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MULTI-COUNTERPROPAGATION NETWORK MODEL FOR COLOUR RECOGNITION

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ABSTRACT

*Minolta Chroma Meters was used to convert colours into numbers. It offers five different colour systems for measuring absolute chromaticity, that is, CIE Yxy, L*a*b*, L*C*H^o, Hunter Lab and XYZ. In this study, only L*a*b* is used, and combinations of two counterpropagation network (CPN) are required to recognise 808 colours produced by The Royal Horticultural Society, based on RHS Colour Chart [1]. Our proposed neural network model is tested; the result shows that 99% of trained data are recognised, against 98% for untrained data.*

Keywords : ***CPN model, competitive layer, unsupervised learning, supervised learning, Minolta Chroma Meters***

1.0 INTRODUCTION

An infinite number of colours surround us in our everyday lives. We take colour pretty much for granted, but its role in our daily lives ranges from influencing our tastes in food and other purchases to telling us whether plants are healthy or not.

The need for an automatic colour recognition system for industrial and commercial applications is very widespread. Existing examples include colour coding in the manufacturing of electrical equipment, colour matching of tones in tanneries and paints in the automotive industry, colour recognition as an aid for the blind and colour-blind, and colour recognition as a powerful and reliable parameter for object recognition in robotics. Specific examples include diamond color sorting and quality control for the manufacturing of coloured paper [2].

Colour is a matter of perception, of subjective interpretation. To express the same colour, different people draw upon different references and express the exact same colour in different words. It is because there are such varied expressions that communicating a particular colour is so difficult and vague.

1.1 Colours

Colour is a visual object attribute, which results from combined output of three sets of retinal cones, each sensitive to different portions of the visible part of the electromagnetic spectrum. The cones have peak sensitivities in the red, green and blue portions of the spectrum, respectively. Any perceived colour may usually be created by a variety of sets of "primary" colours when combined in the correct proportions.

Colours are generally described by hue, value and chroma [2]. Hue is the combination of different wavelengths that produce a colour. Value is lightness or intensity and depends on the amount of energy present in all the wavelengths of a colour; this is not however the same as the luminance of a colour. Chroma is saturation whereby saturation can be described as the purity of a colour, and indicates the range of wavelengths around the colour wavelength in which most of the energy is present. Therefore, a single wavelength would have a high saturation, whereas a colour consisting of a number of wavelengths would have a low saturation.

Hue, value and chroma can be visualized in three dimensions as shown Fig. 1. Colour hues are on the outside around the central axis, with value forming the vertical axis and chroma the horizontal axis from the centre. If the three attributes shown in Fig. 1 were actually combined into a three-dimensional system, they would appear as a colour solid. Because the chroma steps on the horizontal axis vary with each hue and value, the final solid assumes a fairly complicated configuration. When expressed in a figure, the relationship between hue, value and chroma becomes much clearer [3].

1.2 Counter Propagation Network (CPN)

Neural networks are mathematical models of the way in which neurons (hence the name) in the brain fire and interact. Just as the brain learns by strengthening connections between neurons, so do neural networks, which can also be trained. Typical functions for neural networks include learning functions such as time-series, recognition tasks (image recognition etc.), extraction of features within data (data mining), statistical clustering (statistical correlation) and predictive functions, such as sales predictions.

A CPN is a multilayer network based on a combination of input, clustering, and output layer. CPN can be used to compress data, to approximate functions, or to associate patterns. CPN provides an excellent example of a network that combines different layer from other paradigms to construct a new type of network. Two different types of layer are used in CPN: the hidden layer is a Kohonen layer, with competitive units that do unsupervised learning; the top layer is the Grossberg layer, which is fully interconnected to the hidden layer, and is not competitive. The Grossberg layer is trained by a Widrow-Hoff or Grossberg rule [4].

In supervised learning, there is a “teacher” who in the learning phase “tells” the net how well it performs (“reinforcement learning”) or what the correct behavior should have been (“fully supervised learning”). In unsupervised learning, the net is autonomous: it just looks at the data it is presented with, finds out about some of the properties of the data set, and learns to reflect these properties in its output. What exactly these properties are, that the network can learn to recognise, depends on the particular network model and learning method.

Fig. 2 shows the topology of a typical three-layered CPN. The first layer of units is solely for input, the second is the competitive-Kohonen layer, and the third is the layer of output units (the Grossberg layer). Each layer is fully interconnected to the layer above it [4].

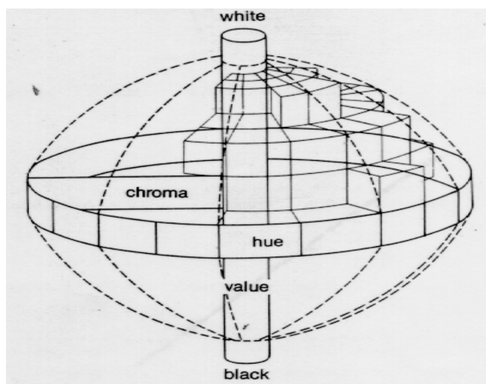


Fig. 1: Three-Dimension (3D) Colour System

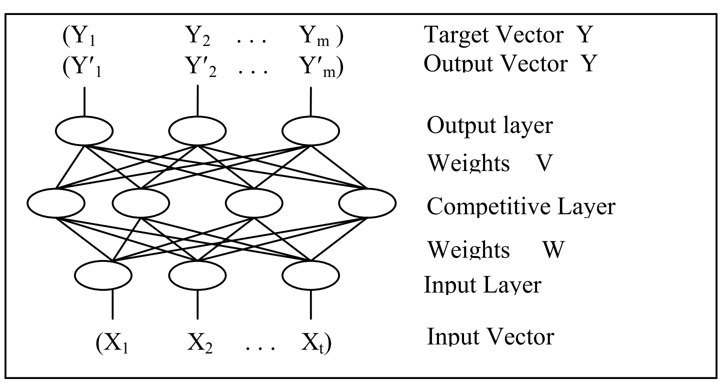


Fig. 2: A Three-layer CPN

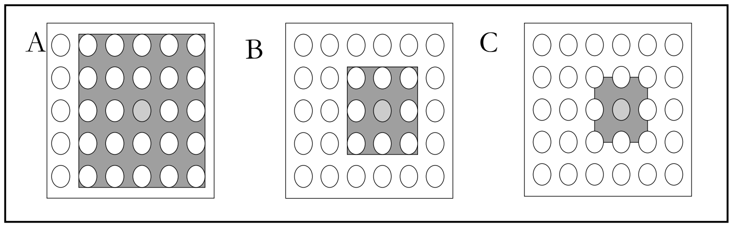


Fig. 3: Training a Localised Neighbourhood

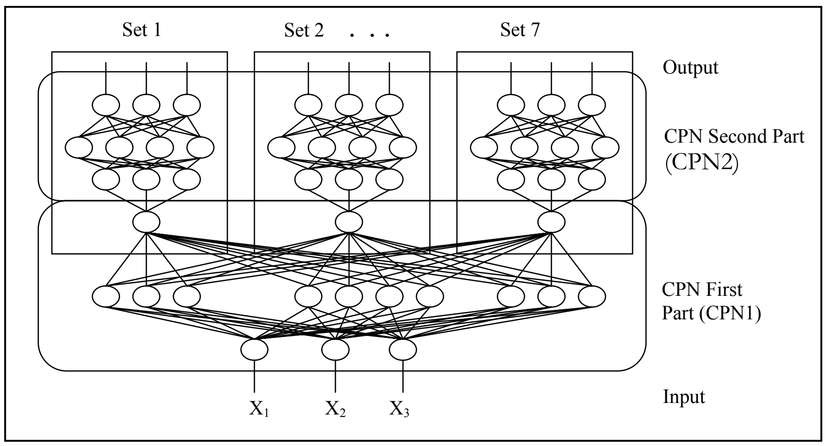


Fig 4: Architecture of Multi-CPN

At the competitive layer (Kohonen layer), Kohonen introduces the idea of topological neighbourhoods which is a dynamically changing boundary that defines how many nodes surrounding the winning node will be affected with weight modifications during the training process.

Fig. 3 shows the effect of shrinking the neighbourhood by localising areas of similar activity. All the units with the shaded area in A are initially affected, and realign themselves slightly towards the winning node's weight vector. As time passes, the neighbourhood is reduced and only the nodes in the neighbourhood of the winning node are altered. These latter align themselves more and more, until the area around the winner consists of similar weight vectors. In the resulting network, an input which is close to the one that triggered the original node will elicit a response from a node that is topogically closed [5].

2.0 COLOUR RECOGNITION AND MULTI-CPN MODEL

The L*a*b* colour system is presently one of the most popular colour systems for measuring object colour, and is widely used in all fields. In this colour system, L*, a* and b* are the three coordinates that can be put together to create the three-dimensional colour solids as shown in Fig. 1. The L* coordinates indicate the lightness which forms the vertical axis with values ranging from 0 (black) to 100 (white). The a* and b* coordinates form the horizontal axis, whereby their coordinates are redness (+a*) to greenness (-a*), and yellowness (+b*) to blueness (-b*). The a* and b* coordinates are used to calculate the hue angle (h^o) and chroma (C*) [3].

Running CPN using 100 colours as input [6], will take 24 minute 43.32 seconds for 100% recognition for trained and untrained data. But, if trained with 808 colours produced by The Royal Horticultural Society, it required a large size of memory and the training process took quite a time. So, to solve this problem, two combined CPNs models are proposed; the main CPN and a second CPN. The main CPN has three input nodes and seven output nodes. These seven output nodes represent seven groups of colours. The second CPN is the group that, for each colour, consists of seven CPNs. Fig. 4 shows the architecture of the multi-neural network.

3.0 METHODOLOGY

In multi-CPN, 808 colours will be divided into seven groups. Each group has different amount of data, as shown in Table 1.

Table 1: Groups of Data for Second CPNs

Group	Amount of data (colours)
1	140
2	156
3	96
4	104
5	120
6	36
7	156
Total	808

The algorithm for multi-CPN model as follows:

Step 1. Each group of second CPN runs separately with the same initial neighbourhood, size of competitive layer and the number of cycles to get their respective weights.

Step 2. The main CPN will run after the second CPN finish.

Step 3. Recalls the data using the final weight.

The learning rule for weights (v_{iJ}, i=1,2,…,m and J=1,2,…,n) from input units (x_i, i= 1,2,…,m) to competitive units (z_j, j=1,2,…,q) [7] is

$$\begin{aligned} v_{iJ}(\text{new}) &= v_{iJ} + \alpha(x_i - v_{iJ}) \\ &= (1 - \alpha)\, v_{iJ}(\text{old}) + \alpha x_i \end{aligned}$$

and the learning rule for weights (w_{Jk}, J=1,2,…,n and k=1,2,…,p) from competitive units to output units (y_k, k=1,2,…,p) is

$$\begin{aligned} w_{Jk}(\text{new}) &= w_{Jk} + \text{a}(y_k - w_{Jk}) \\ &= (1 - \text{a})\, w_{Jk}(\text{old}) + \text{a}y_k \end{aligned}$$

However, if w_{jk} is interpreted as the computed output (i.e., $y_k = w_{jk}$), and the activation of the competitive units is included as

$$z_j = 1 \text{ if } j = J$$

or $$z_j = 0 \text{ if } j \neq J$$

then, the learning rule for the weights from the competitive units to the output units can be written in the form of delta rule:

$$w_{jk}(\text{new}) = w_{jk} + \text{a}z_j(y_k - w_{jk})$$

4.0 RESULTS AND DISCUSSION

Data used for the training phase were taken from the Minolta Chroma Meters that can convert colours into numbers, see Table A01 in Appendix A. The data were then normalised within the range of –1 and 1 using the formula

$$D_{scl} = R_{min} + (R_{max} - R_{min}) \text{ x } (D - D_{min}) \ / \ (D_{max} - D_{min})$$

where

D	real data
D_{scl}	scale data
D_{min}	minimum value from set of data
D_{max}	maximum value from set of data
R_{min}	minimum value from a range
R_{max}	maximum value from a range

For the initial experiment, 100 colours will be run first to see the effectiveness of multi-CPN. The results show (Table 2) that all experiments get 100% recognition for trained and untrained data.

From Table 2 and Table 3, it is shown that multi-CPN can recognise much better than CPN and that the training time is faster than for CPN [6]. Then, the data was increased to 808. The results are shown from Table 4 to Table 9, and CPN1 is the first part of multi-CPN, whereas CPN2 is the second part of multi-CPN.

Table 2: Percentage of Recognition Multi-CPN (100 colours) with Initial Neighbourhood are 5 and Size of Competitive Layer are 500

	No. of Cycle		
Set of Data	100	300	500
Trained	100	100	100
Untrained	100	100	100
Time Taken for Training	0:00:14.93	0:00:43.97	0:01:16.55

Table 3: Percentage of Recognition Multi-CPN (100 colours) with Initial Neighbourhood are 10 and Size of Competitive Layer are 500

	No. of Cycle		
Set of Data	100	300	500
Trained	100	100	100
Untrained	100	100	100
Time Taken for Training	0:00:15.1	0:00:45.31	0:01:15.55

From Table 4, it can be seen that, when the number of cycles was increased from 1000 to 2000, percentage recognition for trained data increased of about 0.2%. Untrained data, however, decreased of about 0.5%. When the number of cycles was increased from 2000 to 5000, percentage recognition decreased of about 1.5% for trained data, and 1.2% for untrained data. This may have been caused by an extreme value of the initial neighbourhood.

After that, when the initial neighbourhood was increased from 10 to 12, and the size of competitive layer kept to 1000 (Table 5), the percentage recognition decreased for each number of cycle. It shows here that, when the initial neighbourhood is increased, it does not mean that the percentage of recognition will also increase. For the next step, the initial neighbourhood was kept at 10, and the size of competitive layer was increased from 1000 to 1500 (Table 6). At this level, the percentage of recognition for trained and untrained data increased.

From Table 7, the results show that when the initial neighbourhood was increased from 10 to 12, and the competitive layer were kept to 1500, for a number of cycles of 1000, percentage recognition for trained data still remained 96.8%. However, untrained data increased of about 0.4%. When the number of cycles was increased from 1000 to 2000, percentage recognition for trained data increased from 96.8% to 97.0% and, for untrained data, it increased from 95.4% to 95.8%. Percentage recognition for trained data increased of about 0.3%, and about 0.6% for untrained data when the number of cycles was increased from 2000 to 5000.

When the competitive layer were increased from 1500 to 2000 and the initial neighbourhood kept at 10, percentage recognition for trained data increased of about 0.8%, 1.3% and 0.8% for number of cycles of 1000, 2000 and 5000, respectively.

From Table 9, the results show that multi-CPN can recognise up to 99.3% for trained data, and 98.4% for untrained data. This means that, from 808 colours, 802 were recognised for trained data, and 795 for untrained data.

Table 4: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 10 and Size of Competitive Layer are 1000

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN1	CPN 2	CPN1	CPN 2
Trained	91	91	91.2	91.2	89.7	89.7
Untrained	90.6	90.6	90.1	90.1	88.9	88.9
Time taken for training	0:39:25.71		1:18:46.03		2:41:52.12	

Table 5: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 12 and Size of Competitive Layer are 1000

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN 1	CPN 2	CPN 1	CPN 2
Trained	88.1	88.1	90.3	90.3	89.0	89.0
Untrained	87.4	87.4	89.6	89.6	88.5	88.5
Time taken for training	0:39:41.77		1:19:17.37		2:48:06.45	

Table 6: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 10 and Size of Competitive Layer are 1500

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN1	CPN2	CPN1	CPN2
Trained	96.8	96.8	96.3	96.3	96.9	96.9
Untrained	95.8	95.8	95.3	95.3	95.9	95.9
Time taken for training	0:49:05.25		1:36:02.25		4:04:01.59	

Table 7: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 12 and Size of Competitive Layer are 1500

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN1	CPN2	CPN1	CPN2
Trained	96.8	96.8	97	97	97.3	97.3
Untrained	95.4	95.4	95.8	95.8	96.4	96.4
Time taken for training	0:49:01.06		1:36:32.08		4:00:17.68	

Table 8: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 10 and Size of Competitive Layer are 2000

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN1	CPN2	CPN 1	CPN 2
Trained	97.6	97.6	98.3	98.3	98.1	98.1
Untrained	96.9	96.9	97.5	97.5	97.4	97.4
Time taken for training	1:04:47.12		2:10:19.24		5:20:16.64	

Table 9: Percentage of Recognition Multi-CPN (808 colours) with Initial Neighbourhood are 12 and Size of Competitive Layer are 2000

	No. of Cycle					
	1000		2000		5000	
Set of Data	CPN1	CPN2	CPN1	CPN2	CPN1	CPN2
Trained	98.3	98.3	99.3	99.3	99.0	99.0
Untrained	97.4	97.4	98.4	98.4	98.0	98.0
Time taken for training	1:09:11.16		2:10:26.20		5:29:53.49	

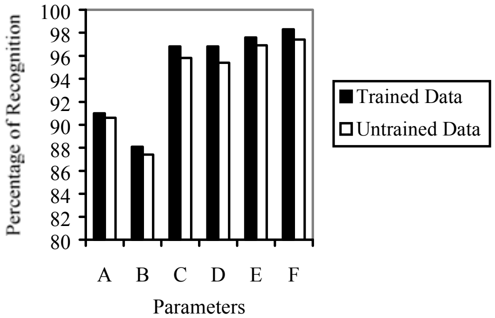
From Fig. 5(a), 5(b) and, 5(c), for parameters A and B, with size of competitive layer at 1000, the average of percentage recognition for trained data was about 89.88%, and about 89.18% for untrained data. Parameters C and D, with size of competitive layer at 1500 generated an average of percentage recognition of about 96.85% for trained data and 95.77% for untrained data. Averages of percentage for trained and untrained data for parameters E and F are 98.43% and 97.6%, respectively.

Fig. 6 shows that, for the initial stage, the number of cycles with 1000 gives a better performance than the number of cycles with 5000. But, at the final stage, percentage recognition for the number of cycles with 5000 becomes 99% for trained data, compared to the number of cycles with 1000 which becomes 98.3% for trained data, as well. However, the number of cycles with 2000 are much better than the number of cycles with 5000, whereby, for the initial stage, the number of cycles with 2000 got 91.2% recognition for trained data and, at the final stage, got 99.3% for trained data, whereas the number of cycles with 5000 got 89.7% recognition for trained data at the initial stage and 99% recognition for trained data at the final stage.

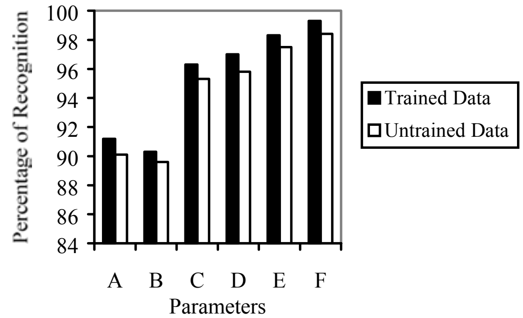
5.0 CONCLUSION

From this study, it shows that, if the number of cycles were increased or decreased, this causes over learning or not enough learning for the network. Also, if the initial neighbourhood is too small, it causes the competitive nodes that have the same potential to be neglected. However, if the initial neighbourhood is too big, the time of learning increases. The optima values of the number of cycles, the initial neighbourhood and the size of the competitive layer are very important in order to have a good percentage of recognition.

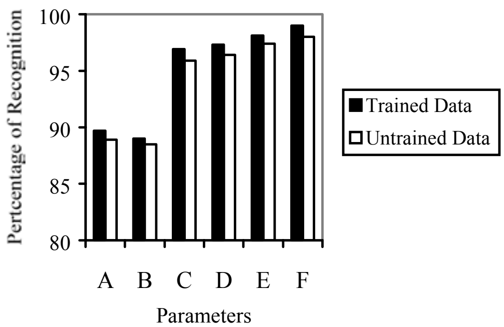
The results show that training with multi-CPN is able to produce a satisfying output with 99.3% recognition for trained data, that is, from 808 colours which were tested, about 802 were recognised, and 98.4% recognition for untrained data, that is, about 795 out of 808 colours were recognised.



(a) 1000 Cycles



(b) 2000 Cycles

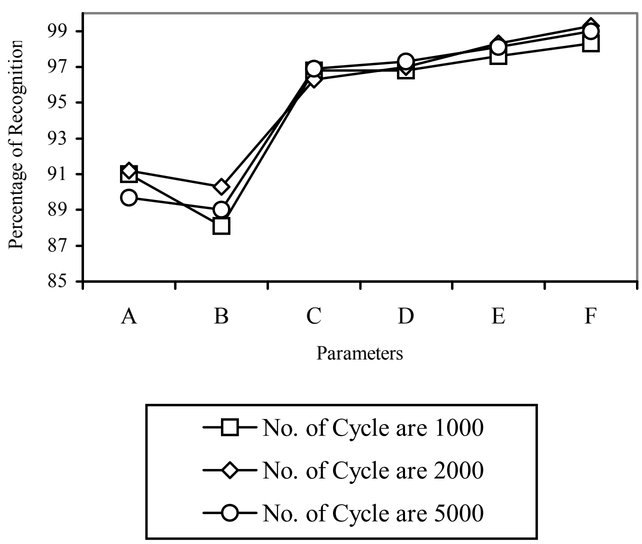


© 5000 Cycles

Parameters

	Initial Neighbourhood	Size of Competitive Layer
A	10	1000
B	12	1000
C	10	1500
D	12	1500
E	10	2000
F	12	2000

Fig. 5: Percentage of Recognition for Multi-CPN with 808 Colours



Parameters

	Initial Neighbourhood	Size of Competitive Layer
A	10	1000
B	12	1000
C	10	1500
D	12	1500
E	10	2000
F	12	2000

Fig. 6: Percentage of Recognition vs Initial Neighbourhood and Competitive Layer Representations

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APPENDIX A

Table A01 : Samples of 808 Colours Before and After Normalisation

Name of Colour	Samples of Input Before Normalised			Samples of Input After Normalised		
RHS1A_BRILLIANT_GREENISH_YELLOW	89.67	-15.41	66.60	0.2487	0.2037	0.4643
RHS1B_BRILLIANT_GREENISH_YELLOW	89.17	-18.42	61.64	0.5615	-0.0409	0.7237
RHS1C_LIGHT_YELLOW_GREEN	91.55	-14.68	41.28	0.7174	-0.2150	0.8448
RHS1D_PALE_GREENISH_YELLOW	93.38	-10.21	33.05	0.9434	-0.5715	1.0000
RHS2A_BRILLIANT_GREENISH_YELLOW	90.07	-12.20	70.11	0.3914	-0.0710	0.3407
RHS2B_BRILLIANT_GREENISH_YELLOW	91.22	-14.01	61.54	0.6425	-0.3401	0.5393
RHS2C_LIGHT_GREENISH_YELLOW	93.53	-11.87	39.75	0.8194	-0.5252	0.7430
RHS2D_PALE_GREENISH_YELLOW	93.12	-7.80	28.44	0.9983	-0.7336	0.9373
RHS3A_BRILLIANT_GREENISH_YELLOW	90.40	-10.90	68.20	-0.6821	0.3424	0.3082
RHS3B_BRILLIANT_GREENISH_YELLOW	91.60	-11.96	62.28	-0.2070	0.3778	0.2426
RHS3C_LIGHT_GREENISH_YELLOW	92.52	-11.12	47.93	0.2894	0.1283	0.4586
RHS3D_LIGHT_GREENISH_YELLOW	93.97	-9.79	38.44	0.4748	-0.0703	0.5883
RHS4A_BRILLIANT_GREENISH_YELLOW	91.56	-12.30	62.26	-0.5900	1.0000	0.0493
RHS4B_LIGHT_GREENISH_YELLOW	93.12	-11.48	50.51	-0.2762	0.7377	0.1261
RHS4C_LIGHT_GREENISH_YELLOW	93.89	-9.28	40.42	0.0959	0.3394	0.3162
RHS4D_PALE_YELLOW_GREEN	94.69	-5.36	21.58	0.3487	0.0658	0.4718
RHS5A_BRILLIANT_GREENISH_YELLOW	88.68	-9.38	69.67	-0.9122	-0.4260	0.6906
RHS5B_BRILLIANT_GREENISH_YELLOW	90.63	-10.34	68.90	-0.8353	-0.2761	0.5129
RHS5C_LIGHT_GREENISH_YELLOW	92.49	-10.43	54.40	-0.6886	-0.0601	0.3874
RHS5D_PALE_GREENISH_YELLOW	93.85	-7.62	38.62	-0.4700	-0.1328	0.4473
RHS6A_BRILLIANT_GREENISH_YELLOW	89.99	-7.20	72.50	-0.5391	0.8651	–0.1771
RHS6B_BRILLIANT_GREENISH_YELLOW	90.33	-7.77	69.79	-0.1854	0.5530	–0.0021
RHS6C_BRILLIANT_GREENISH_YELLOW	91.73	-8.28	62.72	0.1952	0.1815	0.2389
RHS6D_LIGHT_GREENISH_YELLOW	93.21	-7.03	42.78	0.3409	0.0126	0.3601
RHS7A_BRILLIANT_GREENISH_YELLOW	86.16	-6.17	73.68	-0.6937	0.8474	–0.3148
RHS7B_BRILLIANT_GREENISH_YELLOW	89.62	-6.28	67.15	-0.3738	0.6959	–0.2214
RHS7C_BRILLIANT_GREENISH_YELLOW	90.79	-7.94	66.70	0.0617	0.2553	0.0922
RHS7D_LIGHT_GREENISH_YELLOW	92.16	-9.03	55.41	0.2918	0.0254	0.2709
RHS8A_BRILLIANT_GREENISH_YELLOW	90.98	-6.65	65.49	-0.5632	0.6397	–0.5624
RHS8B_LIGHT_YELLOW	92.09	-7.27	55.34	-0.1962	0.2941	–0.2450
RHS8C_LIGHT_YELLOW	92.97	-6.29	41.58	0.0915	0.0288	0.0163
RHS8D_PALE_YELLOW	94.02	-4.15	23.29	0.2931	-0.1438	0.1959
RHS9A_VIVID	88.85	-4.39	78.22	-0.8689	-0.1773	0.3685
RHS9B_BRILLIANT_YELLOW	89.96	-5.30	73.49	-0.7255	0.0823	0.1540
RHS9C_BRILLIANT_YELLOW/LIGHT_YELLOW	91.65	-7.13	58.94	-0.5368	-0.0073	0.1210
RHS9D_PALE_YELLOW	93.33	-5.06	33.28	-0.3456	0.0699	0.0587
RHS10A_LIGHT_YELLOW	89.98	-5.09	56.58	-0.1786	0.1208	0.0153
RHS10B_LIGHT_YELLOW	90.55	-5.54	49.72	0.2938	0.0560	0.3634
RHS10C_LIGHT_YELLOW	91.57	-5.72	42.47	0.5896	-0.2670	0.5992
RHS10D_PALE_YELLOW	93.70	-4.85	27.61	0.8160	-0.6898	0.7015
RHS11A_BRILLIANT_YELLOW	86.36	-2.21	58.71	0.1701	-0.3635	0.2912
RHS11B_LIGHT_YELLOW	88.66	-3.67	43.76	0.3351	-0.4909	0.2488
RHS11C_PALE_YELLOW	91.12	-3.33	32.13	0.5388	-0.4603	0.3289
RHS11D_PALE_YELLOW/YELLOWISH_WHITE	93.84	-1.92	17.09	0.8638	-0.7377	0.7095
RHS12A_BRILLIANT_YELLOW	88.43	-1.77	74.67	-0.8197	-0.0865	0.1648
RHS12B_BRILLIANT_YELLOW	89.59	-4.21	66.10	-0.5581	0.0375	-0.0842
RHS12C_LIGHT_YELLOW	91.41	-3.70	50.36	-0.3494	-0.0514	-0.0719
RHS12D_PALE_YELLOW	92.48	-2.32	32.31	-0.1461	-0.1506	-0.0516