Examining the Role of Color in Predicting Fruit Freshness using Convolutional Neural Networks

Technical Report

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Abstract

Color is a commonly used visual cue for assessing fruit freshness, which is a concern that remains critical in food supply chain management. Computer vision techniques offer a way to reduce the subjectivity and improve the consistency of freshness evaluation. This study uses an image dataset containing eight fruit types, with balanced samples of fresh and rotten images, to investigate how different color transformations influence the behavior of a convolutional neural network. The model is trained on the original images and on five color-based variants, namely grayscale, red-blue channel swap, and isolated red-only, green-only, and blue-only channels, to examine how color information affects classification performance. The model trained on the original images has training and validation accuracies of 91% and 81%, only exceeded by the swap variant with training accuracy 93%. Confusion matrix analyses were primarily utilized to identify performance differences across the variants and highlight fruit-specific trends. This revealed that the swapped variant outperforms the original variant for apples, bananas, guavas, and pomegranates; the red variant beats the original for grapes and oranges; the blue variant surpasses the original for jujubes, while the grayscale variant is an equally-performing alternative for strawberries.

Keywords Color channels · Convolutional neural network · Fruit freshness classification

1 Introduction

The freshness of fruits is commonly associated with better nutritional quality and lower risk of spoilage, so evaluating their freshness persists as a critical challenge in food supply chain management to reduce the risk of contamination through shared storage or transport [Rizzo et al., 2022]. Color is frequently used as a convenient visual cue for ripeness or spoilage by producers, consumers, and distributors alike. Unfortunately, manual inspection, which is the traditional method still widely used today, is often laborious, subjective, and prone to human error, especially when large volumes of fruits must be processed [Bhargava and Bansal, 2021]. Thus, there is a growing interest in automated, computer vision-based methods that can consistently and efficiently distinguish fresh from rotten fruits.

For this study, we adopt the publicly available dataset titled *Fresh and Rotten Fruits Dataset for Machine-Based Evaluation of Fruit Quality* from Mendeley Data [Sultana et al., 2022]. This dataset includes two hundred (200) images each for sixteen (16) classes, which is a combination of eight (8) fruit types (i.e., apple, banana, grape, guava, jujube, orange, pomegranate, and strawberry) with two (2) freshness labels (fresh and rotten). The dataset has already been previously utilized to automate freshness classification using AlexNet, which is a classical convolutional architecture that uses five (5) convolutional layers and three (3) fully connected layers [Amin et al., 2023].

The primary goal of the present work is to investigate how color-based transformations of the fruit images affect the ability of a convolutional neural network (CNN) to classify both fruit type and freshness correctly. Prior studies have shown that CNNs often rely strongly on color and texture cues, and that their performance can decline when these cues are altered. This indicates that a model may rely on color simply because the dataset makes color a convenient shortcut for classification, rather than because the architecture is inherently dependent on color [Aditya et al., 2020].

In this study, we test this possibility on five (5) color-based variants of the fruit image data: grayscale conversion, red-blue channel swap, and isolation of the red-only, green-only, and blue-only channels. An example of this is shown in Figure 1. We aim to determine whether simpler or altered color representations can still support acceptable classification accuracy. These findings may have implications for computational efficiency, data storage, or deployment in environments where full-color imaging is costly, limited, or impractical.

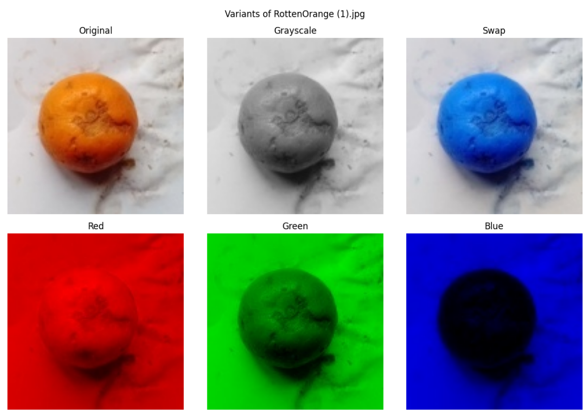

Figure 1: Variants of a sample image in the dataset

Thus, this research explores the following questions:

1. How do color-based transformations on fruit image data affect accurate fruit freshness classification in a CNN?
2. How accurately does the CNN classify each fruit type and freshness label, and which fruits or freshness labels are most prone to misclassification, either as a different fruit or with the incorrect freshness label?

By addressing these questions, the study seeks to assess the dependency of fruit freshness classification models on color and potentially propose more resource-efficient pre-processing strategies without a substantial loss in the model's predictive power.

2 Methods

The images originate from the *Fresh and Rotten Fruits for Machine-Based Evaluation of Fruit Quality* dataset hosted on Mendeley Data. The dataset contains eight (8) fruit categories, namely apple, banana, grape, guava, jujube, orange, pomegranate, and strawberry, with 200 images for each fruit under two (2) freshness labels (fresh and rotten). The images were generally photographed from above on a white background, with only minor shadows, providing a relatively controlled visual environment.

For the present study, fifty (50) images per fruit and freshness label were manually selected such that each image only contained one fruit, except for grapes, where each image contained one bunch instead. The chosen subset ensures a balanced representation across fruits and freshness types while reducing confounding factors, such as multiple instances of a fruit in a single frame.

2.1 Image pre-processing

The initial images had high resolution, so they were first resized such that the smaller dimension became 512 pixels while keeping the aspect ratio. This step reduces computational load without distorting the fruit shapes.

Seam carving [Avidan and Shamir, 2007] (implemented using the `seam_carving` library, developed by andrewdcampbell [2020]) was then applied on the longer dimension to resize the images into 512×512 pixels. This was performed on fruits whose natural shape is close to circular, namely apples, grapes, guavas, jujubes, oranges, and pomegranates, since preliminary runs showed that these fruits, having both round shapes and near-square image aspect ratios, tolerated seam removal without meaningful shape deformation.

On the other hand, nearest-neighbor padding was applied to the images of bananas and strawberries, which have elongated shapes and are frequently photographed in rectangular orientations. Preliminary runs using seam carving on these images have resulted in a distortion of the fruits' structure, but padding seeks to extend the image outwards by repeating the color of the border pixels. Consequently, this allows us to preserve the original shape of the fruits.

After formatting the images to squares by seam carving or nearest-neighbor padding, each image was resized to 128×128 pixels, which served as the final input resolution for all experiments.

2.2 Data augmentation

Data augmentation was applied by performing the following random processes on each image:

- `rotation_range = 20`: Each image can be rotated up to 20° clockwise or counterclockwise
- `width_shift_range = 0.1` and `height_shift_range = 0.1`: Each image can be shifted by up to 10% of its width and height
- `shear_range = 0.15`: Applies a slanting transformation by up to 0.15 radians ($\approx 8.6°$)
- `zoom_range = 0.15`: Each image is zoomed in or out by up to 15%
- `horizontal_flip = True`: Each image may be flipped horizontally

An 80%-20% train-validation split was applied, so the training and validation data were composed of 40 and 10 images per class, respectively, for a total of 640 and 160 images across all classes, respectively.

2.3 Neural network

The neural network model consists of four (4) convolutional-maximum pooling blocks for hierarchical feature extraction, followed by a flattening operation and two (2) fully connected or dense layers for classification, with a final dropout layer (with parameter 0.2) included to reduce overfitting. Overall, its components can be described as follows: 4 `Conv2D` layers, 4 `MaxPooling2D` layers, 1 `Flatten` layer, 2 `Dense` layers, and 1 `Dropout` layer. Its architecture diagram, made using the `plot_model` function in TensorFlow, can be found in Figure 4 of the Appendix.

Other specifications of the neural network include using the Adam optimizer, the categorical cross-entropy loss, the accuracy metric, a random seed of 42, and training each neural network for 20 epochs.

3 Results and discussions

3.1 Numerical results

Table 1 shows the train and validation accuracies of the model at the 20th epoch. The original and swap variants achieved a much higher accuracy than the other four variants. Figure 2 shows the progression of accuracies across epochs. A notable observation is the fluctuation. This may be due to a small validation set (160 images) or the fact that the learning rate (0.001) was not adjusted.

Table 1: Accuracies at epoch 20

Variant	Train Accuracy	Validation Accuracy
Original	0.9094	0.8062
Grayscale	0.7797	0.6375
Swap	0.9297	0.7812
Red	0.7594	0.6812
Green	0.7812	0.6562
Blue	0.8156	0.6125

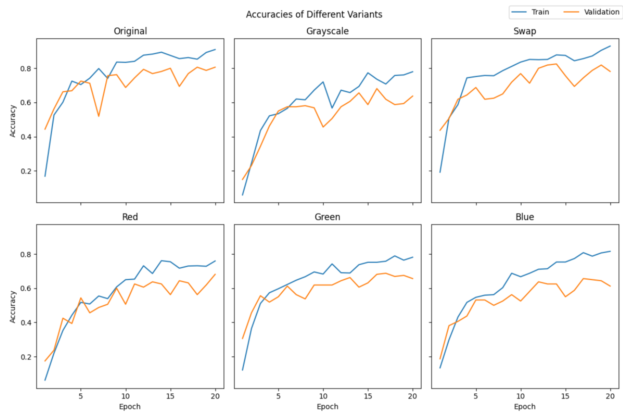

Figure 2: Accuracies across epochs

3.2 Variant analysis

Figure 3 shows the confusion matrices for each of the six variants of the dataset. Each row and column is labeled with an abbreviated form of each class (f for fresh, r for rotten, followed by the first three letters of the fruit's name). These are used to discuss the notable trends in terms of misclassification for each variant and for each fruit. We expound on these relationships based on observations about how the fruits look like under each color-based variant and ultimately assess their implications in fruit freshness detection.

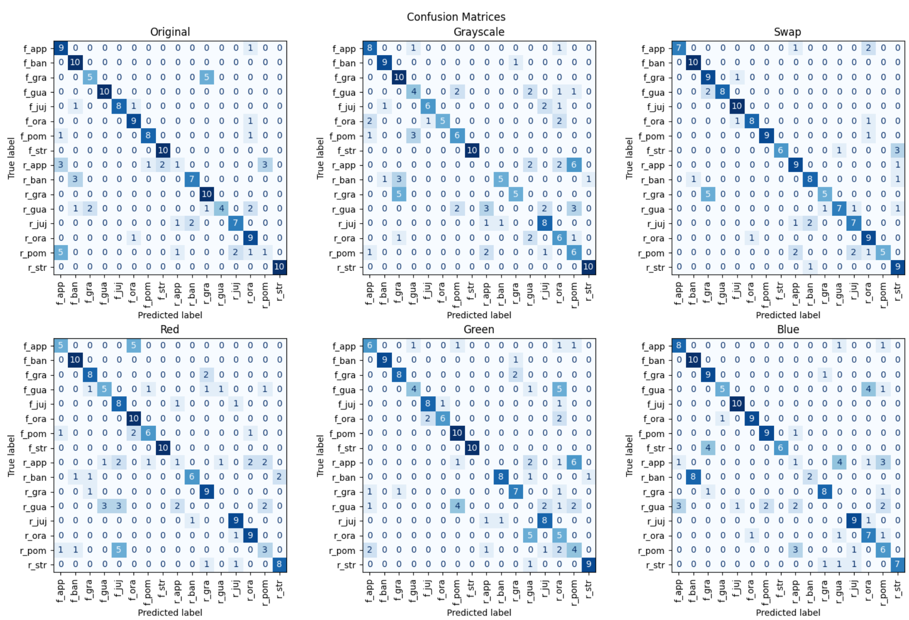

Figure 3: Confusion matrices for different variants of the dataset

3.2.1 Original variant

We first identify baseline observations. To begin, rotten apples and rotten pomegranates were the most difficult to identify accurately, with only 1 out of 10 correct. Rotten apples are mistakenly predicted as fresh apples, fresh strawberries, or rotten pomegranates, while rotten pomegranates are classified as fresh apples instead. These may stem from the fact that apples, pomegranates, and strawberries are all red, with the first two being circular as well.

We also note that some fresh fruits are predicted as rotten and vice versa. Fresh grapes are predicted as rotten grapes for half the time, which may be because the rotten parts of the grapes are relatively small compared to the rotten parts of the other fruits. On the other hand, rotten bananas were predicted as fresh bananas 3 out of 10 times, which might be due to dark streaks observed in both types.

3.2.2 Grayscale variant

In the grayscale variant, rotten apples and guavas were never predicted correctly, though all but 2 were predicted as rotten. This is expected behavior because rotten fruit tends to cause the fruit to darken, which would still be detected in a grayscale image.

However, a notable observation can be made about grapes: in contrast to the original variant, only half of the rotten grapes were predicted correctly, with the rest being predicted as fresh. Meanwhile, fresh grapes were all classified correctly. By observing the original and grayscale images, some rotten grapes exhibit a purple discoloration against their green color when ripe. This becomes indistinguishable when converting it to a grayscale image, which may have contributed to the difficulty in predicting the freshness labels correctly.

3.2.3 Swap variant

Most fruits under consideration in this study adopt warm colors, such as red, orange, and yellow, when ripe, so the switch between red and blue channels caused most fruits to be displayed in cyan or blue colors, which revealed interesting results about the model's behavior.

Under this case, rotten grapes still exhibited the same behavior as the grayscale variant, which can be explained once again by the lack of distinguishing discoloration. Rotten pomegranates were only predicted correctly half the time, with the rest predicted as other rotten fruits. In this regard, it may be inferred that rotten pomegranates possess distinguishing characteristics of rotten fruits, but the lack of color led the model to struggle in correctly identifying the fruit.

Though the swap variant obtained the highest accuracy by the 20th epoch, fresh strawberry prediction suffers here as they are incorrectly predicted as rotten; this result shows that the red and blue channels are critical in identifying fresh strawberries.

3.2.4 Single-color channels

We now assess the results of isolating the red, green, and blue channels.

Under the red-only channel, apple and guava prediction suffer the most. Fresh apples are incorrectly predicted as fresh oranges half the time, which may be because both fruits appear bright red and round. Fresh guavas are only predicted correctly 5 out of 10 times, while rotten guavas are never predicted correctly. For the latter, they get mistakenly predicted as fresh guavas or jujubes instead, which are typically green or yellow in color, so this indicates a difficulty in predicting fruits of this color under red light. Rotten pomegranates are also predicted as fresh jujubes for half the time, which may be due to the discoloration in rotten pomegranates being mistakenly interpreted as the natural color variation in ripe jujubes.

Meanwhile, in the green channel, confusion occurs between apples, guavas, oranges, and pomegranates. Rotten apples and guavas are never predicted correctly; instead, they are mostly classified as rotten (6 out of 10) and fresh (4 out of 10) pomegranates, respectively. Fresh guavas, on the other hand, were predicted as rotten oranges for 5 out of 10 instances, while rotten oranges were predicted as rotten guavas at the same frequency. This confusion between guavas and oranges may have arisen due to the fruits' similarity in shape when ripe and rotten.

However, different patterns arise with the blue channel. Similar to the original variant, rotten bananas were predicted as fresh bananas, but this happened more frequently, with 8 out of 10 occurrences. It also persists that rotten apples are mistakenly predicted as rotten guavas (4 out of 10) or pomegranates (3 out of 10), and rotten guavas are never predicted correctly, with 3 predictions as fresh apples instead. Conversely, though, rotten pomegranates also get misclassified as rotten apples 3 times in this set. We note that this confusion between red circular fruits is a pattern that also occurred in the original variant. Finally, it is interesting to note that fresh strawberries are predicted as fresh grapes 4 out of 10 times. Despite the two fruits differing drastically in shape and texture, this may be explained by the idea that they both appear dark under blue light, with the grapes bunching together to look similar to the strawberry's shape.

3.3 Fruit analysis

Generally, the predictions for each fruit have different behaviors: some have relatively stable performance across variants, while others perform much better in one variant. The ideas in this section can be applied, for example, to a logistics company that deals with more of a certain fruit, since the company can prioritize the usage of certain variants where the prediction for that fruit is better.

For apples, the swap variant shows the highest accuracy with 7 and 9 correct predictions for the fresh and rotten apples, respectively. Other variants almost never identify rotten apples correctly, and they are usually predicted as fresh apples, rotten pomegranates, or rotten guavas instead.

For bananas, the swap variant also shows the highest accuracy with only 2 mistakes in the rotten bananas, closely followed by the original and green variants. The grayscale and red variants can identify fresh bananas but not rotten ones, while the blue variant is the worst, since rotten bananas often get predicted as fresh ones. This is likely because bananas are primarily yellow, which is formed by adding red and green, but these were not available in the blue variant.

For grapes, the red and blue variants perform the best with three mistakes, followed by the green variant with five. Interestingly, the original variant, which combines the three channels, results in half of the fresh grapes being predicted as rotten, and the grayscale and swap variants have the reverse result, where half of the rotten grapes are predicted as fresh.

For guavas, only the swap variant is a feasible option, since rotten guavas perform poorly in every other variant.

For jujubes, the blue variant is optimal because it only has one mistake, though the other variants are not far off, with the poorest-performing variant (grayscale) having only 6 mistakes. This relative lack of variation is likely since the jujubes are relatively small compared to the other fruits, and the model may have used size as a predictor instead of color.

For oranges, the red variant is the best choice, while the grayscale and green variants are to be avoided. Notably, fresh and rotten oranges perform relatively similarly for each variant.

Rotten pomegranates have average to poor performance across the variants, but the best among these is the swap variant, closely followed by the blue one. The original and red variants are the worst choices since half of the time, rotten pomegranates were predicted as fresh apples and jujubes, respectively.

Strawberries have a perfect score for both the original and grayscale variants. Interestingly, strawberries falter in the swap variant, which is the best variant for most of the fruits.

4 Conclusion and recommendations

4.1 Conclusion

This study examined how color-based image transformations influence a convolutional neural network's ability to classify fruit type and freshness. By altering color channels, the model was effectively constrained to rely on structural, textural, and luminance-based cues rather than full-spectrum color information. Among the six variants tested, the red–blue channel swap achieved the highest training accuracy (93%), followed closely by the original images (91%). However, for validation accuracy, the original dataset performed best (81%), with the swap variant slightly lower (78%). Meanwhile, the other variants achieved training and validation accuracies between $70-80\%$ and $60-70\%$, respectively. These results suggest that, while the model is capable of adapting to altered color information during training, the full color information remains beneficial for generalization.

Fruit-specific analyses further demonstrate how color transformations affect classification performance. Apples, bananas, and guavas showed improved prediction under the swap variant compared to the original setup, indicating that their defining features remain robust under shifted color channels. However, pomegranates exhibited notable difficulty since half of the rotten samples were predicted as other rotten fruits. This pattern suggests that, in the absence of strong color cues, the model defaults to broader indicators of rottenness rather than fruit-specific traits.

Next, grapes performed well under the red-only and blue-only channels, but it must be nuanced that fresh strawberries were frequently misclassified as fresh grapes under the blue-only variant. This was likely because both appear similarly dark in this channel, so the clustered structure of grapes may resemble the silhouette of a single, darkened strawberry, leading to misclassification.

We also make notable observations about jujubes: they already performed reasonably well under the original setup, but they showed substantial improvement under the blue-only variant, achieving nearly perfect accuracy. This indicates that the features distinguishing jujubes remain robust against color-based transformations, which is an encouraging result for systems that require reduced-color imaging.

Finally, the performance for oranges also improved under the red-only variant compared to the original images, but this comes with an increased tendency for apples to be misclassified as oranges. This highlights an important trade-off, where transformations that improve classification for one fruit may introduce ambiguity for others, depending on overlaps in hue, brightness, or shape.

Overall, the findings demonstrate the complex role that color plays in fruit freshness classification. While some fruits remain identifiable with minimal color information, others rely heavily on the full spectrum for accurate discrimination. For supply chain applications, these insights can guide the design of practical imaging systems: full-color imaging remains to be the most reliable option, but color-based transformations may be viable for specific fruits, such as grapes and jujubes, especially in environments with limited imaging capabilities.

4.2 Recommendations

Given more time, this study can be extended by conducting a systematic analysis of the internal representations learned by the CNN when exposed to the different color variants. This would provide deeper insights into which visual features the model relies on, thereby clarifying the basis of its decisions and improving interpretability.

Another limitation of the present work concerns the absence of fruit classes that rely heavily on the blue color channel (such as blueberries or blackberries). The dataset used in this study is dominated by fruits with red–green color compositions, which contributed to reduced performance under the red-only and green-only variants. In addition, fruits with similar red hues and rounded shapes proved difficult to distinguish even in the original RGB variant. Including blue-colored fruits in future work would broaden the color diversity of the dataset and help establish whether the observed behaviors generalize across a wider range of hue distributions.

Future extensions may also examine the impact of the dataset composition. Although each class contains an equal number of samples, this did not incorporate the full available dataset consisting of 200 images each, with some images containing multiple fruits. Incorporating these more complex frames may assess the model's robustness in less controlled environments.

Finally, cropping the images to isolate the fruit more precisely can also be explored as an additional pre-processing step. This may reduce the model's reliance on size-related cues, such as the naturally smaller appearance of jujubes, and instead place greater weight on shape, texture, and color information. This approach could clarify whether the CNN is unintentionally exploiting contextual or size-based features.

Altogether, these steps can contribute to a more comprehensive understanding of the model's learning behaviors and improve the overall generalizability of our findings.

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A Additional figures

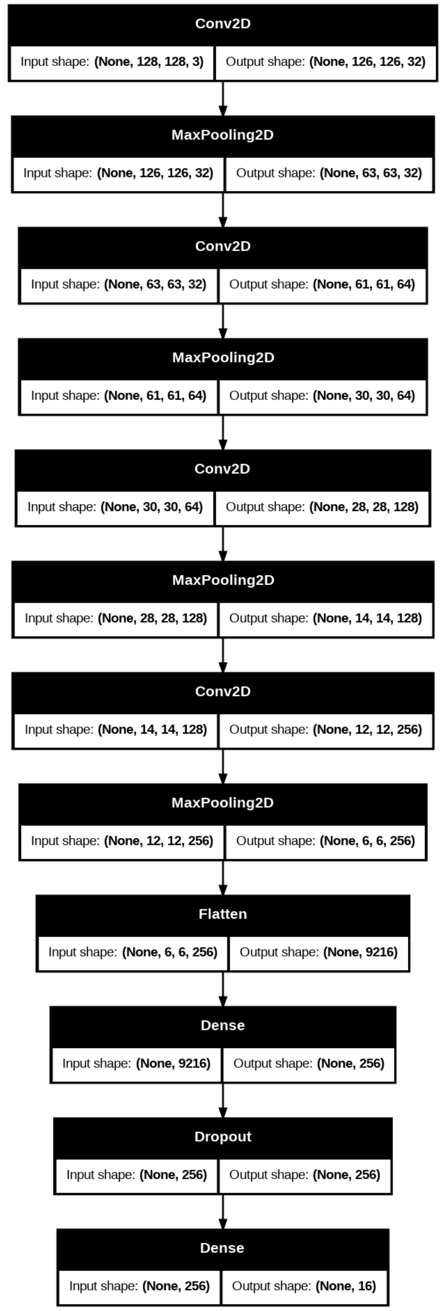

Figure 4: Convolutional neural network architecture diagram