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STYLE-SYNC : ML Powered Style Suggestion for every Occasion

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ABSTRACT

Fashion analytics has been a hot topic, such as predicting trends and fashion recommendations. As one of the dominant clothing features, color dramatically influences people's shopping behaviors. Understanding popular colors and color combinations is of high business value. The AI-based stylist model intends to identify the exact shades of colors with a specific prediction of their name and predict the other colors harmonizing with the detected one. Mixing and matching colorful clothes is an essential feature of having a good fashion sense. A study is reliable that a typical human can perceive about 1 million different shades of colors. Nevertheless, in several instances, an individual with "chroma" can see only 1% of them (i.e., 10,000 colors). On the other hand, most human beings get confused about finding the best harmonizing colors for their attire, and this may culminate in dowdy. In this thesis, we investigate compatible color combinations in fashion.

I. INTRODUCTION

Before going into the speculations of the project it is important to know the definition of color detection. It is simply the process of identifying the name of any color. It is obvious that humans perform this action naturally and do not put any effort into doing so. While it is not the case for computers. Human eyes and brain work in coordination to translate light into color. Light receptors that are present in the eyes transmit the signal to the brain which in turn recognizes the color. There is no exaggeration in saying that humans have mapped certain lights with their color names since childhood. The same strategy is useful in detecting color names in this project. Three different colors Red, Green, and Blue are being tracked by utilizing the fundamentals of computer vision. After successful compilation when we execute the code a window redirects to the image displayed on it whose path is given as an argument. Additionally, we obtain the color name of the pixel along with the composition of three different colors red, blue, and green values. It helps recognize colors and in robotics. One of the applications of color detection by computer vision is in driverless cars. This system is useful in detecting traffic and vehicle backlights and decidesto stop, start, and continue driving. This also has much application in industry to pick and place different colored objects by the robotic arm. Color detection is also used as a tool in various image editing and drawing apps.

Through empirical evaluation and comparative analysis, we demonstrate the efficacy of our proposed method in detecting anomalies within video streams. We provide insights into the strengths and limitations of our approach, along with potential avenues for future research and refinement.

Ultimately, our research endeavors to contribute to the advancement of intelligent video surveillance systems, fostering safer and more secure environments through enhanced anomaly detection capabilities. By harnessing the power of deep learning with YOLO, we aim to unveil anomaly empowerment and pave the way for more robust and adaptive surveillance solutions.

II. LITERATURE REVIEW

The main objective of the base thesis is to implement an application which is the methodology for identifying the shades of colors with an exact prediction with their names. A study says, a normal human is able to clearly identify nearly 1 million shades of colors. But in the case of humans having enchroma, they would be able to see only 1 percent (i.e.,10,000 colors) from the normal humans. While painting pictures, a painter needs to identify the color patterns exactly or else the reality of the image is not clear. In this paper we defined to get the required color field from an RGB image. In this various step are implemented using openCv platform. Below is the Literature Survey in Tabular form. It gives idea about all the supportive papers

[1]Color Detection of RGB Images Using Python and OpenCv [1]

The main objective of this paper is the methodology for identifying the shades of colors with an exact prediction with their names. In this phase, the 3 layered colors are extracted from the input image. All the color images on screens such as televisions, computer, monitors, laptops and mobile screens are produced by the combination of Red, Green and Blue light. Each primary color takes an intensive value 0 (lowest) to 255 (highest). When mixing 3 primary colors at different intensity levels a variety of colors are produced. For Example: If the intensity value of the primary colors is 0, this linear combination corresponds to black. If the intensity value of the primary colors is 1, this linear combination corresponds to white

(c)

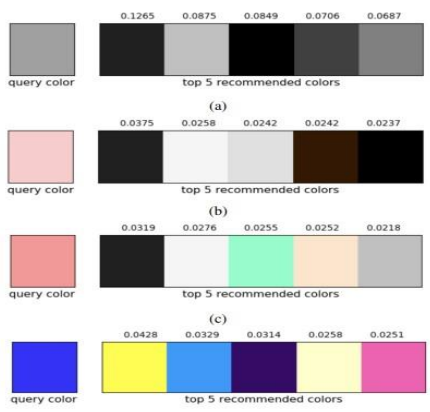
Figure 3: (a) Original input image of Salt Lake (b) Output image with Color intensity RGB values as R=3 G=9 B=97 for Royal Blue (c) Output image with Color intensity RGB values as R=252 G=229 B=13 for Golden Yellow

Towards color compatibility in fashion using machine learning (Xinhui Wang)

In this thesis, we tackle the problem towards compatible color combinations of clothing items in fashion. We separate the task in two parts. First, we employ Deeplab V2 trained on ModaNet dataset to segment clothing items out. Due to the large-scale and high-quality dataset we use for training, our semantic segmentation model achieves state-of-the-art performance comparing to other models proposed in this field, with 0.64 mIoU and 0.96 accuracy of the test set. Then we propose two methods to learn color compatibility and possibly make recommendations. The first method doesn't work well because of the relatively high loss of the model. Alternatively, the second method item-to-item collaborative f exploits the relationship between color to color and constructs a recommendation system to quantify color compatibility in fashion. Our system makes highquality color recommendations with a hit-rate of 0.49 for top 5 recommendations matrix factorization to predict the color values of the missing garments in order to make recommendations. However, this method has a relatively high loss because of the sparsity of data and inner connections among R, G, B values of one clothing item. It turns out that using matrix factorization to predict ratings is different from using it to directly predict color values where the values are dependent on others.

Object color recognition and sorting robot based on OpenCV and machine vision (Wenbin Zhang, Chengliang Zhang*, Chengbin Li, He Zhang)

This system takes the OpenCV image processing library as the core, uses image processing algorithms such as colorspace conversion, histogram equalization, filtering, Huff circle transformation, and combines the traditional three-axis truss mechanical structure to design an intelligent color recognition analysis Picking robot system. In order to realize the sorting function, the key technologies such as camera calibration, image filtering, object recognition, and positioning are studied. However, there are certain misjudgements of this system in special light and object angles, which need to be improved in the future research process.



III. METHODOLOGY

Image Capture: The first step is to fetch a high-quality image with resolution. To load an image from a file we useCv2.imread(). The image should be in the working directory or the full path of the image should be given. Img=cv2.imread(img path) Extraction of RGB Colors: In this phase, the 3 layered colors are extracted from the input image. All the color images on screens such as televisions, computers, monitors, laptops, and mobile screens are produced by the combination of Red, Green, and Blue light. Each primary color takes an intensive value from 0 (lowest) to 255 (highest). When mixing 3 primary colors at different intensity levels a variety of colors are produced. For Example: If the intensity value of the primary colors is 0, this linear combination corresponds to black. If the intensity value of the primary colors is 1, this linear combination corresponds to white. Index=["color", "color_name", "hex", "R", "G", "B"] Calculate minimum distance from coordinates: The minimum distance is calculated by considering moving towards the origin point from all colors to get the most matching color. The panda's library serves as an important utility to perform various operations on commaseparated values like pd.read_csv() reads the CSV file and loads it into the panda's data frame. D = abs(Rint(CSV.loc[i, "R"])) + abs (G-int (CSV. loc[i, "G"])) + abs (B- int (CSV. loc [i, "B"])) Image Display with Shades of Color: The rectangle window is used to display the image with shades of color. After the double-click is triggered, the RGB values and color names are updated. To display an image Cv2.imshow () method is used. By using the cv2.rectangle and cv2.putText () functions, the color name and its intensity level can be obtained. text=getColorName(r,g,b) + 'R='+str(r) + 'G='+str(g) + 'B=' +str(b).

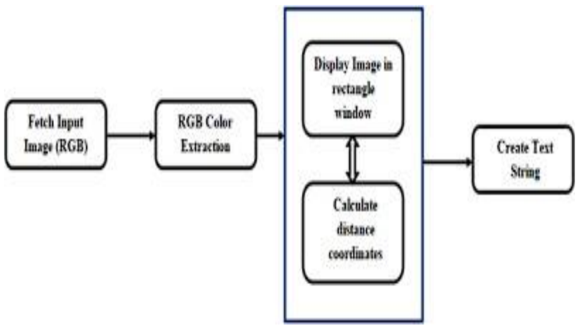


Fig - 1**: Architecture Diagram**

The above architecture shows the capability of the project. It consists of a well-defined sequence diagram that is abstracted from the source code. It leverages the rich capabilities of technology such as the OpenCV library in Python. The above architecture makes the process more efficient based on principles and properties related to each other. As we know Red, Green, and Blue are the primary colors that can be mixed to produce different colors. The present color detection project takes the path of an image as an input and looks for the composition of three different colors red, green, and blue

II.[A]Exploratory Factor Analysis (EFA)

EFA using a principal component analysis method was performed on 27-scale items of the exogenous variables and endogenous variables. Because of high cross-loading (>.40; Hair, Black, Babin, & Anderson, 2010), 1 item of the technology attitudes was dropped. The final factor analysis solution had a total of 26 items that measured six factors and accounted for approximately 85.06% of the total variance. All commonalities ranged between .666 and .966, while Cronbach's ranged from .785 to .982, demonstrating the good reliability of the scales. EFA loadings ranging from .748 to .932 are reported in Table 3.

II.[B]Confirmatory Factor Analysis (CFA)

CFA was conducted on perceived usefulness, perceived ease of use, performance risk, technology attitudes, attitude toward AI, and purchase intention of Echo Look. Three items with high modification indices were dropped from further analysis. Dropped items included one from perceived usefulness and two from perceived ease of use. CFA on all remaining 23 items showed an excellent fit (w2 ¼ 339.827; df ¼ 215; w2 /df ¼ 1.581; p < .001; root mean square residual [RMSEA] ¼ .043; comparative fit index [CFI] ¼ .985; goodness-of-fit index [GFI] ¼ .913), providing evidence of convergent validity. The good fit indices lend support for the construct validity of individual constructs in the model, as indicated by the earlier EFA. As reported in Table 4, each item loaded significantly on its proposed constructs, with composite reliabilities above .80, providing evidence of the reliability of the measures (Hair et al., 2010)

Table 2. Demographic Characteristics of Research Sample.

Characteristic	Percent	Characteristic	Percent
Gender		Education	
Male	39.3	Less than high school	1
Female	60.7	High school graduate	12.7
Age		Some college	22.7
18–24	8.9	2-Year degree	9.3
25–34	28.2	4-Year degree	37.7
35–44	22.7	Professional degree	14.7
45–54	15.6	Doctorate	1.9
55–64	23.6	Total household income	
65 and above	1.0	Less than $5,000	1.9
Ethnicity		$5,000–9,000	2.9
Caucasian	72.2	$10,000–19,999	5.1
African American	11.2	$20,000–29,999	10.5
Asian/Asian American	9.9	$30,000–39,999	8.3
Hispanic/Latino	6.1	$40,000–49,999	9.3
Native American	0.3	$50,000–59,999	10.5
Other	0.3	$60,000–69,999	9.3
Employment		$70,000–79,999	7.0
Employed full time (40 or more hr per week)	47	$80,000–89,999	6.1
Employed part time (up to 39 hr per week)	9.9	$90,000–99,999	4.5
Unemployed and currently looking for work	6.1	$100,000–149,999	14.4
Unemployed and not currently looking for work	1.9	$150,000–199,999	6.4
Graduate student	1	$200,000–249,999	2.2
Undergraduate student	2.2	$250,000 or more	1.6
Retired	8	Marital status	
Homemaker	15.7	Married	54.0
Self-employed	3.7	Single	42.2
Unable to work	4.5	Other	3.8

Note. $n = 313$.

Results showed good internal consistency of multiple indicators for each construct. The average variance extracted (AVE), which ranged from .559 to .948, exceeded the recommended value of .50 (Fornell & Larcker, 1981). All standardized CFA loadings were significant (p < .001) and exceeded .70 (ranging from .745 to .982), showing strong convergent validity (items that are indicators of a specific construct share a high proportion of variance in common; Anderson & Gerbing, 1988; Hair et al., 2010). Also, as shown in Table 5, AVE for each construct was greater than the estimates of squared correlations between constructs, confirming discriminant validity (the extent to which a construct is truly distinct from other constructs; Fornell & Larcker, 1981; Hair et al., 2010). Model Development and Hypotheses Testing SEM (Hair et al., 2010; Kline, 2010) was used to test the research model. The model fit was very good (w2 ¼ 409.591; df ¼ 218; w2 /df ¼ 1.879; p < .001; RMSEA ¼ .053; CFI ¼ .977;

GFI ¼ .895). A comparison of these values against recommended values suggests that the model estimation result is satisfactory (Kline, 2010; MacCallum, Browne, & Sugawara, 1996). The results ofhypothesized relationships are summarized in Table 6. As shown in Table 6, perceived usefulness, perceived ease of use, performance risk, and technology attitudes positively influence consumers' attitudes toward AI. Attitudes toward AI had a direct positive effect on consumers' purchase intention. Therefore, we found support for Hypotheses 1, 2, 3, 4b, and 5. We do not find support for Hypothesis 4a, in which we suggested that technology attitude positively influences consumers' attitudes toward AI.

Table 3. Exploratory Factor Analysis (EFA) Results.

Factor	Scale Item	EFA Loadings	Reliability
Perceived usefulness (PU)	Choose my outfit faster (PU 1)	.834	.980
	Improve my performance in choosing the most trendy outfit (PU 2)	.862	
	Increase my efficiency in choosing the most trendy outfit (PU 3)	.864	
	Enhance my effectiveness in choosing the most trendy outfit (PU 4)	.866	
	Make it easier for me to pick out what to wear (PU 5)	.841	
	Be useful for choosing the most trendy outfit (PU 6)	.860	
Perceived ease of use (PEOU)	Learning to operate this device would be easy (PEOU 1)	.810	.953
	I think I would find it would be easy to get this device to do what I want it to do (PEOU 2)	.801	
	My interaction with this device would be clear and understandable (PEOU 3)	.822	
	This device would be flexible to interact with (PEOU 4)	.803	
	It would be easy to become skillful at using this device (PEOU 5)	.862	
	I think this device would be easy to use (PEOU 6)	.857	
Performance risk (PR)	I am concerned that the product advertised in the video is different from the actual product (PR 1)	.891	.894
	I am afraid that the product advertised in the video would not perform the way I expect (PR 2)	.932	
	I am concerned about whether this product would really "perform" as well as it is supposed to (PR 3)	.863	
Technology attitudes (TechAtt)	Technology will provide solutions to many of our problems (TechAtt 2)	.779	.785
	With technology anything is possible (TechAtt 3)	.756	
	I feel that I get more accomplished because of technology (TechAtt 4)	.748	
Attitude toward AI	Worthless—Valuable (Attitude 1)	.761	.949
	Unfavorable—Favorable (Attitude 2)	.859	
	Disagreeable—Agreeable (Attitude 3)	.834	
	Harmful—Beneficial (Attitude 4)	.861	
	Dislike—Like (Attitude 5)	.801	
Purchase intention (PI)	The likelihood that I would purchase Echo Look (PI 1)	.808	.982
	The probability that I would consider buying Echo Look (PI 2)	.785	
	My willingness to buy Echo Look (PI 3)	.789	

Note. AVE = average variance extracted; AI = artificial intelligence.

Testing Moderating Effects The sum of respondents' evaluation on all 11 items of fashion involvement was calculated, and the median score (33.00) was used to form two groups. The items were obtained from O'Cass's (2004) study, which evaluated how much participants are interested in fashion clothing (e.g., "I am very interested in fashion clothing") and how much they value the importance of fashion clothing in their life (e.g., "Fashion clothing is an important part of my life"). Multivariate analysis of variance showed that consumers of higher fashion involvement were younger and had more stable occupations than consumers of lower fashion involvement, but there was no difference in ethnicity, gender, education, and income between the groups. The multigroup comparison was conducted to examine

Table 4. Confirmatory Factor Analysis (CFA) Results of Measurement Properties.

Scale Item	Composite Reliability	AVE	CFA Loadings
Perceived usefulness (PU)	.977	.896	
PU 1			.893
PU 2			.953
PU 3			.966
PU 4			.957
PU 6			.961
Perceived ease of use (PEOU)	.945	.811	
PEOU 2			.876
PEOU 3			.949
PEOU 4			.899
PEOU 5			.877
Performance risk (PR)	.899	.750	
PR 1			.818
PR 2			.978
PR 3			.790
Technology attitude (TechAtt)	.791	.559	
TechAtt 2			.822
TechAtt 3			.669
TechAtt 4			.745
Attitude toward AI	.952	.800	
Attitude 1			.766
Attitude 2			.946
Attitude 3			.929
Attitude 4			.900
Attitude 5			.919
Purchase intention (PI)	.982	.948	
PI 1			.962
PI 2			.982
PI 3			.977

Note. AI = artificial intelligence.

whether the magnitude of the influences from perceived usefulness, perceived ease of use, performance risk, technology attitudes on attitude toward AI, and the magnitude of the influence from attitude toward AI on purchase intention differed across these two groups (Hair et al., 2010). A constrained multigroup model (Model 1/base model—no moderating effects) was estimated. Each structural weight wasconstrained to be equal across the two

groups. This mode had an acceptable fit (w2 ¼ 754.404; df ¼ 447; w2 /df ¼ 1.688; CFI ¼ .959; RMSEA ¼ .047). An unconstrained multigroup model (Model 2—moderating effects) was then estimated, in which the structural weights were estimated uniquely for each group. The unconstrained model exhibited an acceptable fit (w2 ¼ 657.128; df ¼ 436; w2/df ¼ 1.507; CFI ¼ .971; RMSEA ¼ .04) Therefore, the w2 difference (Dw2 ¼ 97.276; df ¼ 11; p < .001) between the two models was significant at the group level, indicating the influences from perceived usefulness, perceived ease of use, performance risk, technology attitudes on attitude toward AI, and the magnitude of the influence from attitude toward AI on purchase intention do differ for consumers of high fashion involvement and low fashion involvement. To further test the influence of each exogenous variable, each path was constrained separately and the w2 difference was compared with the w2 threshold. The results indicate that the relationship between technology attitude and purchase intention is significantly different (with 99% confidence) for consumers of high versus low fashion involvement. Specifically, the effect of technology attitude on purchase intention is significant only for consumers of higher fashion involvement. Therefore, Hypothesis 6a was supported.

Table 5. Squared Correlation Matrix With AVE on the Diagonal.

Variables	Attitude Toward AI	Perceived Usefulness	Technology Attitude	Performance Risk	Purchase Intention	Perceived Ease of Use
Attitude toward AI	.894					
Perceived usefulness	.610	.946				
Technology attitude	.439	.536	.748			
Performance risk	−.256	−.161	−.125	.866		
Purchase intention	.636	.716	.492	−.147	.947	
Perceived ease of use	.546	.608	.600	−.282	.502	.901

Note. Values along the diagonal indicate the average variance extracted for each construct. Off-diagonal values indicate squared correlations between constructs. AVE = average variance extracted; AI = artificial intelligence.

Table 6. Summary of Hypotheses (1–5) and Testing Results.

Path to	Path From	Path Coefficient	*p*	Hypothesis Testing
Attitude toward AI	Perceived usefulness	.445	**	Hypothesis 1 supported
	Perceived ease of use	.225	*	Hypothesis 2 supported
	Performance risk	−.116	*	Hypothesis 3 supported
	Technology attitudes	.032	*ns*	Hypothesis 4a not supported
Purchase intention	Technology attitudes	.313	**	Hypothesis 4b supported
	Attitude toward AI	.506	**	Hypothesis 5 supported

Note. AI = artificial intelligence.
*$p < .05$. **$p < .001$.

Limitations and Future Research

The current study has some limitations that suggest interesting opportunities for future research. This study recruited participants from the top 10 metropolitan areas in the United States, which may have limited the representativeness of the results. Future researchers may explore the attitudes and purchase intentions of consumers from both urban and rural areas. Moreover, as this study used the Echo Look as a stimulus and consumers did not have the experience of using it before, research findings need to be interpreted cautiously due to dynamic and ever-changing technology advancement. This study's focus on a single product (i.e., Amazon's Echo Look) limits its generalization to other fashion AI products. Future researchers may extend this current model to other types of fashion AI products (such as in- store technology and VPAs) and compare the perceptions with consumers' postadoption evaluations.

COLOR COMPOSITION INFORMATION EXTRACTION

This module forms the building block of the entire system, which extracts color-related information from an input image. Specifically, it consists of the following two

steps: 1) extract distinct colors, along with their proportions, from the image by applying a multi-resolution color quantization and indexing mechanism; and

2) name each color based on a mapping table of color values (in RGB format) and color names, which is pre-constructed based on some web sources. In particular, we have applied an octree structure-based color quantization approach to cluster and identify distinct colors, which has been approved to be very efficient and effective in the context of image indexing and retrieval. Since these colors are represented by RGB values, we then name them with specific color names. This is achieved by finding the closest color in the mapping table based on Euclidean distance in LUV color space. Fig. 2 illustrates this process where the output of the given image is shown on the right. Proportions of extracted colors are represented by the stacked vertical bar alongside. As we expected, the top four colors of this particular image are identified to be linen white, brown, black, and dark golden rods.

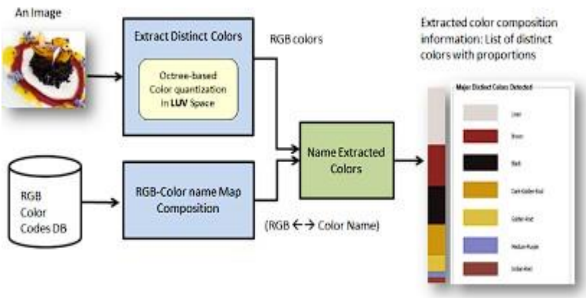


Fig. 2. Process of color composition information extraction.

COLOR-MESSAGE GRAPH CONSTRUCTION

Color psychology is the study of color as a determinant of human behavior. A general model of color psychology relies on basic principles such as "color can carry specific meaning, which is either based on learned meaning or biologically innate meaning" and "the perception of a color causes automatic evaluation by the person perceiving, which forces color motivated behavior". Very rich literature can be found on studying colors and their psychological effects in a broad range of areas. Examples include marketing [1], academic and sports performance store designs, etc. While it is true that color meanings are subjective and vary with people, there are indeed broadermessaging patterns to be found in color perceptions. Research has also shown that there is a real connection between the use of colors and customers' perceptions of a brand's personality. For instance, Apple uses white color to show its love of clean and simple design, while black is the color of power, authority, and control. Black makes products appear heavier and more expensive and transmits a higher perceived value [16]. On the other hand, as red conveys energy, passion, and strength, using red for packaging can stimulate senses and excite potential purchasers. Based on the aforementioned prior academic research as well as the domain expertise in this area we have thus compiled a comprehensive table that maps a message to color(s) that convey corresponding psychological meanings. One portion of such a table is shown in Table 1, where we see that one message can be represented by multiple colors, and one color can have multiple meanings. Note that culture and context would be two dynamic factors in interpreting color messages, so theoretically, we could compile multiple tables w.r.t. these two parameters. Nevertheless, we use one table to ease the illustration of the approach here

Table 1. A map from messages to packaging colors.

Message	**Packaging Color**
Adventure	Orange
Affordability	Orange
Authority	Black
Calmness	Blue
Cheerful	Yellow, Orange
Cleanliness	Blue, Turquoise, White
Creativity	Black & Magenta, Light Blue, Yellow
Innovation	Yellow, Purple, Magenta
Health	Green, Brown
Passion	Red
Security	Blue, Brown, Green
Wholesome	Dark Green, Brown

From the table, we also see that there are certain interrelationships among the messages. For instance, creativity and innovation are synonyms, while adventure and security are likely antonyms. We have thus built a message ontology by exploring the relationships among messages according to certain knowledge sources such as Thesaurus. shows one portion of such ontology graph, where each node indicates one message and is filled with a representative color. A solid link between two nodes indicates a synonymic relationship while a dashed line indicates an antonymic relationship. Note that for illustration purposes, when a message is conveyed by multiple colors, we only use one of its colors in the graph.

COLOR PALETTE GENERATION

We are now ready to generate color palettes to assist product packaging design. This process consists of both divergence and convergence (or pruning) steps. Fig. 4 shows the overall processing flow. Specifically, it takes three inputs from users including the targeted product, brand, and messages. An example of such a design task could be "Design a Cereal product package for Quaker which conveys fun and nutritious messages to the market". Other parameters such as the targeted customer segments or countries can also be taken asinputs but for now, we omit them here.

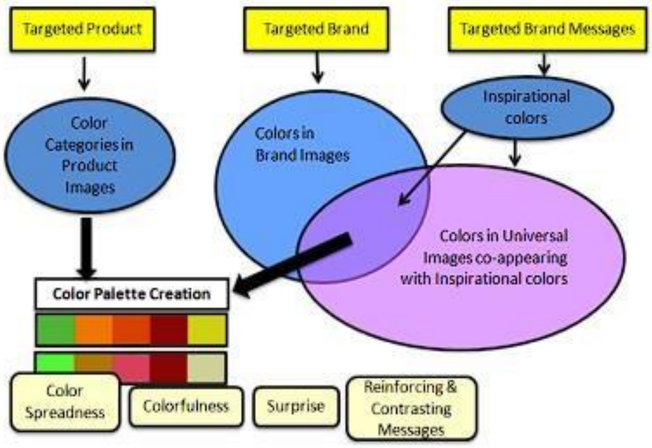


Fig. 4. Process flow of color palette generation.

CONCLUSION

The Project is developed using OpenCV a library of Python which provides vision to computers. The detection of the color of attire is taken as input by the model and the perfect combination of the colors is printed in the form of color strings. It is capable of bringing revolution in the field of Fashion Industry introducing various aspects of Machine Learning and Artificial intelligence in it. The base paper used givesus an idea about the detection of exact color by finding coordinates of color in theRGBscale. The developedrecommendation model uses a color palletdataset through Machine learning to give the output. 1) Commercial use in fashion malls: If combined with various aspects of IoT and hardware can be used for various Fashion Stores locally as well as Online helping customers to find perfect attire based on color scheme. 2) Social Media impact: It can be integrated with various social media platforms to so to make itselfa tool for marketing. 3) Personal use: Various aspects of personal use can be exploited if combined with daily facilities. In short, the techniques we have opted forcan be integrated to achieve a highly reliable model to recommend combinations as well as to set new trends in apparel. The fashion industry is ever- increasing and expanding and the role of this application is an important.

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