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Color Space Influence on Photosynthetic Pigment Measurement Accuracy Using CNN in Color Constancy

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ABSTRAK

Penelitian ini bertujuan untuk merancang sistem pengukuran pigmen tanaman menggunakan citra digital dan deep learning, dengan mengintegrasikan berbagai ruang warna seperti RGB, HSV, LAB, dan YCbCr. Metode yang diusulkan merupakan alternatif yang lebih cepat, lebih hemat biaya, dan lebih akurat dibandingkan metode tradisional seperti analisis spektrofotometri dan HPLC. Hasil eksperimen menunjukkan bahwa pemilihan ruang warna dan pengaturan preprocessing inpaint secara signifikan mempengaruhi akurasi model CNN P3Net. Kombinasi RGB+YCbCr dengan inpaint serta RGB+LAB tanpa inpaint menghasilkan nilai MAE validasi terendah. Studi ini juga membuktikan bahwa fenomena color constancy memengaruhi akurasi model, di mana ruang warna yang mempertimbangkan fenomena ini, seperti RGB+YCbCr dengan inpaint, memberikan akurasi lebih baik dibandingkan yang tidak.

Kata Kunci: *CNN, Ruang Warna, Citra Digital, Pengukuran Pigmen*

ABSTRACT

This study aims to design a plant pigment measurement system using digital images and deep learning, incorporating various color spaces including RGB, HSV, LAB, and YCbCr. The proposed method serves as a faster, more cost-effective, and accurate alternative to traditional methods such as spectrophotometric analysis and HPLC. Experimental results indicate that the choice of color space and inpaint preprocessing settings significantly impacts the accuracy of the CNN P3Net model. The combination of RGB+YCbCr with inpaint and RGB+LAB without inpaint yielded the lowest validation MAE values. The study also demonstrates that color constancy phenomena influence model accuracy, with color spaces that account for this phenomenon, such as RGB+YCbCr with inpaint, providing better accuracy than those that do not.

Keywords: CNN, Color space, Digital image, Pigment measurement

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1. INTRODUCTION

Plant metabolism occurs through a chemical process known as photosynthesis [1]. The mechanism of photosynthesis involves triggering a chemical reaction using light energy to convert carbon dioxide and water into glucose and oxygen as a byproduct [2]. The produced glucose can then be utilized as energy for plant metabolism or transformed into starch, which is stored and used when needed [3]. In the photosynthesis process, there are pigment molecules responsible for absorbing light energy for the chemical reaction, specifically chlorophyll and carotenoids [4]. Essentially, pigment molecules capture and reflect light energy within a specific spectrum [5]. The absorbed light energy is used to support the photosynthesis process, while the reflected light energy causes the color effect in plants, limited to the wavelength of the reflected light energy [6]. Chlorophyll pigments are green pigments, meaning they reflect the green spectrum of light. Carotenoid pigments, on the other hand, reflect light within the red, orange, and yellow spectrums [7].

Pigment content in plants is generally measured through laboratory extraction using spectrophotometric analysis, which measures the absorbance and reflectance of the leaf pigment solution, or through High-Performance Liquid Chromatography (HPLC) [8]. Both methods provide accurate results, but they differ in their measurement outcomes. Spectrophotometric analysis can only separate the results for chlorophyll a and chlorophyll b pigments, but not for other pigments like carotenoids or anthocyanins [9]. In contrast, HPLC analysis can provide detailed information on individual pigments [10]. The drawbacks of both measurement methods are that they are relatively time-consuming, costly, and destructive, as the leaves must be crushed to extract the pigments [11]. Therefore, there is a need for an easy, fast, cost-effective, and accurate method for measuring plant pigment content [12].

The proposed method is to measure pigments using digital images taken with a smartphone camera, which are then processed using deep learning methods to estimate the pigment content in the leaves. Previous research [13] discussed measuring pigment content (chlorophyll, carotenoids, anthocyanins) in plants using digital images and deep learning, but the study was limited to only onecolor space, RGB (Red, Green, Blue). Therefore, this study aims to design a plant pigment measurement system using digital images and deep learning, incorporating multiple different color spaces, including RGB, HSV (Hue, Saturation, Value), LAB, and YCbCr as inputs.

2. RESEARCH METHOD

2.1. Method of Data Collection

The data collected were 212 leaf image data along with the content of photosynthetic pigments from each leaf object in the image. The plants used in the collection of leaf image data were piper betle, jasminum, syzigium oleina, and graphtophyllum pictum [14]. The method used for data acquisition is divided into 2 steps [15]. The first step is to acquire leaf image data using a smartphone digital camera. The second step is the measurement of photosynthetic pigment levels. The measurement of photosynthetic pigment levels goes through a preparatory stage before being inserted into a UV-vis spectrophotometer [16]. The preparation stage is the division of the leaf into 2 parts which are then crushed into small parts with a weight of 0.05 grams each [17]. The first part is for the measurement of chlorophyll and carotenoid levels, while the second part is for the measurement of anthocyanin levels. The solution used for pigment extraction is distinguished by the type of pigment. For chlorophyll and anthocyanins, the solvent contains 100% acetone, while for anthocyanins the solvent is a mixture of methanol, concentrated hydrochloric acid, and filtered water [18]. A solvent of 1.5 mL is then added calcium carbonate and sodium ascorbate and put into the tube [19]. The solution and leaf samples were then mixed using *vortex* for 1 minute, and cooled for 1 minute for 3 times for each tube, then centrifuged at 14,000 rpm for 2 minutes and then cooled [20]. After the preparation stage was completed, the sample was measured for absorption using a spectrophotometer and the pigment level was calculated using the [21] and [22] method.

Figure 1. Leaf sample image data

Table 1 presents the data on photosynthetic pigment content, including anthocyanins, carotenoids, and chlorophyll, measured in different sample images. The values indicate the concentration of each pigment in the respective samples, which can provide insights into the physiological and biochemical characteristics of the plants. Anthocyanins are expressed in Abs/g, while carotenoids and chlorophyll are measured in μg/g. The variations in pigment content among the samples highlight differences in pigmentation, which may be influenced by factors such as species, environmental conditions, and developmental stages.

Table 1. Photosynthetic pigment content data

Image code	Anthocyanins (Abs/g)	Carotenoids (μg/g)	Chlorophyll (μg/g)
G01	25.8532	0.0000	461.9024
J01	0.0000	0.0000	1011.7251
PB01	0.7897	11.6864	102.6544
PM01	0.0296	8.8892	357.2901

2.2. The Creation of Datasets

To facilitate comparison and further analysis, the photosynthetic pigment content data were normalized. Normalization ensures that the values are scaled within a specific range, allowing for better interpretation of differences across samples. Table 2 presents the normalized pigment levels for anthocyanins, carotenoids, and chlorophyll in the analyzed images. These normalized values provide a standardized representation of pigment concentrations, aiding in identifying patterns and relationships among the samples.

Table 2. Normalized photosynthetic pigment level data

Image code	Anthocyanins (Abs/g)	Carotenoids (μg/g)	Chlorophyll (μg/g)
G01	0.2881	0.0000	0.4565
J01	0.0000	0.0000	1.0000
PB01	0.0088	0.2195	0.1015
PM01	0.0003	0.1670	0.3531

The creation of datasets was carried out on two types of data, namely photosynthetic pigment level measurement data and leaf image raw data. The measured data of photosynthetic pigment levels obtained was changed by performing a normalization operation to reduce the magnitude of the data [23]. The normalized pigment level data is shown in Table 2. The raw data of the images obtained from the data collection stage still requires the preprocessing stage to become a suitable dataset [24]. The data preprocessing process is divided into 3 types, namely, the elimination of white light reflections on the surface, the creation of color space channels of RGB, HSV, LAB, and YCbCr, and then the data augmentation process which then becomes the input dataset that is entered into the CNN [25]. The use of datasets in the training process of the CNN model is 80% data for training data and 20% for validation data. The explanation of the stage of creating a dataset is as follows [26]:

a. Removal of the effect of white light reflection on the surface
White light reflection is minimized using the algorithms of Alexandru Telea and Navier Stokes. Both algorithms are available in the form of an inpaint function in the OpenCv library. The inpaint operation is carried out accompanied by a mask element so that the inpaint operation is properly carried out on the white light reflection part of the leaf image. The surgical steps for the elimination of white light reflection on the leaf surface are as follows:
    1. Access leaf image data.
    2. Segmentation of leaf objects.
    3. Making *a mask* for the target position of the white light reflection on the leaf image.
    4. Inpaint operation.

b. Creation *of channels* for each color space
The creation *of* color space channels is achieved by converting RGB color spaces into HSV, LAB, and YCbCr color spaces. After the color space conversion operation is performed, the color space components are separated and stored individually as independent components. From the process carried out, a dataset of components from various color spaces is formed that can be combined as a dataset that is included in the CNN model. The use of color space channels as input data refers to research conducted by Prilianti et al. which used 10 multispectral color channels as input data to CNNs. The steps to create a color space channel are as follows.
    1. Access leaf image data.
    2. Color space conversion.
    3. Channel separation.
    4. Channel file storage.

c. Data Augmentation
The data augmentation process was carried out to overcome the possibility of low CNN performance due to the lack of available datasets. The data augmentation carried out is an addition to data variation by rotating the data with various rotation angles, zooming in, and applying standardization. The data generated from the previous 2 processes is applied data augmentation operations.

This study focuses on analyzing the effects resulting from the use of different types of color spaces on the accuracy of CNN, therefore the architecture used is the CNN architecture. The following is a description of the architectural design used with Table 3. and illustrated with Figure 2.

Table 3. CNN Model Architecture

Layer		Feature Map	Size	Kernel Size	Stride	Activation	Dropout
Input	Image						
1	*Convolution*	32	Input	3x3	2x2	ReLU	-
2	*Convolution*	32		3x3	1x1	ReLU	-
3	*Pooling*	-		3x3	2x2		-
4	*Flattening*	-		-	-		-
5	*Dense*	-	90	-	-	Sigmoid	0.03
6	*Dense*	-	3	-	-	LeakyRelu (alpha=0.3)	-

The CNN architecture in this study uses mean squared error as the loss function and Nesterov Adam as the optimization function. Technically the CNN model is built using the Hard library and the Python language. The CNN input is leaf image data from various color spaces and the output produced is an estimate of the content of photosynthetic pigments, namely chlorophyll, carotenoids, and anthocyanins.

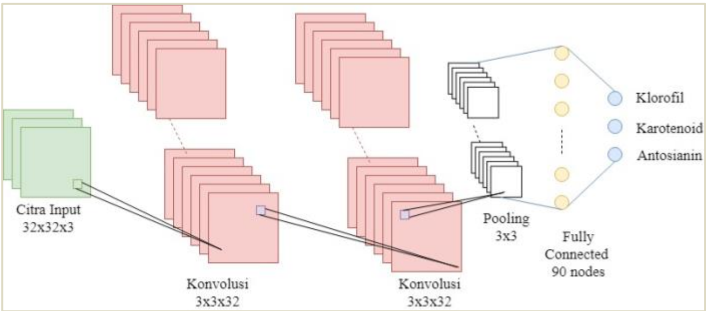

Figure 2. CNN model architecture

3. RESULTS AND DISCUSSIONS

3.1 Single Color Space with The Best Accuracy Without Inpainting

Figure 3 illustrates the sequence of accuracy values for a single-color space model without inpainting. This graph provides insight into the model's performance over different iterations, highlighting variations in accuracy across the dataset. Analyzing this trend helps evaluate the model's consistency and effectiveness in processing images without inpainting techniques**.**

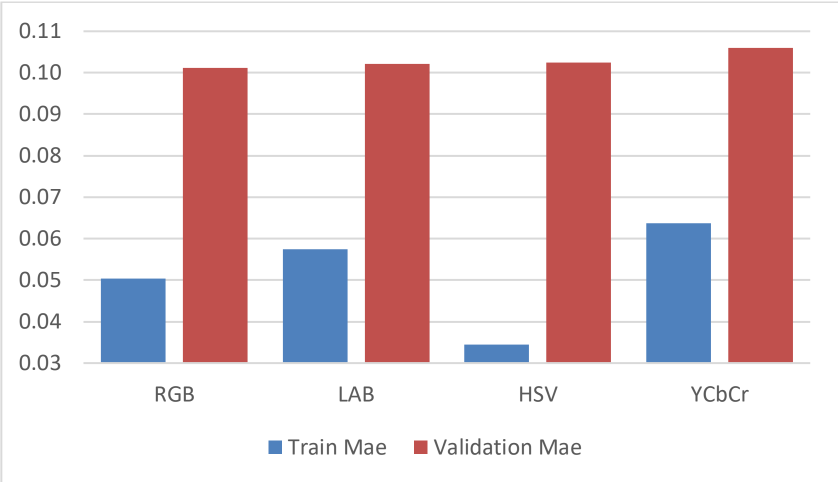

Figure 3. Graph Sequence 0f Accuracy Values of a Singlecolor Space Model Without Inpaint

Table 4 presents the sequence of accuracy values for a single-color space model without inpainting, measured using the Mean Absolute Error (MAE) for both training and validation. The table compares the performance of different color spaces, including RGB, LAB, and YCbCr, by evaluating their respective MAE scores. Lower MAE values indicate better model accuracy, with differences in scores reflecting the impact of each color space on model performance.

Table 4. Sequence of accuracy values of a singlecolor space model without *inpaint*

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB	0.05031	0.10115
2	LAB	0.05738	0.10221
3	YCbCr	0.06376	0.10603

The results of the experiment carried out by conducting a training process on models that use a singlecolor space without the inpaint process as input data are recorded. Then the singlecolor space without the inpaint process is sorted based on the average validation MAE value from the smallest to the largest as shown in Figure 3. The color space compared in the MAE value table is the color space that does not give rise to symptoms of overfitting. Table 3. shows the sequence of the results of the training experiment on a singlecolor space without the inpaint process.

From the data obtained, it is shown that the tw color spaces with the smallest MAE values for model validation are RGB and LAB with MAE values of 0.10115 and 0.10221. Therefore, the singl color space without the inpaint process that is recommended for input data in the use of CNN as a method of estimating pigment content is the RGB and LAB color space which is the color space with the smallest MAE value result of model validation.

3.2 Combination Color Space with The Best Accuracy Without Inpainting

Figure 4 illustrates the sequence of accuracy values for a combination color space model without inpainting. This graph compares the model's performance when multiple color spaces are utilized together, providing insights into how different combinations affect accuracy. By analyzing this trend, it is possible to determine the effectiveness of integrating multiple color spaces in improving model performance.

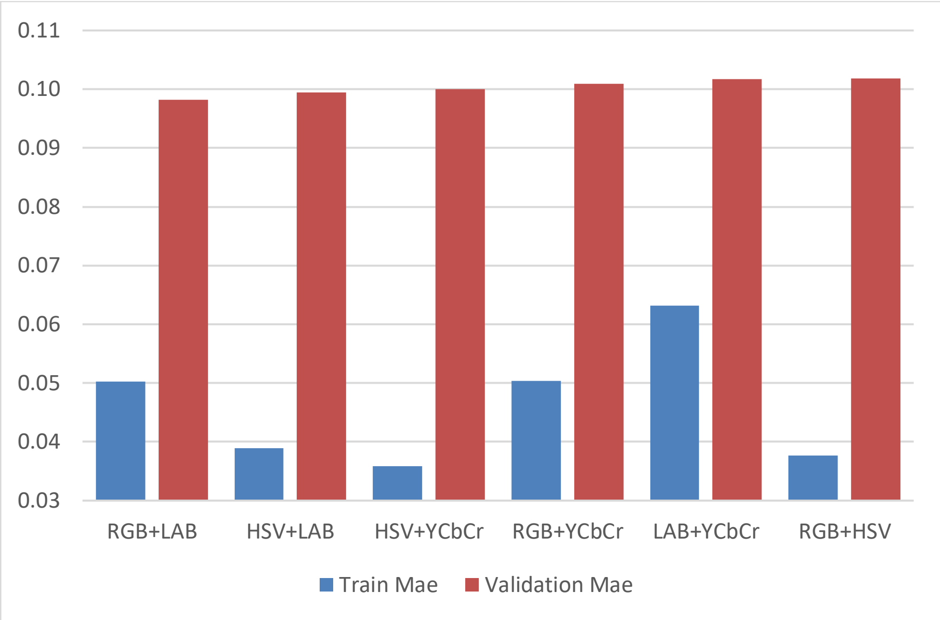

Figure 4. Graph Sequence of Accuracy Values of a Combination Color Space Model Without Inpaint

The results of the experiment carried out by conducting a training process on models that use a combination color space without the inpaint process as input data are recorded. Then the combination color space without the inpaint process is sorted based on the average validation MAE value from the smallest to the largest as shown in Figure 4. Table 5 shows the sequence of the results of the training experiment on a singlecolor space without inpaint. From the data obtained, it is shown that the twocolor spaces of the model with the smallest validation MAE values are RGB+LAB and RGB+YCbCr. Therefore, the recommended color space for input data in the use of CNN as a method of estimating pigment content is the RGB+LAB and RGB+YCbCr color space. The validation MAE value of the RGB+LAB color space is 0.09820, while for the RGB+YCbCr color space is 0.10089.

Table 5. Sequence of Accuracy Values of Combination Color Space Model Without Inpaint

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB+LAB	0.05020	0.09820
2	RGB+YCbCr	0.05033	0.10089
3	LAB+YCbCr	0.06322	0.10171

3.3 Comparison of Accuracy of Single and Combined Color Spaces Without Inpaint Process

Figure 5 presents the sequence of accuracy values for both the single-color space model and the combination color space model without inpainting. This graph allows for a direct comparison of the performance between the two approaches, highlighting how the integration of multiple color spaces influences accuracy in contrast to using a singlecolor space. The analysis of this sequence provides valuable insights into the advantages and limitations of each model configuration.

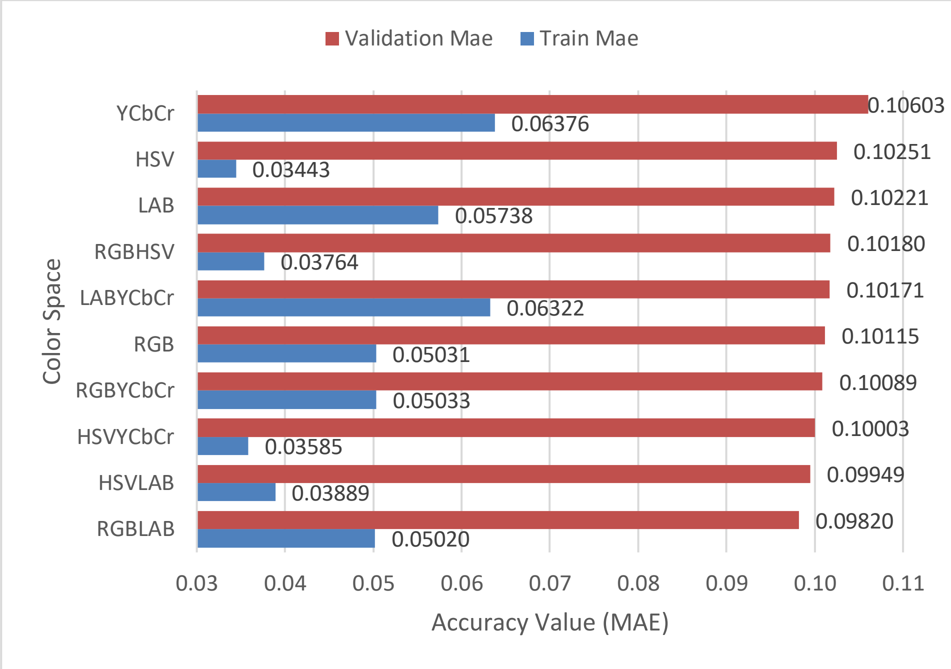

Figure 5. Graph Sequence of Accuracy Values of Singlecolor Space Model and Combination Without Inpaint

The type of color space without using the recommended inpaint process is obtained by comparing the average value of the validation MAE of the color space as a whole, both single color space and combination color space. The average value data of single and combined color space MAE is shown in Figure 5. Table 6 shows the color space data that has been sorted based on the average value of the MAE validation and the model is not overfitted. From the experiments carried out, the threecolor spaces of the model with the smallest MAE values of model validation are RGB+LAB, RGB+YCbCr, and RGB color spaces with values of 0.09820, 0.10089, and 0.10115. Therefore, the threecolor spaces without the inpaint process that are recommended as CNN input data as a method of estimating leaf pigment levels are RGB+LAB, RGB+YCbCr, and RGB.

Table 6. Order of Accuracy Values of All Color Space Models Without Inpaint

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB+LAB	0.05020	0.09820
2	RGB+YCbCr	0.05033	0.10089
3	RGB	0.05031	0.10115
4	LAB+YCbCr	0.06322	0.10171
5	LAB	0.05738	0.10221
6	YCbCr	0.06376	0.10603

3.4 Single Color Space with The Best Accuracy with Inpaint Process

Figure 6 displays the sequence graph of accuracy values for a single-color space model with inpainting. This graph illustrates how the inpainting technique affects the model's performance over different iterations. By comparing this sequence with models without inpainting, we can assess the impact of inpainting on improving the accuracy of the single-color space model.

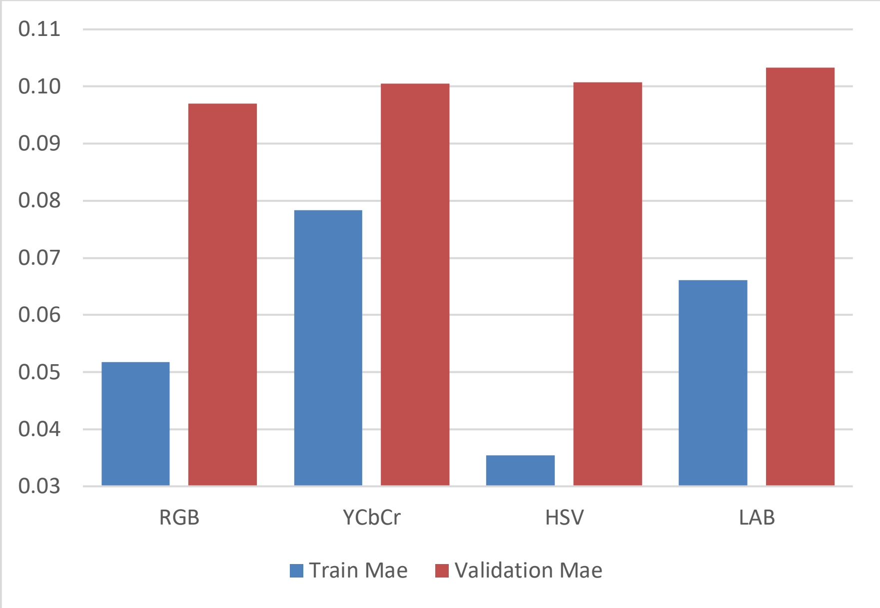

Figure 6. Sequence Graph of Accuracy Values of a SingleColor Space Model with Inpaint

The results of the experiment in the form of the average value of MAE validation from the color space with the inpaint process were obtained by conducting a training process on the CNN models of each color space that had previously gone through the inpaint process. Figure 7 shows the accuracy results of a CNN model with a singl color space with inpaint as the input data. Table 6. shows the order of MAE average values of singlecolor space validation with the inpaint process as input data on the CNN model from smallest to largest.

Table 7. Sequence of accuracy values of a singlecolor space model with inpaint

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB	0.05173	0.09696
2	LAB	0.06606	0.10333
3	YCbCr	0.06489	0.11199

The average value of MAE validation of a singlecolor space with *the inpaint process* shows that the twocolor spaces with the smallest MAE validation values of the model are RGB and LAB color spaces with average MAE validation values of 0.09696 and 0.10033. Therefore, the recommended singlecolor space with *the inpaint* process is RGB and LAB.

3.5 Combination color space with the best accuracy with the inpaint process

The results of the experiment carried out by training the CNN model with a combination color space obtained from images that have gone through the inpainting process are shown in Figure 7. From the results of the experiment of training the CNN model using a combination color space with the *inpaint process*, the twocolour spaces of the model with the smallest MAE validation values are RGB+YCbCr and LAB+YCbCr color spaces with average MAE validation values of 0.09486 and 0.10239. Therefore, the recommended color space for the color space input data combined with *inpaint* in the CNN model is RGB+YCbCr and LAB+YCbCr color spaces.

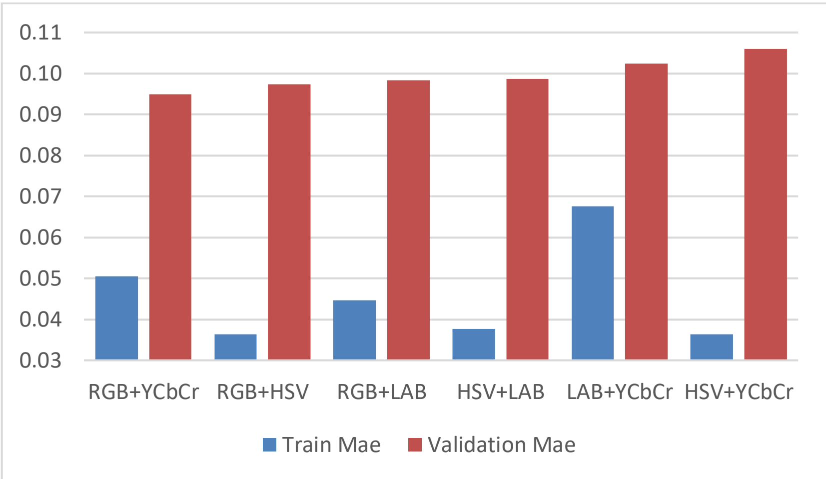

Figure 7. Graph Sequence of Accuracy Values of Color Space Model Combination with Inpaint

Table 8 presents the order of accuracy values for the color space model combination with inpainting. This table compares the performance of different combinations of color spaces, with inpainting applied, to determine which configuration provides the highest accuracy. The accuracy values provide insight into how the integration of multiple color spaces, combined with inpainting techniques, influences the model's effectiveness.

Table 8. Order of Accuracy Values of Color Space Model Combination with Inpaint

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB+YCbCr	0.05051	0.09486
2	LAB+YCbCr	0.06761	0.10239

3.6 Comparison of the Accuracy of Single and Combined Color Spaces with The Inpaint Process

The type of color space with the recommended inpaint process can be obtained by obtaining the color space with the smallest average validation MAE value of the entire color space, both single and combined color spaces. Figure 8. shows the accuracy value of the model in the form of the average MAE of each color space both for training and validation that has been determined based on the average value of the MAE validation, while for the sequence of color spaces with *the* inpaint process that is not overfitting and sorted based on the average value of the MAE validation is shown in Table 8.

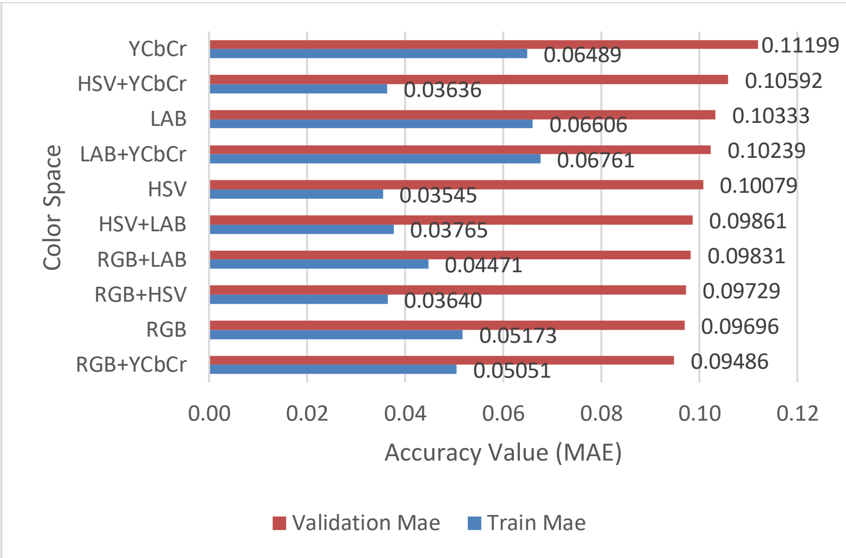

Figure 8. Graph Sequence of Accuracy Values of a Singlecolor Space Model and Combination with Inpaint

Table 9 presents the order of accuracy values for both the single-color space model and the combination color space model with inpainting. This table allows for a direct comparison between the performance of single-color space models and combination models, both utilizing inpainting. By examining these values, we can determine which approach yields the highest accuracy and evaluate the benefits of combining multiple color spaces with inpainting.

Table 9. Order of accuracy values of singlecolor space model and combination with inpaint

No	Color space	Average MAE training score	Average MAE Validation score
1	RGB+YCbCr	0.05051	0.09486
2	RGB	0.05173	0.09696
3	LAB+YCbCr	0.06761	0.10239
4	LAB	0.06606	0.10333
5	YCbCr	0.06489	0.11199

From the results of the experiment, it can be seen that the threecolor spaces with the smallest MAE accuracy values of the color space with the smallest inpaint process are RGB+YCbCr, RGB, and LAB+YCbCr with MAE accuracy values of 0.09486, 0.09696, and 0.10239. Therefore, the recommended color spaces with the inpaint process are RGB+YCbCr, RGB, and LAB+YCbCr.

3.7 Best Color Space from A Comparison of All Inpainted and Non-Inpainted Color Spaces

Table 10 presents the order of the best accuracy values for all color space models with inpainting preprocessing. This table ranks the performance of each color space model, incorporating inpainting as a preprocessing technique, to identify the configurations that achieve the highest accuracy. Analyzing these results helps determine the most effective color space models and preprocessing methods for optimizing model performance.

Table 10. Order of Best Accuracy Values for All Color Space Models and Inpaint Preprocessing

No	Color space	*Inpaint*	Average value of MAE trainer	Average MAE validation score
1	RGB+YCbCr	Yes	0.05051	0.09486
2	RGB	Yes	0.05173	0.09696
3	RGB+LAB	It	0.05020	0.09820
4	RGB+YCbCr	It	0.05033	0.10089

5	RGB	It	0.05031	0.10115
6	LAB+YCbCr	It	0.06322	0.10171
7	LAB	It	0.05738	0.10221
8	LAB+YCbCr	Yes	0.06761	0.10239
9	LAB	Yes	0.06606	0.10333
10	YCbCr	It	0.06376	0.10603
11	YCbCr	Yes	0.06489	0.11199

The experimental results showed that the 3 types of CNN model input data for pigment content estimation with the smallest average value of MAE validation were RGB+YCbCr color space with inpaint with an average value of 0.09486 MAE validation, RGB with inpaint with an average value of 0.09696 MAE validation, and RGB+LAB without inpaint with an average value of 0.09820 MAE validation. From the results obtained, the recommended color spaces are RGB+YCbCr with inpaint, RGB with inpaint, and RGB+LAB without inpaint. From the results obtained, color spaces with characteristics that consider lighting elements are included in the color spaces that produce the best accuracy values. This can be explained by the previous hypothesis regarding the relationship between how the type of color space gets the color value of an object, namely the separation of the lighting element from other elements such as "L" (luminance) in LAB or "Y" in YCbCR. In color space models such as LAB or YCbCr, color elements other than lighting are always consistent under different lighting, so that it can reduce the influence of the color constancy phenomenon. Table 9. shows the results of experiments on the entire singlecolor space and combination with or without the inpainting process. Table 9. shows the sequence of color space models and types of preprocesses that are sorted based on the average value of the MAE validation and do not experience overfitting.

Regarding the effect of inpainting on the accuracy of the CNN model, by looking at the data of the training MAE value and validation shown in Table 9. it can be concluded that the preprocessing of inpaint on the training image data does not provide a large decrease in the accuracy value. This conclusion was obtained from the difference from the MAE value of the training and validation between the models with image data that went through the inpainting process and did not go through the inpainting process. However, there is another conclusion related to inpaint preprocessing, namely the accuracy value of the model with the RGB color space that goes through the inpaint process is included in the group of threecolor spaces with the smallest validation MAE value. The twocolor spaces from the group of threecolor spaces with the smallest MAE validation values are RGB+YCbCr and RGB+LAB color spaces which consider lighting elements that can minimize the effect of the color constance phenomenon, while RGB does not consider lighting elements. However, from the results of the research, the application of the inpainting process to RGB training image data is able to provide accuracy results that rival color spaces that consider lighting elements.

4. CONCLUSION

Experiments conducted by training the CNN model using different color space types and preprocessing settings showed differences in training accuracy values and model validation for input data types. By sorting the color space type and preprocessing settings based on the average value of the validation MAE, the recommended color space type for the CNN P3Net model input data of the estimated pigment content can be determined. For input data without inpaint process from a single or combination of color spaces, the recommended color spaces are RGB+LAB, RGB+YCbCr, and RGB. However, for input data without an inpaint process with a singlecolor space, the recommended color spaces are RGB and LAB. As for input data without an inpaint process with a combination color space, the recommended ones are RGB+LAB and RGB+YCbCr.

The results of the CNN P3Net model training experiment using the inpaint process on the image data resulted in the conclusion that of the entire color space, either single or combined color space, the recommended ones are RGB+YCbCr, RGB, and LAB+YCbCr. The recommended singlecolor space for input data with the inpaint process is RGB and LAB. Meanwhile, the recommended combination color space for input data with the inpaint process is RGB+YCbCr and LAB+YCbCr.

The results of the comparison of all color spaces and inpaint preprocessing settings show that the recommended color spaces are RGB+YCbCr with inpaint, RGB with inpaint, and RGB+LAB without inpaint. The experimental results showed that the type of color space and inpaint preprocessing settings affected the accuracy of the CNN P3Net model. The entry of RGB+YCbCr color space with inpaint and RGB+LAB without inpaint is the color space by considering the lighting element as model input data CNN P3Net which produces the smallest validation MAE accuracy value and the consistency of the type of color space that considers lighting elements is included in the smallest result in the comparison of the validation MAE value both with inpaint and not, proving that the type of color space by considering the phenomenon of color constancy can affect the accuracy of the CNN P3Net model and provides a better accuracy value when compared to the type of color space that does not consider the phenomenon color constancy (RGB), in this case the color space that considers the color constancy phenomenon that provides the best accuracy value is RGB+YCBCr with inpaint. The influence of the inpainting process obtained from the results of the study is twofold, namely, the inpainting process on the training image data does not provide a large decrease in MAE values and the inpainting process in the RGB color space which has the characteristic of not considering lighting elements can produce an accuracy value that occupies the second position in the group of the three smallest color spaces, so that it can compete with models that use color spaces that consider lighting elements.

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