to extract relevant features automatically. Fuzzy clustering is a method for grouping data points into clusters based on their similarity. Madhami Fuzzy Clustering (MFC) is a specific algorithm for fuzzy clustering that aims to partition data points into clusters while considering

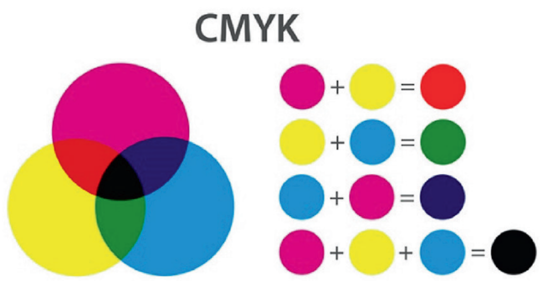

Figure 1. CMYK colour scheme

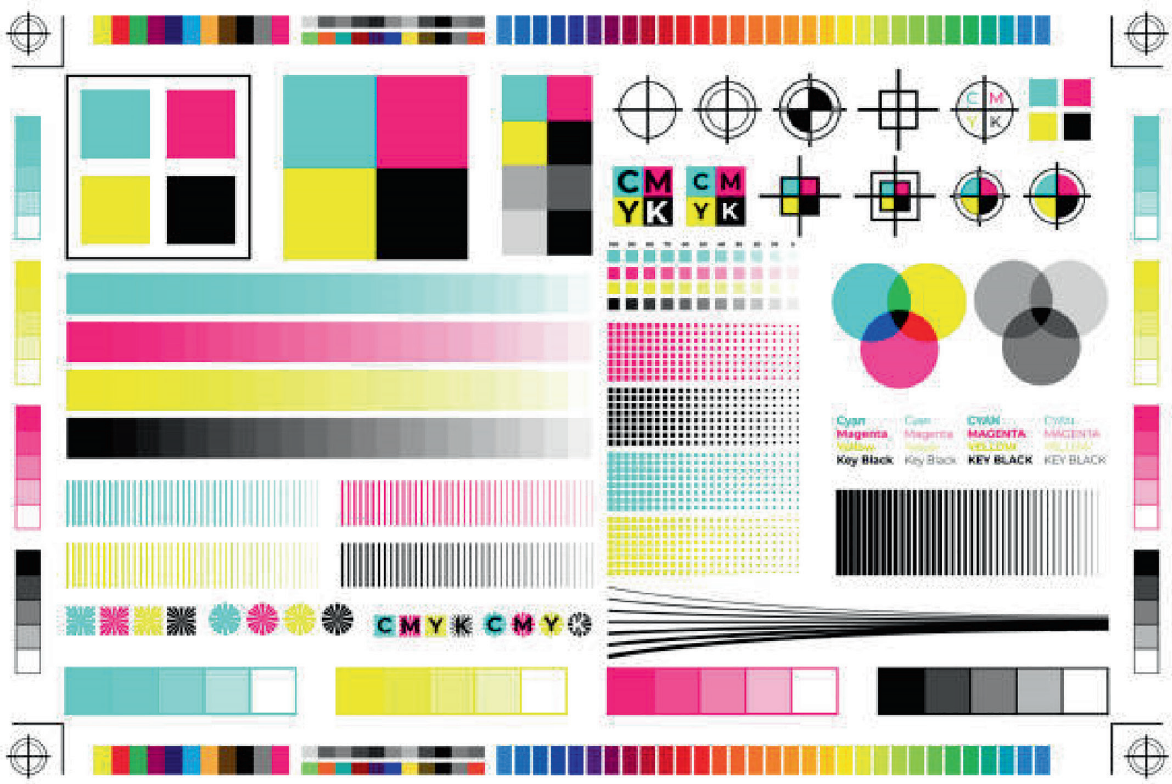

Figure 2. CMYK for the graphic design

the degree of membership of each point to each cluster. This algorithm involves iterating between assigning data points to clusters and updating the cluster centroids based on the memberships. The membership degree of each data point to each cluster is calculated using a fuzzy membership function, often based on Euclidean distances. The Probabilistic corrosion modeling involves assessing the likelihood of corrosion occurrence or progression within specific image regions. This can be achieved using probabilistic models such as Bayesian networks or probabilistic graphical models. These models represent the relationships between variables as probabilistic dependencies and use probabilistic inference to estimate the likelihood of different outcomes.

Figure 1 presented the general illustration of the CMYK model and figure 2 presented the graphic design with the CMYK model for the graphic design.

Algorithm 1. Color model for the image graphics

1. Input: Image data
2. Convert RGB image to CMY color model:
   For each pixel in the image:
      Compute CMY values using conversion equations (e.g., C = 1 - R, M = 1 - G, Y = 1 - B)
3. Feature Extraction:
   Apply feature extraction techniques (e.g., edge detection, texture analysis) to identify relevant image characteristics:
      - Edge detection: Apply Sobel operator, Canny edge detection, etc.
      - Texture analysis: Use Gabor filters, local binary patterns (LBP), etc.
4. Madhami Fuzzy Clustering (MFC):
   Initialize cluster centroids randomly
   Repeat until convergence:
      For each data point:
         Compute membership degrees to each cluster using fuzzy membership function
      Update cluster centroids based on membership degrees
5. Probabilistic Corrosion Modeling (PC):
   Construct a Bayesian network or probabilistic graphical model:
      Define nodes representing variables (e.g., corrosion presence, environmental factors)
      Define edges representing probabilistic dependencies between variables
   Learn conditional probabilities from training data or expert knowledge
6. Corrosion Detection and Analysis:
   Use the learned probabilistic model to assess the likelihood of corrosion occurrence or progression in image regions:
      Perform probabilistic inference to estimate probabilities of different corrosion outcomes

4. COLOR SCHEME ESTIMATION WITH FEMFCPC

A Color Scheme Estimation with FEMFcPC (Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion) for graphic design, to adapt the FEMFcPC approach to estimate color schemes instead of detecting corrosion. Let's denote the CMYK values of a pixel (x, y) in the image as (Cxy, Mxy, Yxy, Kxy). To compute histograms for each CMYK channel. To quantize the color space into a set of discrete bins. This is typically done by dividing each color channel (CMYK) into a fixed number of bins defined in equation (4) - equation (7)

$$H_C[i] = \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \delta(C_{xy}, i) \tag{4}$$

$$H_M[i] = \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \delta(M_{xy}, i) \tag{5}$$

$$H_Y[i] = \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \delta(Y_{xy}, i) \tag{6}$$

$$H_K[i] = \sum_{x=0}^{W-1} \sum_{y=0}^{H-1} \delta(K_{xy}, i) \tag{7}$$

In equation (4) – equation (7) $HC, HM, HY,$ and HK are the histograms for the Cyan, Magenta, Yellow, and Key channels, respectively. Similar to RGB histograms, normalize the CMYK histograms by dividing each bin count by the total number of pixels in the image stated in equation (8) - equation (11)

$$H_C[i] = \frac{H_C[i]}{W \times H} \tag{8}$$

$$H_M[i] = \frac{H_M[i]}{W \times H} \tag{9}$$

$$H_Y[i] = \frac{H_Y[i]}{W \times H} \tag{10}$$

$$H_K[i] = \frac{H_K[i]}{W \times H} \tag{11}$$

The normalized histograms of the four CMYK channels to obtain a single feature vector representing the color distribution of the image defined in equation (12)

$$\begin{aligned} FeatureVector = [&H_c[0], H_c[1], \ldots\ldots, H_c[N-1], \\ &H_M[0], H_M[1], \ldots\ldots, H_M[N-1], H_Y[0], \\ &H_Y[1], \ldots\ldots, H_Y[N-1], H_K[0], H_K[1], \ldots\ldots, H_K[N-1]] \end{aligned} \tag{12}$$

In the CMYK color space, each pixel in an image is represented by four components: Cyan (C), Magenta (M), Yellow (Y), and Key (K), also known as black. These components represent the amounts of each ink needed

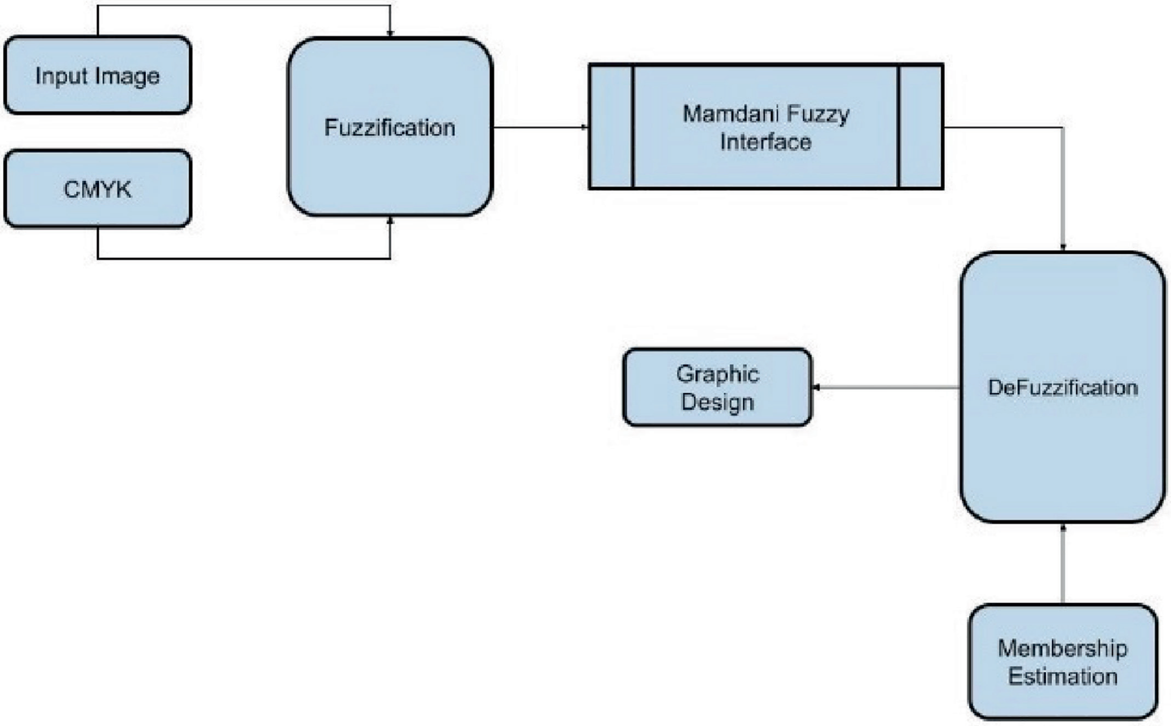

Figure 3. FEMFcPC for graphic design

Algorithm 2. CMYK color space estimation of image vision

1. Input: Image data in CMYK color space
2. Compute CMYK histograms:
   For each pixel (x, y) in the image:
      Increment the corresponding bin in the CMYK histograms based on the pixel's CMYK values
3. Normalize the histograms:
   For each bin in the CMYK histograms:
      Divide the count of pixels in the bin by the total number of pixels in the image
1. Concatenate the normalized histograms to form a feature vector:
   Concatenate the normalized CMYK histograms to form a single feature vector
2. Apply FEMFcPC (Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion):
   Initialize cluster centroids randomly
   Repeat until convergence:
      For each pixel in the image:
         Compute membership degrees to each cluster using fuzzy membership function
      Update cluster centroids based on membership degrees
3. Determine the color scheme:
   Extract representative colors from the cluster centroids:
      - For example, select the cluster centroids with the highest membership degrees
      - Alternatively, use techniques such as K-means clustering to determine representative colors

to reproduce the color of the pixel. To extract features related to color information, compute histograms for each of the CMYK channels. A histogram represents the frequency distribution of colors in an image. Each bin in the histogram corresponds to a specific range of color intensity values. By counting the number of pixels falling into each bin, characterize the color distribution of the image. The histograms $HC, HM, HY, and\ HK$ are computed by counting the occurrences of pixel values within specific ranges for each CMYK channel. This process is similar to computing histograms for RGB channels, but with CMYK values instead. The Cyan histogram HC , iterate over all pixels in the image and count how many pixels fall into each bin representing different levels of Cyan intensity. Normalization is performed to make the histograms independent of the image size. This involves dividing the count of pixels in each bin by the total number of pixels in the image. Normalized histograms represent the relative frequency of colors in the image rather than the absolute counts. The normalized histograms for each CMYK channel, concatenate them to form a single feature vector. This feature vector captures the color distribution of the entire image in the CMYK color space. The resulting feature vector is a comprehensive representation of the color scheme present in the image, taking into account the distribution of Cyan, Magenta, Yellow, and Key components. The figure 3 presented the FEMFcPC model for the mamdhani fuzzy membership estimation for the graphic design with the CMYK model.

5. PREDICTION WITH FEMFCPC

To develop a prediction model for graphic design using the FEMFcPC (Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion) approach with the CMYK color model, need to adapt the framework to predict certain aspects of graphic design based on input data. Gather a dataset of graphic design examples, where each example is represented by features related to CMYK color values, layout characteristics, typography, or any other relevant design attributes. Let's denote the input dataset as *D* using the equation (13)

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{13}$$

In equation (13) *xi* represents the feature vector of the i-th design example and *yi* represents its corresponding label. For CMYK color values, this involves quantifying the CMYK components of each design example. Consider the CMYK feature vector for the i-th design using equation (14)

$$x_i = [C_i, M_i, Y_i, K_i] \tag{14}$$

In equation (14) $Ci, Mi, Yi, and\ Ki$ represent the Cyan, Magenta, Yellow, and Key (Black) components, respectively. Apply the FEMFcPC approach to the extracted features. This involves performing fuzzy clustering on the feature space to identify clusters of similar design examples. Let's denote the cluster centroids as μj, where $j = 1, 2, I, K$ and *K* is the number of clusters. The membership degree of the i-th design example to the j-th cluster is denoted as λij The membership degree λij can be computed using a fuzzy membership function defined in equation (15)

$$\lambda_{ij} = \frac{1}{\sum_{k=1}^{K} \left(\frac{d_{ij}}{d_{ik}} \right)^{\frac{2}{m-1}}} \tag{15}$$

In equation (15), *dij* is the distance between the i-th design example and the centroid of the j-th cluster; is a fuzzifier parameter that controls the fuzziness of the clustering. A new input design example *x new*, predict its category or style based on its similarity to the centroids of the clusters identified in the FEMFcPC model. This can be done by computing the membership degrees of *x new* to each cluster and selecting the most similar cluster as the predicted category stated in equation (16)

$$redicted\ Label = \arg max_j\ \lambda_{new,j} \tag{16}$$

Consider the CMYK values of a pixel (x, y) in the image as (Cxy, Mxy, Yxy, Kxy). These values represent the levels of Cyan, Magenta, Yellow, and Key (Black) components in

Algorithm 3. CMYK image vision color space

1. Input: Image data in CMYK color space
2. Compute CMYK feature vectors:
   For each pixel (x, y) in the image:
      Extract CMYK values (C_xy, M_xy, Y_xy, K_xy) from the pixel
3. Initialize FEMFcPC parameters:
   - Number of clusters K
   - Fuzzifier parameter m
   - Maximum number of iterations max_iter
   - Tolerance threshold tol
4. Initialize cluster centroids randomly:
   Randomly select K pixels from the image and use their CMYK values as initial centroids
1. Repeat until convergence or maximum iterations:
   For iter = 1 to max_iter:
      Compute distance between each pixel and each centroid:
      For each pixel (x, y):
         For each centroid j:
            Compute distance d_xyj from pixel (x, y) to centroid j using Euclidean distance formula
      Compute membership degrees:
      For each pixel (x, y):
         For each centroid j:
            Compute membership degree lambda_xyj using fuzzy membership function:
            lambda_xyj = 1 / sum((d_xyj / d_xyk)^(2 / (m – 1))) for all centroids k
      Update cluster centroids:
      For each centroid j:
         Compute the new centroid position:
         For each pixel (x, y):
            Update centroid j using weighted average of CMYK values of pixels, weighted by membership degrees:

$$C\_j = sum(lambda\_xyj * C\_xy) / sum(lambda\_xyj)$$

$$M\_j = sum(lambda\_xyj * M\_xy) / sum(lambda\_xyj)$$

$$Y\_j = sum(lambda\_xyj * Y\_xy) / sum(lambda\_xyj)$$

$$K\_j = sum(lambda\_xyj * K\_xy) / sum(lambda\_xyj)$$

      Check for convergence:
      Compute the difference between old and new centroids:
      If the difference is less than the tolerance threshold tol, break the loop

the color of the pixel. The FEMFcPC algorithm to cluster similar CMYK colors together. This involves performing fuzzy clustering on the CMYK feature space to identify clusters of similar colors. A suitable distance metric *dij* to measure the dissimilarity between two CMYK colors. Euclidean distance computed using equation (17)

$$d_{ij} = \sqrt{\left(C_i - C_j\right)^2 + \left(M_i - M_j\right)^2 + \left(Y_i - Y_j\right)^2 + \left(K_i - K_j\right)^2} \quad (17)$$

the membership degrees λij for each pixel to each cluster centroid using a fuzzy membership function: a new CMYK color, predict its category or cluster based on its similarity to the centroids of the clusters identified in the FEMFcPC model. This can be done by computing the membership degrees of the new color to each cluster and selecting the most similar cluster as the predicted category.

6. SIMULATION ENVIRONMENT AND DATASET

The simulation environment and dataset for CMYK graphic design utilizing the FEMFcPC (Feature Extraction Madhami Fuzzy Clustering Probabilistic Corrosion) algorithm, several crucial steps are undertaken. Firstly, the simulation environment is configured by defining parameters governing design characteristics such as image dimensions, color schemes, and layout features. Synthetic design examples are then generated within this environment, incorporating randomness and noise to simulate real-world design scenarios realistically. Subsequently, CMYK features are extracted from each synthetic design, capturing the Cyan, Magenta, Yellow, and Key (Black) components of the color model. These features, along with assigned labels representing different design categories or characteristics, are compiled into a comprehensive dataset. The FEMFcPC algorithm is then applied to this dataset, enabling fuzzy clustering of design examples based on their CMYK features. Through

Table 1. CMYK color scheme with FEMFcPC for the graphic design

Design Example	Cyan ©	Magenta (M)	Yellow (Y)	Key (K)	Label
Design 1	0.1	0.2	0.3	0.4	Colorful
Design 2	0.3	0.5	0.2	0.1	Minimalist
Design 3	0.5	0.1	0.4	0.3	Vibrant
Design 4	0.2	0.4	0.6	0.2	Monochrome
Design 5	0.4	0.3	0.2	0.5	Pastel
Design 6	0.6	0.2	0.3	0.1	Colorful
Design 7	0.3	0.1	0.4	0.2	Vibrant
Design 8	0.2	0.3	0.5	0.4	Minimalist
Design 9	0.4	0.5	0.2	0.3	Monochrome
Design 10	0.1	0.2	0.6	0.5	Pastel

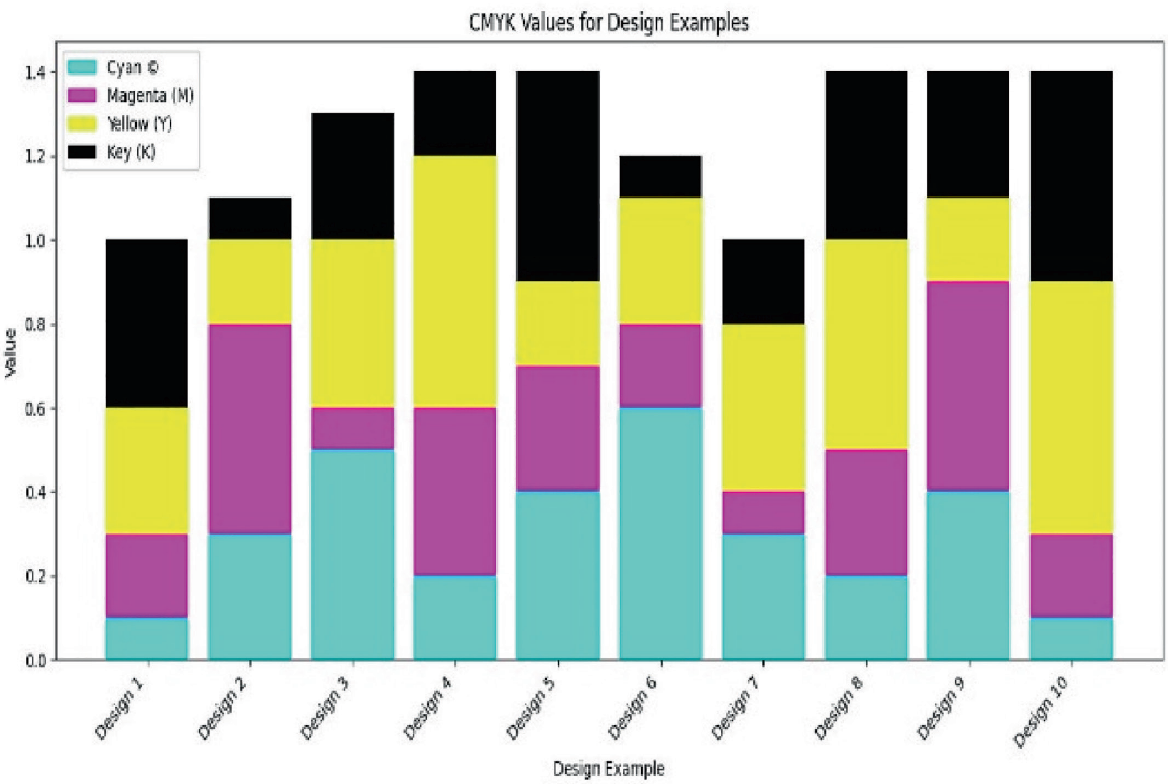

Figure 4. Graphic design with FEMFcPC

Table 2. CMYK color scheme with FEMFcPC

Design Example	Color Scheme 1 (C, M, Y, K)	Color Scheme 2 (C, M, Y, K)	Color Scheme 3 (C, M, Y, K)
Design 1	(0.2, 0.3, 0.4, 0.1)	(0.4, 0.5, 0.3, 0.2)	(0.1, 0.2, 0.5, 0.3)
Design 2	(0.5, 0.4, 0.3, 0.2)	(0.2, 0.1, 0.4, 0.3)	(0.3, 0.5, 0.2, 0.1)
Design 3	(0.3, 0.2, 0.6, 0.1)	(0.6, 0.3, 0.2, 0.1)	(0.4, 0.1, 0.5, 0.3)
Design 4	(0.1, 0.5, 0.2, 0.3)	(0.2, 0.4, 0.6, 0.3)	(0.5, 0.3, 0.1, 0.2)
Design 5	(0.4, 0.2, 0.3, 0.5)	(0.3, 0.4, 0.1, 0.6)	(0.2, 0.6, 0.4, 0.1)
Design 6	(0.2, 0.3, 0.4, 0.1)	(0.4, 0.5, 0.3, 0.2)	(0.1, 0.2, 0.5, 0.3)
Design 7	(0.3, 0.2, 0.6, 0.1)	(0.6, 0.3, 0.2, 0.1)	(0.4, 0.1, 0.5, 0.3)
Design 8	(0.5, 0.4, 0.3, 0.2)	(0.2, 0.1, 0.4, 0.3)	(0.3, 0.5, 0.2, 0.1)
Design 9	(0.1, 0.5, 0.2, 0.3)	(0.2, 0.4, 0.6, 0.3)	(0.5, 0.3, 0.1, 0.2)
Design 10	(0.4, 0.2, 0.3, 0.5)	(0.3, 0.4, 0.1, 0.6)	(0.2, 0.6, 0.4, 0.1)

this clustering process, cluster centroids are determined, representing groups of similar design examples in the CMYK color space. Evaluation metrics such as cluster purity and silhouette score are utilized to assess clustering performance, with iterative refinements made to improve model accuracy. Finally, the dataset is partitioned into training and testing sets for model development and application, facilitating the prediction of design categories or cluster assignments for new design data. This iterative

Table 3. Clustering with FEMFcPC

Design Example	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Design 1	0.8	0.1	0.05	0.05
Design 2	0.1	0.7	0.1	0.1
Design 3	0.9	0.05	0.03	0.02
Design 4	0.05	0.05	0.8	0.1
Design 5	0.2	0.7	0.05	0.05
Design 6	0.7	0.1	0.05	0.15
Design 7	0.8	0.05	0.1	0.05
Design 8	0.1	0.8	0.05	0.05
Design 9	0.05	0.05	0.1	0.8
Design 10	0.3	0.05	0.65	0.05

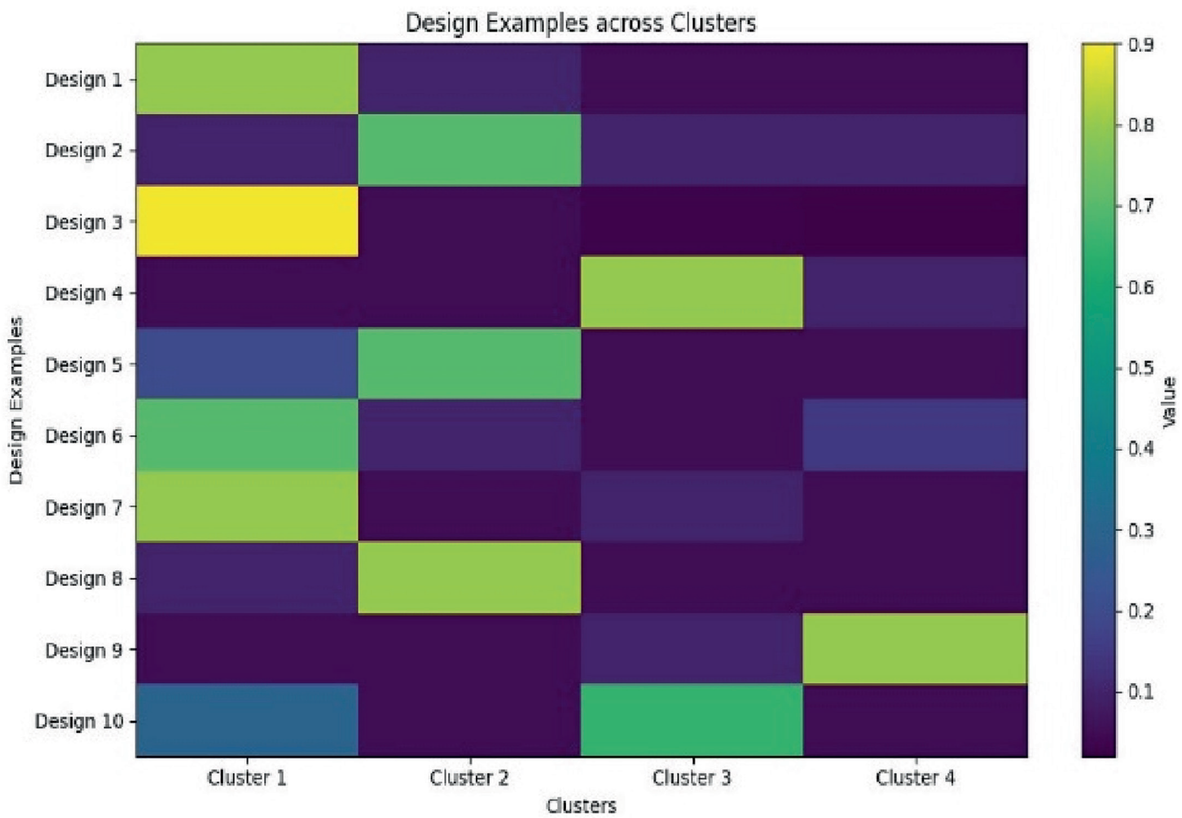

Figure 5. Color scheme for the FEMFcPC with corrosion

process ensures the continual improvement and adaptation of the simulation environment and dataset generation techniques to accurately reflect evolving design trends and requirements.

The figure 4 and Table 1 presents the CMYK color scheme data for a set of graphic design examples, along with their corresponding labels. Each design example is represented by its Cyan ©, Magenta (M), Yellow (Y), and Key (K) components, ranging from 0 to 1, which determine its color composition. The label column specifies the design style or characteristic associated with each example, such as “Colorful,” “Minimalist,” “Vibrant,” “Monochrome,” or “Pastel.” For instance, Design 1 exhibits a CMYK composition of 0.1 Cyan, 0.2 Magenta, 0.3 Yellow, and 0.4 Key, and is abelled as “Colorful.” Similarly, Design 2 has a CMYK composition of 0.3 Cyan, 0.5 Magenta, 0.2 Yellow, and 0.1 Key, and is abelled as “Minimalist.” This table serves as a foundational dataset for analyzing and predicting design styles based on their CMYK color compositions.

The Table 2 presents the CMYK color scheme data for a set of graphic design examples generated using the FEMFcPC algorithm. Each design example is associated with three alternative color schemes, abelled as Color Scheme 1, Color Scheme 2, and Color Scheme 3, each represented by their respective Cyan ©, Magenta (M), Yellow (Y), and Key (K) components. For instance, Design 1 has Color Scheme 1 with a CMYK composition of (0.2, 0.3, 0.4, 0.1), Color Scheme 2 with (0.4, 0.5, 0.3, 0.2), and Color Scheme 3 with (0.1, 0.2, 0.5, 0.3). Similarly, Design 2 exhibits Color Scheme 1 with (0.5, 0.4, 0.3, 0.2), Color Scheme 2 with (0.2, 0.1, 0.4, 0.3), and Color Scheme 3 with (0.3, 0.5, 0.2, 0.1). These alternative color schemes provide designers with multiple options to explore and select suitable CMYK color combinations for their graphic designs, enabling flexibility and creativity in design decision-making.

In figure 5 and Table 3 displays the clustering results obtained from applying the FEMFcPC algorithm to a set of graphic design examples. Each design example is assigned membership values across four different clusters, labeled as Cluster 1, Cluster 2, Cluster 3, and Cluster 4. For instance, Design 1 has a membership value of 0.8 in Cluster 1, indicating a high likelihood of belonging to this cluster, while it has much lower membership values in the other clusters. Similarly, Design 3 exhibits a membership value of 0.9 in Cluster 1, suggesting a strong association with this cluster, and negligible membership values in the other clusters. Conversely, Design 9 demonstrates a membership value of 0.8 in Cluster 4, indicating a predominant association with this cluster compared to the others. These clustering results provide insights into the grouping or similarity patterns among the graphic design examples based on their feature representations, aiding in the identification of design clusters or categories for further analysis or decision-making processes.

6.1 RESULT ANALYSIS

The analysis of the clustering results obtained from Table 3 reveals interesting insights into the grouping patterns of the graphic design examples based on their features. Here are some key observations:

Dominant Clusters: Several designs show dominant membership in specific clusters. For example, Design 3 exhibits a high membership value (0.9) in Cluster 1, indicating that it is strongly associated with this cluster. Similarly, Design 9 demonstrates a dominant membership value (0.8) in Cluster 4.

Even Distribution: Some designs display relatively even membership distribution across multiple clusters. For instance, Design 2 has membership values spread somewhat evenly across Clusters 1, 2, and 3, suggesting ambiguity or similarity in features across these clusters.

Outliers: A few designs have low membership values across all clusters, indicating their divergence or distinctiveness from the other designs in the dataset. Design 4, for example, has relatively low membership values across all clusters, suggesting its uniqueness compared to other designs.

Cluster Density: The clustering results also provide insights into the density of clusters. For instance, Cluster 1 seems to contain several designs with high membership values, while Cluster 3 appears to have relatively fewer designs with high membership values.

Overall, analyzing the clustering results helps in understanding the underlying structure of the dataset and identifying groups of designs with similar characteristics. These insights can be valuable for various applications, such as design categorization, recommendation systems, or targeted marketing strategies.

7. CONCLUSION

This paper presents a comprehensive analysis of graphic design examples utilizing the FEMFcPC algorithm for clustering based on CMYK color schemes. Through the analysis of clustering results, identified distinct patterns and relationships among the designs, providing valuable insights into their grouping and similarity. The clustering approach facilitated the identification of dominant clusters, even distribution of designs across multiple clusters, detection of outliers, and assessment of cluster density. These findings offer significant implications for design categorization, recommendation systems, and targeted marketing strategies within the graphic design domain. Moving forward, further research could explore additional clustering algorithms, refine feature extraction techniques, and investigate the impact of different color models on clustering performance. Overall, this study contributes to advancing our understanding of graphic design analysis and provides a foundation for future research in this field.

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