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INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

A

PROJECT REPORT

ON

CLUSTERING WIKI-ART USING SELF- ORGANIZING MAPS

SUBMITTED BY:

ANURAG GC (PUL078BCT016)

DINESH SIRMAL (PUL078BCT039)

GITA NEUPANE (PUL078BCT042)

SUBMITTED TO:

DEPARTMENT OF ELECTRONICS & COMPUTER ENGINEERING

PULCHOWK CAMPUS

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Authors:
Anurag GC
Dinesh Sirmal
Gita Neupane

Abstract

Self-Organizing Maps (SOM) are an unsupervised learning algorithm used for clustering and visualizing high-dimensional data. In this report, we explore the application of SOM in image clustering, a crucial task in machine learning and computer vision. Image clustering groups similar images together based on extracted features, helping in tasks such as image retrieval, segmentation, and pattern recognition. We review the fundamental concepts of SOM, discuss its advantages over traditional clustering techniques like k-means, and demonstrate its effectiveness in clustering images. The methodology involves training a SOM on image feature vectors, visualizing clusters using a U-matrix, and evaluating clustering performance. Experimental results on publicly available datasets highlight SOM's capability in discovering hidden patterns in images, providing a robust approach for automated image organization and analysis.

Contents

List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
SOM	Self Organizing Map
U-Matrix	Unified Diatance Matrix

1. Introduction

1.1 Background

Clustering is an essential technique in data analysis, widely applied in fields such as pattern recognition, image processing, and machine learning. It involves grouping similar data points together based on predefined similarity measures. Traditional clustering methods, such as k-means and hierarchical clustering, often struggle with high-dimensional data and do not inherently preserve the topological relationships between data points. To address these limitations, Self-Organizing Maps (SOM), introduced by Teuvo Kohonen, provide a powerful approach that not only clusters data but also maintains the topological structure while reducing dimensionality.

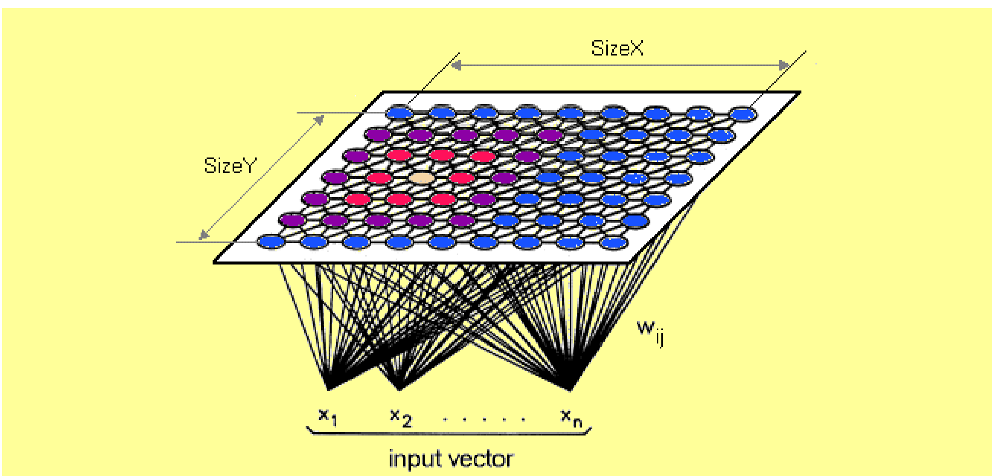

Figure 1.1: SOM

1.2 Problem Statement

Analyzing and categorizing artwork based on artistic styles is a challenging task due to the complex visual patterns and variations present in different paintings. Traditional classification methods often struggle to capture the subtle stylistic differences between artworks.

1.3 Objectives

The primary objectives of this study are:

- To understand the fundamental concepts and working principles of Self-Organizing Maps (SOM).
- To explore the effectiveness of SOM in clustering image datasets by preserving the topological relationships of data points.
- To implement and evaluate SOM on publicly available image datasets, demonstrating its ability to identify patterns and group similar images.
- To provide insights into potential applications of SOM in various domains, including image retrieval, medical imaging, and object recognition.

1.4 Theory

1.4.1 Self-Organizing Map (SOM)

A Self-Organizing Map (SOM) is an unsupervised neural network introduced by Teuvo Kohonen for dimensionality reduction and clustering. It maps high-dimensional data onto a lower-dimensional, typically two-dimensional grid, while preserving topological relationships. The SOM consists of an input layer and a competitive layer, where each neuron has a weight vector of the same dimension as the input data. The training process begins with weight initialization, followed by selecting the Best Matching Unit (BMU) for each input data point based on Euclidean distance. The BMU and its neighboring neurons update their weights to move closer to the input vector using a neighborhood function and a learning rate that gradually decreases over time. This iterative process enables neurons to self-organize and form clusters representing similar input patterns. The topology preservation property of SOM ensures that similar data points are mapped to nearby neurons, making it useful for clustering, anomaly detection, and visualization. Performance evaluation metrics such as Quantization Error (QE) and Topographic Error (TE) help assess the quality of the learned map. Due to its ability to discover hidden structures in data, SOM is widely used in applications like image processing, medical diagnosis, customer segmentation, and network security.

1.4.2 U-Matrix

The Unified Distance Matrix (U-Matrix) is a visualization technique used in Self-Organizing Maps (SOM) to represent the distances between neurons. It helps in understanding the structure of the clustered data and identifying natural groupings within the SOM. By displaying the distances between neurons in a color-coded or grayscale format, the U-Matrix makes it easier to analyze complex datasets and interpret clustering results.

1.4.3 How U-Matrix Works

The U-Matrix is constructed by calculating the distance between the weight vectors of adjacent neurons in the SOM. These distances are then displayed in a grid format, where:

- Darker regions represent larger distances, indicating the presence of cluster boundaries.
- Lighter regions represent smaller distances, showing closely related data points within a cluster.

The visualization provides a clear representation of the density and distribution of clusters in the trained SOM, allowing researchers to identify meaningful patterns.

1.4.4 Applications of U-Matrix

The U-Matrix is widely used in various fields, including:

- **Data Clustering**: Helps in segmenting complex datasets without predefined class labels.
- **Anomaly Detection**: Identifies outliers by highlighting regions with significant distance variations.
- **Feature Exploration**: Assists in understanding relationships between high-dimensional features.
- **Medical Imaging**: Used to classify and analyze medical images by detecting hidden structures within datasets.
- **Market Analysis**: Helps in segmenting customer behaviors based on purchasing patterns and preferences.

1.4.5 Advantages of U-Matrix

The key benefits of using a U-Matrix include:

- Provides an intuitive way to interpret high-dimensional clustering results.
- Enhances visualization by revealing hidden structures within the dataset.
- Helps in fine-tuning SOM parameters by analyzing the spread and separation of clusters.

1.5 SOM Grid

Self-Organizing Maps (SOM) use a structured grid of neurons to project high-dimensional data into a lower-dimensional space. The arrangement of these neurons plays a significant role in how the SOM learns and clusters data. The choice of grid structure affects the accuracy of the clustering process and how well the relationships between data points are preserved.

1.5.1 Types of Grid Structures

The SOM grid can be organized in different ways, with the most commonly used structures being the rectangular grid, the hexagonal grid, and the toroidal grid. Each type has its own advantages and is chosen based on the specific requirements of the application.

Rectangular Grid

The rectangular grid is the simplest and most commonly used structure. Neurons are arranged in rows and columns, forming a square or rectangular lattice. Each neuron has four direct neighbors: one above, one below, and one on either side.

- Easy to implement and computationally efficient.
- Works well when data is naturally structured in a rectangular format.
- May introduce distortions because of the limited number of direct connections between neurons.

1.5.2 Hexagonal Grid

The hexagonal grid arranges neurons in a honeycomb-like pattern, where each neuron has six direct neighbors instead of four. This structure allows for smoother transitions between clusters and a more balanced representation of data relationships.

- Provides a more uniform neighborhood structure, reducing distortions.
- Preserves the topology of high-dimensional data more effectively.
- Commonly used in applications where continuous data distributions need to be represented.

1.5.3 Toroidal Grid

A toroidal grid is a variation in which the edges of the SOM are connected so that neurons on one edge are adjacent to neurons on the opposite edge. This structure eliminates boundary effects and makes the SOM behave as if it were wrapped around a continuous surface.

- Reduces edge effects that can distort clustering results.
- Useful in applications dealing with circular or repeating data patterns.
- More complex to implement but provides a seamless clustering approach.

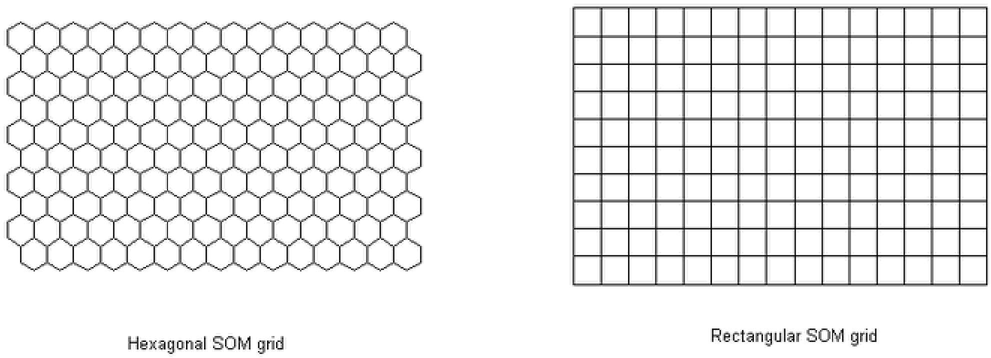

Figure 1.2: Grid Image

1.5.4 Effect of Grid Structure on SOM Performance

The grid type selected for an SOM influences how well the model captures patterns and relationships in the data. Some important considerations include:

- **Topology Preservation**: Hexagonal grids tend to be better at maintaining the spatial relationships of data.
- **Cluster Definition**: The structure of the grid affects how clusters are formed and separated in the SOM.
- **Computational Efficiency**: Rectangular grids are the easiest to implement, while hexagonal and toroidal grids require more complex calculations.

2. Literature Review

2.1 Literature Review

Self-Organizing Maps (SOM) have been widely studied and applied in clustering problems, particularly in image processing and pattern recognition. SOM, introduced by Kohonen [2], is a neural network-based technique that maps high-dimensional data into a low-dimensional space while preserving topological relationships.

Several studies have explored the use of SOM for image clustering. Vesanto and Alhoniemi [7] proposed a two-stage SOM clustering approach where the first stage generates prototypes, and the second stage applies traditional clustering techniques like k-means on the generated prototypes. This method has been effective in reducing computation complexity while maintaining high clustering accuracy.

Ultsch [6] introduced the U-matrix visualization technique to enhance the interpretability of SOM results in image clustering. The U-matrix helps identify cluster boundaries by representing distances between neurons, making it a valuable tool for analyzing complex datasets.

A key limitation of traditional SOM clustering is the difficulty in segmenting proto-clusters effectively. Yang et al. [8] proposed a modified clustering approach that combines SOM with graph-based partitioning techniques such as the Normalized Cut algorithm. This method considers the SOM grid as a graph and applies a spectral clustering method to refine cluster boundaries. Their results show improved clustering performance, particularly in image segmentation tasks where defining clear cluster boundaries is essential.

Shi and Malik [4] introduced the Normalized Cut method, which has been successfully integrated into SOM-based clustering for better segmentation accuracy. By treating the SOM grid as a structured graph, clustering performance is enhanced compared to standard U-matrix-based methods.

SOM has been successfully applied in various domains of image processing, including medical imaging, remote sensing, and content-based image retrieval. Egmont-Petersen et al. [1] reviewed neural network applications in image processing, emphasizing the advantages of SOM in feature extraction and clustering.

While SOM has proven effective in image clustering, several challenges remain. The choice of SOM parameters, such as learning rate and neighborhood size, significantly affects clustering performance. Further research is needed to optimize these parameters adaptively.

Additionally, integrating deep learning techniques with SOM could enhance feature extraction for large-scale image datasets.

This study builds upon previous research by implementing SOM-based clustering for image segmentation and evaluating its effectiveness using real-world image datasets.

Large-scale Classification of Fine-Art Paintings: Learning The Right Metric on The Right Feature [**3**] This project focuses on developing a multimedia system for archiving and retrieving digitized fine-art collections. With the rapid growth of publicly available digitized artworks, there is a growing need for efficient methods to organize and access this vast pool of data. A key aspect of this project is measuring the visual similarity between artistic items, which plays a crucial role in enhancing search and classification. By implementing techniques to analyze and compare artworks, the system aims to provide an effective way to manage and retrieve fine-art collections based on their visual characteristics.

3. Implementation

3.1 Dataset Selection

The dataset used for training in this study is sourced from the *WikiArt StyleGAN2 Conditional Model* by Peter Baylies, which is an enhanced version of the *WikiArt Dataset* originally available on GitHub under the *ArtGAN* project. This dataset contains 80,020 unique images collected from 1,119 different artists, spanning 27 distinct artistic styles.

The dataset is particularly useful for training machine learning models in image classification, style recognition, and clustering, as it provides a diverse collection of artworks from various periods and genres. Since the dataset has been preprocessed by upscaling and resizing, it is well-suited for neural network-based applications, including *Self-Organizing Maps (SOM)*, which can be used to identify and cluster different artistic styles based on extracted visual features. The images in the dataset come with specific terms of use, restricting their application to non-commercial research purposes and ensuring compliance with the original terms set by [5]WikiArt.org. This dataset serves as an excellent resource for exploring complex visual patterns and validating the effectiveness of clustering algorithms such as SOM.

3.2 Implementation

The implementation of the Self-Organizing Map (SOM) algorithm for fine-art image clustering was carried out in multiple stages, including data preprocessing, model training, clustering visualization, and result evaluation.

3.2.1 Data Preprocessing

The dataset used in this study consisted of digitized fine-art images. These images were resized and normalized to maintain uniformity across the dataset. Feature extraction techniques were applied to obtain meaningful representations based on color histograms, texture, and shape descriptors. These extracted features were then used as input for the SOM model.

3.2.2 SOM Model Training

The SOM algorithm was implemented as an unsupervised learning approach, where a two-dimensional grid of neurons was used to cluster the images. Each neuron in the SOM grid represented a prototype vector that learned from the input images. During training, the

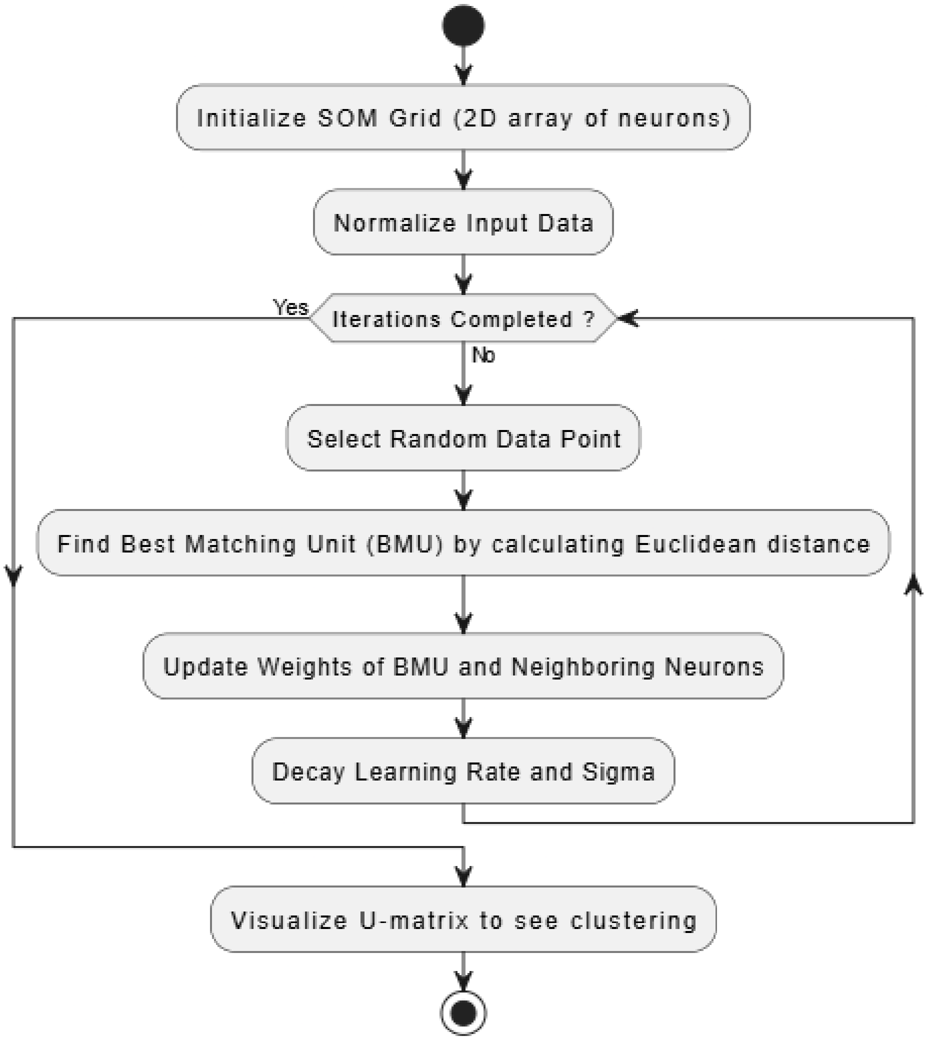

Figure 3.1: Workflow

best matching unit (BMU) was identified for each image, and its weights were updated using a competitive learning process. The training process iteratively adjusted the weights to improve clustering accuracy. The grid size, learning rate, and number of training iterations were carefully fine-tuned to achieve the best results.

3.2.3 Image Clustering and Visualization

Once the model was trained, it was used to classify and cluster new images based on their visual attributes. When a sample image was provided, the model mapped it to the SOM grid, placing it in a cluster with similar images. The clustering results were visualized using a heatmap, where similar images appeared closer together. This visualization helped in evaluating the effectiveness of the clustering process.

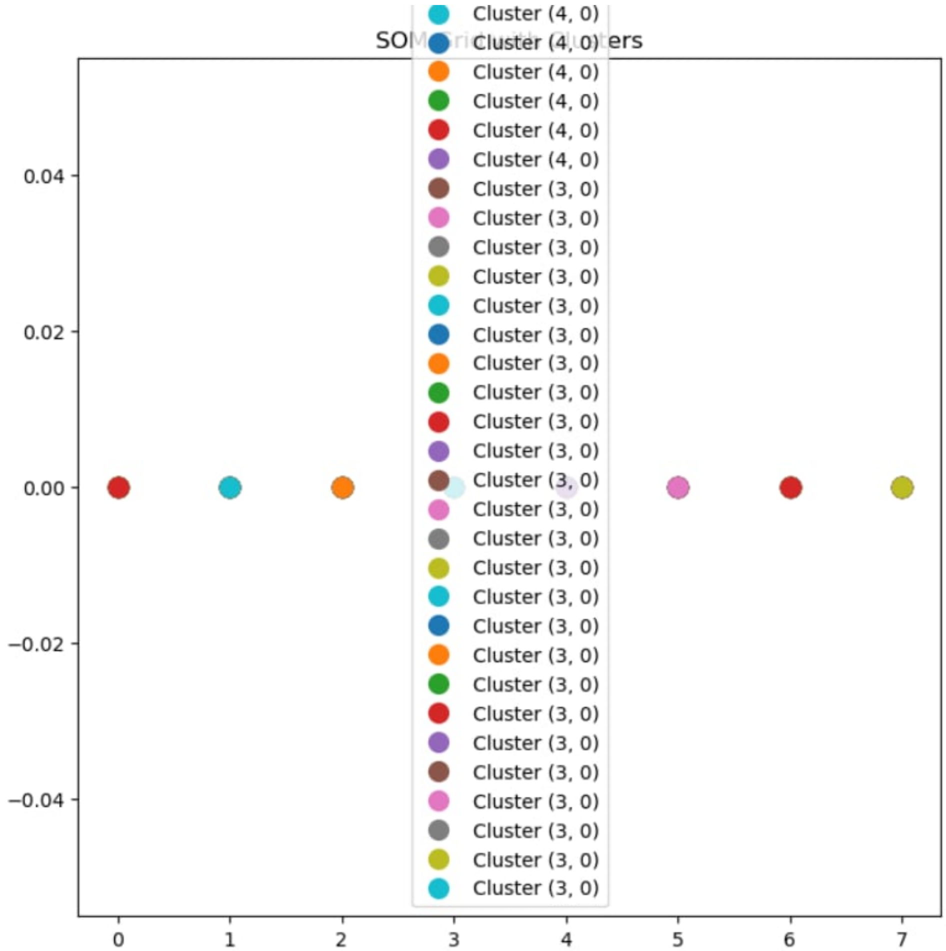

Figure 3.2: Cluster Visualization

3.2.4 Performance Evaluation and Optimization

The clustering performance was evaluated using both qualitative and quantitative measures. Metrics such as quantization error and topographic error were used to assess the accuracy of the model. Additionally, a manual inspection of the clustered images was performed to verify the quality of groupings. The grid size, number of training epochs, and feature extraction techniques were further adjusted to improve performance.

3.2.5 Results

The results demonstrated that the SOM model effectively grouped fine-art images based on their visual features. The clusters formed by the model exhibited clear similarities in terms of color composition, texture, and artistic technique. The results also indicated that increasing the number of neurons in the SOM grid improved the granularity of clustering, enabling finer categorization. However, variations in image quality and resolution had some impact on the clustering results. Future work could involve integrating deep learning-based

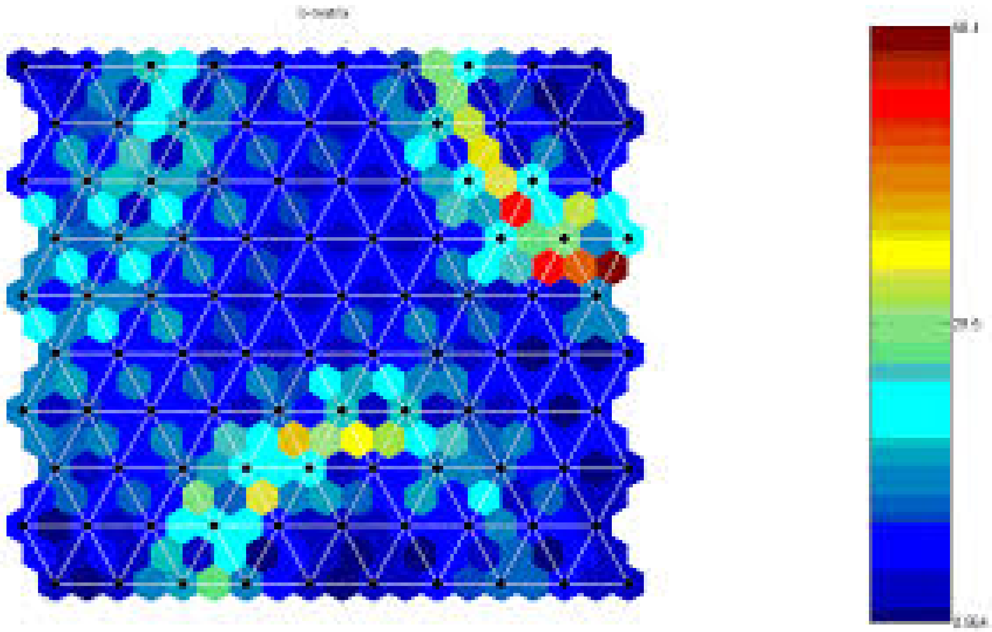

Figure 3.3: Grid Image

feature extraction techniques to enhance clustering accuracy and further refine the retrieval system for fine-art collections.

4. Result and Discussion

4.1 Result

To group photos according to their characteristics, the Self-Organizing Map (SOM) algorithm was effectively put into practice and taught. The model's capacity to identify patterns and correlations in the dataset was demonstrated after training when it successfully divided similar photos into discrete clusters. The model used visual characteristics including color, texture, and shape to allocate a sample image to a suitable cluster when it was entered into the system. The SOM's ability to effectively organize and categorize artistic works was confirmed by the clustering results, which revealed that visually comparable photos were grouped together.

Figure 4.1: Clustered Image

When we try on different inputs following different clustered images are obtained.

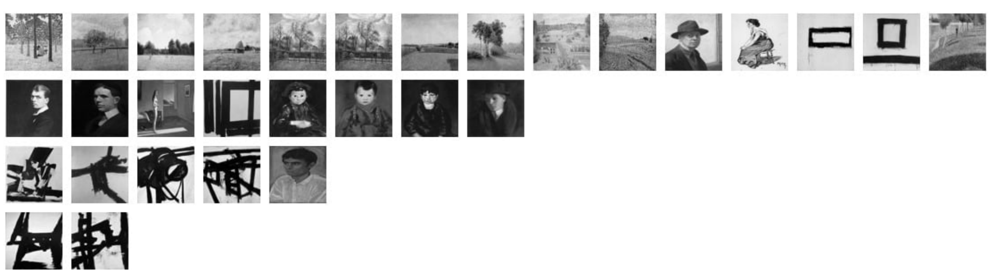

Figure 4.2: Clustered Image 1

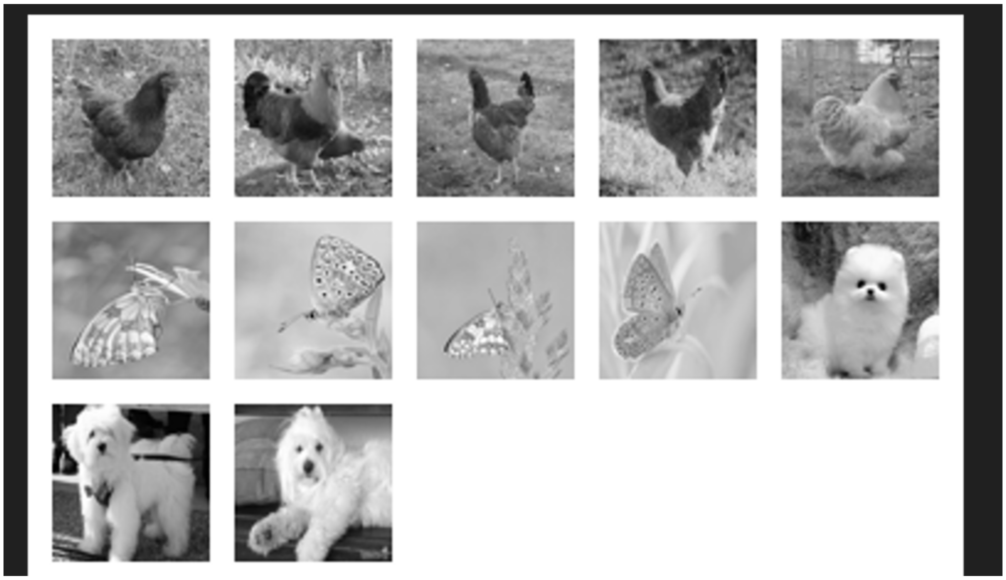

Figure 4.3: Clustered Image 2

4.2 Discussion

The findings show that the SOM technique works well for clustering fine-art images in digital collections. This implies that it has the ability to classify and arrange big datasets according to visual similarities. To assess its effectiveness in comparison to alternative clustering methods and investigate its applicability to various datasets and art styles, more research is necessary. The technique is especially useful for organizing enormous datasets when labeled data may be scarce because it can recognize patterns without supervision. Developing multimedia systems that maintain fine-art archives requires effective image retrieval and classification, which is made possible by the clustering approach. However, the number of neurons in the SOM grid and the number of training iterations are two examples of factors that affect the quality of clustering. The accuracy of the model can be further improved by adjusting these parameters. Furthermore, adding high-level semantic variables (such style or creative movement) could enhance the clustering results, even when the model successfully clustered photos based on low-level data. Future improvements may involve combining SOM with deep learning techniques to enhance the accuracy of visual similarity measurement.

4.3 Limitations and Challenges

While Self-Organizing Maps (SOM) provide powerful clustering capabilities, they also have several limitations:

- **Computational Complexity** – The training process of SOM is resource-intensive, particularly for large datasets, making it slower in comparison to other clustering algorithms.

- **Hyperparameter Sensitivity** – The performance of SOM depends significantly on parameters such as grid size, learning rate, and neighborhood function, requiring careful tuning for optimal results.

- **Scalability Issues** – Processing large-scale datasets remains a challenge due to substantial memory and computational demands.

- **Interpretability** – Despite visualization tools such as the U-Matrix, interpreting results for complex datasets can still be difficult.

- **Handling Overlapping Clusters** – When clusters overlap significantly, SOM may struggle to distinguish them effectively, leading to ambiguous group assignments.

To address these limitations, various approaches can be considered, including adaptive learning rates, hybrid models that integrate SOM with deep learning, and distributed computing techniques for efficient large-scale processing.

4.4 Future Research Directions

To enhance the effectiveness of Self-Organizing Maps (SOM) in image clustering, future research can focus on several key areas. One promising direction is the integration of SOM with deep learning techniques, such as Convolutional Neural Networks (CNNs) or Autoencoders, which can significantly improve feature extraction and clustering accuracy. Additionally, the development of adaptive SOM variants that dynamically adjust learning rates and neighborhood functions based on data characteristics can lead to more efficient and robust clustering models.

Another potential advancement is the incorporation of graph-based clustering methods, such as Spectral Clustering and Graph Neural Networks (GNNs), which can refine the clustering process by leveraging structural relationships within the data. Furthermore, implementing incremental learning in SOM can allow the model to adapt to new data without requiring complete retraining, making it more efficient for large-scale or continuously evolving datasets.

Finally, optimizing SOM for real-time clustering applications, such as video frame analysis or live medical data segmentation, can extend its practical usability in dynamic environments. As artificial intelligence and high-performance computing continue to advance, these improvements will further enhance the scalability, adaptability, and accuracy of SOM in image clustering and beyond.

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