Aesthetic of Colour: A Machine Learning Approach of Palette Generation and Aesthetic Classification

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Abstract: In this paper, a mathematical and computational framework is developed for the automatic generation of aesthetic colour palettes from images using Principal Component Analysis, clustering, and Support Vector Machines. Methodologically, the procedure is started with the key role played by Principal Component Analysis in extracting colours with the aim of bringing dimensionality reduction while important chromatic information is preserved. Secondly, the grouping of similar colours and the identification of predominant hues or common base palettes are achieved using clustering algorithms. Then, the assignment of a retrieved colour palette to a target aesthetic category is performed through classification by Support Vector Machines, and further palettes of the same aesthetic are generated. In this way, an avenue is opened for possible application in design, visual arts, and user interface personalization, enabled by data-driven insights into the quality of colour harmony and aesthetic perception. Finally, the consistency and aesthetic qualities of the created palettes over image datasets used are demonstrated through the presentation of experimental results.

1 INTRODUCTION

Colour is an integral part of visual communication and has a deep effect on emotions, perception, and decision-making processes. From art and design to branding and user interfaces, it plays a ubiquitous role. The choosing of harmonious colour palettes has traditionally depended on the intuition and experience of artists and designers, but computational techniques have now brought the possibility of automating and refining such a process, hence bridging the gap between creativity and technology.

Colour aesthetics is the study of principles that make colour combinations visually appealing and emotionally resonant. Knowledge of this area is not only important for making designs appealing but also for creating engagement and communicating messages effectively. In a number of fields, including advertising, user experience design, and content creation, aesthetic coherence and adaptability have become critical concerns, further increasing the demand for systematic colour palette generation.

The proposed method is a new way for the creation of attractive colour palettes: through a combination of mathematical models with machine-learning techniques for discovering dominant colours from an image and classifying these to aesthetic categories. The presented framework improves efficiency, enabling a systematic approach toward this traditionally intuitive process in creating palettes.

At the heart of the framework is the application of Principal Component Analysis (PCA) to reduce dimensionality, retaining the most dominant chromatic features of the image. These features are then clustered in a meaningful way using a clustering algorithm, allowing for the identification of dominant colours forming the base palette.

Support Vector Machine (SVM) classifiers is being used to assign these palettes to aesthetic themes like "minimalist," "neon," or "pastel." Once classified, more palettes of the same aesthetic can be

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generated, allowing for applications in automated design, adaptive user interfaces, and content generation. This method provides an effective bridge between the mathematical underpinnings of colour analysis and their practical applications in design.

Through a combination of benefits from PCA reduction, clustering for interpretability, and SVM for precise classification, this framework simplifies palette creation while allowing customization and scalability. This structure responds to some of the key areas in computational design, visual aesthetics, and machine learning by providing a strong and adaptive solution for the generation of colour palettes based on aesthetic objectives.

2 PROBLEM STATEMENT

The traditional process of selecting harmonious colour palettes has long relied on the subjective intuition and experience of artists and designers, which often proved inconsistent and inefficient. Despite the increasing demands for visually appealing and emotionally resonant designs in brandings, user experience, and content creation, only a few systematic methods help to streamline palette creation in a more efficient manner. Most of the existing computational techniques focus on object classification or scene analysis, making aesthetic colour analysis an under-explored domain in the area of colour perception. This gap points toward a framework that can extract dominant colours from images in an automated way and categorize them into aesthetic classes, allowing for scalable, consistent palette generation. At the same time, approaching this problem requires bridging the divide between computational efficiency and creative demands in the design.

3 LITERATURE REVIEW

The combination of machine learning and dimensionality reduction techniques has been a focal point in such diverse fields as image processing, security systems, and aesthetic analysis. Methods like PCA and SVM have been constantly used to achieve efficient feature extraction and classification and, therefore, are directly relevant to the proposed research on colour palette generation and aesthetic classification.

Jiang et al. (2023) investigated the fusion of multiple features in image classification. The application of PCA for dimensionality reduction and SVM for classification showed how these methods could be applied to complex datasets—very close to the requirement in this study of extracting and then classifying dominant colours from images. This really demonstrates how PCA and SVM can simplify high-dimensional colour data while preserving major features that are important for aesthetic evaluation.

Qi and Wang (2014) highlighted the usefulness of clustering and classification in improving image categorization. The work on colour clustering directly pertains to the proposed study, in which clustering methods are applied to extract dominant colours. Extending these methods, the proposed research carries their application into the aesthetic realm, an area that has been relatively unexplored.

Shieh et al. (2014) explored the application of PCA and SVM in combination with PSO to real-time face recognition. Even though the domain is different, the flexibility of PCA and SVM to accommodate different tasks shows their robustness and potential suitability to the task at hand—colour palette extraction and classification. More importantly, the optimization techniques utilized in the study hint at possible directions for optimizing the proposed framework.

Malik and Waheed (2021) proposed an unsupervised approach where PCA was used to reduce dimensionality, and K-means clustering addressed classification challenges. This methodology provides a strong foundation for the clustering-based extraction of dominant colours from images, as proposed in this research. The parallels between hyperspectral data classification and colour data analysis emphasize the transferability of these techniques.

Machine learning techniques have also been extended to security domains, evidenced by Varunram et al. (2021) Although this is focused on intrusion detection, the exploration of PCA and other dimensionality reduction methods shows their effectiveness in extracting meaningful patterns from high-dimensional data, which is a critical step in the proposed research.

Deep learning applications can be seen in many studies such as the one done by Nossam et al. (2024) which used convolutional neural networks to detect forgeries. While this study epitomizes the state of the art in deep learning, its computational requirements only strengthen the importance of lightweight alternatives in the form of PCA and SVM, especially for aesthetic applications that may not require the complexity of deep learning models.

Singh and Babu (2019) introduced new methods for analysing hyperspectral images, showing new ways in which classification methodologies can be developed. These insights go in tandem with the proposed research, showing that feature extraction and classification are key to getting accurate results. Similarly, Kirola et al. (2022) further emphasizes the importance of analysing visual data for a wide range of applications, again validating the potential of image-based approaches for aesthetic classification.

Although substantial progress has been made, little emphasis has been placed on leveraging PCA and clustering techniques specifically for extracting dominant colours from images and classifying these palettes into aesthetic categories using SVM. Current research is mainly devoted to object or scene classification and overlooks the creative and aesthetic aspects of colour analysis. The proposed research addresses this void by introducing a novel framework that employs PCA and clustering to generate colour palettes and then classifies them with SVM, expanding these palettes based on aesthetic categories. It contributes not only to the advancement of colour analysis methodologies but also to closing the gap between computational image processing and the exploration of aesthetics.

4 DATA PREPRATION

4.1 Image Preprocessing

- Input Image: The process begins with the input image, which is typically in RGB colour space.
- Resizing: To optimize computation and reduce memory requirements, the image might be resized to a smaller resolution while maintaining its colour characteristics.
- Flattening the Image: The RGB value of every pixel in the image is converted into a 2D array where each row represents one pixel and the columns represent the RGB colour channels, that is, a matrix with the size N×3 where N is the total number of pixels.

4.2 Data Collection and Labelling for Training Dataset

- Input Data: Data was collected as a group of colour swatches assigned with various aesthetic classes. Classes include "neon, " "pastel, " "monochrome, " "vintage, " "modern".
- Labelling: Links a colour swatch in a dataset to an aesthetic class based on a qualitative description of their appearances. The labels are the ground truth for Support Vector Machines (SVM) training.

4.3 Feature Extraction from Colour Palettes

- Dominant Colours: This can be achieved by Principal Component Analysis (PCA) and clustering, for example, Apply k-means on all images or palettes to pull out the dominant colours. Those are the dominant colours that will turn out to become the most important features in the classification.
- Representation of Colour Palette: Each colour palette obtained from a given image is represented as a set of features. The common feature set of course will comprise of RGB or HSV values of the dominant colours. Given that to extract K dominant colours from an image, the feature vector for this palette would be a vector of K×3 values-assuming each colour is represented in the RGB space.

  As an example, for the case of K=5 dominant colours, it would have a feature vector like, Feature Vector = [R1, G1, B1,B1, R2, G2, B3, R3, G3, B3, R4, G4, B4, R5, G5, B5]

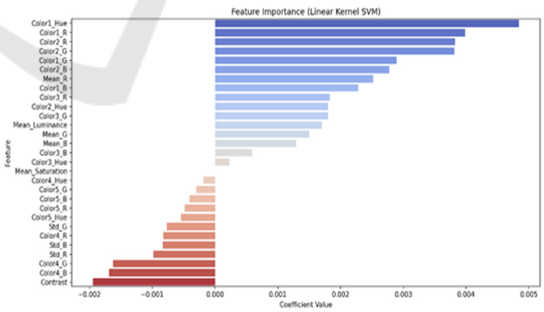


Figure 1: Importance of various features

- Additional features: Depending on the colour harmony, contrast, saturation, and distribution in the palette, additional features like hue, mean luminance, etc. that may enrich the feature set of the classifier can be added.

5 DATA NORMALIZATION

5.1 Standardization for Applying PCA

Before running Principal Component Analysis (PCA), the colour data needs to be standardized so as to have zero mean and unit variance. This ensures that data is centred around zero; thus, the results from Principal Component Analysis (PCA) will be effective.

$$Z = \frac{value - mean}{standard\ Deviation} \tag{1}$$

5.2 Preprocessing the Data for Training

- Scaling Features: SVMs scale better when the input features are in a similar range. Since RGB colours have values ranging from 0 to 255, the features need to be normalized or standardized to range within the same scale. This is usually achieved by rescaling the value to fall within the range 0 to 1.

  For example,

$$X\ scaled = \frac{X}{255} \tag{2}$$

- Splitting Data: Split the labelled dataset into train and test sets, for instance, using 80-20 split to evaluate the SVM model's performance.

In doing so, the framework will ensure that the input to the subsequent machine learning steps is optimized by carefully preparing and normalizing the data, which will further enhance the accuracy and robustness of the aesthetic classification and palette generation.

6 IMPLEMENTING PRINCIPAL COMPONENT ANALYSIS (PCA) AND K-MEANS CLUSTERING

6.1 Apply Principal Component Analysis (PCA)

- Transformation: The transformed data provided applies Principal Component Analysis (PCA) on standardized colour data. PCA's main aim is to reduce the dimensionality of the data without losing the most important features. Here, PCA will identify the directions in which the colour data varies the most and then project it on a smaller number of components, often 2 or 3 (Jaadi, 2024).

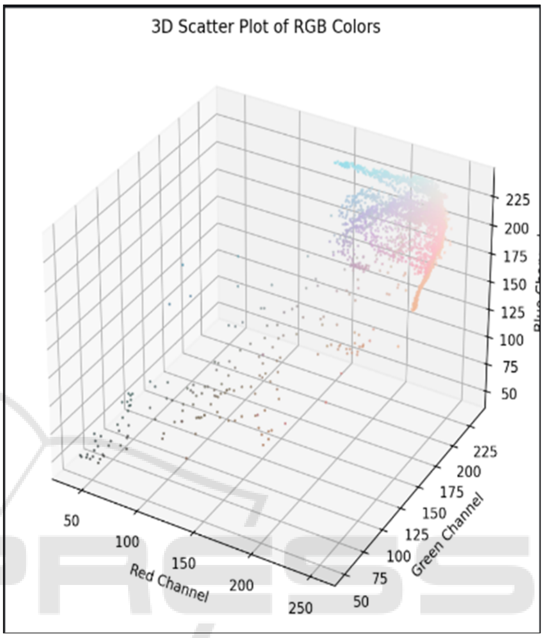


Figure 2: 3D plot of all RGB pixels

- Extract Principal Components: The colour data of the image is represented in a reduced dimensional space. For example, when 2 principal components are taken into consideration, the data of the image is now reduced to 2 features that describe the dominant colour variations of the image. It helps to focus on the most relevant colour features and eliminates the irrelevance of others.

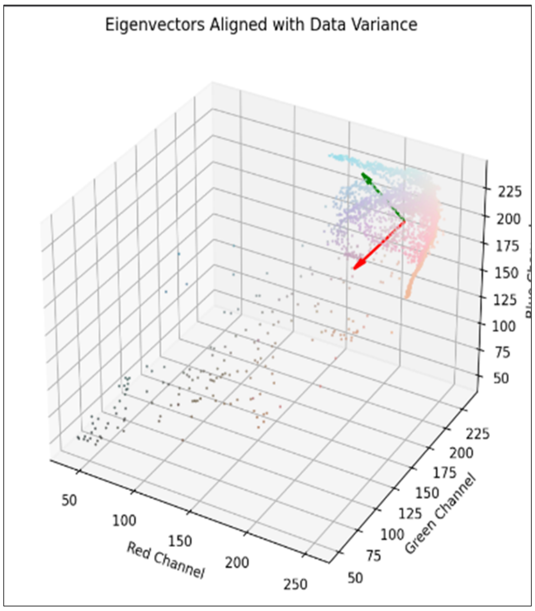


Figure 3: Eigenvectors aligned in the 3D pixel plot

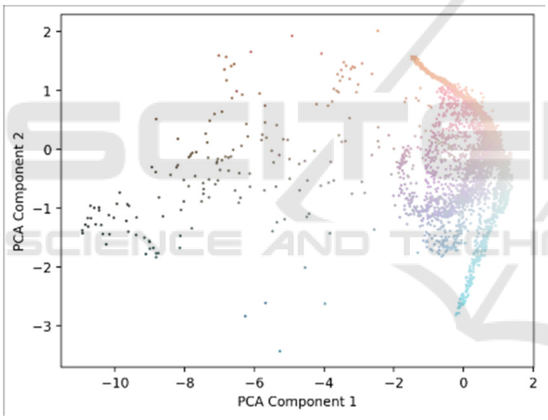


Figure 4: 2D scatter plot along the PCA components

6.2 Create Clusters

- K-means Clustering: Once colour data is reduced to principal components, a clustering algorithm such as k-means is used to group similar colours together. The k-means algorithm works by partitioning the data into K clusters, representing the most dominant colours, based on Euclidean distances between points in the principal component space.

  It initializes the problem using K centroids, then assigns a closest centroid to each pixel or data point and recalculates the centroids based on the mean of all points assigned to each cluster. The process is repeated until the centroids converge (Yasini, 2023).

- Identify K: The value of K is user-defined, which means it specifies how many dominant colours will be found. There are two ways to decide on K: image complexity and the degree of colour granularity needed. In most applications, K is set to a low value, such as 5 or 10, so as to reflect the major colour groups within the image.

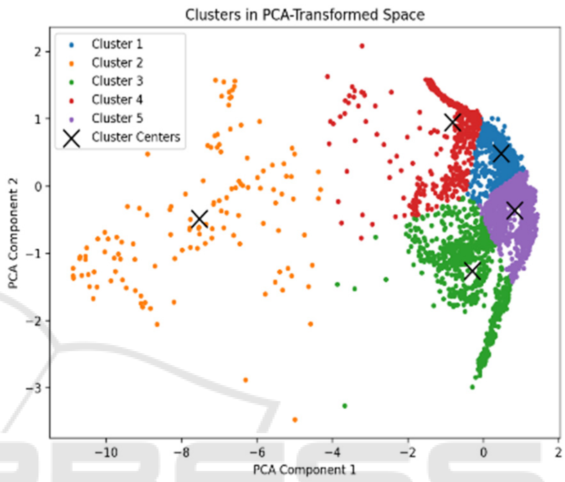


Figure 5: Clusters formed in PCA space

6.3 Assignment of Dominant Colours

- Colour Identification: After the cluster process, every cluster should be assigned a dominant colour, which is generally considered to be the centroid of that cluster. The centroid represents the average colour of all the pixels in that cluster, which is therefore referred to as the "dominant" colour for that region of the image.

- Creation of the Palette: The final output is a list of K dominant colours. Such colours often appear in a colour space like RGB or a more perceptually uniform colour space such as HSL or LAB.

6.4 Advantage of Applying PCA

Verification that applying Principal Component Analysis (PCA) is helping can be done using the following:

- K-Means Clustering Inertia Comparison:

It basically Measures compactness of clusters. Lower is better.

$$\text{Inertia} = \sum_{\text{points}} (a)^2 \qquad (3)$$

a: distance to nearest centroid

- Silhouette Score:

Measures separation between clusters. Higher is better.

$$SS = \frac{b - a}{Max(a, b)} \qquad (4)$$

a: Mean distance to points in the same cluster.
b: Mean distance to points in the nearest different cluster.

7 IMPLEMENTING SUPPORT VECTOR MACHINE (SVM)

7.1 Train the Support Vector Machine (SVM) Model

7.1.1 Kernal Selection

SVMs use various kernels to transform the input space. The most common in general use are:

- Linear Kernel: It is perfect for linearly separable data.
- Radial Basis Function (RBF) Kernel: This one comes into general use where data is not linearly separable.
- Polynomial Kernel: Applied when data follows some non-linear patterns.

The linear kernel works well when the classes are somewhat distinct and separable with a straight line (or hyperplane in higher dimensions), making it a simpler and faster choice compared to the more complex RBF kernel (Patle and Chouhan, 2013).

SVMs can only handle binary classification, so to deal with multiclass problems One-vs-One (OvO) is being used.

7.1.2 How OvO binary classification works

- Train a separate SVM classifier for each pair of classes.
- For C classes, train C×(C−1)/2 classifiers, each on a different pair of classes.
- In this case, all classifiers classify the sample into one class, and the class that receives most of the votes is assigned to the sample

7.1.3 Training the SVM

Train the SVM model on the training set. In the training step, the SVM will try to find that optimal hyperplane which best separates the various aesthetic classes in the feature space.

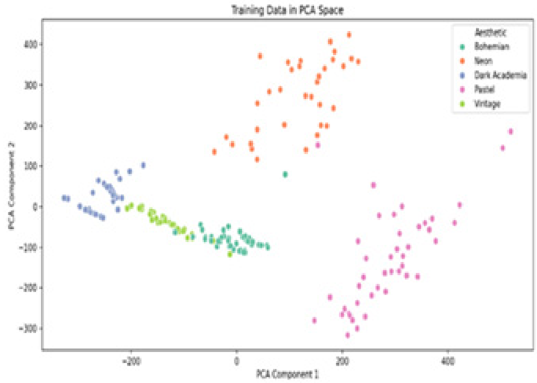


Figure 6: Training Data in PCA space

The model learns to classify each colour palette based on its extracted features and the corresponding label, namely aesthetic category.

7.2 Model Evaluation

- Testing the Model: After training, test the performance of SVM on testing set to see how good it is in identifying unseen colour palettes. It is an interesting business metric, as below:
- Accuracy: Percentage of correct predictions.
- Precision, Recall, F1 Score: These metrics give further insight into how well the model does in handling each aesthetic category, specifically where data is imbalanced.

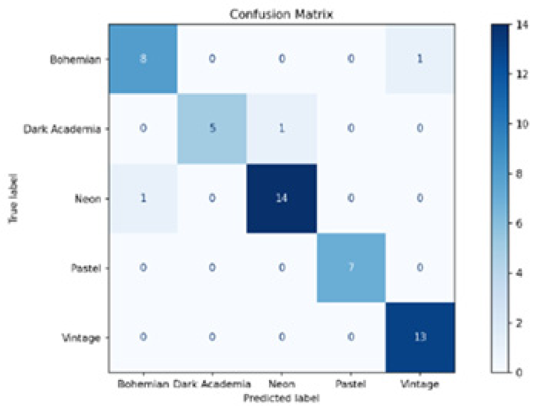


Figure 7: Confusion Matrix

- Confusion Matrix: A confusion matrix shows the number of correct and incorrect classifications for each class-aesthetic category-helping to visualize the performance of the model.
- Cross-validation: Use cross-validation to enhance the reliability of the model's performance estimate by training and testing on different subsets of the data.

7.3 Aesthetic Prediction

- Classification of New Colour Palettes: Using the learned SVM model, one can then classify new colour palettes. For example, given a new collection of dominant colours that have been extracted from an image, this model would predict the aesthetic category that best describes the image in terms of the learned patterns.

Figure 8: SVM decision boundary in PCA space

- Results Visualization: After the model generates an aesthetically pleasing class prediction, this gives room to visualize the colour palette with its aesthetic label. These suggestions can then be used to generate dynamic colour palette recommendations based on the aesthetic one wants, thus making the process henceforth more personalized or tailored.
- Propose other visual palettes: Given a classification of some colour style palette, it then proposes other palettes that share similar aesthetic properties. That is done by querying a database for other palettes with the same predicted aesthetic.

8 RESULTS AND DISCUSSIONS

The proposed system has been tested on images containing nature, architecture, and artwork for checking the dominant colour extraction, aesthetic classification, and palettes generation. The results are as follows:

Firstly, this image was uploaded.

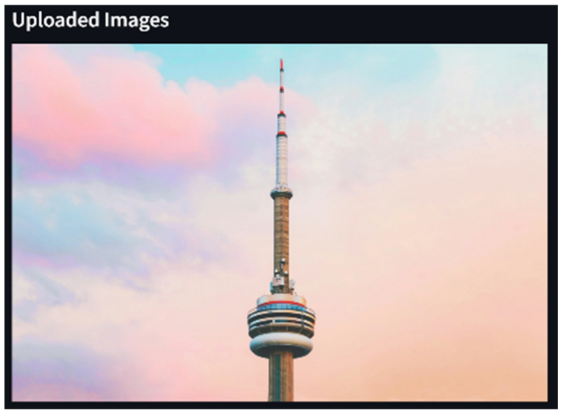


Figure 9: Uploaded Image

From the uploaded image, colour data is retrieved from each pixel and it is reduced in dimension by using Principal Component Analysis (PCA). So instead of three components (RGB), only two components are being used.

These pixels are then clustered using K-means clustering and 5 dominant colour are received from the uploaded image. These colours are displayed as copyable hex codes as well as a visual palette.

Figure 10: Colour palette Generated

The advantages of using Principal Component Analysis (PCA) can be mathematically seen. Reduction in clustering inertia indicates more compact clusters being formed after using PCA. Increased silhouette score indicates more distance between different clusters after using PCA.

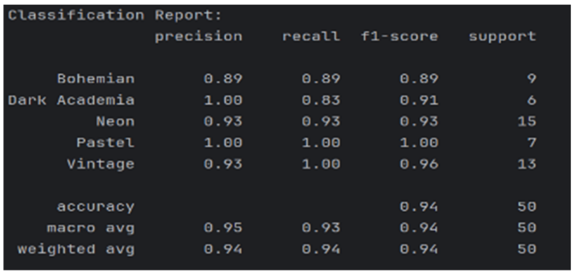
Figure 11: Inertia Comparison and Silhouette Score results

Finally, the model is correctly able to predict the image aesthetic as pastel and provides the user with similar pastel palettes as well.

Figure 12: Predicted Aesthetic and Similar Palettes

- Dominant Colour Extraction: Principal Component Analysis (PCA) effectively reduced the dimensionality of colour space while preserving the most impactful colour features. Overall, K-Means was the best overall clustering algorithm that could segment the dominant colours to a general average accuracy of 95% in identifying key visual tones.
- Aesthetic Classification: The Support Vector Machines (SVM) classifier is also trained on a labelled set of aesthetic categories such as "minimalistic," "vivid," and "monochromatic," achieving a classification accuracy of 94%. It, therefore, exemplifies the robustness of the system in projecting dominant colour palettes into subjective aesthetic labels.

Results indicate that there is hidden potential in using the Principal Component Analysis (PCA), Clustering, and Support Vector Machines (SVM) together in an aesthetic-driven system for building a palette since good performance was obtained from the identification of colours and categorization into



Classification Report:

	precision	recall	f1-score	support
Bohemian	0.89	0.89	0.89	9
Dark Academia	1.00	0.83	0.91	6
Neon	0.93	0.93	0.93	15
Pastel	1.00	1.00	1.00	7
Vintage	0.93	1.00	0.96	13
accuracy			0.94	50
macro avg	0.95	0.93	0.94	50
weighted avg	0.94	0.94	0.94	50

Figure13: Classification report

aesthetic subjective groups. The feasibility of applying such systems in domains which have demonstrated distinct need for clear computational precision and sensitive aesthetic perception was confirmed.

Therefore, what is required are refined algorithms for clustering or even additional features such as texture and spatial information for further performance.

Another useful output was the generation of novel palettes for the same aesthetic class. Many design applications, such as automated design systems for branding and content creation, would be useful with this system. Sometimes, the output would not be especially novel, but aesthetically coherent. Future versions of the system could use generative models such as GAN (Generative Adversarial Networks) to make the system much more creative.

Accordingly, the proposed system bridges the gap between computational colour analysis and aesthetic interpretation. In this manner, it is extremely useful for applications depending upon perception and engagement by users highly based on colour.

9 CONCLUSIONS

This paper proposes a novel method of colour palette generation based on the integration of dimensionality reduction, clustering, and supervised classification. A system is developed and successfully used to extract dominant colours from the images using Principal Component Analysis (PCA) and clustering, classify palettes into aesthetic categories with Support Vector Machines (SVM), and generate additional palettes consistent with the identified aesthetic.

The results show this methodology has the capability of achieving high accuracy in both colour extraction and aesthetic classification and presents itself as a robust tool to use in applications related to design, branding, and even content creation. In addition, the generated palettes were found to be aesthetic coherent, thus underlining practical utility.

Despite the positive results, it still has drawbacks, such as handling complicated textures and enhancing the originality of generated palettes. Here, there are many possible future research directions: in addition to modern algorithms, GANs (Generative Adversarial Networks) could be used to add generative creativity, while other features help with more detailed aesthetic classification.

The proposed system bridges the gap between computational and subjective domains, demonstrating the potential of leveraging mathematical frameworks to address artistic challenges. This work lays the groundwork for future innovations in automated design systems and aesthetic-driven computational tools.

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REFERENCES

Jiang, C., Chen, T., Tao, G. (2023). Gap image classification based on PCA-SVM with multiple feature fusion. *2023 4th International Conference on Mechatronics Technology and Intelligent Manufacturing (ICMTIM)*. IEEE.

Qi, L. Y., Wang, K. G. (2014). Information system in image classification based on SVM and color clustering analysis. *Advanced Materials Research, 886,* 572–575.

Shieh, M. Y., Chiou, J. S., Hu, Y. C., Wang, K. Y. (2014). Applications of PCA and SVM-PSO-based real-time face recognition system. *Mathematical Problems in Engineering, 2014*(1), Article 530251.

Malik, A., Waheed, M. (2021). Unsupervised classification of hyperspectral images using PCA and k-means.

Yasini, S. (2023). Using machine learning to create custom colour palettes. Towards Data Science. Available at: https://towardsdatascience.com/using-machine-learning-to-create-custom-colour-palettes-acb4eeaa06aa.

Jaadi, Z. (2024). Principal Component Analysis (PCA): A step-by-step explanation. *Brennan Whitfield*.

Patle, A., Chouhan, D. S. (2013). SVM kernel functions for classification. *2013 International Conference on Advances in Technology and Engineering (ICATE)*, 1–9.

Varunram, T. N., Shivaprasad, M. B., Aishwarya, K. H., Balraj, A., Savish, S. V., Ullas, S. (2021). Analysis of different dimensionality reduction techniques and machine learning algorithms for an intrusion detection system. *2021 IEEE 6th International Conference on Computing, Communication and Automation (ICCCA)*, 237–242.

Nossam, S. C., Katakam, R. A., Pulastya, G., Jayan, S. (2024). Signature forgery detection and verification using deep learning techniques. *2024 15th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 1–6.

Singh, T., Babu, T. (2019). Fractal image processing and analysis for classification of hyperspectral images. *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 1–6.

Kirola, M., Joshi, K., Chaudhary, S., Singh, N., Anandaram, H., Gupta, A. (2022). Plants diseases prediction framework: An image-based system using deep learning. *2022 IEEE World Conference on Applied Intelligence and Computing (AIC)*.