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COMS W4735 COURSE PROJECT
COLOR SEASON ANALYSIS SYSTEM

1. Abstract

The goal of the following described system is to determine a color season of a user when given an input image of the user. The motivation behind color seasons is to use the natural distinguishing color features of a person in order to inform their decisions regarding the colors of their clothing, makeup or jewelry. Choosing items in colors that complement their natural appearance will overall improve the aesthetics of said person. The following system will take a single image of a person and use this image to categorize the person into one of twelve established color seasons: Bright Spring, True Spring, Light Spring, Light Summer, True Summer, Soft Summer, Soft Autumn, True Autumn, Deep Autumn, Deep Winter, True Winter or Bright Winter. A diagram of the color seasons is presented below in Figure 1.1. From the diagram it can be seen that each of the color seasons flow into one another with characteristics being shared between sister seasons. The seasons take into account a person's warmth or coolness, their saturation or brightness, and their value either dark or light. The cool seasons are Summer and Winter, while the warm seasons are Spring and Autumn. Likewise, the bright seasons are Winter and Spring and the soft seasons are Summer and Autumn. Finally, the light seasons are Spring and Summer and the deep seasons are Autumn and Winter. The different seasons will place more emphasis on the different aspects of a person's coloring. Each season has a primary aspect and a secondary aspect. The primary aspect can be either hue, value, or chroma whereas the secondary aspect will then either be hue or chroma.

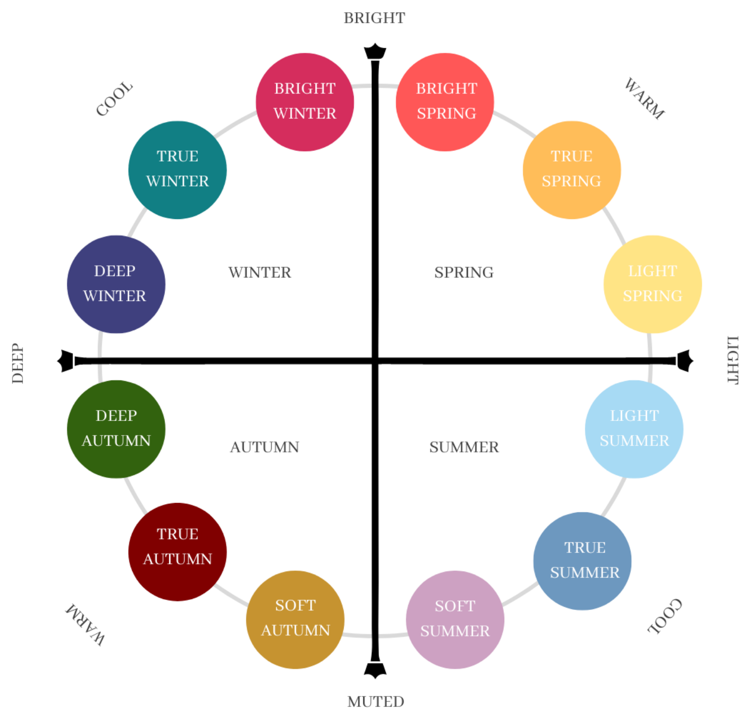

Figure 1.1 Color Seasons Diagram

The system will use the input image to find the person's skin, hair, and eye color values and use these to determine their most likely color season. The system will first perform skin, hair, and eye segmentation and then use the pixels to calculate a hue, value, and chroma for each of the three features. The hue will range from cool to warm, the value from light to dark, and the chroma from soft to bright. Then, the combination of the three features and their findings will be used to finally declare a season. The system will output a description of the found season, a recommendation of colors to wear and colors to avoid, and a graphical representation of the person's overall hue, value, and chroma.

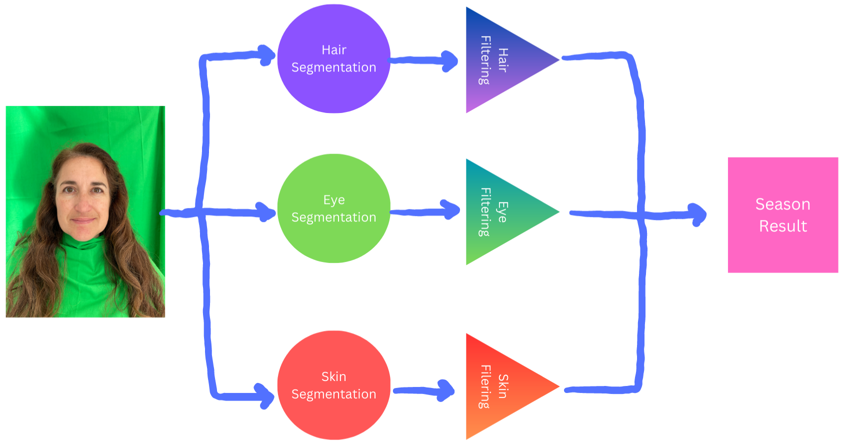

Figure 1.2 Flowchart of System Process

2. System Domain

The system will take an input image in .JPG format of a person's face with the background being a green screen and with a piece of green cloth covering their shoulders. In the case of longer hair the hair will be placed over the covering green cloth. The images will be taken using a iPhone 12 mini camera with a focal length of 1.6 and must be of a minimum size of 2000x2000 pixels. The images will be taken in natural lighting and shadows will be reduced as much as possible. An example image is given below in Figure 2.1, and the full library of test images can be found in Appendix A.

Figure 2.1 Sample Input Image

A set of 36 images are used to create the system thresholds containing three images of the same person per season. The images are annotated with a ground truth season determined by the subject in the image. The subjects are given a description of the requirements of each season and are then instructed to declare the season they most feel they represent. Similarly, the evaluation images will consist of 36 new images with 3 images per season. The test images will meet the same requirements as described above.

3. Skin Detection and Analysis

3.1 Skin Segmentation

The first step to finding the overall hue, value, and chroma of the skin of the user is to segment the skin pixels. The method used to segment the skin in these images is based on the concept that there is a range of hues and chrominance found within human skin-tones. (Elgammal, Muang, Hu, 2009) (Kolkurl et. al, 2017) The image is first converted to the HSV color space. Then a mask is placed on the image to include only the pixels within the skin-tone range. The range was determined by beginning with the ranges detailed in Kolkur1, Kalbande, Shimpi, Bapat, and Jatakia's paper and then iterated upon to fit the conditions of the specific input images. The HSV color space was able to segment pixels relatively well, however, it would sometimes include hair pixels if they were a shade that could reasonably also be another's skin tone. In order to reduce the amount of hair that may be detected as skin in the image, the detection area for skin pixels was reduced through the use of facial detection. Now, before HSV processing the face in the image is detected using Haar cascades using OpenCV's open-source default frontal face detection classifier. Then, the image is cropped to only include the rectangle of the area detected as face. The results of the HSV skin detection for the sample input image in Figure 2.1 are shown below in Figure 3.1.1.

Figure 3.1.1 HSV Detection of Skin Pixels

As can be seen in Figure 3.1.1, there are a number of false positives within the detection. There are still hair pixels being designated as skin, as well as the eyes of the user. The ranges of chrominance found within human skin are much smaller than the ranges of hues, especially across races. (Elgammal, Muang, Hu, 2009) So, in order to improve upon the skin segmentation generated by the HSV method, the image is also converted to the YCbCr color space. The YCbCr color space represents an image using its luminance and chrominance components. The chrominance values are used to mask the pixels in the image which would be likely not to be a skin pixel. The values used for the skin tone ranges were once again chosen from the paper's method and then fit to the input images of this system. The results of the YCbCr skin segmentation are shown in Figure 3.1.2.

Figure 3.1.2 YCbCr Detection of Pixels

The results are greatly improved with very few hair pixels being falsely detected as skin pixels and also the exclusion of parts of the eyebrows, eyes, and lips. There are some skin pixels that are falsely detected as negative. In order to generate the best results, the HSV and YCbCr results are combined through a bitwise AND operation to identify pixels that are skin in both of the images. The results for the merged skin detections are shown in Figure 3.1.3.

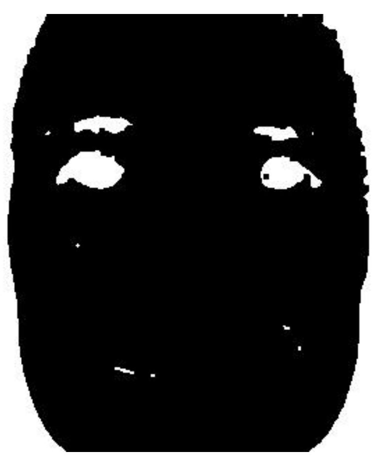

Figure 3.1.3 Combined HSV and YCbCr Detection of Pixels

Figure 3.1.4 Skin Segmentation Results of Sample Image

The skin segmentation algorithm generally performs well across different images. The algorithm struggles with lighter colored eyebrows and sometimes detects them as skin pixels. Overall, the skin pixels that are detected are sufficient as a representation of the user's skin tone and can be used for seasonal analysis.

3.2 Skin Analysis

The detected skin pixels are then processed to find the overall hue, value, and chroma of the user's skin. The saturation and value are simple; each pixel's results from the HSV image are summed and normalized over the detected amount of skin within the image.

$$average\ value\ = \frac{\sum_{p_i} value(p_i)}{number\ of\ skin\ pixels\ in\ image} \quad (1)$$

$$average\ saturation\ = \frac{\sum_{p_i} saturation(p_i)}{number\ of\ skin\ pixels\ in\ image} \quad (2)$$

This results in a value from 0-255 for each, where 0 represents completely dark and completely muted, and 255 represents completely light and completely bright. These values are then converted to a percentage from 0 - 100% by dividing the value by 255 and then binned. The possible bins for value are the following: {0 : very light, 1 : neutral-light, 2 : neutral, 3 : neutral-dark, 4 : very dark}. The possible bins for saturation are the following: {0 : very soft, 1 : neutral-soft, 2 : neutral, 3 : neutral-bright, 4 : very bright}. A consideration was made to have the thresholds based on the standard deviations of the entire sample, however, due to the limited sample size the results were not as accurate as using predetermined ranges.

The final step for the skin analysis is to determine if the user's skin is cool-toned or warm-toned. There are two major definitions for determining warm and cool colors. There is the idea that blue is the coolest color and red is the warmest and colors closer to blue are cool and colors closer to red are warm. The second idea is that there can be warm and cool blues, as well as warm and cool reds. In this case if a blue has some amount of red added to it, it will be a warm blue and if a red has some amount of blue added to it, it will be a cool red. This second definition will be used for this system. Otherwise, all skin-tones would read as warm since the color of blood is red and is the major defining basis for skin. Therefore, the system will use the BGR values of each skin pixel and if the blue value is greater than a certain threshold in comparison to the red value, the pixel will be considered cool, else it will be considered warm.

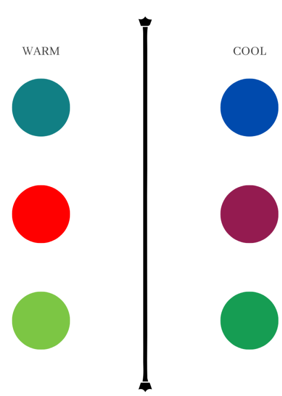

Figure 3.2.1 Visual Examples of Warm and Cool Colors

As a further measure to only consider valid skin pixels for analysis, the system only analyzes pixels that have a greater concentration of red than blue and green. Then, each pixel's red and blue values are compared. If the blue value is greater than 80% of the red value then the pixel is considered to be a cool-tone. The results are then normalized by taking the number of cool pixels and dividing by the number of skin pixels measured. Once again the results are binned into the following categories: {0: Very Warm, 1: Neutral Warm, 2: Neutral, 3: Neutral-Cool, 4: Very Cool}. The binning for the hue, saturation, and value of the skin pixels uses the following ranges:

```
    if hue <= .2:
        #more than one std away from average hue, very warm
        s_coolness = 4
    elif hue <= .4:
        #near neutral still warm
        s_coolness = 3
    elif hue <= .6:
        #neutral
        s_coolness = 2
    elif hue <= .8:
        #neutral, leaning cool
        s_coolness = 1
    else:
        #very cool
        s_coolness = 0

    if sat <= .05:
        #not saturated
        s_sat = 0
    elif sat <= .1:
        s_sat = 1
    elif sat <= .2:
        s_sat = 2
    elif sat <= .3:
        s_sat = 3
    else:
        s_sat = 4
```

```
    if val <= .2:
        s_val = 4
    elif val <= .4:
        s_val = 3
    elif val <= .6:
        s_val = 2
    elif val <= .8:
        s_val = 1
    else:
        s_val = 0
```

Combining the three factors generated each image will be given a resultant set of values from 000 to 444, with the first value representing the hue, the second representing the saturation, and the third representing the value. These numbers will be used in conjunction with the hair and eye values in order to find an average for each factor. This then can be used to classify the person into one of the 12 color seasons.

4. Hair Detection and Analysis

4.1 Hair Segmentation

Hair is notoriously difficult to segment, given the wide range of hair colors, values, and chromas. Furthermore, hair can be located in many different areas on a person's head such as for longer hair down by the shoulders and for a bald person only on the sides of the head. Since the algorithm needs only a representative sample of the hair colors within the image, the segmentation is done by detecting the face within the image removing this from consideration and then removing the background. The domain for the background is very strict and falls within the unnatural shades of green which are very rarely found in hair colors. This can safely be removed along with the face resulting in most of the hair remaining for analysis. This method will result in some portions of the hair not being included, however, the rest of the hair is usually enough to result in an accurate conclusion. The face detection is done in the same fashion as previously described for skin detection using Haar cascades. The rectangular box designated as the face is then converted to a green color. Then a range of green shades to match the background will be masked resulting in mostly only hair being the only pixels left in the image. The algorithm struggles with bald persons and will sometimes include no hair or skin pixels as the hair. And, sometimes for those with higher hairlines the algorithm will include a row of skin pixels.

Figure 4.1.1 Hair Segmentation Results for Sample Image

The system may also include parts of the chin which is helpful for those with facial hair which is then included in the calculation. The tradeoff of this is that sometimes for those without facial hair the chin pixels are included in the calculation. There is a far greater number of hair pixels than non-hair pixels included during the segmentation, therefore, it is admissible to use these results for hair pixel processing.

4.2 Hair Analysis

The hair pixels are processed in a similar fashion as the skin pixels. Once again, the only pixels considered for evaluation are those with a greater value of red than blue or green. When analyzing the pixels present in the images colors with great values of green were usually an effect from the green screen reflecting through the hair. Very few pixels were not majorly-red based and for this reason it was found admissible for the system to ignore them. The rate of non-based red pixels was no higher than 4%. The saturation and value results were again found by summing the pixel values and then normalizing based on the amount of hair pixels.

$$average\ value\ =\ \frac{\sum_{p_i} value(p_i)}{number\ of\ hair\ pixels\ in\ image} \quad (3)$$

$$average\ saturation\ =\ \frac{\sum_{p_i} saturation(p_i)}{number\ of\ hair\ pixels\ in\ image} \quad (4)$$

Then, the level of coolness within the hair is computed by finding the number of pixels with a large ratio of blue in regards to the red value within the pixel. These calculations are done using the BGR color space. The normalizations and binning are the same as for the skin pixels. It again was considered to use the standard deviation to bin the hue, saturation, and values, however, due to the small sample size these results were found to be inaccurate. The final output of the hair analysis resulted in a set of values 000 - 344. The system had an issue with detecting the difference between blonde and light brown hair versus darker brown hair. Many users would indicate their value as deep due to their darker brown hair where others would consider their light brown hair to be light. The system struggled to make this same distinction. In order to counteract this issue, the systems ranges for dark vs. light hair were not linear. Furthermore, many users would more likely consider their coloring to be cool if their hair was cool as it is easier to determine coolness in hair than in skin. So, the coolness or warmth of one’s hair is given a stronger priority within the algorithm. The binning for the hair pixels fell in the following ranges:

```
if hue <= .4:
    h_coolness = 3
else:
    #very cool
```

```
        h_coolness = 0

    if sat <= .2:
        #not saturated
        h_sat = 0
    elif sat <= .4:
        h_sat = 1
    elif sat <= .6:
        h_sat = 2
    elif sat <= .8:
        h_sat = 3
    else:
        h_sat = 4

    if val <= .24:
        #dark
        h_val = 4
    elif val <= .3:
        h_val = 3
    elif val <= .5:
        h_val = 2
    elif val <= .7:
        h_val = 1
    else:
        h_val = 0
```

5. Eye Detection and Analysis

5.1 Eye Segmentation

The first method developed for this system to segment the iris from the face involved using Canny edge detection to outline the major features of the eye region. The eye region was found using the open source Haar cascade classifier from OpenCV for identifying eyes. Then, the biggest circle within the edged eye region was considered the eye. However, this method was ineffective for those whose eyelids cover more of the iris. In these cases, the edges within the image around the iris look more like a half-circle than a full circle. The algorithm was then unable to detect any eye within the image.

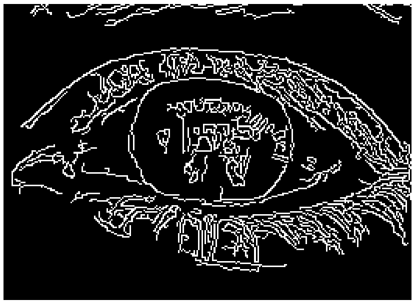

Figure 5.1.1 Canny Edge Detection of Right Eye from Sample Image

A new method was needed to be able to detect the iris of all eye shapes. A new classifier was used, Multi-Task Cascaded Convolutional Neural Networks (MTCNN) which is a neural network that is trained to classify facial landmarks. This method proved much better at detecting eye regions across the sample images. After the eye region is identified, the next step is to find the iris pixels. The irises are estimated by finding the linear distance between the left and right eye regions and then dividing this by a standard factor to estimate iris radius. For most images this resulted in a small portion of each iris being segmented. This proved to be enough to generally determine the eye color characteristics.

Figure 5.1.2 Iris Detection of Sample Image Using MTCNN

5.2 Eye Analysis

The pixels within the eye regions required a more robust algorithm than skin and hair because blue and green based colors were also to be expected. The algorithm detected if each pixel belonged to a set of expected eye color ranges. These colors were green, blue, gray-green, gray-blue, gray-brown, brown, and brown-black. The ranges for these colors were based upon the "What is my eye color?" open-source algorithm developed by Jeffrey Olchovy. Then the counts were used of each color to determine the warmth vs cool tones present within the eyes. The cool colors were assumed to be blue, green, gray-green, gray-blue, and gray-brown. The warm colors were assumed to be brown and brown-black. The coolness ratio was then found by dividing the sum of cool-toned pixels by the total amount of eye pixels. Earlier iterations of the algorithm tested used a similar method as the skin and hair analysis and attempted to identify warm greens and warm blues by the ratio of red within them, and cool reds by the ratio of blue within them. This method proved ineffective in the case of eyes as blue and green eyes appear cool in person, but in the image would be muddied by reflections. The algorithm would categorize cool blue and green eyes as warm which did not reflect the true appearance of the user's eyes.

The final iteration of the algorithm using the hue ranges was able to more accurately identify the warmth or coolness of the user's eyes. The range of lightness values for the eyes was much smaller than skin and hair. Eyes that would be considered light blue by human perception were consistently reading as very dark values. This could be due to reflections within the image, or the system detecting a large amount of pupil as iris. The system ranges for values were reduced so it generated more accurate designations. Once again the results were converted from percentages to a score of 0-4 as the skin and hair results were. The final results from the eye analysis algorithm were an output in the range 000 - 443.

```
    if val <= .19:
        e_val = 3
    elif val <= .6:
        e_val = 2
    elif val <= .8:
        e_val = 1
    else:
        e_val = 0
```

6. Gestalt Analysis

The final step was to combine the three features skin, hair, and eyes to determine a final result. The hue value from each feature was averaged, along with the saturation and values for each feature.

$$total\ coolness = \frac{coolness_{skin} + coolness_{hair} + coolness_{eye}}{3} \quad (5)$$

$$total\ brightness = \frac{saturation_{skin} + saturation_{hair} + saturation_{eye}}{3} \quad (6)$$

$$total\ value = \frac{value_{skin} + value_{hair} + value_{eye}}{3} \quad (7)$$

Then, the ranges for each of the color seasons needed to be determined. Each season would require a primary and secondary feature to meet the requirements. The “True” seasons would have wider ranges than the more specific seasons in order to fit users who may have conflicting features such as being warm-toned and bright but also leaning dark. In this case the user could fall into either True Spring (warm and bright) or Deep Autumn (warm and deep). The algorithm would then rely on if the bright factor or the deep factor is more present. If they are around the same, then the system will default to the last category the user’s results fit in. This is a less than ideal scenario and would happen in cases of very neutral features or very conflicting features.

```
seasons = {
    "True Spring": ((2, 2, 0), (4, 4, 4)),
    "True Autumn": ((2, 0, 0), (4, 2, 4)),
    "True Summer": ((0, 0, 0), (2, 2, 4)),
    "True Winter": ((0, 2, 0), (2, 4, 4)),

    "Bright Spring": ((2, 2.5, 0), (4, 4, 4)),
    "Light Spring": ((2, 0, 0), (4, 4, 1.5)),

    "Light Summer": ((0, 0, 0), (2, 4, 1.5)),
    "Soft Summer": ((0, 0, 0), (2, 1.5, 4)),

    "Soft Autumn": ((2, 0, 0), (4, 1.5, 4)),
    "Deep Autumn": ((2, 0, 2.5), (4, 4, 4)),

    "Deep Winter": ((0, 0, 2.3), (2, 4, 4)),
    "Bright Winter": ((0, 2.3, 0), (2, 4, 4))
}
```

After the results have been calculated by the system a final season is returned to the user. The final results include an image with a description of the season and its color palettes. The system also displays a line plot of the user's scores of coolness, brightness, and lightness. An example of a season output can be seen below in Figure 6.1 and Figure 6.2.

Figure 6.1 Sample Season Results Output

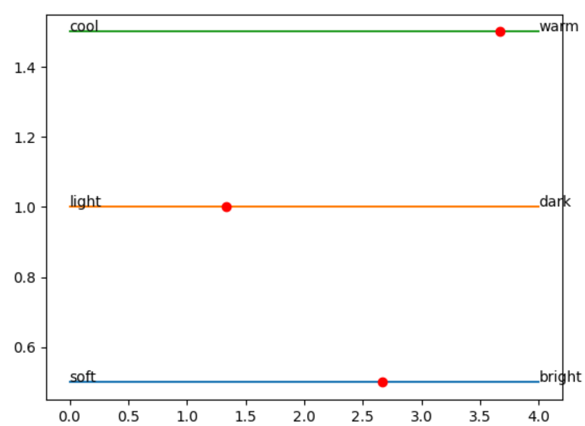

Figure 6.2 Sample Seasonal Graphical Output

7. Evaluation

For the system development three images of one person representing each season were taken. These images were then processed through the system and compared to the ground truth of the image. The ground truth was found by allowing the subject within the image to read a short description of the requirements of each of the twelve seasons and then placing themselves into one of them. Then, two metrics were developed from the results. The pure correctness was a score out of 36 and the system would receive one point per image if it were correct. The second score was a weighted score where the system would receive 2 points if the result matched the ground truth season and 1 point if the system matched the image to a sister season of the ground truth. Sister seasons carry some of the same qualities of the other and different lighting conditions could result in a reading of a sister season. This score also takes into account that a user may have identified themselves as a sister season when determining their ground truth. This second score would be out of 72. The development images scores were 21/36 or 58% and 48/72 or 67%.

A second set of test images were captured to further evaluate the system. These images were not taken into account while developing the system. Another difference for these images is that they were captured by the user or the user's friend instead of the author. The author gave instructions regarding the domain of the image and the user was then encouraged to test the system themselves. The test images included 36 images, 3 of the same person once again for each of the twelve seasons. The ground truth was determined by the user's opinion of their personal color season. The results were 12/36 and 33/72 using the same metric calculation as above. The results were much lower than the development results. There are a number of factors that could have affected these results. Most of the incorrect results in the test set were users estimating themselves to be deeper than the results indicated. This could be due to the user-taken images generally being brighter based on how the users took them. Furthermore, this test set included users who were bald which causes the system to incorrectly determine the "lightness" of their hair and overestimate it. These users also considered their past hair color when determining their ground truth season. Furthermore, since the saturation thresholds were tuned to the previous set of images this could have been overfit to the development set causing incorrect results to appear in the test set. The system was generally correct in determining if a user would consider themselves warm or cool.

8. Project Continuation

There are a multitude of avenues for continuation for this project. A greater sample size of input images would greatly improve the system by allowing the ranges to be more fit to the general population. In this case the standard deviation from the mean could be used to determine where a user should be binned. Furthermore, if there were a way to make the system more robust to lighting changes it would also help with the precision of the system. Due to the nature of the classifications very similar images of the same person could result in slightly different seasonal results. The skin and eye detection algorithms do not rely on the green screen being present. If the hair detection method could be changed to allow for any background this would also make the system more user friendly. Users could submit any image of their face on any background and find the results of their color season. The system also could benefit from a different method to detect a lack of hair such as in the case of bald persons. If this is the case in the image, the system could then ignore the hair results and only use the skin and eyes tones. The system managed well for a narrow range of samples, but has a great area of opportunity for improving robustness and accuracy.

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Appendix A - Development and Test Images

Bright Spring

True Spring

Light Spring

Light Summer

True Summer

Soft Summer

Bright Winter

True Winter

Deep Winter

Deep Autumn

True Autumn

Soft Autumn

Bright Spring

True Spring

Light Spring

Light Summer

True Summer

Soft Summer

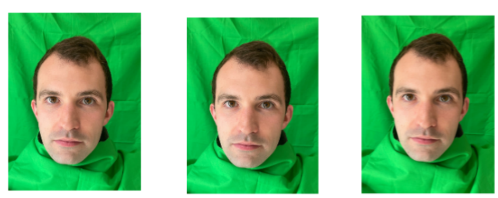
Bright Winter

True Winter

Deep Winter

Deep Autumn

True Autumn



Soft Autumn

Appendix B - Possible Season Result Outputs

Bright Spring

Bright + Warm

Bright Spring colouring combines brightness with warmth. And while this colour season has the typical freshness that is characteristic of all the Spring seasons, it also has some of the crisp and starker contrast of Winter. You have warm to neutral coloring with very high saturation and equal lightness and darkness.

The primary aspect of the Bright Spring colour palette is its vibrancy. The colours are bright and highly saturated. These are the most intense of the Spring colours. But they do retain the relative lightness of the Spring family. And so the colours are warm, fresh and full of new life, like the first budding signs of spring.

The palette features a broad range of hues with a heavy focus on pinks and jewel-like tones, such as turquoises and lime greens.

Colors to Avoid

Bright Winter

Bright + Cool

Bright Winter colouring combines brightness with coolness. And if anything, Bright Winter colours are extreme – extremely intense, light, dark and vibrant. Bright Winter sits on the cusp between Winter and Spring. Its colours – like those of all Winter seasons – are mainly cool, dark and bright.

But Spring increases the brightness of the already bright Winter palette, which creates the most intense, vibrant colours of all the seasons.

The palette contains acid greens, neon yellows and bright fuchsias that would overpower any other season. Spring also warms up the colours slightly, so that they are not as frosty as True Winter colours.

Colors to Avoid

Deep Autumn

Dark + Warm

Dark Autumn colouring combines depth with warmth. Consequently, Dark Autumn colours are the most pigmented and darkest of the Autumn family. Dark Autumn sits at the darkest and least warm end of the Autumn spectrum but still retains some warmth without drifting into the cool Winter palette.

True to Dark Autumn's primary colour aspect, the colours are deep. But there also lighter colours on the palette, which are necessary to create the high contrast naturally present in a Dark Autumn's appearance.

Most colours are yellow-based, making them naturally warm. The range of colours is also quite broad, but the focus lies on golden hues such as mustard yellow, oranges and reds. And although the colours may appear bright, they are not. It's their warmth that makes them rich. But this is not actual brightness.

Colors to Avoid

Deep Winter

Dark + Cool

Dark Winter combines depth with coolness. As a result, this season's colour palette is dark and intense. Often carrying hints of warmth, Dark Winter sits on the Autumn end of the Winter family. However, it needs the frosty influence of Winter rather than Autumn's rich, earthy tones.

True to Dark Winter's primary colour aspect, the colours are dark, neutral-cool, and somewhat bright to match the natural intensity of this season's natural colouring.

The colour palette includes highly saturated, highly contrasted and relatively bright colours. Though quite broad, the palette heavily features pinks, reds and purples as well as blues. The high contrast between the colours is required to replicate the natural contrast level of a Dark Winter.

Colors to Avoid

Light Spring

Light + Warm

Light Spring combines lightness with warmth. And while this season has the freshness characteristic of all Spring seasons, it also has some of the softness of Summer. True to this season's primary colour aspect, the colours are light. And even though they are gentle, the colours are by no means muted.

As part of the Spring family, this palette is pretty bright and colourful. It includes medium-saturated, low-contrast and warmish colours, like rose pinks and grass greens.

The Light Spring colour palette is essentially the standard Spring palette with some of the intensity and saturation removed. White has been added to the original Spring colours to make them lighter – the colours are not dark and heavy. In fact, the darkest of the Spring browns will often be too gloomy.

Colors to Avoid

Light Summer

Light + Cool

Light Summer combines lightness with coolness. Consequently, the colours are overall light in value to complement the appearance of a Light Summer. Light Summers have very light coloring with low contrast between features and have neutral to neutral-cool tones.

The palette contains medium-saturated, coolish colours, such as light pinks and delicate blue-greens. There are no harsh contrasts between the colours, only nuances.

And while this season's colour palette has the typical coolness that is characteristic of all the Summer seasons, it also has some of the warmth of its neighbouring season Spring. Moreover, Spring adds some brightness and saturation to the otherwise muted Summer palette. So much so, that this is the brightest and least faded season of the Summer family.

Colors to Avoid

Soft Autumn

Muted + Warm

Soft Autumn combines low chroma with warmth. Thus, the Soft Autumn colour palette is the original Autumn palette with some of the intensity removed.
True to Soft Autumn's primary colour aspect, the colours are muted and desaturated. There is little contrast between the colours. However, as part of the Autumn family and due to the gentle warmth in the colours, the overall effect of the Soft Autumn palette is rich, soft and inviting.

The best colours for this season are gentle and neither too cool nor too warm. This means the palette lacks colours such as the oranges of True Autumn or the darker colours from the Dark Autumn palette. Instead, the palette includes more gentle colours, such as olive greens and delicate reds and pinks.

Colors to Avoid

Soft Summer

Muted + Cool

Soft Summer is the colour season reminiscent of misty days when the heat carries the fog through the air after a cool summer rain. And the arrival of autumn is not far away. Soft Summers are very muted and cool, however, due to Autumn's influence they are darker than other Summers.

These colours are gentle and mysterious. They contain so many cold and warm tones that their collision gives rise to a surprisingly harmonious image. And like a chameleon, this colour season can show one side or another.

Soft Summer sits on the border to Autumn. Summer is muted, cool and light. The autumn influence also brings warmth, which adds a brownish element to the colours. Autumn also adds depth, and thus, Soft Summer colours are the darkest of the Summer family.

Colors to Avoid

True Autumn *Warm + Muted*

True Autumn is the original Autumn season of the four seasons colour analysis and is the 'standard' Spring palette. The other two Autumn palettes have been modified to accommodate the respective Summer and Winter influence.

True Autumn colouring combines warmth with softness. This season falls at the warmest, most golden end of Autumn. Therefore, the colours are warm with a clear yellow undertone. There is not a hint of coolness in this palette.

The True Autumn palette contains warm greens, golden yellows, orangey reds and lots of golden browns. The colours are dense, rich and warm.
Autumn is a season of muted colours. However, the True Autumn colour palette overall appears rich and vibrant. The colours' softness is only apparent when compared to a truly bright season, such as Spring.

Colors to Avoid

True Spring *Warm + Bright*

True Spring is the original Spring season of the four seasons colour analysis and is the 'standard' Spring palette. The other two Spring palettes have been modified to accommodate the respective Winter and Summer influence. True Springs have very warm coloring and bright to neutral-bright saturation.

True Spring colouring combines warmth with brightness. This season falls at the warmest, most golden end of Spring. Therefore, the colours are warm with a clear yellow undertone. There is not a hint of coolness in this palette.

The True Spring palette contains warm greens, yellows, orangey reds, peachy pinks and every shade of light brown from beige to tan. These colours are naturally yellow-based and warm.

Colors to Avoid

True Summer

Cool + Muted

True Summer is the original Summer season of the four seasons colour analysis and is the 'standard' Summer palette. The other two Summer palettes have been modified to accommodate the respective Spring and Autumn influence. True Summers are very cool-toned and lean lighter and less saturated.

The palette has the gentleness and delicacy typical of the Summer family. The colours are mid-range. And although there is a range of different hues, blues, turquoises and greys, which are naturally cool, feature heavily on the palette.

Cool browns and greyish blues work well as neutrals, accented by brighter hues, like pinks, purples and greens.

Colors to Avoid

True Winter

Cool + Bright

True Winter is the original Winter season of the four seasons colour analysis and is the 'standard' Winter palette. The other two Winter palettes have been modified to accommodate the respective Autumn and Spring influence.

True Winter colouring combines coolness with brightness. This season falls at the coolest, iciest end of Winter. Therefore, the colours are cool with a clear blue undertone. They are quite harsh and seem to be covered with frost.

The True Winter palette contains a broad range of colours, from icy pinks and purples to frosty blues. And even though the contrast between the colours is high, the dark tones are balanced with brighter and much lighter accent colours.

Colors to Avoid