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Implementation of Conditional WGAN-GP, ResNet50V2, and HDBSCAN for Generating and Recommending Traditional Lombok Songket Motifs

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ABSTRACT

Songket is a traditional Indonesian woven textile with profound cultural and aesthetic value, particularly in Lombok, where artisans continue to preserve its distinctive motifs. However, the creation of new designs is still carried out manually, requiring considerable time and relying heavily on the artisans' creativity. This study proposes an integrated system that combines Conditional Wasserstein Generative Adversarial Network with Gradient Penalty (CWGAN-GP), ResNet50V2, and HDBSCAN to automatically generate and recommend Lombok's traditional songket motifs. The dataset consists of primary data collected directly from local artisans and secondary data from the BatikNitik public repository, thereby providing authentic yet diverse motif samples for training. CWGAN-GP is employed to synthesize motifs with stable and realistic structures across multiple epochs. Subsequently, ResNet50V2 is utilized for deep visual feature extraction, HDBSCAN for density-based clustering, and UMAP for two-dimensional visualization of motif distribution. The system successfully groups motifs into meaningful clusters, with the largest cluster containing consistent patterns of high aesthetic value. A recommendation mechanism is also developed to suggest up to five similar motifs from the original dataset within the same cluster, ensuring cultural relevance while fostering design innovation. Despite these promising outcomes, several limitations remain, such as the relatively small number of songket motif samples, variations in motif quality, and challenges during data collection including inconsistent lighting and non-uniform patterns. These factors affect both dataset consistency and generative performance. Nevertheless, this approach demonstrates the potential of artificial intelligence to support the preservation and innovation of cultural heritage by assisting artisans in creating and exploring new motifs more efficiently without losing their traditional identity.

I. INTRODUCTION

Songket is an Indonesian cultural heritage textile with high aesthetic value [1]–[3], particularly in Lombok, which is renowned for its distinctive motifs. One of the weaving communities that continues to preserve this tradition is located in Pringgasela, East Lombok Regency [4]. The motifs produced embody profound philosophies and are passed down through generations. However, the creation of new motifs still heavily relies on the artisans' skills and requires considerable time, making the process less efficient in meeting the growing market demand. With the advancement of technology, artificial intelligence (AI) has been increasingly applied in the creative industry, including textile design [5]. In this context, the Conditional Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP) can be employed to automatically generate new songket motifs while preserving their traditional characteristics [6]. Furthermore, to capture visual patterns of motifs, feature extraction using ResNet50V2 [7] and motif clustering with HDBSCAN can be utilized to provide relevant recommendations. This approach is expected to assist songket artisans in Pringgasela in developing new motifs more efficiently [8].

Several studies have explored the capability of GANs in this domain, although challenges remain, including limited datasets, inconsistent generative quality, and risks of overfitting. For instance [7], employed GANs to generate new textile patterns by mimicking existing design characteristics, thereby accelerating textile design innovation. However, the performance was highly dependent on small training datasets, and the generated outputs did not yet meet industry standards. Similarly, [9] applied Conditional GAN (cGAN) to generate traditional Chinese textile patterns with the aim of expediting design processes and enhancing diversity. Nevertheless, the generated outputs were inconsistent and still required designer intervention, while dataset limitations hindered pattern variability.

Another study [10] proposed TexGAN, which employed DCGAN combined with transfer learning to generate textile patterns. Its advantage lay in producing unique patterns despite small datasets. However, the generative results were less optimal for intricate details, prone to repetition, and focused only on isolated patterns without considering holistic design. Likewise, [5] developed a DCGAN-based system without labeled data by modifying activation functions to generate base patterns from seed images. Although capable of producing motifs with limited data, the outputs lacked detail and faced overfitting risks due to the generator's tendency to replicate training samples.

In a different approach, [11] utilized StyleGAN to generate lace-like textile patterns with high-level details, aiming to integrate traditional design with modern technology, including Neural Inverse Knitting for 3D textile production. However, the results remained insufficient for complex motifs such as traditional lace, while dataset scarcity and overfitting risks persisted. Meanwhile, [12] applied StyleGAN to generate Batak Ulos motifs through the DiTenun platform, with training scenarios based on resolution and iteration adjustments. Yet, the results were still suboptimal, particularly for complex motifs such as *Sori-sori* and *Hati Rongga*, with a tendency to replicate training data rather than introducing meaningful innovation. Lastly, [13] employed StyleGAN with content loss based on neural style transfer to generate batik motifs. The dataset consisted of 326 batik images divided into 32×32pixel patches for reconstruction. Although new motifs were generated, the results lacked fine details due to dataset limitations and were repetitive as the generator overly minimized the loss function.

From this review, it can be concluded that although previous studies have applied Generative Adversarial Networks (GANs) in textile pattern generation, none have specifically integrated multiple advanced methods into a unified system to both generate and recommend motifs automatically. Moreover, no prior research has combined CWGAN-GP, ResNet50V2, and HDBSCAN within a single framework. The novelty of this study lies in the integration of Conditional Wasserstein GAN with Gradient Penalty (CWGAN-GP), ResNet50V2, HDBSCAN, and UMAP into one pipeline. CWGAN-GP is employed to generate new songket motifs with more stable and realistic visual quality, while ResNet50V2 extracts deep visual features from both generated and original motifs. Subsequently, HDBSCAN is applied for density-based clustering to group motifs with similar visual characteristics, and UMAP is utilized to map visual similarity into two-dimensional space, thereby facilitating motif relationship analysis.

The objective of this research is to develop a system that not only generates new songket motifs automatically but also recommends motifs based on visual similarity with traditional designs. In addition, the system validates the generative outputs by retrieving similar motifs from the original dataset within the same cluster. Consequently, the newly generated motifs provide visual innovation while retaining cultural relevance and traditional identity, making them more acceptable to both artisans and consumers. This approach offers an innovative solution to support the preservation and development of songket motif design through artificial intelligence.

II. METHODS

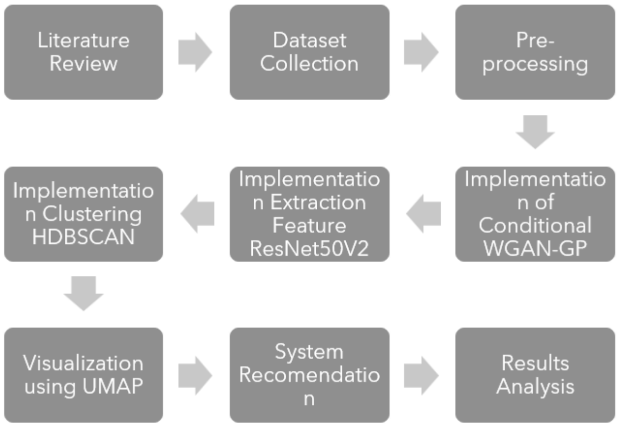

Figure 1. Research Flow Diagram

The following is a detailed explanation based on the provided method figure.

A. Literature Review

This stage aims to understand the concepts and methods employed in studies related to generative design in textiles, particularly songket motifs. The review covers theories of Generative Adversarial Networks (GAN), with a specific focus on Conditional Wasserstein GAN with Gradient Penalty (CWGAN-GP), as well as the application of Style Transfer GAN in preserving cultural characteristics. Additionally, it examines feature extraction techniques using ResNet50V2, motif clustering with HDBSCAN, and data visualization approaches with UMAP to better comprehend the distribution of generated motif patterns.

B. Dataset Collection

The dataset for this study consists of songket motif images collected from artisans in Pringgasela, Lombok, using a Canon EOS 90D DSLR camera at a distance of 15–30 cm to precisely capture motif details. Images were recorded at a resolution of 3468 × 4624 pixels, ensuring sharp documentation of fabric patterns and textures without distortion. These data were used to train the AI model in generating new motifs that preserve the distinctive characteristics of Pringgasela songket. The dataset employed in this study combines both primary and secondary sources. Primary data were obtained directly from artisans, thereby reflecting the authentic conditions of motifs and textile textures, and providing an accurate representation of handcrafted works. Secondary data, on the other hand, were collected from public repositories, namely BatikNitik [14], [15], which offer a diverse and extensive collection of batik images, thereby enriching the variety and volume of samples for model training. In total, the dataset comprises 900 images. Of these, 700 images consist of songket motifs, with 100 images allocated for each of the seven types of songket considered in this study: *bayan*, *ragi bayan*, *ragi bima*, *ragi montor*, *ragi songket*, *sunda*, and *warna alam ragi sunda*. Additionally, 200 images were obtained from the BatikNitik dataset, further expanding the diversity of motif patterns available for training.

C. Pre-processing

The pre-processing stage involves several critical steps to prepare the songket motif image dataset for GAN training. First, the dataset is loaded from a structured folder using TensorFlow, with each image resized to 512 × 512 pixels to ensure consistent input dimensions. Subsequently, pixel values are normalized to the range of [−1, 1] using MinMaxScaler to improve training stability. Class labels are converted into numerical indices for more efficient representation. The dataset is then divided into batches of 16 and shuffled using the shuffle() function to minimize bias during training.

D. Implementation of Conditional WGAN-GP

The implementation of the Conditional Wasserstein Generative Adversarial Network with Gradient Penalty (CWGAN-GP) in this study is designed to generate realistic songket motif images by leveraging the architecture of Conditional GAN. The model consists of two main components: the generator and the discriminator. The generator receives input in the form of a latent vector and class label, and produces 512 × 512 pixel images through a series of Conv2DTranspose layers with PReLU activation and Batch Normalization to enhance training stability. The discriminator, on the other hand, takes as input either real or generated images along with their corresponding class labels, and employs Conv2D layers with LeakyReLU activation to evaluate image authenticity. Model training adopts the Wasserstein loss function, which minimizes the distance between the distributions of real and generated images, while incorporating a gradient penalty to maintain training stability. The discriminator is trained more frequently than the generator (n_critic = 2) to ensure that it provides reliable feedback to the generator.

Feature extraction using ResNet50V2 is implemented to capture deep visual representations of songket motif images, both from the original dataset and from those generated by the model. A pre-trained ResNet50V2 is employed with the fully connected layers removed (include_top=False) and a global average pooling layer added (pooling='avg') to produce low-dimensional feature embeddings. Prior to extraction, images are normalized to the range [0, 1] and resized to 128 × 128 pixels, in accordance with ResNet50V2 input requirements. These extracted features are subsequently used for motif clustering with HDBSCAN and visualization with UMAP, enabling further analysis of the similarities between real and generated motifs. This process facilitates the grouping of songket motifs based on their visual characteristics and provides the foundation for the motif recommendation system.

E. Implementation of HDBSCAN Clustering

Clustering using HDBSCAN is implemented to group songket motif images based on visual feature similarities extracted by ResNet50V2. After the feature extraction process, both original images from the dataset and generated images from the generator are represented in low-dimensional feature space. These features are then used as input for the HDBSCAN algorithm, a density-based clustering method that does not require the explicit specification of the number of clusters. In the implementation, the parameter min_cluster_size=10 is applied to define the minimum cluster size, such that only groups with at least ten members are considered valid clusters. Images that do not belong to any cluster (noise) are labeled as −1.

F. Visualization with UMAP

Visualization with UMAP (Uniform Manifold Approximation and Projection) is conducted to project the image features extracted by ResNet50V2 into a two-dimensional space, thereby facilitating interpretation of clustering patterns. Feature embeddings from the original dataset, which were clustered using HDBSCAN, are reduced to two principal components with UMAP, using the parameter random_state=42 to ensure consistent results. The reduced features are then visualized as a scatter plot, where each point represents an image and the color indicates its cluster membership. This visualization assists in understanding data distribution, identifying clusters, and verifying that generated motifs share visual similarities with those in the original dataset.

G. Recommendation System

The recommendation system utilizes HDBSCAN to cluster both generated images and original dataset images based on visual features extracted with ResNet50V2. For each generated image assigned to a valid cluster (non-noise), up to five original images from the same cluster are recommended. These recommendations are based on visual feature similarity, allowing users to explore songket motifs with comparable characteristics. Visualization is performed using Matplotlib, displaying recommendations in a grid layout to clearly illustrate the relationships between newly generated motifs and traditional motifs.

H. Result Analysis

Result analysis evaluates the quality of images generated by the Conditional WGAN-GP and the effectiveness of the songket motif recommendation system. Generated images are visualized every ten epochs to monitor the progress of the generator. HDBSCAN and UMAP are employed for clustering and dimensionality reduction, grouping similar motifs between generated and original images. The recommendation system displays original motifs within the same cluster, assisting users in discovering visually related patterns. If the results are found to be suboptimal, parameters such as the number of epochs, learning rate, or model architecture can be adjusted accordingly.

III. RESULTS AND DISCUSSION

A. Generation of Motifs Using GAN

The dataset used in this study was obtained from the outputs of the GAN generator, stored as images in multiple epoch folders such as *epoch_100*, *epoch_200*, up to *epoch_n*. Each folder contained a collection of synthetic motif images generated at specific stages of GAN training. The data collection process was carried out by recursively reading all images from the subfolders within the main *HasilGan* directory using the os.walk() function. Images with *.png*, *.jpg*, or *.jpeg* formats were recorded along with their respective epoch folder information. This metadata was crucial for analyzing the evolution of motifs as the number of training epochs increased.

The GAN model used for motif generation was configured with the following parameters: a latent space dimension (latent_dim) of 128, an output image size (img_shape) of (128, 128, 3) representing a resolution of 128×128 pixels with three RGB channels, and a training duration of 5000 epochs with a batch size of 64 and learning_rate=0.0002. In the implementation of Wasserstein GAN with Gradient Penalty (WGAN-GP), additional parameters were included, namely n_critic = 3 (indicating that the discriminator was trained three times for every generator iteration) and gp_lambda = 10 as the gradient penalty coefficient to ensure training stability. The Adam optimizer was applied for both the generator and discriminator, configured with learning_rate=0.0002, β1=0.5, and β2=0.9, to improve convergence and stabilize training. With this configuration, the generator successfully produced various motif variations across different epochs, which were subsequently used as the dataset for further analysis.

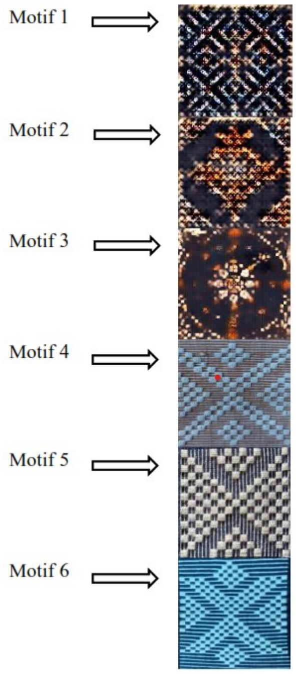

Figure 2. Example of Generated Motifs With CWGAN-GP

Figure 2 illustrates several motif samples generated by the Conditional Wasserstein Generative Adversarial Network with Gradient Penalty (CWGAN-GP). The results demonstrate that CWGAN-GP is capable of producing motifs with visual qualities resembling authentic designs while introducing unique variations. The main advantage of CWGAN-GP lies in its superior training stability compared to conventional GAN models, resulting in patterns that appear smoother, more consistent, and structurally coherent. This visualization highlights the potential of CWGAN-GP for creative and industrial applications, particularly in the automatic creation of novel motifs while preserving the fundamental characteristics of traditional designs.

B. Feature Extraction Using ResNet50V2

At this stage, each GAN-generated motif image collected in the dataset was processed for feature extraction using the ResNet50V2 deep learning architecture, pre-trained on the ImageNet dataset. ResNet50V2 was chosen due to its proven ability to capture rich and hierarchical visual representations of images, making it a suitable feature extractor for subsequent analysis.

The extraction process began by loading ResNet50V2 without its final fully connected layer (*include_top=False*) and applying global average pooling (*pooling='avg'*) to produce 2048-dimensional global feature vectors. Each motif image was resized to (224, 224) pixels to match the input requirements of ResNet50V2, despite their original size of (512, 512) pixels. Preprocessing was performed using the preprocess_input function provided by Keras, which normalized the images according to ImageNet training protocols.

After preprocessing, ResNet50V2 generated unique feature vectors for each image, representing their high-level visual characteristics within the semantic feature space. These vectors were then compiled into a feature matrix, serving as input for the HDBSCAN clustering algorithm in the subsequent stage. This iterative process was applied to all images in the dataset, enabling comprehensive feature representation for motif clustering and analysis.

C. *Clustering with the HDBSCAN Algorithm*

Following the feature extraction process, the next step in this study was to perform clustering on the feature vectors obtained from the ResNet50V2 model. The clustering method employed was HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise), an extension of the DBSCAN algorithm. HDBSCAN offers the advantage of being able to detect clusters with varying shapes and sizes while also identifying outliers or noise within the dataset.

In the implementation, the primary parameter applied was min_*cluster_size* = *5*, meaning that only groups with at least five members were considered valid clusters. This parameter was selected to ensure that the resulting clusters were statistically significant and not overly influenced by minor variations or noise within the motifs. The clustering process produced numerical labels for each image, representing the cluster ID to which the image belonged. Images assigned the label *-1* were considered outliers, indicating that they did not sufficiently resemble any existing clusters and were thus classified as noise within the data structure.

Additionally, the number of images in each cluster was recorded and presented in the form of frequency distributions to provide an overview of the variation and dominance of particular clusters. These results served as the foundation for identifying the most representative cluster in subsequent stages and contributed to the understanding of motif evolution across different GAN training epochs. The clustered motif structures generated by HDBSCAN are illustrated in Figure 2.

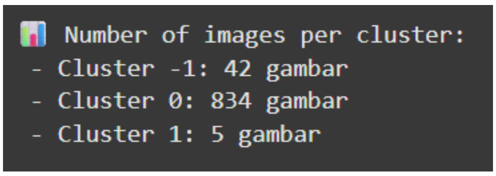

Figure 2. Motifs Clustered Using the HDBSCAN Algorithm

The clustering results using HDBSCAN showed the distribution of GAN-generated motifs into three groups: Cluster -1, Cluster 0, and Cluster 1. Cluster -1 consisted of 42 images categorized as outliers or noise, as they did not sufficiently resemble the patterns of other clusters, potentially representing unique or unstable motifs. Cluster 0 was the largest group, containing 834 images, indicating that the majority of motifs shared similar visual characteristics and formed a dominant group within the dataset. This suggests that the GAN model successfully generated motifs with consistent structures during training. Cluster 1 contained 5 images, which, although relatively few in number, met the minimum threshold of *min_cluster_size = 5* and likely represented motifs with specific, less common patterns. Based on this distribution, Cluster 0 was identified as the primary cluster of interest due to its larger membership size; however, Clusters -1 and 1 also provided valuable insights into the variation and complexity of motifs generated by the GAN model.

D. *Image Storage Based on Clusters*

After the clustering process with the HDBSCAN algorithm, the next step was to organize and store the GAN-generated motif images according to their assigned cluster labels. At this stage, each image was moved or copied into a new directory corresponding to its cluster ID, thereby facilitating subsequent visual analysis and motif selection.

In the implementation, a main output folder (cluster_output_folder) was created to contain all cluster subfolders. Prior to storage, any pre-existing content in the output directory was removed to prevent data overlap from earlier runs. Subfolders were then generated with names corresponding to the cluster IDs, such as cluster_0, cluster_1, and so forth. Each image was copied into the appropriate subfolder based on the cluster label assigned during the clustering stage. It is important to note that images labeled with -1 (outliers) were not stored in specific cluster folders, as they were considered noise or data insufficiently similar to any valid group. Nonetheless, these images could still be evaluated separately for further analysis, particularly in relation to extreme motif variations or anomalies.

This storage procedure was critical for supporting qualitative evaluation and motif recommendation, as it organized images according to visual similarity identified by the clustering model. Furthermore, a well-structured directory system facilitated manual inspection, visualization, and potential integration with other systems, such as recommendation applications or motif design databases.

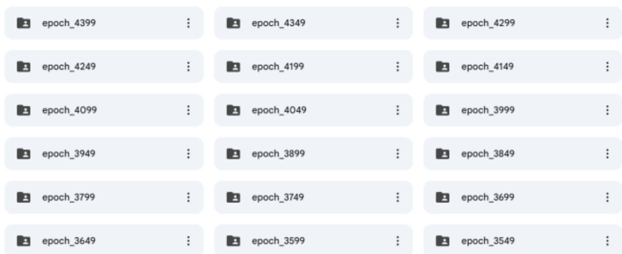

Figure 3. GAN Outputs Automatically Stored at 50-Epoch Intervals

Figure 3 presents an example of motifs generated by the Conditional Wasserstein Generative Adversarial Network with Gradient Penalty (CWGAN-GP), which were automatically saved in multiple folders at intervals of every 50 training epochs. Each folder represents the model's outputs at a specific training stage, enabling researchers to evaluate the progression of motif quality over time. By storing outputs across different epochs, it was possible to observe how the model gradually learned to represent more complex, consistent, and realistic visual patterns. This systematic documentation also provided a basis for selecting the model with the best performance, specifically when the generated motifs appeared sufficiently realistic while still maintaining diversity. Hence, the visualization in Figure 3 not only displays synthetic motif outputs but also illustrates the progressive learning process of CWGAN-GP in producing increasingly refined and structured motifs across epochs.

E. Best Cluster Recommendation

After completing the clustering process and storing images based on their cluster assignments, the subsequent step in this workflow was to recommend the cluster considered to represent the highest quality motifs. The recommendation was made based on the criterion that the cluster with the largest number of members most likely represents stable, consistent motifs with strong visual similarity. In the implementation, the system regrouped all images according to their cluster IDs and calculated the number of members in each cluster. The clusters were then ranked in descending order based on their size, with the largest cluster prioritized as the best cluster. In the execution results, Cluster 0 was identified as the best cluster, containing 407 images, significantly more than the other clusters. As part of the recommendation, the system selected several sample images (by default, five images) from the best cluster for visual display. These samples were not only visualized using Matplotlib but also accompanied by information about their originating epoch. This information was highly useful for understanding at which stage of training the GAN model produced high-quality motifs.

In addition to visualization, the system printed the file names along with their corresponding epoch sources to ensure transparency and facilitate further evaluation. Hence, the best cluster recommendation supported not only automatic motif selection but also manual analysis by designers or end users aiming to choose the most suitable motifs for specific applications, such as textiles, interior decoration, or digital art. Figure 4 illustrates the results of the HDBSCAN-based cluster recommendation.

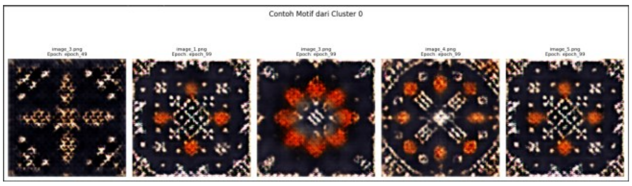

Figure 4. Recommendation Results Based on HDBSCAN Clustering.

Figure 4 illustrates the stage of selecting the best cluster recommendation, where the system identifies Cluster 0 as the most dominant and highest-quality cluster based on the number of members (407 images). This cluster is considered to represent motifs with homogeneous and consistent visual characteristics, making it the primary focus of further analysis.

The recommended results present five motif samples selected from Cluster 0, each accompanied by information on its originating epoch. These motifs exhibit relatively similar structures and patterns, indicating that the clustering process has successfully grouped images according to their visual similarities.

Such motifs are generally well-suited for applications in textile design, wallpapers, or other decorative elements due to their repetitive and harmonious properties. Moreover, the presence of these motifs at relatively early epochs (epoch 199 out of a total of 5000) suggests that the GAN model began to stabilize and produce meaningful patterns at the early stages of training. Consequently, Cluster 0 is not only the largest cluster but also contains high-quality motifs that can be directly utilized or further refined according to end-user needs. Figure 5 presents the best motif recommendation based on its corresponding epoch.

```
Recommended Motifs (with Epoch Origin):
 - image_9.png ← epoch_1899
 - image_1.png ← epoch_1899
 - image_8.png ← epoch_1899
 - image_3.png ← epoch_1899
 - image_0.png ← epoch_1899
```

Figure 5. Best Motif Recommendations Based on Epochs.

Figure 5 shows the system's recommendation of the five best motifs from Cluster 0, identified as the most stable and consistent group with the largest membership (834 images). Each row in the figure displays the motif's file name along with its originating epoch, providing important context on when these motifs were generated during GAN training. Four motifs were found to originate from *epoch_1899* (*image_9.png, image_1.png, image_8.png, image_3.png, and image_0.png*), highlighting the model's ability to produce high-quality patterns at this stage.

The predominance of motifs from *epoch_1899* indicated that during this training phase, the GAN model had sufficiently learned the underlying data structures to consistently generate high-quality motifs. Meanwhile, the presence of a motif from *epoch_189* demonstrated that even at earlier training stages, the model was capable of producing representative patterns that fit into the dominant cluster. This finding suggests that motif evolution is not strictly linear and may vary depending on the dynamics of the training process. Overall, this figure provided a visual recommendation of the best motifs from Cluster 0 while also assisting users in understanding the origins of these motifs within the GAN training timeline. The inclusion of epoch information was critical for further analysis, such as identifying when the model began producing stable motifs or assessing improvements in motif quality over increasing training epochs. Through this approach, motif selection could be performed automatically and objectively, guided by HDBSCAN clustering results.

F. Cluster Visualization using UMAP

Cluster visualization was carried out using UMAP (Uniform Manifold Approximation and Projection) to provide a two-dimensional representation of the feature vectors extracted with the ResNet50V2 model, thereby facilitating the interpretation of the data structure and the clustering results generated by the HDBSCAN algorithm. In this study, UMAP was employed to project the high-dimensional feature vectors (2048 dimensions) into a two-dimensional space (x and y), which were then displayed in a scatter plot. This process greatly aids in understanding how the GAN-generated motifs are distributed in the feature space and whether the clusters formed by HDBSCAN align with the visual similarities among images.

In the implementation, the UMAP model was initialized with default parameters and applied to the feature matrix obtained from ResNet extraction. After the transformation, a scatter plot was generated where the color of each point represents its cluster label: Cluster 0 (a specific color), Cluster 1 (another color), and outliers or Cluster -1 (commonly shown in gray). This visualization allows us to observe the density and distribution of each cluster, whether the clusters are clearly separated or overlapping, and the relative positioning of outliers with respect to the main groups.

The results show that Cluster 0, as the largest cluster, appears dense and dominates a particular region in the scatter plot, indicating that the motifs in this cluster share strong structural and visual similarities. Meanwhile, Cluster 1, although smaller in size, forms a spatially distinct group, reflecting significant differences in its characteristics compared to Cluster 0. Outlier points (Cluster -1) are widely scattered outside the main groups, confirming that these motifs do not exhibit sufficient similarity to belong to any cluster.

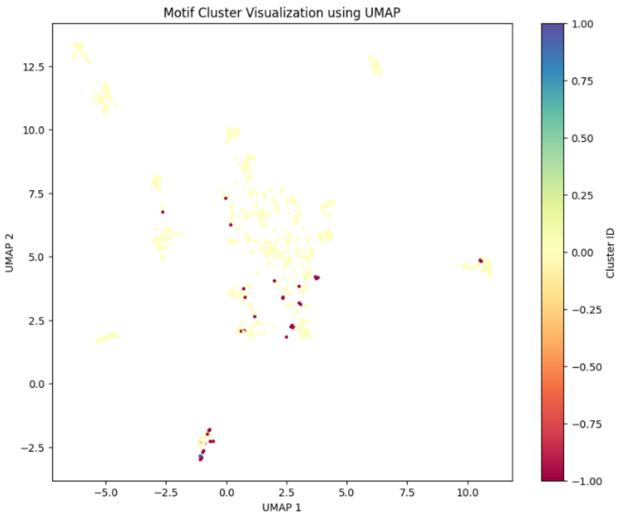

Figure 6. Evaluation Results Using UMAP

Overall, UMAP visualization provides an intuitive understanding of the effectiveness of the clustering process and reveals the latent structure of the GAN-generated motif dataset. Moreover, the scatter plot serves as a qualitative validation tool to assess whether the resulting clusters possess logical semantic and visual coherence. This becomes particularly important in practical applications such as motif recommendation, design variation analysis, and evaluation of motif evolution during GAN training. Figure 6 presents the evaluation results obtained using UMAP.

Figure 6 depicts the visualization of motif clusters using UMAP, which projects the high-dimensional feature vectors into a two-dimensional space to facilitate interpretation of the clustering patterns. Each point in the scatter plot represents a single GAN-generated motif image, with point colors corresponding to the cluster labels obtained from HDBSCAN: Cluster -1 (outliers), Cluster 0 (the main group), and Cluster 1 (a small yet valid group). The visualization indicates that Cluster 0 forms a dense group dominating the central region of the plot and extending toward the lower-left area, suggesting strong structural and visual similarities among motifs. In contrast, Cluster 1 occupies a more spatially separated region, highlighting its distinct characteristics compared to Cluster 0. The outliers labeled as Cluster -1 are scattered outside the main groups, confirming their lack of sufficient similarity to form a coherent cluster. Overall, this visualization provides an intuitive overview of the clustering performance in grouping motifs based on visual similarity while also serving as an evaluation of the quality of the resulting cluster distribution.

G. Discussion

This study provides an in-depth analysis of motif clustering results using deep learning and clustering approaches, specifically by employing ResNet50V2 for feature extraction, HDBSCAN for clustering, and UMAP for cluster structure visualization. The results show that the applied method can effectively group GAN-generated motifs based on their visual similarities. Cluster 0 emerged as the largest group with 834 members, indicating that the GAN model successfully generated motifs with dominant and consistent patterns from the early stages of training, as observed in motifs from epoch_1899. The dominance of Cluster 0 also suggests that the generator model tends to stably produce certain motifs, which are most likely representations of patterns learned from the training dataset.

Meanwhile, Cluster 1, with 5 members, represents motifs with more specific and rare characteristics, while Cluster -1 (outliers) consists of 42 images that were not sufficiently similar to any cluster, thus considered as unique motifs or noise. The UMAP visualization provides additional insights into the spatial distribution of each cluster, where Cluster 0 appears as a tightly grouped cluster, while Cluster 1 is located somewhat apart, indicating significant differences in characteristics. The outlier points are scattered far from the two main clusters, reinforcing the assumption that these motifs possess different or less stable visual structures. The recommendation of the best motifs from Cluster 0 helps in selecting motif samples that can be directly applied in textile design, digital art, or decorative elements, as these patterns are considered the most stable and aesthetically pleasing. Moreover, information about the epochs of motif origin provides an understanding of motif generation evolution during GAN training, where several high-quality motifs were already produced from early epochs.

Overall, the integration of ResNet-based feature extraction, HDBSCAN clustering, and UMAP visualization has proven effective in automatically analyzing and recommending GAN-generated motifs, which can serve as a foundation for AI-based motif recommendation or quality evaluation systems in the future. Nevertheless, the manual process of designing traditional songket motifs generally requires a long time, often taking several weeks to complete a single motif, as the details and complexity of the patterns must be carefully crafted by artisans. This makes the production of new motifs through traditional methods relatively slow and less efficient for meeting the demands of rapid innovation. With the proposed AI-based automated system, motif creation can be performed much faster in just a matter of seconds, thereby accelerating design innovation. From a socio-economic perspective, such automation has the potential to support artisans' productivity, expand the variety of motifs offered to the market, enhance the competitiveness of the traditional textile industry, and preserve the cultural relevance of songket in the digital era.

Although the dataset used in this study consisted of both primary and secondary data, several limitations remain. One major limitation is the relatively small number of songket motifs, which may affect the model's ability to comprehensively learn motif variations. In addition, the data collection process encountered several challenges, such as imperfect or non-uniform motifs, lighting variations, and inconsistent image capture conditions. These factors may introduce visual noise and inconsistencies into the dataset, ultimately influencing the quality of the generated synthetic images.

Another significant limitation is that although new motifs were successfully generated, many of them appeared with very similar or almost identical patterns. This resulted in limited motif diversity, as the clustering process tended to group these motifs into the same cluster. Such a condition indicates that the generator model still tends to replicate certain patterns from the training dataset rather than producing more diverse motif variations. Consequently, the potential for visual innovation becomes restricted, as the model is more stable in reproducing learned patterns than in exploring new motif combinations or structures.

This limitation highlights the need for additional strategies in future research to enhance motif diversity, such as expanding the dataset, introducing regularization mechanisms into the generator, or combining GANs with other approaches like style transfer. These improvements would allow the system not only to generate realistic motifs but also to produce higher levels of diversity, thereby better supporting creativity and innovation in textile design.

IV. CONCLUSION

Based on the analysis conducted using feature extraction with ResNet50V2, clustering with HDBSCAN, and cluster visualization through UMAP, it can be concluded that this approach is effective in grouping and recommending GAN-generated motifs based on their visual structural similarity. The feature extraction process successfully captured high-level semantic representations of each motif image, thus providing a solid foundation for the clustering process. The HDBSCAN algorithm successfully grouped all motifs into three main clusters: Cluster -1 (outliers), Cluster 0 (the largest cluster with 407 members), and Cluster 1 (a small cluster with 16 members). Cluster 0 was identified as the best cluster due to its dominant number of members and consistent visual patterns, making it a reliable source of high-quality motif recommendations.

Visualization using UMAP further strengthened the validation of the clustering results by showing a logical spatial distribution among clusters, where Cluster 0 formed a dense group, Cluster 1 was located in a more separated area, while outliers were scattered outside these two clusters. The recommendation of the top five motifs from Cluster 0 provided concrete examples of stable and aesthetic patterns, most of which originated from the early epochs of training (such as epoch_49 and epoch_99), indicating that the GAN model was capable of generating high-quality motifs from the early training stages. The information on the origin of epochs also provided important insights into understanding the evolution of motifs during the training process.

Overall, the integration of feature extraction methods, density-based clustering, and low-dimensional visualization has successfully delivered an automated solution for evaluating and selecting GAN-generated motifs. This research can be further extended for practical applications such as motif design recommendation systems, detection of artistic style variations, or quality assessment of image generation in GAN models.

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