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Dominant Color Detection For Online Fashion Retrievals*

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ABSTRACT

This paper introduces a novel approach aimed at efficiently extracting dominant colors from online fashion images. The method addresses challenges related to detecting overlapping objects and computationally expensive methods by combining K-means clustering and graph-cut techniques into a framework. This framework incorporates an adaptive weighting strategy to enhance color extraction accuracy. Additionally, it introduces a two-phase fashion apparel detection method called YOLOv4, which utilizes U-Net architecture for clothing segmentation to precisely separate clothing items from the background or other elements. Experimental results show that K-means with YOLOv4 outperforms K-means with the U-Net model. These findings suggest that the U-Net architecture and YOLOv4 models can be effective methods for complex image segmentation tasks in online fashion retrieval and image processing, particularly in the rapidly evolving e-commerce environment.

Çevrimiçi Moda Aramaları İçin Baskın Renk Tespiti

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ÖZET

Bu makale, çevrimiçi moda görüntülerinden baskın renklerin verimli bir şekilde çıkarılmasını amaçlayan yeni bir yaklaşımı tanıtmaktadır. Bu yöntem, üst üste binen nesnelerin tespit edilmesi sırasında ortaya çıkan zorluklara ve hesaplama maliyeti yüksek yöntemlere çözüm sunarak, K-means kümeleme ve graf-kesim tekniklerini birleştiren

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ve adaptif bir ağırlıklandırma stratejisi kullanılarak renk çıkarımının doğruluğu artırmayı amaçlayan bir çerçeve üzerine kurulmuştur. Giysi segmentasyonu için U-Net mimarisini ile giysi öğelerini arka plandan veya diğer unsurlardan hassas bir şekilde ayırmayı sağlayarak giysi öznitelik tahmini ve ayrıştırma görevi için YOLOv4 adlı iki aşamalı bir moda giyim tespit yöntemini tanıtmaktadır ile karşılaştırılmıştır. Deneysel sonuçlar, K-means ile YOLOv4'ün, K-means ile U-Net modeline kıyasla daha üstün performans sergilediğini göstermektedir. Bu bulgular, özellikle hızla gelişen e-ticaret ortamında çevrimiçi moda arama ve görüntü işleme alanlarında ilerlemeye katkı sağlamak amacıyla U-Net mimarisinin ve YOLOv4 mimarilerinin karmaşık görüntü segmentasyon görevlerini için etkin metotlar olarak kullanılabileceğini göstermiştir.

1. INTRODUCTION

Detection of dominant colors in online design pictures is vital due to its profound impact on people's purchasing behaviour. A basic component of vision-based frameworks is color image segmentation since color pictures contain more data than grayscale pictures (Karthick et al., 2023). Image analytics, clothing recognition and parsing are crucial steps and play a pivotal role in online detection and decision systems (Lu, 2023; Gunduz, 2021; Liang,2016). By extracting features from recognized fashion landmarks, we can improve the analysis of clothing images, making it easier to predict attributes and retrieve specific clothing items (Bu et al., 2020).

Recently, there has been an increasing interest among researchers in detection algorithms, spanning traditional and deep learning methods, incorporating image feature extraction for explainable detection (Liu et al., 2023). The study proposed dominant color representations as a way to decrease the size of color descriptors, shifting away from histogram-based methods with numerous bins, such as the reduction to eight colors in MP7DCD (Talib et al., 2013). An approach has been proposed for treating an image as a graph with user inputs as strict constraints (Shih et al., 2016) and similarly (Ngọc et al., 2023) focuses on solving the graph-cut problem to find the minimum cut optimizing an energy function, balancing region and boundary information. To address these challenges, a proposed technique efficiently extracts the dominant color component (DCC) for optimal thresholding (Agrawal et al., 2022), which also proposed a multi-view clustering framework using K-means and graphs. The graph-cut-based multi-view clustering involves calculating similarity matrices, obtaining eigenvectors, and applying K-means to segregate objects into specified clusters. A spatial K-clustering algorithm, outlined in (Chang et al., 2015), which strives to minimize errors in assigning data points to clusters by assessing local texture complexity worked on the selection of optimal features to ensure spatial homogeneity. Furthermore, as discussed in (Tomasi and Manduchi, 1998) filters operating on the three bands of a color image, particularly bilateral filters, play a crucial role in enforcing perceptual metrics in the CIE-Lab color space. These filters are adeptly smooth colors and preserve edges in alignment with human perception.

In the domain of fashion retrieval, as highlighted in (Tomasi and Manduchi, 1998), learning methods have demonstrated success. The inclusion of massive attributes contributes to an improved partitioning of the clothing feature space, facilitating the recognition and retrieval of cross-domain clothing images (Liao et al., 2018). The paper proposes a method where each pixel color in an image is replaced by the color in a common palette that is most similar (Liu et al., 2016). This process classifies all pixels into k-clusters, termed the CHKM feature. An approach outlined in (Lin et al., 2009), involves the extraction of object proposal descriptors. These descriptors are then used to train joint textual and image embeddings. In the context of Fashion Image Retrieval (FIR) (Rubio et al., 2017), the goal is to retrieve relevant fashion images similar to a query image. Features obtained from FIR are utilized in an unsupervised histogram clustering-based segmentation algorithm (Park et al., 2019), to identify regions of uniform texture. The research community's interest in color–texture-based segmentation (Khotanzad et al., 2003), is motivated by the perceptual description of imaged objects and diverse applications. Motion vectors from P-frames are employed for foreground/background segmentation (Mezaris and Kompatsiaris, 2004) and a consensus matrix is generated from multiple views for K-means clustering (Kalantidis et al., 2013).

Deep learning models such as convolutional neural networks have been used to directly classify or segment original color images. Even though they work well, advanced classifiers like convolutional neural networks are computationally expensive and need large sets of precisely annotated training images (Liu, 2021; Lu, 2022). A clustering method, which interprets an image as a dataset with multiple dimensions and divides it into distinct parts, can offer improved segmentation results. Conversely, the edge detection method remains a prevalent strategy for addressing image segmentation challenges. This technique revolves around identifying points where significant shifts in grey levels occur (Wang et al., 2012). This study aims to detect the dominant colors for online fashion retrievals even when multiple objects overlap. The objective is to identify common and popular color combinations associated with a specific object. A k-means clustering algorithm has been developed combining quantizing pixels within the corresponding image segment to achieve this.

The rest of the paper is structured as follows. Section 2 reviews related work for the study. Section 3 describes the proposed models for extracting dominant colors from images and Section 4 presents the hyperparameters of the model and the experimental results. Section 5 concludes the paper.

2. BACKGROUND

Visual aspects play an important role within the dynamic landscape of online fashion retail and offer potential applications in clothing recognition, retrieval, and e-commerce. As the number of digital images continues to rise, it has become essential to efficiently organize and sort fashion items to offer users a personalized and improved shopping experience (Yamaguchi et al., 2012)

Recently, there have been numerous investigations centred around the segmentation and parsing of images focusing on dominant color extraction methods and content-based image retrieval techniques. Various computational techniques, including clustering algorithms (Gunduz et al., 2021), machine learning (Wang et al., 2012), and image processing, are explored for color extraction and trend analysis. Existing approaches often rely on clothing models trained with tagged samples or complex And-Or graph representations, which have limitations in handling diverse clothing styles and poses.

Joint image segmentation and labelling methods have been proposed by Liang et al. as an integrated system to parse a set of clothing images into semantic configurations using machine learning techniques (Liang et al., 2016). The image co-segmentation phase of the system extracts consistent regions from images using the exemplar-SVM (ESVM) technique, and the region co-labelling phase constructs a multi-image graphical model using segmented regions as vertices. Graph Cuts algorithm has been used for joint label assignment. The authors evaluate their framework on both the Fashionista dataset and a newly constructed dataset called CCP.

The study (Hu et al., 2008) proposed method introduces an approach for segmentation using the graph cuts technique that partitions image pixels based on foreground and background seeds. In this method, the algorithm is guided by detected faces, and foreground and background seeds where Foreground seeds are approximated based on the identification of the main color using torso detection, and background seeds are determined using constrained Delaunay triangulation (CDT). Wang introduced a similar semantic segmentation model designed to identify compatible color combinations in everyday photos which utilizes Deeplab V2, trained on the ModaNet dataset (Wang, 2019).

Traditional color detection methods are mainly based on human inferences and manual analysis makes this process time-consuming. In addition to the conventional methods, the garment image retrieval method is proposed based on grab-cut auto segmentation and the dominant color method for handling both simple and complex backgrounds. A color feature extraction using the color coherence vector (CCV) and dominant color method tries to achieve rapid and effective garment image retrieval in the context of the growing demand for online shopping platforms. Experimental results have been done using a database of 300 images that reached up to 60% precision rate (Liu et al., 2023).

Machine learning and deep learning algorithms have also been widely used for color detection tasks as the traditional segmentation methods face limitations. With the data-driven approaches, the fashion industry started to use social media images to automatically analyze fashion images, particularly runway images, for trend prediction. The study (Lai and Westland, 2020) focuses on machine learning techniques to automatically generate color palettes for fashion with a set of ground-truth data. Color palette generation combined with the k-means clustering algorithm has been compared with people detection and foreground/background segmentation before clustering. Experimental results showed that the image segmentation method outperformed the colors of the garments displayed.

The paper introduced a method for semantic segmentation that utilizes deep learning techniques along with color quantization and K-means clustering to extract dominant colors from salient objects (Gunduz et al., 2021). This approach employs a modified Inception-ResNet architecture for semantic segmentation and integrates SALGAN for salient object detection. Furthermore, K-means clustering is utilized to quantize the pixels within the segment and extract the dominant colors. Another study proposed a method for color image segmentation using Support Vector Machine (SVM) and Fuzzy C-Means (FCM) (Wnag et al., 2012) based on a local spatial similarity measure model and Steerable filter. These features are fed into an SVM classifier trained using FCM.

Some studies focused on metaheuristics, fuzzy set theory and graph cut techniques to improve the proposed models' performance. The study (Agrawal et al., 2022) proposes the use of the Adaptive Whale Optimization Algorithm (AWOA) to determine optimal threshold values introducing a new segmentation score for evaluation. While existing methods employ parametric and non-parametric strategies with entropic and non-entropic objective functions for threshold determination, this study proposed a DCC-based method for thresholding color images compared to the Gravitational Search Algorithm (GSA), Differential Evolution (DE), and Whale Optimization Algorithm (WOA). Karthick et al. proposed the S-fuzzy normalized graph cut (S-FNGC) method based on the common S-membership function to improve the image segmentation process (Karthick et al., 2023) To this end, each pixel in the color image has a functioned into a fuzzy region as a fuzzy weighted graph to represent the relationships between pixels. The proposed model has been compared with existing approaches such as mask thresholding, Gabor filter, Genetic algorithm (GA), and K-means clustering algorithm using the Barkey Segmentation dataset. The s-FNGC method outperforms other techniques, offering better segmentation accuracy and lower error rates. By integrating fuzzy set theory and graph cut techniques, it effectively addresses the challenges associated with segmenting complex color images. The findings of the study highlight the potential of the S-FNGC method for various computer vision applications requiring accurate and efficient image segmentation.

3. METHODS

In this section, the proposed model has been given that leverages a uniform framework based on K-means clustering and graph-cut techniques, designed for both single-view and multi-view datasets. To this end, firstly object detection and Graph-Cut Algorithm have been defined and then, the YOLOv4 and U-Net model have been outlined which comprises two distinct phases: data preparation and model training.

3.1. Object Detection and Graph Cut Algorithm

The initial module of the proposed model contains object detection and graph-cut stages. Object Detection algorithm effectively identifies all fashion items within the image which encompasses both classification and localization processes. Within this model, there exist three distinct classes: top, bottom, and middle. The algorithm proceeds with localization to determine the precise position of the identified class after the detection of one or more of these classes within the input image. This step is crucial for subsequent steps of segmentation with the Graph Cut algorithm (Lu et al., 2023). Within the Graph Cut algorithm, the image is represented as a graph and the segmentation problem is framed as finding the optimal cut in this graph. It is especially useful for tasks where the background of the image is complex or where there are other objects in the image that are similar to the foreground object. This algorithm requires precise localization data to effectively segment the image. The sample output of the Object Detection phase and Graph Cut Algorithm is represented in Figure 3.1.

Figure 3.1 Object Detection and Graph Cut Algorithm

3.2. Extraction of Color Candidates from Segmented Images

The k-means clustering method has been employed to extract candidate colors from segmented images. K-means clustering is a widely recognized technique utilized for low-level image segmentation tasks. As an unsupervised clustering algorithm, K-Means effectively groups data points into k clusters, where each cluster represents a distinct colour after removing dominant colours. Initially, a multitude of candidate colors is extracted and subsequently refined based on their respective features.

Before operating the K-Means algorithm, we preprocess images using the Binary Filter. This filter diminishes noise by replacing the intensity of each pixel with a weighted average derived from neighbouring pixels. Additionally, during the application of K-Means, only pixels selected by the Graph Cut Algorithm are considered. Following the extraction of candidate colors, we derive various features such as contrast, saturation, and the area covered by each candidate color. The CIELAB color space is chosen due to its perceptually uniform nature, where equal changes in L*, a*, and b* correspond to equal perceived changes in color. In the CIELAB color space, color is defined in a way that corresponds closely to human perception, with three components: L* (Lightness), a* (Green-Red axis), and b* (Blue-Yellow axis). L* indicates the perceived lightness of a color, ranging from 0 (black) to 100 (white), with higher values indicating lighter colors and lower values indicating darker ones. The a* axis represents the spectrum from green (-a*) to red (+a*), while the b* axis spans from blue (-b*) to yellow (+b*) (Chang and Mukai., 2022). Positive values on both axes indicate the presence of the respective color, while negative values indicate its absence. These components are essential for tasks such as measuring contrast and saturation in image processing, as they provide a precise way to compare colors based on human perception. Contrast represents the brightness of a color, while saturation denotes its richness. These attributes play a pivotal role in ranking candidate colors. Equations 1 and 2 below represent the computation of contrast and saturation. These metrics contribute significantly to the refinement and selection of optimal candidate colors for our research purposes.

$$C = \frac{(L_{max} - L_{min})}{L_{min}} \quad (1)$$

where $L_{min} = Min(L_{values})$ and $L_{max} = Max(L_{values})$.

$$S = \sqrt{a^2 + b^2} \quad (2)$$

Equation 1 defines the contrast, denoted as C, computed from all L values within the Lab color space. This formula yields the contrast value, reflecting the dispersion of L values across the image. Specifically, high-contrast images exhibit a broad spectrum of L values, whereas low-contrast images feature a narrower range of L values. Equation 2 computes the saturation, represented as S, as the square root of the sum of the squares of the a* and b* values divided by the L* value. Saturation serves as an indicator of the distance of the a* and b* values from zero relative to the L* value. Images with high saturation boast significant a* and b* values, whereas those with low saturation present smaller a* and b* values. Consequently, Equation 1 assesses the disparity between the lightness of each pixel and the average lightness of the image, while Equation 2 gauges the deviation of pixel colors from neutral tones (a=0, b=0). Together, these equations facilitate the calculation of contrast and saturation within the CIELAB color space. Additionally, we quantify the area occupied by the color candidate under scrutiny. This metric, termed Area, corresponds to the number of pixels attributed to the candidate color. Such calculations provide valuable insights into the spatial distribution and prominence of color candidates within the image context.

3.3. Sorting Final Colors

In the final stage of our analysis, we aim to refine our candidate colors by eliminating similar hues. This process entails pairwise comparisons of colors, necessitating a metric that amalgamates the three CIELAB components into a singular indicator representing the comprehensive color disparity between two samples. To this end, we employ CIEDE2000, also referred to as ΔE2000, a color difference formula and metric endorsed by the International Commission on Illumination (CIE) for quantifying and evaluating the perceived color disparity between two entities. ΔE2000 yields higher values to signify greater disparities in perceived color. Thus, it inherently serves as a threshold, functioning as a hyper-parameter within our methodology. We use ΔE2000 to set a standard for recognizing colors with noticeable differences, making our color selection more precise. In fashion, we focus on different aspects, with the size of color areas being especially important. This tells us how much space each color takes up and how prominent it is in the product. Contrast is also key because it affects how textures and patterns look and how well colors go together. Saturation, while less critical than area and contrast, still plays a role in how vibrant the colors appear. Our study highlights the importance of area, contrast, and saturation in selecting colors for fashion products, though their significance may vary depending on the product type. Through careful testing, we've determined the varying importance of these factors across different fashion categories, improving how we choose colors for products.

Figure 3.2 represents the flowchart of the proposed method. Utilizing the K-Means algorithm, the color features are organized into a defined number of clusters, facilitating the identification of dominant colors within the image. The cluster centres derived from the K-Means algorithm accurately represent the dominant colors present in the visual content to prepare ground truth. Then object segmentation detection has been done using YOLOv4 and U-Net algorithms. YOLOv4 is known for quickly detecting objects in one go, while U-Net is skilled at precise object detection in high-resolution images. The study compares how these models perform in various contexts and applications. The next section presents the procedure for images which are converted, normalized, and scaled to fit both models' input and output formats. The dataset includes diverse object classes for thorough evaluation. Customized setups are created for both YOLOv4 and U-Net.

3.5. YOLOv4 and U-Net Architectures

The dual-phase application of YOLOv4 presents a streamlined and efficient solution, seamlessly integrating processes encompassing dominant color identification, object detection, and color analysis.

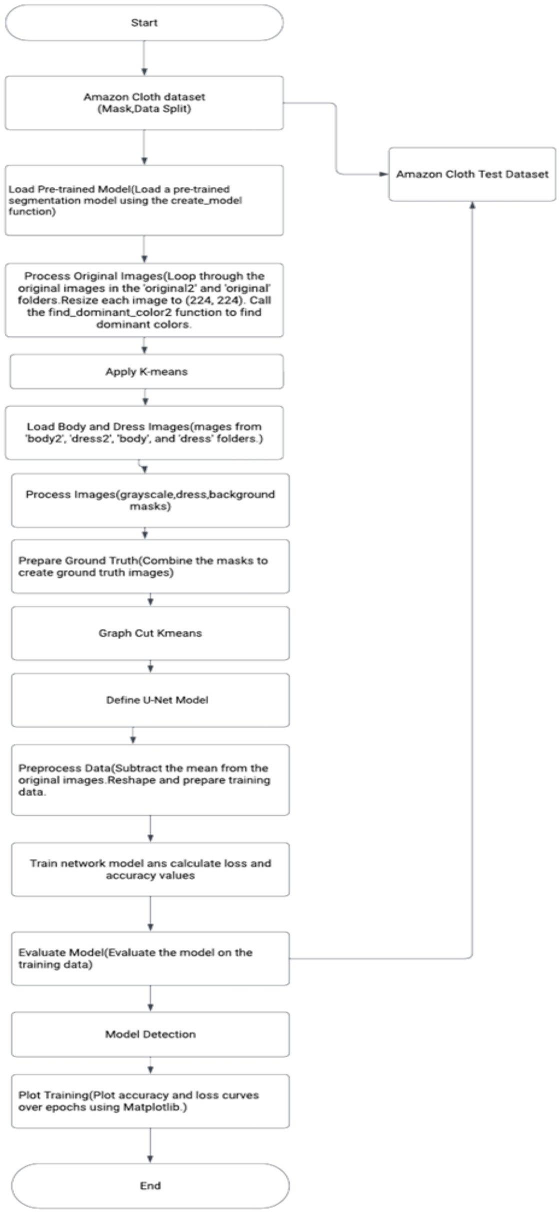

Figure 3.2 Flowchart of the proposed model

This approach not only enhances the effectiveness of color-centric tasks but also offers a swift and reliable methodology for diverse visual analysis requirements. YOLO is trained on the COCO dataset with optimizations for fast detection. U-Net, originally for medical images, is adapted for high-resolution object detection. Training has been done separately for each model, focusing on comparing training times and performance metrics, considering YOLO's quick trainability and U-Net's deep learning requirements. The implementation of a dual-phase methodology entails the breakdown of a given task into more specialized subtasks, thereby enabling a comprehensive analysis of the target domain. In the context of the YOLOv4 application for the identification of dominant colors, the dual-phase approach comprises a systematic progression from general object detection to more focused color analysis. During the initial phase, the YOLOv4 algorithm has been employed to detect and classify objects within the image. Subsequently, in the first phase, the detected objects undergo regional segmentation, wherein each segment encapsulates the color features pertinent to the identified object. These features, including color histograms or RGB values, serve as the basis for subsequent analysis.

4. EXPERIMENTS

This section reports on the experimental setting and comparable performance results of the proposed models.

4.1. Experimental Setup, Dataset, and Preprocessing Steps

In this study, outdoor images of people and semantic segmentation masks of their clothing dataset have been used. This dataset has 1000 images and matching segmentation masks, showing different clothes people wear. It covers 59 types of objects, all in a standard size of 825 by 550 pixels and saved as PNG files. The masks outline areas like shirts, hair, pants, and more, with one class for the background. There's also a CSV file detailing these classes. The dataset contains both JPEG and PNG files, with PNG preferred for its higher quality. It's useful for research in computer vision and fashion analysis, aiding in tasks like person detection and clothing recognition in outdoor scenes.

This dataset has broad applications, from fashion industry progress to improved surveillance and understanding of human behavior. It's a valuable resource for studying attire recognition outdoors and reflects the growing connection between technology and fashion analysis. In the data preprocessing phase, several essential steps are undertaken to prepare the dataset for subsequent analysis and model training. Firstly, images are loaded from the dataset using standard libraries like OpenCV. Next, the images are resized to a uniform size and standardized to ensure consistency across the dataset. Pixel values are then normalized to a standardized scale, typically ranging from 0 to 1, to facilitate model convergence and stability during training. Following this, images are converted to a suitable color space, such as RGB, HSV, or LAB, to enable effective dominant color extraction, considering specific application requirements and computational efficiency. Labelling and preprocessing of training data sets have been done for the stage of effective model training. The model is trained using transfer learning principles, with a primary focus on detecting apparel features based on contour and appearance, irrespective of color variations. Table 1 reports the hyperparameters of the U-Net and Yolov4 models.

Table 1. Hyperparameter setup for U-Net and Yolov4 models

Hyperparameters	Value
Epoch number	120
Activation Function	ReLU
Learning Rate for Adam	0.001
Hidden Layers	18

5. RESULTS AND DISCUSSION

The performance of both models has been evaluated using accuracy and loss metrics with a primary focus on accuracy. Figure 4.1 represents visual representations of accuracy metrics, offering valuable insights into the comparative performance of YOLOv4 and U-Net across evaluation scenarios. Table 2 reports the results for the training set over 120 epochs.

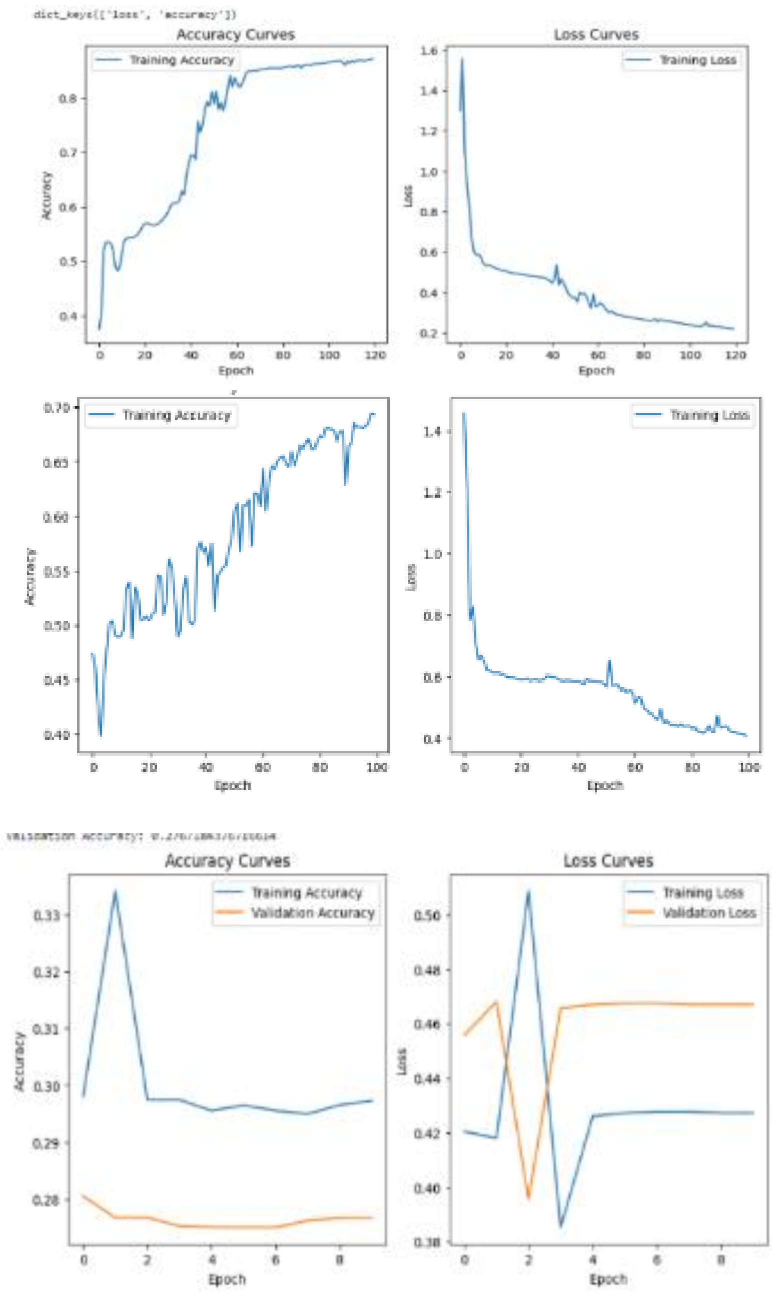

Figure 4.1. Training Accuracy and loss results for the Yolov4 model (top), U-Net model (middle), and training and validation results comparison for Yolov4 (left) and U-Net models over 10 epochs

Table 2. Experimental results over 120 epochs

	K-means with Yolov4	K-means with U-Net	Gaussian Mixture with U-Net
Accuracy	**0.8714**	0.70	0.5077
Loss	**0.2176**	0.30	0.3446

The experimental results demonstrate varying performance metrics across different methods for object segmentation detection. When utilizing K-means with YOLOv4, the accuracy achieved is notably high at 0.8714, accompanied by a relatively low loss value of 0.2176. Conversely, employing K-means with U-Net yields a slightly lower accuracy of 0.70, with a corresponding loss of 0.30. Gaussian Mixture with U-Net shows the lowest accuracy among the methods at 0.5077, accompanied by a loss value of 0.3446. These results suggest that K-means with YOLOv4 outperforms the other methods in terms of both accuracy and loss, indicating its effectiveness in object segmentation detection tasks. The performance of the K-means algorithm has also been compared with Gaussian Mixture Model (GMM) over the precision metric for the selection of dominant colors. The precision metric serves as a pivotal indicator of the algorithm's capability to accurately identify dominant color components within the image dataset under scrutiny.

6.CONCLUSION

This study introduces a novel and adaptable approach to dominant color extraction in the context of online fashion retrieval. By combining K-means clustering with segmentation techniques, our proposed framework demonstrates versatility across images. According to the experimental results, in the U-Net model, the dense layer structure leads to slower training, while YOLOv4 exhibits faster training with higher accuracy rates. The YOLOv4 model represents a promising solution to the longstanding challenges of object detection within the fashion domain, thereby contributing to advancements in computer vision applications geared towards apparel recognition and recommendation systems.

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