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Preparing Images for Embroidery

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This thesis was defended successfully on **23/02/2022** and approved by:

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Declaration

I declare that this thesis has been composed by me and that is has not been submitted in whole or in part, in any previous application for a degree. Except where states otherwise by preference or acknowledgment, the work presented is entirely my own.

Name: Mohammed S. Fuqaha.

Signature:

Date:10/8/2022.

Dedication

I dedicate this thesis to my family and friends for the unconditional love and support that they have shown and given to me. To the person who is no longer around when I needed them most, whose absence made everything much more difficult than it already is. So, to your absence which I have felt in writing this thesis, I dedicate it.

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Acknowledgments

I would like to take this opportunity to express my deep regards to Dr. Muath Sabha for his advice, support, and time he spent reviewing my work. Dr. Muath provided valuable suggestions that have had a significant impact and helped in overcoming many obstacles in writing this thesis in the best way.

Abstract

Embroidery may now be seen on shirts, caps, jackets, and a variety of other items. Our eyes must view embroidery as a fully-meaningful image since it has been knitted with a range of thread colors. Because most colorful photographs contain a large number of different shades of color, we are unable to produce thread in the same color for each of these shades. To overcome this problem, we looked up thread manufacturers and discovered that DMC uses 454 colors based on the Munsell color model, which is similar to the HSV color system. In order to turn each segment into the nearest color in DMC color space, we wish to use the AB dimensions from the CIELAB color space in picture segmentation.

Image colors in the CIELAB color space will be reduced to the complete DMC colors utilized in the colored thread manufacturing process. Our major goal is to divide the image into small segments, each of one color, and then convert it to the nearest DMC Color to receive the thread we need to embroider the canvas. To acquire the requisite number of DMC colors, a k-means clustering technique or a superpixel algorithm would be used. We aim to extract all of the colors that the brain can identify in each embroidered image in this thesis.

To decrease the number of various colors that may be utilized on canvas, we employed the Delta function for the color difference, k-means clustering, and superpixel. Because k-means clustering with delta function has less distortion or noise than superpixel, and because the output is much better with high resolution than low resolution, we may utilize high-quality photos and subsequently scale them as needed for canvas.

Contents

Chapter 1: Introduction

Any photographed image often comprises a large number of colors, making it challenging to employ in embroidery stitches. We suggest developing an algorithm for reducing the number of colors in any image so that it may be stitched (Ripka, Mychko, & Deyneka, 2014). The colors will be reduced in stages, first to the DOLLFUS-MIEG & Compagnie (DMC) color space, which has 454 colors, and then to the CIELAB color space, using the new algorithm "Delta E" (Roehrig et al 2010) for grouping colors instead of the L2Norm, because the L2Norm uses Euclidean distance between two pixels and ignores the importance of hue and saturation. The image's dimensions will then be changed to metric dimensions to fit the embroidery canvas.

Since embroidery is used in a variety of industries and to decorate fabrics, the extraction and reduction of important colors have increased the demand for this field of work, especially because reducing colors usually leads to ease of work, increased production, and lower costs, all of which led to increased profits. As a result, this study aims to assist many companies in using the colors required to produce high-quality embroidery.

We'll apply the Superpixels algorithm, which is defined as the result of perceptual aggregation of pixels with more significance than pixels and better picture edge alignment than rectangular image rectification. So, the k-means algorithm, which refers to repeating the calculation of the centroid to have the ideal centroid (Hui, & Han, 2019), and the cell (superpixel (Ibrahim, & El-kenawy, 2020)) algorithm, will be examined to identify the best manner of segmentation. The Delta E method (Mokrzycki, & Tatol, 2011) will be used to calculate the best-matched outcomes. The picture will be segmented, resulting in a reduction in the number of results based on color grouping and image segmentation.

Many factors influence the image, including resolution, size, and the presence of an unwanted item in the image (Noise) (Ibrahim et al, 2020). As a result, we will analyze all of the elements that may have an impact on our job.

It is critical to study and comprehend color spaces. It's critical to understand how to make advantage of these color areas in our daily life.

Our study will develop a novel method for converting a given picture into Embroidery with the fewest possible colors for usage on canvas.

1.1. Objective

In embroidery, when we want to embroider an image on a canvas, it is impossible to provide threads with the color of all the pixels that make up the image. It is also difficult to use hand embroidery using needles and threads to embroider the image with such a large number of colors. So, it is very difficult to embroider images as they are.

Because DMC makes a variety of colored threads, the overall goal of this study is to figure out how to limit the number of colors in a picture so that it may be embodied using the DMC Color Space. The color reduction is based on a model with many phases:

- The first step of the Delta Function is based on measuring the discrepancies between picture pixel color and the DMC Colors. The colors of the picture that may be embroidered are then acquired by replacing the image pixel color with the appropriate DMC color. To remove noise from photos.
- The second stage uses k-means clustering and superpixels to arrange the nearest colors into groups.

- The third step uses k-means clustering and superpixels to remove noise from images, for replacing the picture pixel colors, the Delta Function is employed again. For reference picture colors, the DMC Color Dataset was used.

1.2. Contribution

This thesis presents several models for reducing the color of pixels based on the DMC Color Space dataset. With regard to classification, k-means clustering and superpixel are evaluated for image segmentation to choose the best segmentation method that produces the lowest number of different colors with a high quality that can be embroidered on canvas.

1.3. Thesis Structure

The remainder of this thesis is organized as follows: In Chapter 2, we provide a background that includes the description of embroidery and how it can be used on canvas. The CIE color system, and the DMC dataset. we descript the methods that we are going to use (Delta Function, K-means Clustering (Khandare, & Alvi, 2016), superpixel) and, review the related work. In chapter 3 we describe the proposed methods and their phases, including the functions that we create. in chapter 4 we provide the experiments and results. And in chapter 5, Conclusion and Future Work.

Chapter 2: Background

Based on the great development in the hand embroidery business and the difficulty of identifying and manufacturing the colors of the threads that are used to embroider pictures that contain a lot of colors, this work allows hand embroidering images regardless of the number of colors, Figure 1.

Figure 1: Embroidery Image Example (Barnes, 2020)

2.1. CIE Color Spaces

The CIE (Commission Internationale d'Eclairage) is an international commission on illumination that developed a mathematical model that tries to numerically characterize any color perceptible to the human eye (Service, 2013). CIE LAB (L*a*b*) is a part of the CIE System, which differs from RGB and CMYK color models in that it is designed to approximate human vision, rather than the color definitions characterized by CIE systems, which are unambiguous, non-restrictive, and influenced by, or dependent on, the characteristics or capabilities of any color capturing or rendering device. In practice, only for a specific observer/illuminant situation with a Euclidean ΔE metric (Zhbanova, 2021) is it employed for color comparisons.

The CIELAB colorimetric reference system has become the industry standard for quantifying and conveying color. The CIELAB Color Model is used as a reference model in the paper and graphic industries (Hassan, 2022). CIELAB manages color using gamut color mapping as a foundation. CIELAB's core design and operational assumption are founded on scientific theory indicating that the brain interprets retinal color inputs into differences between light and dark (lightness) and mutually exclusive zones of opposing colors: red/green and blue/yellow (O'Donovan, 2015).

The CIE LAB color system contains three channels, one for lightness (L*) and the others for color (a* and b*). In the 3D model, the chromatic a* is an axis extending from green to red (+a* to -a*), and the chromatic b* is an axis extending from blue to yellow (+b* to -b*). The lightness dimension,

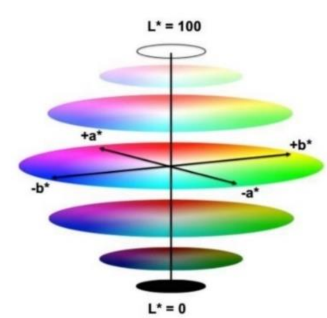


Figure 2: CIE LAB Color Space (Service, 2013)

represented by L*, ranges from 0 (pure black) to 100 (diffuse white), Figure 2.

2.2. DMC Datasets Description

Because of the community's interest in trade, art entered the trade in the manufacture of fabrics, to show the beautiful art in the manufacture of hand-drawn prints and printing on fabrics. Thus, threads were manufactured and processed and given beautiful colors. A group of 454 colors was used in the manufacture of threads used in the manufacture of paints on fabrics (DMC, 2022)].

As mentioned previously, 454 colors were extracted from the colors found in nature and placed in a list to become a reference for the manufacture of embroidery thread colors so that any image is embroidered using these colors which will be our reference for all our work. Table 1.

Table 1: DMC Color Table List (Appendix1) (Camelia, 2021)

R	G	B	Name	
255	226	226	Salmon Very Light	
255	201	201	Salmon Light	
245	173	173	Salmon	
241	135	135	Salmon Medium	
227	109	109	Salmon Dark	
191	45	45	Salmon Very Dark	
254	215	204	Peach	
253	156	151	Coral Light	
233	106	103	Coral	
224	72	72	Coral Medium	
210	16	53	Coral Dark	
187	5	31	Coral Red Very Dark	
255	203	213	Melon Light	
255	173	188	Melon Medium	
255	121	146	Melon Dark	
231	73	103	Melon Very Dark	
227	29	66	Bright Red	
199	43	59	Red	
183	31	51	Red Medium	
167	19	43	Red Dark	
151	11	35	Garnet	
135	7	31	Garnet Medium	
123	0	27	Garnet Dark	
255	178	187	Carnation Very Light	
252	144	162	Carnation Light	
255	121	140	Carnation Medium	
255	87	115	Carnation Dark	
255	223	217	Baby Pink	
253	181	181	Geranium Pale	
255	145	145	Geranium	
214	43	91	Rose Dark	
255	215	215	Dusty Rose Ult Vy Lt	
255	189	189	Dusty Rose Med Vy Lt	
230	138	138	Dusty Rose Medium	
207	115	115	Dusty Rose Dark	
234	134	153	Raspberry Light	
219	85	110	Raspberry Medium	
179	47	72	Raspberry Dark	
145	53	70	Raspberry Very Dark	
255	238	235	Baby Pink Light	
251	173	180	Rose Light	
252	176	185	Pink Medium	
242	118	136	Rose Medium	
238	84	110	Rose	
179	59	75	Rose Very Dark	
240	206	212	Dusty Rose Vry Lt	
228	166	172	Dusty Rose Light	
232	135	155	Dusty Rose	
218	103	131	Dusty Rose Very Dark	
188	67	101	Dusty Rose Ultra Dark	
171	2	73	Dusty Rose Ult Vy Dk	
251	191	194	Mauve Light	
231	169	172	Mauve Medium	
201	107	112	Mauve	
171	51	87	Mauve Dark	
136	21	49	Mauve Very Dark	
255	192	205	Cranberry Very Light	
255	176	190	Cranberry Light	
255	164	190	Cranberry	
226	72	116	Cranberry Medium	
209	40	106	Cranberry Dark	
205	47	99	Cranberry Very Dark	
255	140	174	Cyclamen Pink Light	
243	71	139	Cyclamen Pink	
224	40	118	Cyclamen Pink Dark	
244	174	213	Plum Ultra Light	
234	156	196	Plum Very Light	
197	73	137	Plum Light	
156	36	98	Plum	
155	19	89	Plum Medium	
130	0	67	Plum Dark	
255	223	213	Shell Pink Ult Vy Lt	
235	183	175	Shell Pink Very Light	
226	160	153	Shell Pink Med Light	
204	132	124	Shell Pink Light	
188	108	100	Shell Pink Med	
161	75	81	Shell Pink Dark	
136	62	67	Shell Pink Vy Dk	
223	179	187	Antique Mauve Vy Lt	
219	169	178	Antique Mauve Light	
183	115	127	Antique Mauve Med	
155	91	102	Antique Mauve Dark	
129	73	82	Antique Mauve Md Dk	
113	65	73	Antique Mauve Vy Dk	
130	38	55	Garnet Very Dark	
215	203	211	Antique Violet Vy Lt	
183	157	167	Antique Violet Light	
149	111	124	Antique Violet Medium	
120	87	98	Antique Violet Dark	
186	145	170	Grape Light	
148	96	131	Grape Medium	
114	55	93	Grape Dark	
87	36	51	Grape Very Dark	
227	203	227	Lavender Light	
195	159	195	Lavender Medium	
163	123	167	Lavender Dark	
131	91	139	Lavender Very Dark	
108	58	110	Lavender Ultra Dark	
99	54	102	Violet Dark	
230	204	217	Violet Very Light	
219	179	203	Violet Light	
163	99	139	Violet	
128	58	107	Violet Medium	
92	24	78	Violet Very Dark	
211	215	237	Blue Violet Vy Lt	
183	191	221	Blue Violet Light	
163	174	209	Blue Violet Med Lt	
173	167	199	Blue Violet Medium	
152	145	182	Blue Violet Med Dark	
119	107	152	Blue Violet Dark	
92	84	120	Blue Violet Very Dark	
187	195	217	Cornflower Blue Vy Lt	
143	156	193	Cornflower Blue Light	
112	125	162	Cornflower Blue Med	
96	103	140	Cornflower Blue	
85	91	123	Cornflower Blue Dark	
76	82	110	Cornflower Blu M V D	
70	69	99	Cornflower Blue V D	
176	192	218	Lavender Blue Light	
123	142	171	Lavender Blue Med	
92	114	148	Lavender Blue Dark	
192	204	222	Delft Blue Pale	
148	168	198	Delft Blue	
116	142	182	Delft Blue Medium	
70	106	142	Delft Blue Dark	
19	71	125	Royal Blue	
17	65	109	Royal Blue Dark	
14	54	92	Royal Blue Very Dark	
219	236	245	Blue Ultra Very Light	
189	221	237	Blue Very Light	
161	194	215	Blue Light	
107	158	191	Blue Medium	
71	129	165	Blue Dark	
57	105	135	Blue Very Dark	
48	194	236	Electric Blue Medium	
20	170	208	Electric Blue	
38	150	182	Electric Blue Dark	
6	227	230	Turquoise Bright Light	
4	196	202	Turquoise Bright Med	
18	174	186	Turquoise Bright Dark	
199	202	215	Blue Gray Light	
153	159	183	Blue Gray Medium	
120	128	164	Blue Gray	
238	252	252	Baby Blue Ult Vy Lt	
217	235	241	Baby Blue Very Light	
205	223	237	Baby Blue Pale	
184	210	230	Baby Blue Light	
147	180	206	Baby Blue	
115	159	193	Baby Blue Medium	
90	143	184	Baby Blue Dark	
53	102	139	Baby Blue Very Dark	
44	89	124	Baby Blue Ult Vy Dk	
37	59	115	Navy Blue	
33	48	99	Navy Blue Dark	
27	40	83	Navy Blue Very Dark	
219	226	233	Antique Blue Ult Vy Lt	
199	209	219	Antique Blue Very Lt	
162	181	198	Antique Blue Light	
106	133	158	Antique Blue Medium	
69	92	113	Antique Blue Dark	
56	76	94	Antique Blue Very Dk	
197	232	237	Sky Blue Vy Lt	
172	216	226	Sky Blue Light	
126	177	200	Sky Blue	
79	147	167	Wedgewood Light	
62	133	162	Wedgewood Med	
59	118	143	Wedgewood Dark	
50	102	124	Wedgewood Vry Dk	
28	80	102	Wedgewood Ult VyDk	
229	252	253	Peacock Blue Vy Lt	
153	207	217	Peacock Blue Light	
100	171	186	Peacock Blue	
61	149	165	Peacock Blue Dark	
52	127	140	Peacock Blue Vy Dk	
188	227	230	Turquoise Very Light	
144	195	204	Turquoise Light	
91	163	179	Turquoise	
72	142	154	Turquoise Dark	
63	124	133	Turquoise Vy Dark	
54	105	112	Turquoise Ult Vy Dk	
221	227	227	Gray Green Vy Lt	
189	203	203	Gray Green Light	
152	174	174	Gray Green Med	
101	127	127	Gray Green Dark	
86	106	106	Gray Green Vy Dark	
82	179	164	Teal Green Light	
85	147	146	Teal Green Med	
52	125	117	Teal Green Dark	
169	226	216	Sea Green Light	
89	199	180	Sea Green Med	
62	182	161	Sea Green Dark	
47	140	132	Sea Green Vy Dk	
73	179	161	Green Bright Lt	
61	147	132	Green Bright Md	
55	132	119	Green Bright Dk	
144	192	180	Aquamarine Vy Lt	
111	174	159	Aquamarine Lt	
80	139	125	Aquamarine	
71	123	110	Aquamarine Dk	
185	215	192	Jade Ultra Vy Lt	
167	205	175	Jade Very Light	
143	192	152	Jade Light	
83	151	106	Jade Medium	
51	131	98	Jade Green	
153	195	170	Celadon Green Lt	
101	165	125	Celadon Green	
77	131	97	Celadon Green Md	
71	119	89	Celadon Green Dk	
44	106	69	Celadon Green VD	
196	222	204	Blue Green Vy Lt	
178	212	189	Blue Green Lt	
123	172	148	Blue Green Med	
91	144	113	Blue Green	
57	111	82	Blue Green Dark	
4	77	51	Blue Green Vy Dk	
162	214	173	Nile Green Light	
136	186	145	Nile Green	
109	171	119	Nile Green Med	
27	157	107	Emerald Green Lt	
24	144	101	Emerald Green Med	
24	126	86	Emerald Green Dark	
21	111	73	Emerald Green Vy Dk	
17	90	59	Emerald Grn Ult V Dk	
215	237	204	Pistachio Green Vy Lt	
166	194	152	Pistachio Green Lt	
105	136	90	Pistachio Green Med	
97	122	82	Pistachio Green Dk	
32	95	46	Pistachio Grn Vy Dk	
23	73	35	Pistachio Grn Ult V D	
200	216	184	Forest Green Lt	
141	166	117	Forest Green	
115	139	91	Forest Green Med	
88	113	65	Forest Green Dk	
64	82	48	Forest Green Vy Dk	
228	236	212	Yellow Green Vy Lt	
204	217	177	Yellow Green Lt	
113	147	92	Yellow Green Med	
64	106	58	Hunter Green	
27	89	21	Hunter Green Dk	
27	83	0	Hunter Green Vy Dk	
158	207	52	Chartreuse Bright	
123	181	71	Chartreuse	
71	167	47	Kelly Green	
63	143	41	Green Light	
7	115	27	Green Bright	
5	101	23	Green	
199	230	102	Parrot Green Lt	
127	179	53	Parrot Green Md	
98	138	40	Parrot Green Dk	
85	120	34	Parrot Green V Dk	
216	228	152	Avocado Grn U Lt	

174	191	121	Avocado Grn V Lt
148	171	79	Avocado Grn Lt
114	132	60	Avocado Green
98	113	51	Avocado Green Md
76	88	38	Avocado Grn V Dk
66	77	33	Avocado Green Dk
49	57	25	Avocado Grn Black
171	177	151	Fern Green Lt
156	164	130	Green Gray
136	146	104	Green Gray Md
95	102	72	Green Gray Dk
196	205	172	Fern Green Vy Lt
150	158	126	Fern Green
102	109	79	Fern Green Dark
131	151	95	Pine Green
114	130	86	Pine Green Md
94	107	71	Pine Green Dk
239	244	164	Moss Green Vy Lt
224	232	104	Moss Green Lt
192	200	64	Moss Green Md Lt
167	174	56	Moss Green
136	141	51	Moss Green Dk
199	192	119	Olive Green Lt
188	179	76	Olive Green Md
148	140	54	Olive Green
147	139	55	Olive Green Dk
130	123	48	Olive Green V Dk
185	185	130	Khaki Green Lt
166	167	93	Khaki Green Md
137	138	88	Khaki Green Dk
204	183	132	Mustard Lt
191	166	113	Mustard
184	157	100	Mustard Medium
219	190	127	Golden Olive Vy Lt
200	171	108	Golden Olive Lt
189	155	81	Golden Olive
170	143	86	Golden Olive Md
141	120	75	Golden Olive Dk
126	107	66	Golden Olive Vy Dk
220	196	170	Drab Brown V Lt
188	154	120	Drab Brown Lt
150	118	86	Drab Brown
121	96	71	Drab Brown Dk
231	214	193	Yellow Beige Lt
216	188	154	Yellow Beige Md
188	150	106	Yellow Beige Dk
167	124	73	Yellow Beige V Dk
252	252	238	Off White
245	236	203	Old Gold Vy Lt
198	159	123	Hazelnut Brown Lt
183	139	97	Hazelnut Brown
160	112	66	Hazelnut Brown Dk
131	94	57	Hazelnut Brown V Dk
228	180	104	Topaz
206	145	36	Topaz Medium
174	119	32	Topaz Dark
162	109	32	Topaz Very Dark
148	99	26	Topaz Ultra Vy Dk
229	206	151	Old Gold Lt
208	165	62	Old Gold Medium
188	141	14	Old Gold Dark
169	130	4	Old Gold Vy Dark
246	220	152	Straw Light
243	206	117	Straw
223	182	95	Straw Dark
205	157	55	Straw Very Dark
255	251	139	Lemon Light
253	237	84	Lemon
255	227	0	Canary Bright
255	214	0	Lemon Dark
253	249	205	Golden Yellow Vy Lt
255	241	175	Topaz Vy Lt
253	215	85	Topaz Light
255	200	64	Topaz Med Lt
255	181	21	Canary Deep
255	233	173	Yellow Pale Light
255	231	147	Yellow Pale
254	211	118	Yellow Med
255	191	87	Tangerine Light
255	163	43	Tangerine Med
255	139	0	Tangerine
247	139	19	Pumpkin Light
246	127	0	Pumpkin
255	123	77	Burnt Orange
235	99	7	Burnt Orange Med
209	88	7	Burnt Orange Dark
255	222	213	Apricot Very Light
254	205	194	Apricot Light
252	171	152	Apricot
255	131	111	Apricot Med
253	93	53	Burnt Orange Bright
250	50	3	Orange?Red Bright
255	226	207	Tawny Light
255	211	181	Mahogany Ult Vy Lt
247	151	111	Orange Spice Light
242	120	66	Orange Spice Med
229	92	31	Orange Spice Dark
253	189	150	Pumpkin Pale
226	115	35	Copper Light
198	98	24	Copper
172	84	20	Copper Med
166	69	16	Red Copper
130	52	10	Red Copper Dark
255	238	227	Tawny Vy Light
251	213	187	Tawny
247	167	119	Mahogany Vy Lt
207	121	57	Mahogany Light
179	95	43	Mahogany Med
143	67	15	Mahogany Dark
111	47	0	Mahogany Vy Dk
255	253	227	Yellow Ultra Pale
250	211	150	Autumn Gold Lt
242	175	104	Autumn Gold Med
242	151	70	Autumn Gold Dk
247	187	119	Golden Brown Pale
220	156	86	Golden Brown Light
194	129	66	Golden Brown Med
173	114	57	Golden Brown
145	79	18	Golden Brown Dk
254	231	218	Peach Very Light
247	203	191	Peach Light
244	187	169	Terra Cotta Ult Vy Lt
238	170	155	Terra Cotta Vy Lt
217	137	120	Terra Cotta Light
197	106	91	Terra Cotta Med
185	85	68	Terra Cotta
152	68	54	Terra Cotta Dark
134	48	34	Terra Cotta Vy Dk
248	202	200	Rosewood Ult Vy Lt
186	139	124	Rosewood Light
150	74	63	Rosewood Med
104	37	26	Rosewood Dark
243	225	215	Desert Sand Vy Lt
238	211	196	Desert Sand Light
196	142	112	Desert Sand
187	129	97	Desert Sand Med
182	117	82	Desert Sand Dark
160	108	80	Desert Sand Vy Dk
135	85	57	Desert Sand Ult Vy Dk
215	206	203	Shell Gray Light
192	179	174	Shell Gray Med
145	123	115	Shell Gray Dark
166	136	129	Cocoa Light
125	93	87	Cocoa
98	75	69	Cocoa Dark
255	251	239	Cream
248	228	200	Tan Ult Vy Lt
236	204	158	Tan Very Light
228	187	142	Tan Light
203	144	81	Tan
184	119	72	Brown Very Light
152	94	51	Brown Light
122	69	31	Brown Med
101	57	25	Coffee Brown Dk
73	42	19	Coffee Brown Vy Dk
54	31	14	Coffee Brown Ult Dk
30	17	8	Black Brown
242	227	206	Beige Brown Ult Vy Lt
203	182	156	Mocha Beige Light
164	131	92	Mocha Beige Med
138	110	78	Mocha Beige Dark
75	60	42	Mocha Brown Vy Dk
255	255	255	Snow White
252	251	248	White
249	247	241	Winter White
240	234	218	Ecru
231	226	211	Beige Gray Light
221	216	203	Beige Gray Med
164	152	120	Beige Gray Dark
133	123	97	Beige Gray Vy Dk
98	93	80	Brown Gray Dark
79	75	65	Brown Gray Vy Dk
235	234	231	Brown Gray Vy Lt
177	170	151	Brown Gray Light
142	144	120	Brown Gray Med
99	100	88	Ash Gray Vy Lt
227	216	204	Mocha Brown Vy Lt
210	188	166	Mocha Brown Lt
179	159	139	Mocha Brown Med
127	106	85	Beige Gray Ult Dk
107	87	67	Mocha Brown Dk
250	246	240	Mocha Brn Ult Vy Lt
209	186	161	Beige Brown Vy Lt
182	155	126	Beige Brown Lt
154	124	92	Beige Brown Med
103	85	65	Beige Brown Dk
89	73	55	Beige Brown Vy Dk
230	232	232	Beaver Gray Vy Lt
188	180	172	Beaver Gray Lt
176	166	156	Beaver Gray Med
135	125	115	Beaver Gray Dk
110	101	92	Beaver Gray Vy Dk
72	72	72	Beaver Gray Ult Dk
236	236	236	Pearl Gray Vy Lt
211	211	214	Pearl Gray
171	171	171	Steel Gray Lt
140	140	140	Steel Gray Dk
209	209	209	Pewter Very Light
132	132	132	Pewter Light
108	108	108	Pewter Gray
86	86	86	Pewter Gray Dark
66	66	66	Pewter Gray Vy Dk
0	0	0	Black

We have to take into account that DMC provided us a list of alternate or closest colors of floss in case we have temporarily unavailable thread color or not suitable with our embroidery to find and replace it with the closest colors, which means it will reduce the color suitability image match (Camelia, 2021) Figure 3.

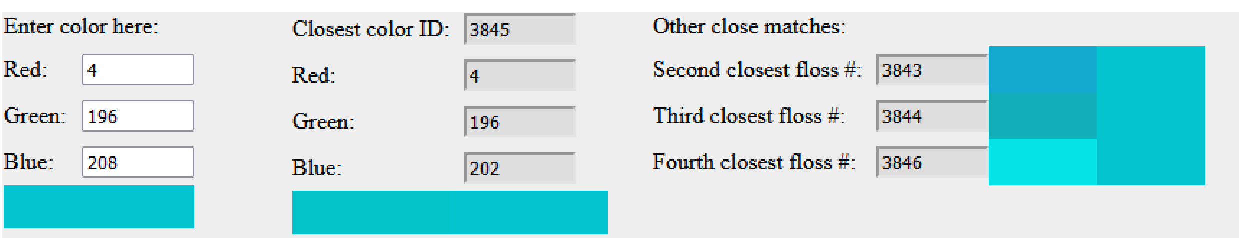


Figure 3:DMC Closest Floss

2.3. Delta Function

In our research, we will convert any image with a large number of different pixel colors into a pixel-colored image that can be used in embroidery. We used CIE Lab color space to measure the difference between colors. Referring to the DMC dataset, we will compare the closes color in the image and the colors of the DMC, then, we will replace the image pixel's color with the corresponding color to get the image with DMC Colors which can be used in embroidery.

There is an L2 norm, also known as a Euclidean metric or Euclidean norm, which may be regarded the shortest distance between two points in any dimensions' space, which is called Euclidean distance, and so there is only one Euclidean distance (Malkauthekar, 2013), which is a unique path between two locations, Equation 1

Delta function is not the only way to calculate the distance between color CIE Lab, there is L2 norm, which is also known as a Euclidean metric or Euclidean norm, which can be considered the shortest distance between two points in any dimensions space which called Euclidean distance, therefore there is one Euclidean distance which is a unique path between two points, Equation 1.

Equation 1: Delta E Function

$$\Delta E = \sqrt{\left(\frac{\Delta L}{lS_L}\right)^2 + \left(\frac{\Delta C}{cS_C}\right)^2 + \left(\frac{\Delta H}{S_H}\right)^2}$$

So, in our proposed methods when we are going to measure the Euclidean distance (L2 norm) see Equation2 in CIE Lab between two color pixels and compare it with DMC color Data set, the variable will be L, a, and b only, and the weaknesses of L2 norm were the effect of total error in measurements on the final result that makes it impossible to track what is make measurement error (Bekta, 2010).

Equation 2: L2 Norm Equation

$$L_2\ norm = \sqrt[2]{\left(L_{img} - L_{DMC}\right)^2 + \left(a_{img} - a_{DMC}\right)^2 + \left(b_{img} - b_{DMC}\right)^2}$$

But there is another important indicator that we can't neglect when we are going to get the correct result, which is the hue and saturation, which are not taken into account in the L2 norm unlike delta which considers them important, so we consider that Delta Function is better than L2 norm.

2.4. Grouping Methods

2.4.1. k-means clustering

k-means clustering is the most important algorithm for over 50 years which is the first k-means established in clustering algorithm to compute the weights for features that were designed more than 30 years ago (de Amorim, 2016). The concept of clustering which refers to grouping or segmenting smeller data together depends on its patterns, which helps us to understand these data uniquely. In our research, we are going to use image segmentation to group similar pixels in the same image together, k-means algorithm (Equation 3) can calculate the distance of the points in the cluster with their centroid so that the main objective is to minimize the sum of the distances between the centroid cluster with their respective points.

Equation 3: K-mean Clustering Equation

$$\frac{1}{m_k} \sum_{i=1}^{m_k} \left\| x^i - \mu_{c^k} \right\|^2$$

To achieve k-means clustering we have to apply these points (De Amorim, 2016):

1. **Picking the number of clusters K**

This is the first step before using k-means which leads us to decide how many clusters we need in the image.

2. **Selecting the centroid point from the data to depend on K**

In this step, we will select randomly centroid points for each cluster which is used to calculate the distance for preparing the clusters.

3. **Assign all the points to the closest cluster centroid**

After initializing the centroids, we will calculate the difference between the point and the centroid to assign each point to the closest centroid.

4. **Recomputing the centroids of newly formed clusters**

Once we have assigned all of the points to either cluster, the next step is to compute the centroids of newly formed clusters.

5. **Repeating steps 3 and 4**

We will repeat these steps until we find nothing change in the centroid or each point remains in the same cluster or a maximum number of iterations are reached.

K-means clustering looks like any clustering algorithm which has some weaknesses the researcher considers, which are (de Amorim, 2016):

1. Number of clusters k must be known beforehand.
2. K-Means will segment a data set into K segments whether there is or not a clustering structure in the data.
3. This is a rapacious algorithm that may get restricted in local minima;

4. The initial centroids, that has been chosen randomly in the first Step heavily affect the final result;
5. It has equally featured treatment whatever their actual degree of relationship.

2.4.2. Superpixel:

In everyday life, image processing applications such as television, remote sensing, photography, industrial inspection, robotics, and diagnosis are in high demand. The segmentation algorithm has an importation portion that combines the global region-based approach and the local edge-based approach, which is deferred on the segmentation color that depends on the processing region (Stricker, 1994). Superpixel is a homogeneous segmentation technique that groups the image regions that look similar. And the most popular superpixel method is the simple linear iterative clustering (SLIC) technique, which is a powerful method for generating meaningful images regions that descript the structure of the object in the images. But SLIC has poor segmentation performance when the image has too much noise (Qin et al, 2014).

The SLIC algorithm creates regions in three main steps:

1. creates initial regions according to a parameter that defines the desired number of superpixel
2. performs region clustering to aggregate pixels to the regions according to the similarity criteria and
3. reinforces connectivity.

2.4.3. Related Works

Embroidered clothing was only worn on vacations or special events in the past since mastering the embroidery skill required a lot of time and experience, so they had to be prepared ahead of time. These days, embroidery has the integrity to be in the couture sector (Indrie et al, 2017).

Hand embroidery fabrication faces significant challenges when compared to prototypes, such as divergence levels of realization and inexactness of reproductions. They discuss the use of digital machines embroidery and embroidery that uses the chemical technique, which supports producing harmonious high-fidelity prototypes for smooth wearables in the form of research products. They designed a Smart Sock process, which is a sensitized sock for rheumatoid arthritis (Goveia et al, 2020).

hand embroidery in the home industries is one of the social causes of poverty alleviation, and it is Pakistan's biggest problem. They investigated the impact of problems and prospects of hand embroidery in the home industries, which plays a major role in the economic development of the country, and is especially important in terms of employment opportunities, and they discovered that the government strongly supports hand embroidery because of its importance (Rind et al, 2021).

In our study, we'll convert the image to Embroidery using the smallest number of colors that may be utilized in stitches while maintaining the image's quality (embroidery) as close to the original as feasible. "To what degree can we minimize the number of colors and how can we segment the image to give us an embroidery without noise that our brain can identify the segmented image?" we must question ourselves.

Hui and Han introduced a novel approach for picture segmentation that is more suited to complicated circumstances than k-means clustering because it does not require prior knowledge of the k value, and this method may take less time, retain the original colors, and deliver a true image segmented in a decent way. However, this method is ineffective in situations where accurate k values are required (Hui et al, 2019).

Li et al. created picture segmentation algorithms that are more successful than Grab Cut. They addressed its flaws, such as a complicated backdrop or a close match between the item and the background. The other difficulty is the time it takes to execute the algorithm, but they discovered that when the image is colorful with a complicated backdrop, the results are bad (Fulkerson et al, 2009).

Because the SAR is a noisy image, Niharika and colleagues used the k-means clustering method, Otsu, and other traditional methods to develop a new method to remove noise from noisy Synthetic Aperture Radar images with a lower error percentage. Because the SAR is a noisy image, they discovered that the threshold value selection creates a segmentation problem that needs to be investigated further in the future (Bruce lind bloom, 2007).

Because high resolution gives additional features that aid picture segmentation, Lei and colleagues propose a method that works simultaneously to create high resolution images and segmentation maps from low-resolution inputs (Hassanien et al, 2018). The combination can boost performance on these two tasks.

Qin and colleagues suggest a new generation of superpixels that address the Polari metric synthetic aperture radar with noise that has been present on the picture, and it has a clear structure and is simple to implement, but the performance has increased (Zitnick, & Kang, 2007).

Radiologists or experts used the medical image to reduce the complexities to understand the issue, and the results show the importance of using filters by comparing the image before processing and after proceeding (Hui et al, 2019). Shukla, M., and Sharma, K. K. used Fuzzy K-means clustering, K-means clustering, and Birch clustering algorithms to increase the accuracy in diagnosis for tumor area magnetic resonance images (MRI) images (Shukla, & Sharma, 2020).

Toskova and Penchev used a Java-based algorithm and a Hopfield neural network to recognize Bulgarian embroidery using an intelligent multi-agent system with three parts: embroidery image recognition, determining whether the embroidery is Bulgarian or not, and finally, workmanship classification. The algorithm requires a pre-existing image to recognize the size and remove noise, making it easy to inspect it by segment (Toskova, & Penchev, 2022).

Most of the research focuses on image segmentation or extracting image that they need with high resolution, but they didn't focus on reducing the number of colors or counting the possible number of colors that we can use so our research focuses on images segmentation and converting it into Embroidery with a minimal number of colors that can be used in stitches (Lei et al, 2019).

On another hand, our research will develop an algorithm that gives us the ability to convert any image into Embroidery using the minimal possible colors that let our brains recognize the image.

Chapter 3: The Proposed Method

This chapter illustrates the proposed method which aims to reduce the number of colors in images to allow us to embroider them on the canvas in a quality that human eyes can understand and have a useful meaning, on another hand may we can embroider them on a small canvas or large canvas that depend on the canvas size and several stitches that we will use.

3.1 Colors Reduction Phases

Reducing color is an important step in embroidering an image which allows us to count the number of thread colors that the image will be embroidered. Different sub-steps may be used depending on the image, Delta Function, k-means clustering, and superpixel. We will describe these steps in this section.

Color Reduction is three phases,

1- Delta function (The reduction from true colors (up to 16 M colors) to 454 DMC colors (as maximum)
2- K-means (Jamel, & Akay, 2019).
3- Superpixel (Ibrahim et al, 2018).

3.1.1. Delta Function

Calculation and comparing color differences are an important step in our proposal process because the Delta function is the most suitable method to convert the image color into DMC Color Dataset, we will calculate the difference between each pixel color image with a DMC Color dataset, and replace image pixel color with the DMC Color that has the lower difference value, and we will repeat it with all image pixel color. To do that we will follow the delta equation (Equation 2):

ΔE is the color difference (Bruce lind bloom, 2017), between image color (L2, a2, b2) and a DMC color (L1, a1, b1) is:

Equation 4: Delta Functions Equations

$$\Delta E = \sqrt{\left(\frac{\Delta L}{lS_L}\right)^2 + \left(\frac{\Delta C}{cS_C}\right)^2 + \left(\frac{\Delta H}{S_H}\right)^2}$$

$$C1 = \sqrt{{a_1}^2 + {b_1}^2}$$

C1 refers to chroma which is the hypotenuse for a1 and b1 for the original color in XY cartesian plane.

$$C2 = \sqrt{{a_2}^2 + {b_2}^2}$$

C2 refers to Chroma which is the hypotenuse for a2 and b2 for the sample color in XY cartesian plane

$$\Delta C = C1 - C2$$

$$\Delta L = L1 - L2$$

ΔL is the different lightness value (0-100) between the original color and sample color.

$$\Delta a = a1 - a2$$

Δa is the difference an (a is red to green where red is the positive value on x access and green is the negative value on x access) between original color and sample color

$$\Delta b = b1 - b2$$

Δb is the different b (a is yellow to blue where yellow is the positive value on y access and blue is the negative value on y access) between original color and sample color

$$\Delta H = \sqrt{\Delta a^2 + \Delta b^2 + \Delta C^2}$$

$$S_L = \begin{cases} 0.511 & if\ L_1 < 16 \\ \dfrac{0.040975 L_1}{1 + 0.01765 L_1} & if\ L_2 > 16 \end{cases}$$

$$S_C = \frac{0.0638 C_1}{1 + 0.0131 C_1} + 0.638$$

$$S_H = S_C (FT + 1 - F)$$

$$T = \begin{cases} 0.56 + |0.2 \cos(H_1 + 168^o)| & if\ 164^o \leq H_1 \leq 345^o \\ 0.36 + |0.4\ \cos(H_1 + 35^0)| & otherwise \end{cases}$$

$$F = \sqrt{\frac{C_1^4}{C_1^4 + 1900}}$$

$$H = arctan\left(\frac{b_1}{a_1}\right)$$

$$H_1 = \begin{cases} H & if\ H \geq 0 \\ H + 360\ ^0 & otherwise \end{cases}$$

H is the measure of hue and represent as an angle ranging from 0 to 360.

Red is the angle from 0 to 90 (oranges and yellows).

Yellow is the angle from 90 to 180 (yellow-greens and green).

Green is the angle from 180 to 270 (cyans and blues).

Blues is the angle from 270 to 360 (purples and magentas).

In our project we wrote the Delta function Figure 4 in MATLAB to reduce the number of image colors:

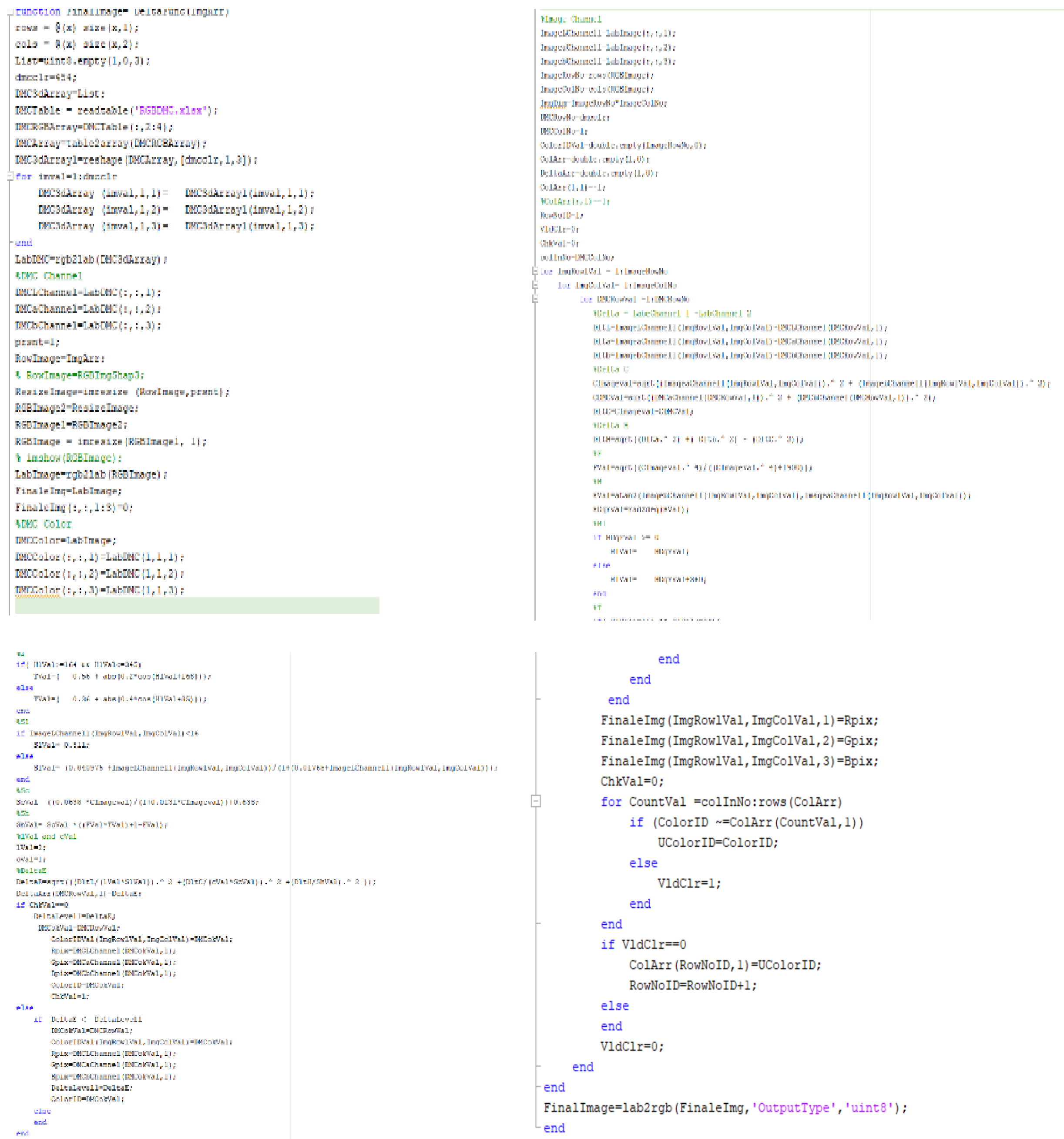


Figure 4: Delta Function (Appindex2)

Delta function is the first phase of our proposal that gave us an image with DMC Colors, but we also need to decrease the number of pixel colors of the image and the next phase will decrease the number of pixels as much as we need and k-means clustering and superpixel will decrease the number of image pixel as much as we need but may that will decrease image performance.

3.1.2. K-Means Clustering

K-Means Clustering is a technique that aims to cluster the image pixel's color into k clusters in which each pixel belongs to the centroid pixel color and k is the number of centroids for each cluster that has been chosen randomly, using a k-means algorithm we will calculate the difference between each pixel with the centroid, and then we will replace each pixel in the same cluster with the prober centroid color that belongs to.

The k-means clustering algorithm mostly has two functions:

- Using an iterative process to determine the best value for K centroids or center points
- creating a cluster by assigning each data point to its closest k-center. which particular to its k-center

First, we will convert the image from RGB color into LAB color space which allow us to calculate the difference between each color, using the equation (Equation 5)

Equation 5: K-means Clustering Equation

$$Dif = \sqrt{\left(L_{img} - L_{DMC}\right)^2 + \left(a_{img} - a_{DMC}\right)^2 + \left(b_{img} - b_{DMC}\right)^2}$$

Using equation 5 we will calculate the difference pixel by pixel in the image with the centroid pixels and take the lowest difference for each image pixel color, then we replace the image pixel color with the centroid pixel color.

K centroid is always updated by recomputing centroids of recently formed image clusters as much as we iterate the k-means cluster process.

K-means clustering process usually stopped when the centroids do not change in the newly formed clusters or there is no changed in the pixels from one cluster to another or the process has reached the number of iterations.

In our project, we wrote the K-means function below in MATLAB to reduce the number of image colors see Figure 5:

```
function FinalImageKmean= Fkmean(ImgArr,K)
RowImage=ImgArr;
rows = @(x) size(x,1);
cols = @(x) size(x,2);
k=K;
RGBimg=RowImage;
%RGB image Converted To Lab Image
Labimg=rgb2lab(RGBimg);
Lchannel=Labimg(:,:,1);
achannel=Labimg(:,:,2);
bchannel=Labimg(:,:,3);
% Image Colomn And Row
ImgCol=cols(Labimg);
ImgRow=rows(Labimg);
ImgDim=ImgCol*ImgRow;
% Reshap the Image into One Column
RGBImgShap=reshape(Labimg,[ImgDim,1,3]);
%Create Empty Array
CentroidindList=double.empty(1,0);
CentroidList=double.empty(1,0);
CentroidListVal=double.empty(5,0);
DefList=double.empty(k,0);
% DalList=double.empty(1,0);
LabImgList=double.empty(1,0,3);
CLRlist=double.empty(ImgDim,0);
% BWimg=reshape(BW2,[ImgDim,1]);
% Number Of Rows In reshap Image
LabImgRow=rows(LabImgList);
% Centroid Point
A=randi(ImgDim,1);
CentroidindList(1,1)=A;
CentroidList(1,1,1:3)=RGBImgShap(A,1,1:3);
for kval=1:k-1
    if A~=CentroidindList(kval,1)
        CentroidindList(kval,1)
    else
        A=randi(ImgDim,1);
    end
    CentroidindList(kval+1,1)=A;
    CentroidList(kval+1,1,1:3)=RGBImgShap(A,1,1:3);
end
```

```
ChkDlt=0;
RGBCentroidList=lab2rgb(CentroidList,'OutputType','uint8');
templist= RGBCentroidList;
clt=0;
Num=1;
RGBImgShap1=RGBImgShap;
RGBImgShap1(:,:,1:3)=0;
CentroidListVal(1:k,4)=0;
as=0;
for itr=1:1
    for ClrVal=1:ImgDim
        Itemp=-1;
        for cntVal =1:k
            DefList (cntVal,1) = sqrt(((RGBImgShap(ClrVal,1,1)-CentroidList(
        end
        [M,I] = min(DefList (1:cntVal,1)) ;
        CLRlist(ClrVal,1)=I;
        % if Itemp==I
        Ach=0;
        Bch=0;
        Lch=0;
        TotalCh=0;

        for cl=1:ClrVal
            if CLRlist(cl,1)==I
                Lch= RGBImgShap(cl,1,1)+Lch;
                Ach= RGBImgShap(cl,1,2)+Ach;
                Bch= RGBImgShap(cl,1,3)+Bch;
                TotalCh=TotalCh+1;
            else
            end
        end
        CentroidList(I,1,1)=Lch/TotalCh;
        CentroidList(I,1,2)=Ach/TotalCh;
        CentroidList(I,1,3)=Bch/TotalCh;
        ChkDlt=0;
        DefList (1:cntVal,1)=0;
    end

    for ClrVal=1:ImgDim
        aaa=CLRlist(ClrVal,1);
        %  SubVal
        RGBImgShap1(ClrVal,1,1:3)=CentroidList(aaa,1,1:3);
    end
    RGBImgShap2=reshape(RGBImgShap1,[ImgRow,ImgCol,3]);
    FinalImageKmean=lab2rgb(RGBImgShap2,'OutputType','uint8');
    as=as+4;
end
end
```

Figure 5: K-means Clustering MATLAB Code (Appendix 3)

3.1.3. Superpixel

The idea of superpixel was introduced through group the images into regions that have meaningful meaning that can be replaced the image pixel in the images redundancy and primitives can be reduced extremely (Mokrzycki, et al, 2011). Furthermore, a region in the image is more useful to compute the image features than pixels, so that the performance of computer vision tasks can be improved via superpixel image segmentation, they have occupied the main key building blocks for many algorithms in computer vision and image processing, and the important performance measures for superpixel algorithms are:

- quality.
- superpixel shape, size.

We have is many superpixel segmentation algorithms and we used a simple linear iterative clustering method (SLIC), based on the similarity of color in its proximity in the XY image plan, and this can be done in 5-dimensional space which is (Lab) color victor that belongs to CIELAB color space and the XY pixel position in the image which depend on the image size. There are two feature vectors defined for the CIELAB color space image color, which are Si = [xi, yi]T and Ci = [Li, ai, bi]T, and these values refer to the position for the 2D in the ith for the color values. Then we initial the K that refers to avoiding the superpixel center edge which will be moved according to the lowest gradient magnitude locations in a 3×3 neighborhood then, each pixel will be labeled by the closes cluster center depending on the distance D as (Equation 4)

Equation 6: Superpixels Equation

$$D(i,j) = \sqrt{\left(\frac{||Ci - Cj||}{Nc}\right)^2 + \left(\frac{||Si - Sj||}{Ns}\right)^2}$$

where j=1, 2, …, K, which is the cluster centers index; NC and NS are the normalization constants for a spatial distance color.

Superpixels can divide an image by a number of clusters with equally size superpixels K., therefore, for an image with size A pixels, the approximate size will be A/K pixels.

Superpixel is predefined in MATLAB as a superpixel Function, so we create the function below to use superpixel see Figure 6.

```
function SpexFunc= Spxel(ImgArr,K)
A1 = ImgArr;
A=rgb2lab(A1);
[L,N] = superpixels(A,K);
outputImage = zeros(size(A),'like',A);
idx = label2idx(L);
numRows = size(A,1);
numCols = size(A,2);
for labelVal = 1:N
    redIdx = idx{labelVal};
    greenIdx = idx{labelVal}+numRows*numCols;
    blueIdx = idx{labelVal}+2*numRows*numCols;
    outputImage(redIdx) = mean(A(redIdx));
    outputImage(greenIdx) = mean(A(greenIdx));
    outputImage(blueIdx) = mean(A(blueIdx));
end
SpexFunc=lab2rgb(outputImage,'OutputType','uint8');
```

Figure 6: Superpixel MATLAB Code (Appendix 5)

Chapter 4: Experiments and Results

Our proposed method was evaluated through several experiments to achieve the image pixel reduction for embroidery canvases. This allows us to measure several indicators that will affect pixel reduction, so high resolution is the important aspect that gave us a good result. In the first experiment, we will the performance on reducing the number of colors that depend on the closest color values. In experiment two we will reduce the resolution in several stages and measure the variation in different color numbers. In experiment three we will use k-means clustering to view color dereference that depends on k that changed from 1-30.

To apply our experiments, we installed MATLAB R2020b on a computer with the following specification:

- CPU core i7 8550U 1.8 GH
- RAM 16GB
- Hard Disk SSD 480 GB
- Graphics Card Nvedia Geforce MX 130.

4.1. Experiment 1

Experiment 1 was evaluated by applying it to the DMC color data set that contain 454 Different colors to four images with high resolution using the Delta function, K-means Clustering, and superpixel, Figure 7:

Image 1

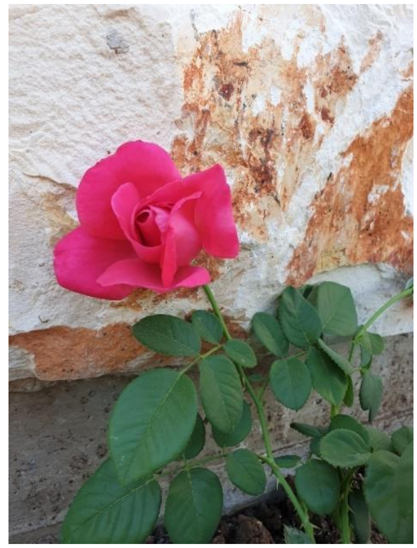


Image 2

Image 3

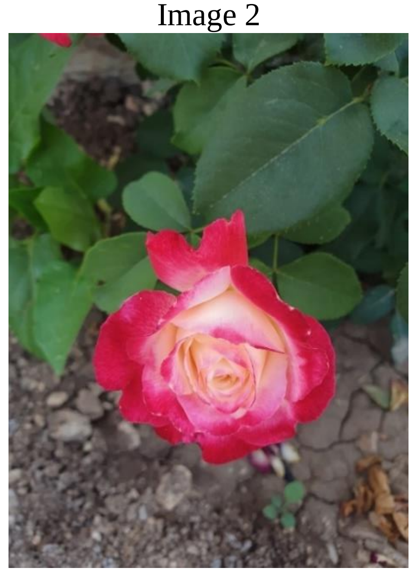


Image 4

Figure 7: Images used in Experiment 1

This experiment will test Figure 7 with the DMC Color dataset, which has 12,192,768 pixels with different colors, we will use the delta function, k-means clustering, and superpixel to reduce the number of colors that can be a thread on embroidery canvas, first of all, we will apply Delta function on each image then we will calculate the number pixels for each different color, then we will apply k-means clustering algorithm on the delta function output image with k= number of delta function output image different color for each image to reduce the number of different colors, then we will apply k =30 to see the different performance for each image, on another hand we will use superpixel function with 80X80 rejoins on the delta function output image, with mean color value for each rejoins, which make changes on color values that forcing us to apply Delta Function again.

4.1.1. Delta Faction

Before we apply the delta function, we tried to count the different colors that belong to each image, we found they have more than millions of different pixel colors. So, we apply the delta function for each image then and we count the color pixel image we found that we reduce the image color as Figure 8:

Image1: 191 Color Image2: 307 Color Image3: 266 Color Image4: 242 Color

Figure 8: Delta Function Result (Number of colors and Images form)

Because each image contains a huge number of different colors, we used the delta function to reduce the number of different colors to be less or equal to 454 DMC colors, with a clear vision that the human eye can recognize the meaning of the image, we notice that each image has some accepted distortion on the original image.

We reduced the image size to 50% we found that color was also rescued but it is simply reduced which means the number of image colors is directly proportional to the size of the image see Table 2.

Table 2: Delta Function Different Color values while reducing size

Image Names	Image 1	Image 2	Image 3	Image 4
Image size reduced (100% ➔ 50%)	191➔180	307➔293	266➔256	242➔237

4.1.2. K-means Clustering

k-means clustering is one of the best Artificial intelligent techniques that we can use to reduce the image color, so after we apply Delta Function in our exponents we need to reduce the number of different colors, so we found that we can reduce the number of colors as we want using K-means Clustering depend on the number of K, knowing the k value from Delta Function we found k-means clustering is useful exact as (Hui and Han) said, so we choose K is the number of reduced Delta Functions Different Color Number, and the images have high resolution make details clear with good result, the process will take a lot of time to depend on LAB Environment but a good result is opposite of (Li et. Al) algorithms result, we found that the image pixel different color has been reduced see Figure 9.

Original Image 1
3024x4032 Pix

Delta Function
191 Different Color

K-means (K=191)
67 Different Color

Original Image 2
3024x4032 Pix

Delta Function
307 Different Color

K-means (K=307)
122 Different Color

Original Image 3
3024x4032 Pix

Delta Function
266 Different Color

K-means (K=266)
85 Different Color

Original Image 4
3024x4032 Pix

Delta Function
242 Different Color

K-means (K=242)
80 Different Color

Figure 9: K-means Clustering Images color values and image forms

Hand embroidery is the main objective of our project, it needs to know thread color that is equivalent to the image pixel color. DMC produces 454 different threads colors, so the delta function will help us to convert each pixel color in the image to the equivalent thread color that produced by DMC, so we applied the delta function on each image in figure 9 we found that each image will contain less or equal 454 different colors, Table 3.

Using k-means cluster to reduce the number of image different color we found that our eyes will not notice that the different between delta function image and k-means cluster image, at the same time we have reduction less than 50%, Table 3:

Table 3: Image Reduction Ratio

Image Name	Delta Functions Dif. Color	K-means Clustering Dif. Color	Redaction Ratio
Image 1	191	67	35%
Image 2	307	122	40%
Image 3	266	85	32%
Image 4	242	80	33%

On another hand we tried to reduce color number using k-means clustering less than 30 different colors we used k= 30, we found that the image performance depends on the image color if it is closer to each other or not, so Figure 10 shows us that image no1 and image no3 high distortion in the flower color, On the contrary of image no2 and image no4 has less distortion difference in flower color.

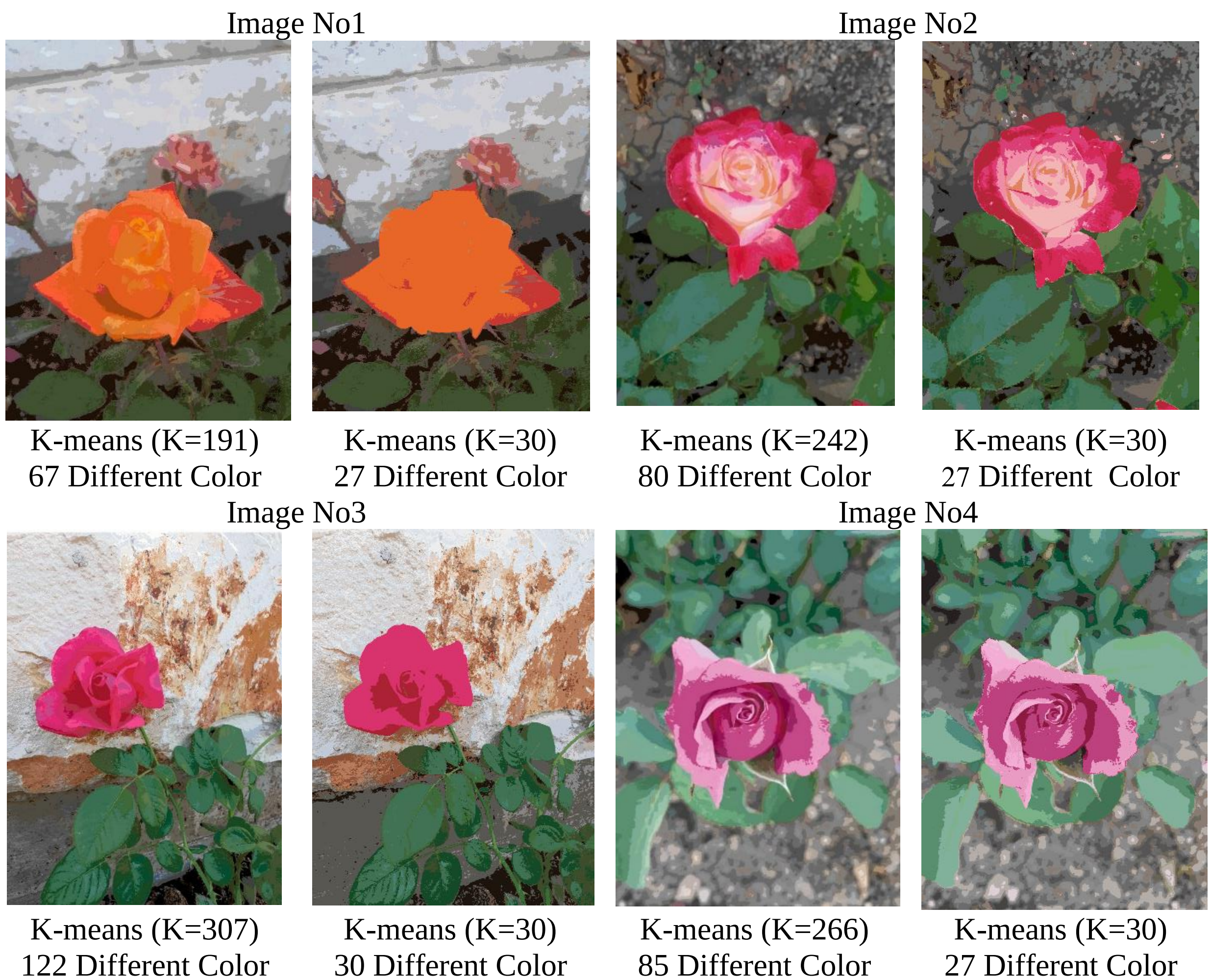


Figure 10: K-means Color Difference comparison between k= Delta Function color No and k=30

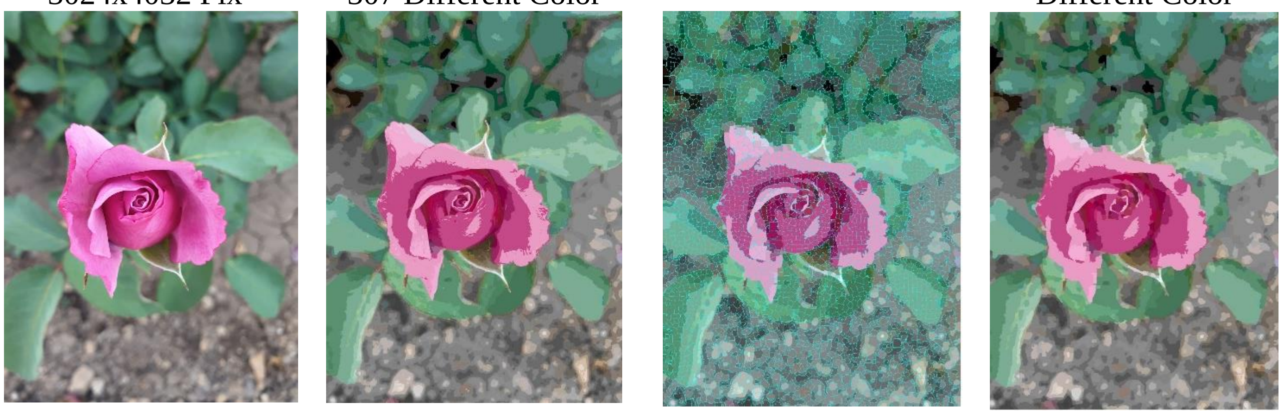
4.1.3. Superpixel

The Superpixel segmentation algorithm is one of the most image processing segmentation techniques have been used these days. As mentioned before, we are using the MATLAB superpixel function (SLIC) to reduce the number of different color pixels in the image to be able to embroider the image on the canvas. In the first phase, we converted the images' colors using the Delta function, so in this phase, we are going to use superpixel to reduce the color image by dividing the images into (x by y) regions and taking the mean color values for each region, and replacing them with DMC Color using Delta Functions.

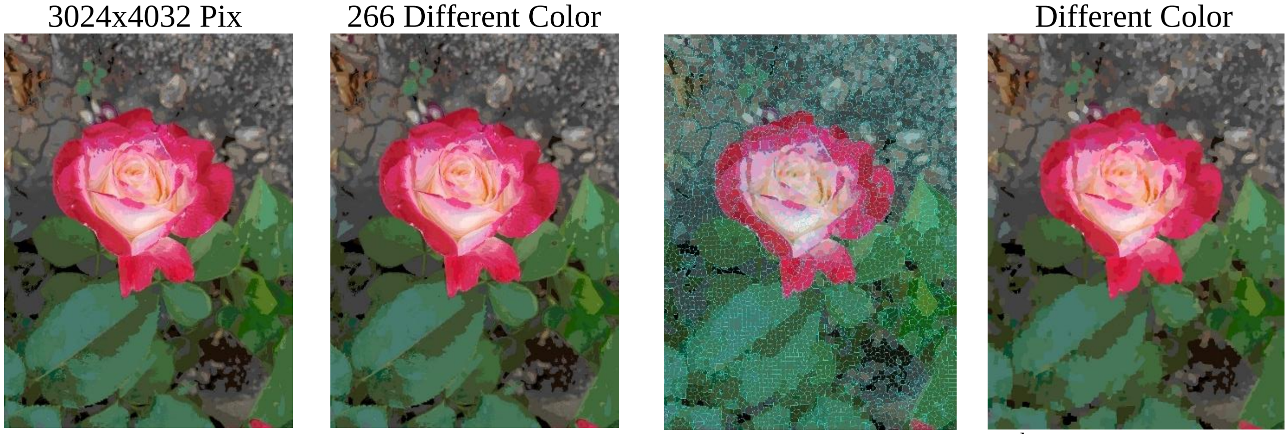
In our project, we test the four images using the superpixel function with a different number of rejoins and we found that image quality increased when the number of regions increase and vice versa. Figure 11.

Original Image 3024x4032 Pix | Delta Function 191 Different Color | Superpixel (K=6400) | 2nd Delta Function 116 Different Color

Original Image 3024x4032 Pix	Delta Function 307 Different Color	Superpixel (K=6400)	2nd Delta Function 164 Different Color



Original Image 3024x4032 Pix	Delta Function 266 Different Color	Superpixel (K=6400)	2nd Delta Function 128 Different Color



Original Image 3024x4032 Pix	Delta Function 242 Different Color	Superpixel (K=6400)	2nd Delta Function 158 Different Color

Figure 11: Superpixel Image color values and image forms

The proposed method was evaluated by applying the Delta Function, K-means Clustering, and Superpixel segmentation methods on four images to convert the color values into DMC color values that can be able to embroider the image on the canvas, we found that the Delta Function decreases the number of different colors for each image and that it is also directly proportional when we resize the image, Table 4:

Table 4: Delta Function Results with reducing image size in half

Image Name	Image 1		Image 2		Image 3		Image 4	
Image Size Percent	% 100	%50	%100	%50	%100	%50	%100	%50
Number Of Dif. Color	191	180	307	293	266	256	242	237

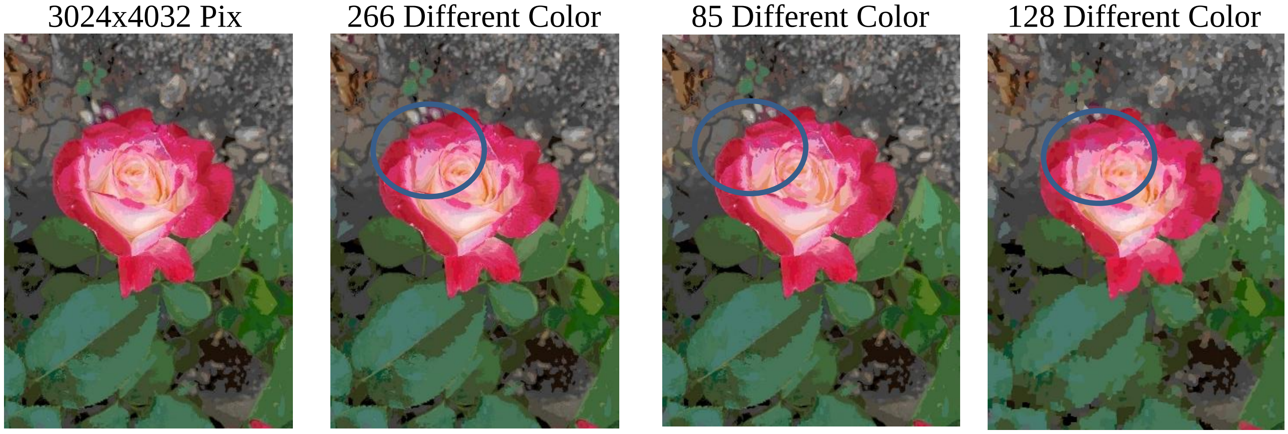
K-means clustering has a good effect on decreasing the number of different colors in each image we assume that K= number of different colors, and we applied the k-means algorithm we found that the number of the different colors has been reduced by less than 50%.

While comparing the results between the k-means clustering and superpixel, we found that k-means clustering is better than superpixel in the image we found k-means clustering is better than superpixel, but when we increase the superpixel region, we found that the superpixel is better because the region number is close to the image resolution, Figure 12.

Original Image 3024x4032 Pix | Delta Function 191 Different Color | K-means (K=191) 67 Different Color | Superpixel (K=6400) 116 Different Color

Original Image	Delta Function	K-means (K=307)	Superpixel (K=6400)
3024x4032 Pix	307 Different Color	122 Different Color	164 Different Color

Original Image	Delta Function	K-means (K=266)	Superpixel (K=6400)
3024x4032 Pix	266 Different Color	85 Different Color	128 Different Color



Original Image	Delta Function	K-means (K=242)	Superpixel (K=6400)
3024x4032 Pix	242 Different Color	80 Different Color	158 Different Color

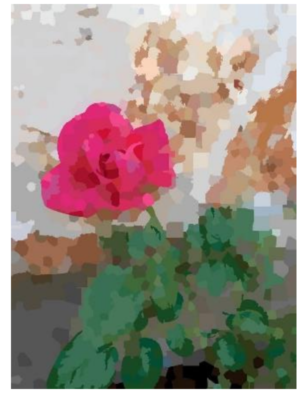
Figure 12: Comparison between k-means clustering and Superpixel No of color and image forms

We reduce the image regions in superpixel to show the relationship between the superpixel region and the image quality and a number of different colors we found that the superpixel region directs proportional to image quality and a number of different colors, Figure 13.

Superpixel
(80X80→K=6400)
116 Different Color

Superpixel
(40X40→K=1600)
88 Different Color

Superpixel
(80X80→K=6400)
164 Different Color



Superpixel
(40X40→K=1600)
116 Different Color

Superpixel
(80X80→K=6400)
128 Different Color

Superpixel
(40X40→K=1600)
94 Different Color

Superpixel
(80X80→K=6400)
158 Different Color

Superpixel
(40X40→K=1600)
110 Different Color

Figure 13: Superpixel Image Quality with reducing image size in half

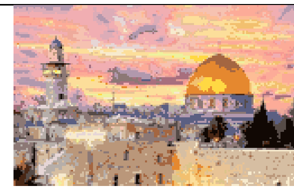
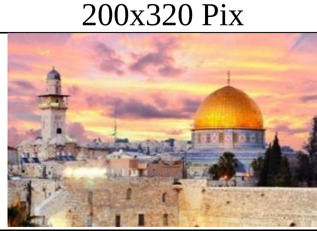
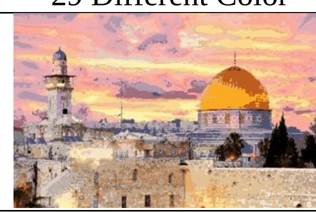
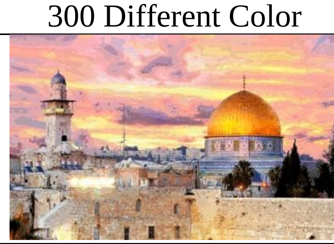
4.2. Experiment 2

In this experiment we are going to measure the proposed method depending on the image size, we choose Figure 14 as a reference for experiment 2

Figure 14: Jerusalem

Figure 14 contains 480000 Pixel. For different color values, we applied delta and k-means functions, and we found that image quality directly proportional to the number of pixels in the same number of colors

In this experiment, we are going to resize the original image 10 times, starting from 10%, 20%, 30%, …...100% to measure the color number variation that depends on image size when we apply Delta Function with K-means clustering and also when we apply Delta Function with super Pixel Figure 15.

Original Image 10% Percent	 Image Size 50x80 Pix	 Delta Function 185 Different Color	 K-means (K=30) 30 Different Color
Original Image 20% Percent	 Image Size 100x160 Pix	 Delta Function 239 Different Color	 K-means (K=30) 30 Different Color
Original Image 30% Percent	 Image Size 150x240 Pix	 Delta Function 269 Different Color	 K-means (K=30) 30 Different Color
Original Image 40% Percent	 Image Size 200x320 Pix	 Delta Function 285 Different Color	 K-means (K=30) 29 Different Color
Original Image 50% Percent	 Image Size 250x480 Pix	 Delta Function 300 Different Color	 K-means (K=30) 29 Different Color
Original Image 60% Percent	 Image Size 300x480 Pix	 Delta Function 303 Different Color	 K-means (K=30) 30 Different Color

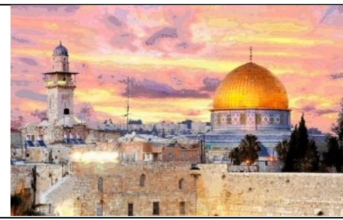
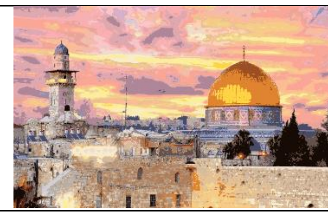
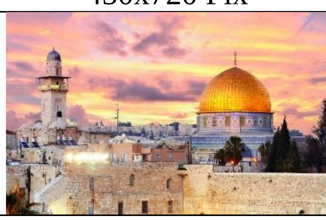
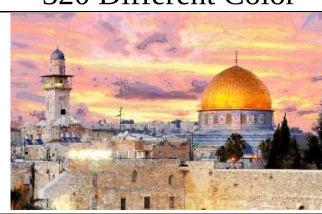
70% Percent Original Image			
	Image Size 350x560 Pix	Delta Function 313 Different Color	K-means (K=30) 29 Different Color
80% Percent Original Image			
	Image Size 400x640 Pix	Delta Function 322 Different Color	K-means (K=30) 29 Different Color
90% Percent Original Image			
	Image Size 450x720 Pix	Delta Function 320 Different Color	K-means (K=30) 30 Different Color
100% Percent Original Image			
	Image Size 500x800 Pix	Delta Function 333 Different Color	K-means (K=30) 30 Different Color

Figure 15: Delta Function with K-means Clustering Result (No of color and image forms) through increasing size image.

From experiment No 2 we observe that number of delta function different color Is directly proportional to image size with the same number of k-means clustering different color, but sometimes in k-means clustering the number of different colors is simply increase or decrease Figure 16.

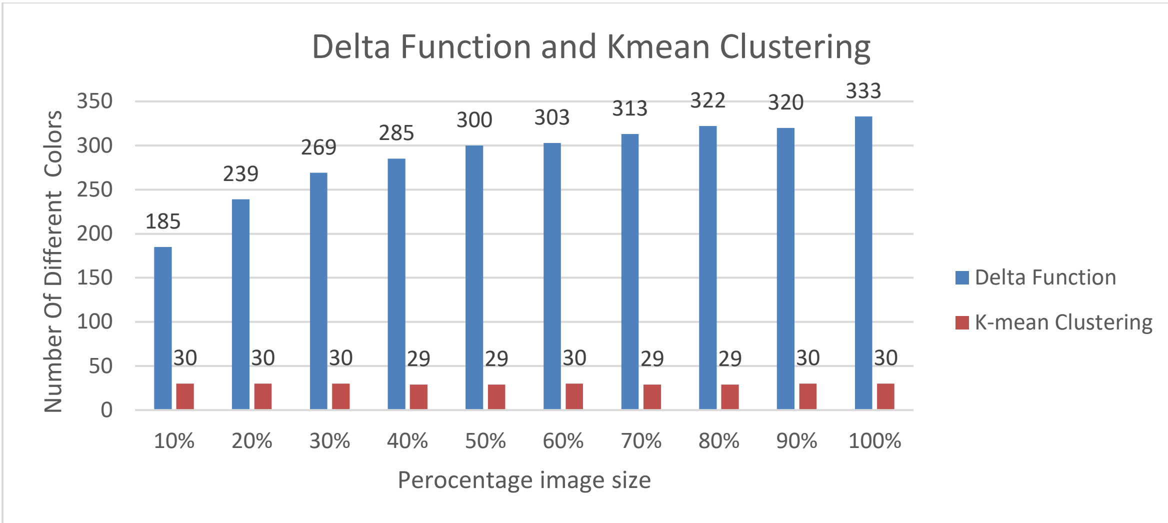


Figure 16: Comparison Delta Function and K-means Clustering result with image sine

Superpixel slice the image into 2 diminution x by y segmented arias, so while we are resizing the image into 20%,30%....100% we observed that the image has high performance when the number of arias is close to the number of pixels, and vice versa, at the same time, increasing the number of different colors depends on decreasing the number of areas in Figure 17.

20% Percent Original				
	Image Size 100x160 Pix	Delta Function 239 Different Color	Superpixel(80X80)	Delta Function 236 Different Color
30% Percent Original				
	Image Size 150x240 Pix	Delta Function 269 Different Color	Superpixel(80X80)	Delta Function 226 Different Color
40% Percent Original				
	Image Size 200x320 Pix	Delta Function 285 Different Color	Superpixel(80X80)	Delta Function 220 Different Color

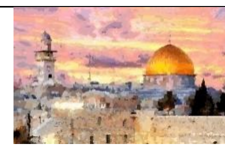
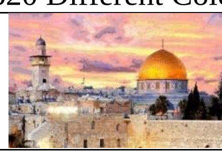
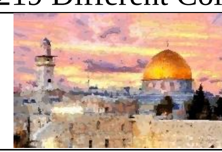
50% Percent Original				
	Image Size 250x480 Pix	Delta Function 300 Different Color	Superpixel(80X80)	Delta Function 225 Different Color
60% Percent Original				
	Image Size 300x480 Pix	Delta Function 303 Different Color	Superpixel(80X80)	Delta Function 221 Different Color
70% Percent Original				
	Image Size 350x560 Pix	Delta Function 313 Different Color	Superpixel(80X80)	Delta Function 215 Different Color
80% Percent Original				
	Image Size 400x640 Pix	Delta Function 322 Different Color	Superpixel(80X80)	Delta Function 221 Different Color
90% Percent Original				
	Image Size 450x720 Pix	Delta Function 320 Different Color	Superpixel(80X80)	Delta Function 219 Different Color
100% Percent Original				
	Image Size 500x800 Pix	Delta Function 333 Different Color	Superpixel(80X80)	Delta Function 219 Different Color

Figure 17: Delta Function with Superpixel result (No of color and image forms) through increasing size image.

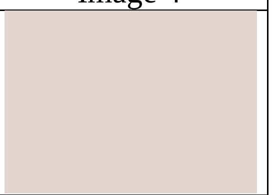
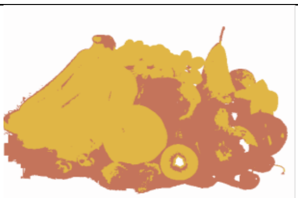
In this experiment, we applied k-means clustering and superpixel. We notice that the color reducing percentage in k-means clustering is less than in superpixel. That means k-means clustering is much better than superpixels.

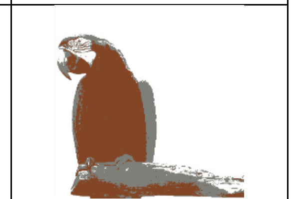
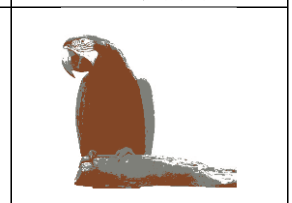
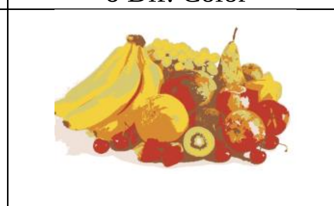
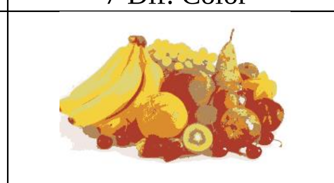
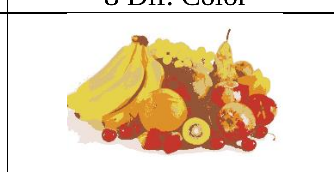
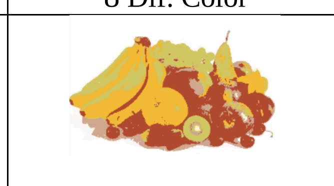
4.3. Experiment 3

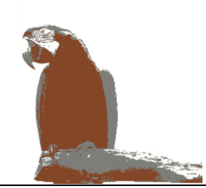
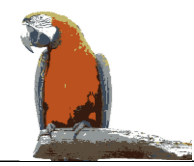
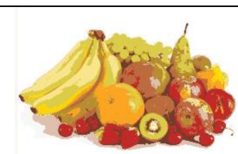
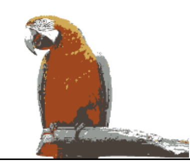
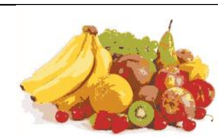
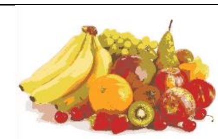
We know that k-means clustering depends on the number of k and the centroid value, so we will test k from 1 to 30 to see how many different colors we get. See figure 18.

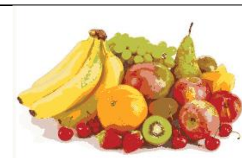
Original Img				
	(DK Findout)	(1 Free Wallpaper, 2020)	(Toppng, 2019)	(Pixabay, 2016)
Delta E				
	317 Dif. Color	149 Dif. Color	96 Dif. Color	318 Dif. Color

Figure 18: Original and DeltaE image dif. color Number

	Image 1	Image 2	Image 3	Image 4
Image K= 1				
	1 Dif. Color	1 Dif. Color	1 Dif. Color	1 Dif. Color
K-means K= 2				
	2 Dif. Color	2 Dif. Color	2 Dif. Color	2 Dif. Color
K-means K= 3				
	3 Dif. Color	3 Dif. Color	3 Dif. Color	3 Dif. Color

K-means K= 4				
	4 Dif. Color	4 Dif. Color	3 Dif. Color	3 Dif. Color
K-means K= 5				
	5 Dif. Color	5 Dif. Color	5 Dif. Color	4 Dif. Color
K-means K= 6				
	4 Dif. Color	6 Dif. Color	6 Dif. Color	4 Dif. Color
K-means K= 7				
	5 Dif. Color	7 Dif. Color	7 Dif. Color	5 Dif. Color
K-means K= 8				
	6 Dif. Color	7 Dif. Color	8 Dif. Color	3 Dif. Color
K-means K= 9				
	5 Dif. Color	8 Dif. Color	8 Dif. Color	4 Dif. Color
K-means K= 10				
	5 Dif. Color	9 Dif. Color	7 Dif. Color	3 Dif. Color

K-means K= 11				
	9 Dif. Color	9 Dif. Color	8 Dif. Color	3 Dif. Color
K-means K= 12				
	10 Dif. Color	8 Dif. Color	11 Dif. Color	3 Dif. Color
K-means K= 13				
	8 Dif. Color	10 Dif. Color	12 Dif. Color	8 Dif. Color
K-means K= 14				
	9 Dif. Color	10 Dif. Color	9 Dif. Color	6 Dif. Color
K-means K= 15				
	6 Dif. Color	13 Dif. Color	12 Dif. Color	5 Dif. Color
K-means K= 16				
	6 Dif. Color	12 Dif. Color	11 Dif. Color	7 Dif. Color
K-means K= 17				
	9 Dif. Color	12 Dif. Color	12 Dif. Color	6 Dif. Color
K-means K= 18				

	6 Dif. Color	10 Dif. Color	12 Dif. Color	6 Dif. Color
K-means K= 19				
	13 Dif. Color	14 Dif. Color	14 Dif. Color	10 Dif. Color
K-means K= 20				
	7 Dif. Color	16 Dif. Color	15	6 Dif. Color
K-means K= 21				
	9 Dif. Color	16 Dif. Color	17 Dif. Color	6 Dif. Color
K-means K= 22				
	10 Dif. Color	17 Dif. Color	15 Dif. Color	9 Dif. Color
K-means K= 23				
	6 Dif. Color	17 Dif. Color	21 Dif. Color	8 Dif. Color
K-means K= 24				
	15 Dif. Color	15 Dif. Color	17 Dif. Color	8 Dif. Color
K-means K= 25				
	7 Dif. Color	15 Dif. Color	16 Dif. Color	10 Dif. Color

K-means K= 26	 10 Dif. Color	 16 Dif. Color	 22 Dif. Color	 9 Dif. Color
K-means K= 27	 14 Dif. Color	 18 Dif. Color	 19 Dif. Color	 13 Dif. Color
K-means K= 28	 10 Dif. Color	 18 Dif. Color	 17 Dif. Color	 12 Dif. Color
K-means K= 29	 10 Dif. Color	 18 Dif. Color	 17 Dif. Color	 12 Dif. Color
K-means K= 30	 14 Dif. Color	 22 Dif. Color	 16 Dif. Color	 11 Dif. Color

Figure 19: Comparison number of dif. color and image forms using K-means Cluster with k from 1 to 30

Chapter 5: Conclusion and Future Works

Because there are so many colors in real life, embroidering a picture on the canvas is impossible. We utilized the Delta Function to compress the picture colors into DMC color space after DMC retrieved 454 distinct colors from a large number of real-life hues.

We calculated the number of different colors and found it to be less than 454 DMC colors, and the number of colors and image quality is directly proportional to image size, so we used two methods to reduce the image colors, one of which is k-means clustering, which leads us to reduce the number of colors. the number of different colors less than 50% with accepted image distortion or noise, k-means clustering iteration is also affected on image quality.

Superpixel is another method that can be used to reduce the number of colors by dividing the images into regions and we found that the number of colors and image quality is directly proportional to the number of regions and image size, at the same time when we compare k-means clustering and superpixel we found that k-means clustering is much better than superpixel.

In future work, datasets from other resources can be measured to validate the accuracy of our proposed methods, and we may find other methods that may give us better results. On the other hand, we need to find a way to reduce the time that the k-means clustering needs in high image resolution1.

الملخص

يمكن الآن رؤية التطريز على القمصان والقبعات والسترات ومجموعة متنوعة من العناصر الأخرى. يجب أن تنظر أعيننا إلى التطريز على أنه صورة ذات مغزى كامل لأنه تم حياكته بمجموعة من ألوان الخيوط. نظرًا لأن معظم الصور الملونة تحتوي على عدد كبير من درجات الألوان المختلفة، فلا يمكننا إنتاج خيوط بنفس اللون لكل من هذه الظلال. للتغلب على هذه المشكلة، بحثنا عن الشركات المصنعة للخيوط واكتشفنا أن DMC تستخدم 454 لونًا بناءً على نموذج ألوان Munsell ، والذي يشبه نظام ألوان HSV. من أجل تحويل كل جزء إلى أقرب لون في مساحة ألوان DMC ، نرغب في استخدام أبعاد AB من مساحة ألوان CIELAB في تجزئة الصورة.

سيتم تقليل ألوان الصورة في مساحة ألوان CIELAB إلى ألوان DMC الكاملة المستخدمة في عملية تصنيع الخيوط الملونة. هدفنا الرئيسي هو تقسيم الصورة إلى أجزاء صغيرة، كل منها بلون واحد، ثم تحويلها إلى أقرب لون DMC لاستقبال الخيط الذي نحتاجه لتطريز اللوحة القماشية. للحصول على العدد المطلوب من ألوان DMC ، سيتم استخدام تقنية التجميع k-mean أو خوارزميةsuperpixel . نهدف إلى استخراج جميع الألوان التي يمكن للدماغ تحديدها في كل صورة مطرزة في هذه الدراسة.

لتقليل كمية الألوان المختلفة التي يمكن استخدامها على القماش، استخدمنا وظيفة دلتا لاختلاف اللون، وتجميع الوسائل k ، و superpixel نظرًا لأن مجموعات k-mean مع وظيفة دلتا لها تشويه أو ضوضاء أقل من superpixel ، ولأن الإخراج أفضل بكثير مع دقة عالية من الدقة المنخفضة، فقد نستخدم صورًا عالية الجودة ومن ثم قياسها حسب الحاجة للقماش.

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Appendix

Table 5: DMC Color List

R	G	B	Name	
255	226	226	Salmon Very Light	
255	201	201	Salmon Light	
245	173	173	Salmon	
241	135	135	Salmon Medium	
227	109	109	Salmon Dark	
191	45	45	Salmon Very Dark	
254	215	204	Peach	
253	156	151	Coral Light	
233	106	103	Coral	
224	72	72	Coral Medium	
210	16	53	Coral Dark	
187	5	31	Coral Red Very Dark	
255	203	213	Melon Light	
255	173	188	Melon Medium	
255	121	146	Melon Dark	
231	73	103	Melon Very Dark	
227	29	66	Bright Red	
199	43	59	Red	
183	31	51	Red Medium	
167	19	43	Red Dark	
151	11	35	Garnet	
135	7	31	Garnet Medium	
123	0	27	Garnet Dark	
255	178	187	Carnation Very Light	
252	144	162	Carnation Light	
255	121	140	Carnation Medium	
255	87	115	Carnation Dark	
255	223	217	Baby Pink	
253	181	181	Geranium Pale	
255	145	145	Geranium	
214	43	91	Rose Dark	
255	215	215	Dusty Rose Ult Vy Lt	
255	189	189	Dusty Rose Med Vy Lt	
230	138	138	Dusty Rose Medium	
207	115	115	Dusty Rose Dark	
234	134	153	Raspberry Light	
219	85	110	Raspberry Medium	
179	47	72	Raspberry Dark	
145	53	70	Raspberry Very Dark	
255	238	235	Baby Pink Light	
251	173	180	Rose Light	
252	176	185	Pink Medium	
242	118	136	Rose Medium	
238	84	110	Rose	
179	59	75	Rose Very Dark	
240	206	212	Dusty Rose Vry Lt	
228	166	172	Dusty Rose Light	
232	135	155	Dusty Rose	

218	103	131	Dusty Rose Very Dark	
188	67	101	Dusty Rose Ultra Dark	
171	2	73	Dusty Rose Ult Vy Dk	
251	191	194	Mauve Light	
231	169	172	Mauve Medium	
201	107	112	Mauve	
171	51	87	Mauve Dark	
136	21	49	Mauve Very Dark	
255	192	205	Cranberry Very Light	
255	176	190	Cranberry Light	
255	164	190	Cranberry	
226	72	116	Cranberry Medium	
209	40	106	Cranberry Dark	
205	47	99	Cranberry Very Dark	
255	140	174	Cyclamen Pink Light	
243	71	139	Cyclamen Pink	
224	40	118	Cyclamen Pink Dark	
244	174	213	Plum Ultra Light	
234	156	196	Plum Very Light	
197	73	137	Plum Light	
156	36	98	Plum	
155	19	89	Plum Medium	
130	0	67	Plum Dark	
255	223	213	Shell Pink Ult Vy Lt	
235	183	175	Shell Pink Very Light	
226	160	153	Shell Pink Med Light	

204	132	124	Shell Pink Light	
188	108	100	Shell Pink Med	
161	75	81	Shell Pink Dark	
136	62	67	Shell Pink Vy Dk	
223	179	187	Antique Mauve Vy Lt	
219	169	178	Antique Mauve Light	
183	115	127	Antique Mauve Med	
155	91	102	Antique Mauve Dark	
129	73	82	Antique Mauve Md Dk	
113	65	73	Antique Mauve Vy Dk	
130	38	55	Garnet Very Dark	
215	203	211	Antique Violet Vy Lt	
183	157	167	Antique Violet Light	
149	111	124	Antique Violet Medium	
120	87	98	Antique Violet Dark	
186	145	170	Grape Light	
148	96	131	Grape Medium	
114	55	93	Grape Dark	
87	36	51	Grape Very Dark	
227	203	227	Lavender Light	
195	159	195	Lavender Medium	
163	123	167	Lavender Dark	
131	91	139	Lavender Very Dark	
108	58	110	Lavender Ultra Dark	
99	54	102	Violet Dark	
230	204	217	Violet Very Light	

219	179	203	Violet Light	
163	99	139	Violet	
128	58	107	Violet Medium	
92	24	78	Violet Very Dark	
211	215	237	Blue Violet Vy Lt	
183	191	221	Blue Violet Light	
163	174	209	Blue Violet Med Lt	
173	167	199	Blue Violet Medium	
152	145	182	Blue Violet Med Dark	
119	107	152	Blue Violet Dark	
92	84	120	Blue Violet Very Dark	
187	195	217	Cornflower Blue Vy Lt	
143	156	193	Cornflower Blue Light	
112	125	162	Cornflower Blue Med	
96	103	140	Cornflower Blue	
85	91	123	Cornflower Blue Dark	
76	82	110	Cornflower Blu M V D	
70	69	99	Cornflower Blue V D	
176	192	218	Lavender Blue Light	
123	142	171	Lavender Blue Med	
92	114	148	Lavender Blue Dark	
192	204	222	Delft Blue Pale	
148	168	198	Delft Blue	
116	142	182	Delft Blue Medium	
70	106	142	Delft Blue Dark	
19	71	125	Royal Blue	
17	65	109	Royal Blue Dark	
14	54	92	Royal Blue Very Dark	
219	236	245	Blue Ultra Very Light	
189	221	237	Blue Very Light	
161	194	215	Blue Light	
107	158	191	Blue Medium	
71	129	165	Blue Dark	
57	105	135	Blue Very Dark	
48	194	236	Electric Blue Medium	
20	170	208	Electric Blue	
38	150	182	Electric Blue Dark	
6	227	230	Turquoise Bright Light	
4	196	202	Turquoise Bright Med	
18	174	186	Turquoise Bright Dark	
199	202	215	Blue Gray Light	
153	159	183	Blue Gray Medium	
120	128	164	Blue Gray	
238	252	252	Baby Blue Ult Vy Lt	
217	235	241	Baby Blue Very Light	
205	223	237	Baby Blue Pale	
184	210	230	Baby Blue Light	
147	180	206	Baby Blue	
115	159	193	Baby Blue Medium	
90	143	184	Baby Blue Dark	
53	102	139	Baby Blue Very Dark	
44	89	124	Baby Blue Ult Vy Dk	

37	59	115	Navy Blue	
33	48	99	Navy Blue Dark	
27	40	83	Navy Blue Very Dark	
219	226	233	Antique Blue Ult Vy Lt	
199	209	219	Antique Blue Very Lt	
162	181	198	Antique Blue Light	
106	133	158	Antique Blue Medium	
69	92	113	Antique Blue Dark	
56	76	94	Antique Blue Very Dk	
197	232	237	Sky Blue Vy Lt	
172	216	226	Sky Blue Light	
126	177	200	Sky Blue	
79	147	167	Wedgewood Light	
62	133	162	Wedgewood Med	
59	118	143	Wedgewood Dark	
50	102	124	Wedgewood Vry Dk	
28	80	102	Wedgewood Ult VyDk	
229	252	253	Peacock Blue Vy Lt	
153	207	217	Peacock Blue Light	
100	171	186	Peacock Blue	
61	149	165	Peacock Blue Dark	
52	127	140	Peacock Blue Vy Dk	
188	227	230	Turquoise Very Light	
144	195	204	Turquoise Light	
91	163	179	Turquoise	
72	142	154	Turquoise Dark	

63	124	133	Turquoise Vy Dark	
54	105	112	Turquoise Ult Vy Dk	
221	227	227	Gray Green Vy Lt	
189	203	203	Gray Green Light	
152	174	174	Gray Green Med	
101	127	127	Gray Green Dark	
86	106	106	Gray Green Vy Dark	
82	179	164	Teal Green Light	
85	147	146	Teal Green Med	
52	125	117	Teal Green Dark	
169	226	216	Sea Green Light	
89	199	180	Sea Green Med	
62	182	161	Sea Green Dark	
47	140	132	Sea Green Vy Dk	
73	179	161	Green Bright Lt	
61	147	132	Green Bright Md	
55	132	119	Green Bright Dk	
144	192	180	Aquamarine Vy Lt	
111	174	159	Aquamarine Lt	
80	139	125	Aquamarine	
71	123	110	Aquamarine Dk	
185	215	192	Jade Ultra Vy Lt	
167	205	175	Jade Very Light	
143	192	152	Jade Light	
83	151	106	Jade Medium	
51	131	98	Jade Green	

153	195	170	Celadon Green Lt	
101	165	125	Celadon Green	
77	131	97	Celadon Green Md	
71	119	89	Celadon Green Dk	
44	106	69	Celadon Green VD	
196	222	204	Blue Green Vy Lt	
178	212	189	Blue Green Lt	
123	172	148	Blue Green Med	
91	144	113	Blue Green	
57	111	82	Blue Green Dark	
4	77	51	Blue Green Vy Dk	
162	214	173	Nile Green Light	
136	186	145	Nile Green	
109	171	119	Nile Green Med	
27	157	107	Emerald Green Lt	
24	144	101	Emerald Green Med	
24	126	86	Emerald Green Dark	
21	111	73	Emerald Green Vy Dk	
17	90	59	Emerald Grn Ult V Dk	
215	237	204	Pistachio Green Vy Lt	
166	194	152	Pistachio Green Lt	
105	136	90	Pistachio Green Med	
97	122	82	Pistachio Green Dk	
32	95	46	Pistachio Grn Vy Dk	
23	73	35	Pistachio Grn Ult V D	
200	216	184	Forest Green Lt	

141	166	117	Forest Green	
115	139	91	Forest Green Med	
88	113	65	Forest Green Dk	
64	82	48	Forest Green Vy Dk	
228	236	212	Yellow Green Vy Lt	
204	217	177	Yellow Green Lt	
113	147	92	Yellow Green Med	
64	106	58	Hunter Green	
27	89	21	Hunter Green Dk	
27	83	0	Hunter Green Vy Dk	
158	207	52	Chartreuse Bright	
123	181	71	Chartreuse	
71	167	47	Kelly Green	
63	143	41	Green Light	
7	115	27	Green Bright	
5	101	23	Green	
199	230	102	Parrot Green Lt	
127	179	53	Parrot Green Md	
98	138	40	Parrot Green Dk	
85	120	34	Parrot Green V Dk	
216	228	152	Avocado Grn U Lt	
174	191	121	Avocado Grn V Lt	
148	171	79	Avocado Grn Lt	
114	132	60	Avocado Green	
98	113	51	Avocado Green Md	
76	88	38	Avocado Grn V Dk	

66	77	33	Avocado Green Dk	
49	57	25	Avocado Grn Black	
171	177	151	Fern Green Lt	
156	164	130	Green Gray	
136	146	104	Green Gray Md	
95	102	72	Green Gray Dk	
196	205	172	Fern Green Vy Lt	
150	158	126	Fern Green	
102	109	79	Fern Green Dark	
131	151	95	Pine Green	
114	130	86	Pine Green Md	
94	107	71	Pine Green Dk	
239	244	164	Moss Green Vy Lt	
224	232	104	Moss Green Lt	
192	200	64	Moss Green Md Lt	
167	174	56	Moss Green	
136	141	51	Moss Green Dk	
199	192	119	Olive Green Lt	
188	179	76	Olive Green Md	
148	140	54	Olive Green	
147	139	55	Olive Green Dk	
130	123	48	Olive Green V Dk	
185	185	130	Khaki Green Lt	
166	167	93	Khaki Green Md	
137	138	88	Khaki Green Dk	
204	183	132	Mustard Lt	

191	166	113	Mustard	
184	157	100	Mustard Medium	
219	190	127	Golden Olive Vy Lt	
200	171	108	Golden Olive Lt	
189	155	81	Golden Olive	
170	143	86	Golden Olive Md	
141	120	75	Golden Olive Dk	
126	107	66	Golden Olive Vy Dk	
220	196	170	Drab Brown V Lt	
188	154	120	Drab Brown Lt	
150	118	86	Drab Brown	
121	96	71	Drab Brown Dk	
231	214	193	Yellow Beige Lt	
216	188	154	Yellow Beige Md	
188	150	106	Yellow Beige Dk	
167	124	73	Yellow Beige V Dk	
252	252	238	Off White	
245	236	203	Old Gold Vy Lt	
198	159	123	Hazelnut Brown Lt	
183	139	97	Hazelnut Brown	
160	112	66	Hazelnut Brown Dk	
131	94	57	Hazelnut Brown V Dk	
228	180	104	Topaz	
206	145	36	Topaz Medium	
174	119	32	Topaz Dark	
162	109	32	Topaz Very Dark	

148	99	26	Topaz Ultra Vy Dk	
229	206	151	Old Gold Lt	
208	165	62	Old Gold Medium	
188	141	14	Old Gold Dark	
169	130	4	Old Gold Vy Dark	
246	220	152	Straw Light	
243	206	117	Straw	
223	182	95	Straw Dark	
205	157	55	Straw Very Dark	
255	251	139	Lemon Light	
253	237	84	Lemon	
255	227	0	Canary Bright	
255	214	0	Lemon Dark	
253	249	205	Golden Yellow Vy Lt	
255	241	175	Topaz Vy Lt	
253	215	85	Topaz Light	
255	200	64	Topaz Med Lt	
255	181	21	Canary Deep	
255	233	173	Yellow Pale Light	
255	231	147	Yellow Pale	
254	211	118	Yellow Med	
255	191	87	Tangerine Light	
255	163	43	Tangerine Med	
255	139	0	Tangerine	
247	139	19	Pumpkin Light	
246	127	0	Pumpkin	

255	123	77	Burnt Orange	
235	99	7	Burnt Orange Med	
209	88	7	Burnt Orange Dark	
255	222	213	Apricot Very Light	
254	205	194	Apricot Light	
252	171	152	Apricot	
255	131	111	Apricot Med	
253	93	53	Burnt Orange Bright	
250	50	3	Orange?Red Bright	
255	226	207	Tawny Light	
255	211	181	Mahogany Ult Vy Lt	
247	151	111	Orange Spice Light	
242	120	66	Orange Spice Med	
229	92	31	Orange Spice Dark	
253	189	150	Pumpkin Pale	
226	115	35	Copper Light	
198	98	24	Copper	
172	84	20	Copper Med	
166	69	16	Red Copper	
130	52	10	Red Copper Dark	
255	238	227	Tawny Vy Light	
251	213	187	Tawny	
247	167	119	Mahogany Vy Lt	
207	121	57	Mahogany Light	
179	95	43	Mahogany Med	
143	67	15	Mahogany Dark	

111	47	0	Mahogany Vy Dk	
255	253	227	Yellow Ultra Pale	
250	211	150	Autumn Gold Lt	
242	175	104	Autumn Gold Med	
242	151	70	Autumn Gold Dk	
247	187	119	Golden Brown Pale	
220	156	86	Golden Brown Light	
194	129	66	Golden Brown Med	
173	114	57	Golden Brown	
145	79	18	Golden Brown Dk	
254	231	218	Peach Very Light	
247	203	191	Peach Light	
244	187	169	Terra Cotta Ult Vy Lt	
238	170	155	Terra Cotta Vy Lt	
217	137	120	Terra Cotta Light	
197	106	91	Terra Cotta Med	
185	85	68	Terra Cotta	
152	68	54	Terra Cotta Dark	
134	48	34	Terra Cotta Vy Dk	
248	202	200	Rosewood Ult Vy Lt	
186	139	124	Rosewood Light	
150	74	63	Rosewood Med	
104	37	26	Rosewood Dark	
243	225	215	Desert Sand Vy Lt	
238	211	196	Desert Sand Light	
196	142	112	Desert Sand	

187	129	97	Desert Sand Med	
182	117	82	Desert Sand Dark	
160	108	80	Desert Sand Vy Dk	
135	85	57	Desert Sand Ult Vy Dk	
215	206	203	Shell Gray Light	
192	179	174	Shell Gray Med	
145	123	115	Shell Gray Dark	
166	136	129	Cocoa Light	
125	93	87	Cocoa	
98	75	69	Cocoa Dark	
255	251	239	Cream	
248	228	200	Tan Ult Vy Lt	
236	204	158	Tan Very Light	
228	187	142	Tan Light	
203	144	81	Tan	
184	119	72	Brown Very Light	
152	94	51	Brown Light	
122	69	31	Brown Med	
101	57	25	Coffee Brown Dk	
73	42	19	Coffee Brown Vy Dk	
54	31	14	Coffee Brown Ult Dk	
30	17	8	Black Brown	
242	227	206	Beige Brown Ult Vy Lt	
203	182	156	Mocha Beige Light	
164	131	92	Mocha Beige Med	
138	110	78	Mocha Beige Dark	

75	60	42	Mocha Brown Vy Dk	
255	255	255	Snow White	
252	251	248	White	
249	247	241	Winter White	
240	234	218	Ecru	
231	226	211	Beige Gray Light	
221	216	203	Beige Gray Med	
164	152	120	Beige Gray Dark	
133	123	97	Beige Gray Vy Dk	
98	93	80	Brown Gray Dark	
79	75	65	Brown Gray Vy Dk	
235	234	231	Brown Gray Vy Lt	
177	170	151	Brown Gray Light	
142	144	120	Brown Gray Med	
99	100	88	Ash Gray Vy Lt	
227	216	204	Mocha Brown Vy Lt	
210	188	166	Mocha Brown Lt	
179	159	139	Mocha Brown Med	
127	106	85	Beige Gray Ult Dk	
107	87	67	Mocha Brown Dk	
250	246	240	Mocha Brn Ult Vy Lt	

209	186	161	Beige Brown Vy Lt	
182	155	126	Beige Brown Lt	
154	124	92	Beige Brown Med	
103	85	65	Beige Brown Dk	
89	73	55	Beige Brown Vy Dk	
230	232	232	Beaver Gray Vy Lt	
188	180	172	Beaver Gray Lt	
176	166	156	Beaver Gray Med	
135	125	115	Beaver Gray Dk	
110	101	92	Beaver Gray Vy Dk	
72	72	72	Beaver Gray Ult Dk	
236	236	236	Pearl Gray Vy Lt	
211	211	214	Pearl Gray	
171	171	171	Steel Gray Lt	
140	140	140	Steel Gray Dk	
209	209	209	Pewter Very Light	
132	132	132	Pewter Light	
108	108	108	Pewter Gray	
86	86	86	Pewter Gray Dark	
66	66	66	Pewter Gray Vy Dk	
0	0	0	Black	

Appendix 2: Delta Function Matlab Code

```
function FinalImage= DeltaFunc(ImgArr)
rows = @(x) size(x,1);
cols = @(x) size(x,2);
List=uint8.empty(1,0,3);
dmcclr=454;
DMC3dArray=List;
DMCTable = readtable('RGBDMC.xlsx');
DMCRGBArray=DMCTable(:,2:4);
DMCArray=table2array(DMCRGBArray);
DMC3dArray1=reshape(DMCArray,[dmcclr,1,3]);
for imval=1:dmcclr
    DMC3dArray (imval,1,1)=   DMC3dArray1(imval,1,1);
    DMC3dArray (imval,1,2)=   DMC3dArray1(imval,1,2);
    DMC3dArray (imval,1,3)=   DMC3dArray1(imval,1,3);
end
LabDMC=rgb2lab(DMC3dArray);
%DMC Channel
DMCLChannel=LabDMC(:,:,1);
DMCaChannel=LabDMC(:,:,2);
DMCbChannel=LabDMC(:,:,3);
prsnt=1;
RowImage=ImgArr;
% RowImage=RGBImgShap3;
ResizeImage=imresize (RowImage,prsnt);
RGBImage2=ResizeImage;
RGBImage1=RGBImage2;
RGBImage = imresize(RGBImage1, 1);
% imshow(RGBImage);
LabImage=rgb2lab(RGBImage);
FinaleImg=LabImage;
FinaleImg(:,:,1:3)=0;
%DMC Color
DMCColor=LabImage;
DMCColor(:,:,1)=LabDMC(1,1,1);
DMCColor(:,:,2)=LabDMC(1,1,2);
DMCColor(:,:,3)=LabDMC(1,1,3);

%Image Channel
ImageLChannel1=LabImage(:,:,1);
ImageaChannel1=LabImage(:,:,2);
ImagebChannel1=LabImage(:,:,3);
ImageRowNo=rows(RGBImage);
ImageColNo=cols(RGBImage);
ImgDim=ImageRowNo*ImageColNo;
DMCRowNo=dmcclr;
DMCColNo=1;
ColorIDVal=double.empty(ImageRowNo,0);
ColArr=double.empty(1,0);
DeltaArr=double.empty(1,0);
ColArr(1,1)=-1;
%ColArr(:,1)=-1;
RowNoID=1;
VldClr=0;
ChkVal=0;
```

```
colInNo=DMCColNo;
for ImgRowlVal = 1:ImageRowNo
    for ImgColVal= 1:ImageColNo
         for DMCRowVal =1:DMCRowNo
            %Delta = LabeChannel 1 -LabChannel 2
            DltL=ImageLChannel1(ImgRowlVal,ImgColVal)-
DMCLChannel(DMCRowVal,1);
            Dlta=ImageaChannel1(ImgRowlVal,ImgColVal)-
DMCaChannel(DMCRowVal,1);
            Dltb=ImagebChannel1(ImgRowlVal,ImgColVal)-
DMCbChannel(DMCRowVal,1);
            %Delta C
            CImageval=sqrt((ImageaChannel1(ImgRowlVal,ImgColVal)).^ 2 +
(ImagebChannel1(ImgRowlVal,ImgColVal)).^ 2);
            CDMCVal=sqrt((DMCaChannel(DMCRowVal,1)).^ 2 +
(DMCbChannel(DMCRowVal,1)).^ 2);
            DltC=CImageval-CDMCVal;
            %Delta H
            DltH=sqrt((Dlta.^ 2) +( Dltb.^ 2) - (DltC.^ 2));
            %F
            FVal=sqrt((CImageval.^ 4)/((CImageval.^ 4)+1900));
            %H

HVal=atan2(ImagebChannel1(ImgRowlVal,ImgColVal),ImageaChannel1(ImgRowlVal,Img
ColVal));
            HDgrVal=rad2deg(HVal);
            %H1
            if HDgrVal >= 0
                H1Val=    HDgrVal;
            else
                H1Val=    HDgrVal+360;
            end
            %T
            if( H1Val>=164 && H1Val<=345)
                TVal=(   0.56 + abs(0.2*cos(H1Val+168)));
            else
                TVal=(   0.36 + abs(0.4*cos(H1Val+35)));
            end
            %Sl
            if ImageLChannel1(ImgRowlVal,ImgColVal)<16
                SlVal= 0.511;
            else
                SlVal= (0.040975
+ImageLChannel1(ImgRowlVal,ImgColVal))/(1+(0.01765+ImageLChannel1(ImgRowlVal,
ImgColVal)));
            end
            %Sc
            ScVal= ((0.0638 *CImageval)/(1+0.0131*CImageval))+0.638;
            %Sh
            ShVal= ScVal *((FVal*TVal)+1-FVal);
            %lVal and cVal
            lVal=2;
            cVal=1;
            %DeltaE
            DeltaE=sqrt(((DltL/(lVal*SlVal)).^ 2 +(DltC/(cVal*ScVal)).^ 2
+(DltH/ShVal).^ 2 ));
            DeltaArr(DMCRowVal,1)=DeltaE;
```

```
            if ChkVal==0
                DeltaLevel1=DeltaE;
                 DMCokVal=DMCRowVal;
                    ColorIDVal(ImgRowlVal,ImgColVal)=DMCokVal;
                    Rpix=DMCLChannel(DMCokVal,1);
                    Gpix=DMCaChannel(DMCokVal,1);
                    Bpix=DMCbChannel(DMCokVal,1);
                    ColorID=DMCokVal;
                    ChkVal=1;
            else
                if  DeltaE <= DeltaLevel1
                    DMCokVal=DMCRowVal;
                    ColorIDVal(ImgRowlVal,ImgColVal)=DMCokVal;
                    Rpix=DMCLChannel(DMCokVal,1);
                    Gpix=DMCaChannel(DMCokVal,1);
                    Bpix=DMCbChannel(DMCokVal,1);
                    DeltaLevel1=DeltaE;
                    ColorID=DMCokVal;
                else
                end
            end
         end
        FinaleImg(ImgRowlVal,ImgColVal,1)=Rpix;
        FinaleImg(ImgRowlVal,ImgColVal,2)=Gpix;
        FinaleImg(ImgRowlVal,ImgColVal,3)=Bpix;
        ChkVal=0;
        for CountVal =colInNo:rows(ColArr)
            if (ColorID ~=ColArr(CountVal,1))
                UColorID=ColorID;
            else
                VldClr=1;
            end
        end
        if VldClr==0
            ColArr(RowNoID,1)=UColorID;
            RowNoID=RowNoID+1;
        else
        end
        VldClr=0;
    end
end
FinalImage=lab2rgb(FinaleImg,'OutputType','uint8');
end
```

Appendix 3: K-means Clustering MATLAB code:

```
function FinalImageKmean= Fkmean(ImgArr,K)
RowImage=ImgArr;
rows = @(x) size(x,1);
cols = @(x) size(x,2);
k=K;
RGBimg=RowImage;
%RGB image Converted To Lab Image
Labimg=rgb2lab(RGBimg);
Lchannel=Labimg(:,:,1);
achannel=Labimg(:,:,2);
bchannel=Labimg(:,:,3);
% Image Colomn And Row
ImgCol=cols(Labimg);
ImgRow=rows(Labimg);
ImgDim=ImgCol*ImgRow;
% Reshap the Image into One Column
RGBImgShap=reshape(Labimg,[ImgDim,1,3]);
%Create Empty Array
CentroidindList=double.empty(1,0);
CentroidList=double.empty(1,0);
CentroidListVal=double.empty(5,0);
DefList=double.empty(k,0);
% DalList=double.empty(1,0);
LabImgList=double.empty(1,0,3);
CLRlist=double.empty(ImgDim,0);
% BWimg=reshape(BW2,[ImgDim,1]);
% Number Of Rows In reshap Image
LabImgRow=rows(LabImgList);
% Centroid Point
A=randi(ImgDim,1);
CentroidindList(1,1)=A;
CentroidList(1,1,1:3)=RGBImgShap(A,1,1:3);
for kval=1:k-1
    if A~=CentroidindList(kval,1)
        CentroidindList(kval,1)
    else
        A=randi(ImgDim,1);
    end
    CentroidindList(kval+1,1)=A;
    CentroidList(kval+1,1,1:3)=RGBImgShap(A,1,1:3);
end
ChkDlt=0;
RGBCentroidList=lab2rgb(CentroidList,'OutputType','uint8');
templist= RGBCentroidList;
clt=0;
Num=1;
RGBImgShap1=RGBImgShap;
RGBImgShap1(:,:,1:3)=0;
CentroidListVal(1:k,4)=0;
as=0;
for itr=1:1
    for ClrVal=1:ImgDim
        Itemp=-1;
        for cntVal =1:k
```

```
            DefList (cntVal,1) = sqrt(((RGBImgShap(ClrVal,1,1)-
CentroidList(cntVal,1,1)).^2)+((RGBImgShap(ClrVal,1,2)-
CentroidList(cntVal,1,2)).^2)+((RGBImgShap(ClrVal,1,3)-
CentroidList(cntVal,1,3)).^2));
        end
        [M,I] = min(DefList (1:cntVal,1)) ;
        CLRlist(ClrVal,1)=I;
        % if Itemp==I
        Ach=0;
        Bch=0;
        Lch=0;
        TotalCh=0;

        for cl=1:ClrVal
            if CLRlist(cl,1)==I
                Lch= RGBImgShap(cl,1,1)+Lch;
                Ach= RGBImgShap(cl,1,2)+Ach;
                Bch= RGBImgShap(cl,1,3)+Bch;
                TotalCh=TotalCh+1;
            else
            end
        end
        CentroidList(I,1,1)=Lch/TotalCh;
        CentroidList(I,1,2)=Ach/TotalCh;
        CentroidList(I,1,3)=Bch/TotalCh;
        ChkDlt=0;
        DefList (1:cntVal,1)=0;
    end

    for ClrVal=1:ImgDim
        aaa=CLRlist(ClrVal,1);
        %  SubVal
        RGBImgShap1(ClrVal,1,1:3)=CentroidList(aaa,1,1:3);
    end
    RGBImgShap2=reshape(RGBImgShap1,[ImgRow,ImgCol,3]);
    FinalImageKmean=lab2rgb(RGBImgShap2,'OutputType','uint8');
    as=as+4;
end
end
```

appendix 4: superpixel MATLAB Code

```
function SpexFunc= Spxel(ImgArr,K)

A1 = ImgArr;
A=rgb2lab(A1);
[L,N] = superpixels(A,K);
outputImage = zeros(size(A),'like',A);
idx = label2idx(L);
numRows = size(A,1);
numCols = size(A,2);
for labelVal = 1:N
    redIdx = idx{labelVal};
    greenIdx = idx{labelVal}+numRows*numCols;
    blueIdx = idx{labelVal}+2*numRows*numCols;
    outputImage(redIdx) = mean(A(redIdx));
    outputImage(greenIdx) = mean(A(greenIdx));
    outputImage(blueIdx) = mean(A(blueIdx));
end
SpexFunc=lab2rgb(outputImage,'OutputType','uint8');
```