The Importance of Color Spaces for Image Classification using Artificial Neural Networks: A Review.

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Abstract. Image classification is one of the most important applications of artificial neural networks in the field of industry and research. In most research work, when implementing ANN-based image classification models, the images used for training and testing are always represented in the RGB color space. But recent articles show that the use of certain color spaces, other than RGB, can lead to better precision in ANN-based image classification models. Thus, in this work, we present an analysis of several relevant research articles about the importance of color spaces for image classification using artificial neural networks. Thus, through the review of these articles, we will evaluate the behavior and efficiency of several ANN architectures, in different image classification contexts, and using images data sets represented in several color spaces. In the end, we not only found that there is a clear influence of the color spaces in the final accuracy of this type of tasks. But, we also found that both the creation of new special ANN architectures, and the creation of new color spaces formed from the combination of others, can lead to an increase in the performance of ANN-based image classification models.

Keywords: Image Classification · Color Spaces · Artificial Neural Networks

1 Introduction

Image Classification is an important task nowadays for many applications in both the industrial and research field [20]. For example, in the field of medical images analysis, we could detect if a patient has a tumor or not, based on classifying tissue images [15]. Also, in the food industry, we could classify fruits according to their ripeness level [7]. Moreover, in a social media context, we could apply image classification to automatically detect inappropriate or offensive images, for later censorship [32].

As the applications of image classification have evolved, so have the methods of implementing it. In practice, image classification implementations are based on Machine Learning techniques [16]. The most relevant machine learning techniques to do this task include Decision Trees, Support Vector Machines, K-Nearest Neighbor, and Artificial Neural Networks. Each one of them has its advantages and disadvantages when classifying images, in this way we cannot define for sure, which of the methods is better in all cases [14]. But, without any doubt, the more promising techniques in the previous list are which imitate the functioning of biological neural, these are the Artificial Neural Networks. [24].

Now, there are different color spaces through which an image can be represented, such as RGB, XYZ, CIELAB, HSV, CMYK, YIQ, etc. Each of these spaces has its way of representing images, and for this reason, they have particular uses [19]. For example, CMYK space is preferred for printing devices because it creates colors in a "subtractive" way. While the YIQ space was preferred in the first color televisions because it allowed backward compatibility with B/W television signals [31].

Although there are several numbers of different color spaces that have their particular advantages and disadvantages when representing images. Most of the time, the images used to perform Image Classification using Artificial Neural Networks are represented in the RGB Color Space [8]. Perhaps, this is because RGB is the most widely used intuitive color space for rendering images on devices [19]. But, is RGB the most recommended space to perform image classification using artificial neural networks? If not, which is the best color space to perform this type of task?

In this work, we will try to answer these and other questions by reviewing some relevant articles about it. In this way, we will evaluate the behavior and efficiency of several ANN architectures, in different image classification contexts, and using images data sets represented in several color spaces.

1.1 Structure of the work

The general structure of this work is as follow:

In the Theoretical Framework, we will briefly cover the definitions of Image Classification, Artificial Neural Networks, and Color Spaces, which are very important concepts to clearly understand this literature review.

In the Review Section, we will analyze seven research articles, which contains very relevant information and results about the current state of the art related to the Importance of Color Spaces for Image Classification using ANN. At the final of this section, we will include a table defining the key details of each one of these research articles. So, this table will allow us to appreciate and compare the relationship between them.

In the Conclusions Section, we will clearly define the existing relationship between the Color Spaces and Image Classification using ANN, also how much the color spaces influence the overall performance of this type of task. Finally, we will summarize and propose some ideas for future research projects, which can help both fill research gaps, as well as expand the practical applications of this research area.

2 Theoretical Framework

2.1 Image Classification

Image Classification is an important task of Image Recognition. That means that it incorporates aspects from Computer Vision and Artificial Intelligence for detecting and analyzing images [22]. Because Image Detection and Segmentation are also subfields of Image Recognition, usually, the definitions between them are often confused. The key difference is that, in the Image Classification, each image is considered as a whole and is assigned to a particular class. While in the Image Detection and Segmentation, each image can contain several objects of interest, and the objective is to locate the exact position of each of those objects within the image [16]. Thus, although Image Classification, Detection, and Segmentation are similar, the practical applications of them are very different.

In that way, the specific objective of Image Classification is to separate images into "classes" or "labels". For example, let's suppose that you have a data set with different images of animals. You could classify them into two classes: wild or domestic animals, this problem is called Binary Classification. Also, you could classify those images in more than two classes (for example: cat, dog, rabbit, horse, bird, and so on) this problem is called Multiclass Classification [18].

But the applications of Image Classification extend beyond just classifying images of animals. Today, image classification applications are present in many aspects of industrial and research fields[20]. So, image classification is present in facial recognition, fruit image classification, satellite image analysis, mineral image classification, medical image analysis, scene classification, and more. Its importance is so high that even world events, such as ILSVRC, are held to compare new image classification methods in terms of accuracy and efficiency [3].

So, as we mentioned before, the image classification tasks can be implemented in several ways. The most effective methods belong to the area of Machine Learning. Those methods include: Decision Trees, Support Vector Machines, K-Nearest Neighbor, and Artificial Neural Networks [24]. Although the use of each of them depends on the specific application, it must be recognized that the most efficient image classification methods today are based on Artificial Neural Networks [20].

Now, before implementing an image classification method, those images must go through a pre-processing stage. Thus, image pre-processing is a crucial stage to achieve good classification results [16]. Some pre-processing techniques consist of reducing noise, improving edges, improving contrast, or even transforming the color space in which the images are being represented. Each of these techniques, no matter how simple it may seem, can lead to a great improvement in any image classification method to be implemented [22].

2.2 Artificial Neural Networks

Artificial Neural Networks (ANN) are powerful computational models that belong to the field of Artificial Intelligence [29]. Unlike other Machine Learning techniques, these models are inspired by the biological neural networks of animals brains. In that way, the Artificial Neural Networks are composed of basic nodes called Neurons, which are equivalent to Biological Neurons. These nodes communicate between them through connections called Weights, which are equivalent to the Synaptic Process [10].

In general terms, the functioning of an Artificial Neural Network is as follows. First, the ANN takes the input information through Input Neurons. Then, the input information is transferred to other neurons, usually called Hidden Neurons, which are in charge of processing this information, step by step. Finally, once the input information was processed, the ANN gives us the final result through Output Neurons [12].

Now, before a neural network can correctly process the information and gives us the desired output, like other Machine Learning methods, it must first go through a training stage [2]. So, during the training phase, the network architecture is configured for solving a specific problem. This is done through automatic adjustment of the weights. So, when the training phase ends, all the learning has been stored in the weights. And now, the network is ready to complete the task for which it has been trained [9].

Nowadays, Artificial Neural Networks are present in many fields of research and industry, so the number of applications is very huge. In the field of economy, several ANN architectures have been implemented to perform sales forecasting with high accuracy [30]. In the field of information security, some ANN architectures have been implemented to predict credit card frauds with goods results [26]. In the field of Language, ANNs are used to accurately translate both text and voice in real-time between different languages [1]. Also, in the field of image recognition and analysis, several types of neural networks have been applied to perform different tasks, either: Classification, Tagging, Detection, and Segmentation of Images [23].

2.3 Color Spaces

The Color Spaces, also known as Color Models, are essentially systems to organize colors [8]. It also can be defined as a mathematical model to describe colors. So, those colors are usually represented using tuples of three or four numbers. Some of the most common color spaces used nowadays are: RGB, CMYK, CIELAB, XYZ, HSV, YIQ, etc [19].

The Color Spaces can be classified into two different groups: Device-dependent color spaces and Device-independent color spaces. Some Device-dependent color spaces are: RGB, CMYK, HSV, HSL, HSI, YUV, YIQ, YCbCr, and YPbPr. And, in the case of Device-independent color spaces, the most used are XYZ, and CIELAB [31].

On the one hand, a Device-dependent color space is a color space in which the final color representation depends on the physical device configuration and quality used to produce it [17]. For example, if we choose the same CMYK color value and print it on two different types of paper, the printed colors will look different from each other. On the other hand, a Device-independent color space is a color space in which the numerical color values used to specify a color will produce the same color no matter the device. Due to the ability to represent colors in an "absolute way", these color spaces are usually used as Profile Connection Space (PCS)[21]. In Color Management, the Profile Connection Spaces are very important because they allow us to convert between color spaces [11].

The RGB Color Space is one of the most popular Device-dependent color spaces. In this system, each color is formed by the addition of three primary colors, which are: red, green, and blue. So, in this space, a color is represented using a tuple of 3 values, usually between the range of 0 and 255, which represents the amount of each primary color. This color space is widely used on multimedia devices such as: cameras, displays, scanners, etc. [27]

CIE XYZ Color Space is a Device-independent color space derived from the curves of LMS Color Space which represent the response of the three types of cones in the human visual system. Because of this, CIE XYZ Color Space allows us to represent all possible colors that the average human eye is capable of seeing [21].

CIE L*a*b* Color Space, usually called CIELAB, is a Device-independent color space defined by the International Commission on Illumination (CIE) in 1976. This color space was derived from the previous CIE XYZ Color Space. In the CIELAB color space, the colors are represented using three real values for L*, a* and b*, which represent the lightness, the green-red component, and the blue-yellow component respectively [11].

3 Literature Review

In this section, we will analyze seven research articles, which contains very relevant information and results about the current state of the art related to the Importance of Color Spaces for Image Classification using ANN. At the final of this section, we will include a table defining the key details of each one of these research articles. So, this table will allow us to appreciate and compare the relationship between them.

3.1 Javier Diaz Cely, et al. (2019)

In this research [6], the authors explore the impact of the color spaces in the transfer learning of Convolutional Neural Networks. So, the authors analyze the behavior of some pre-trained convolutional neural networks during the classification of a new data set. This new data set has been transformed into other color spaces, and not only in the default RGB color space.

The authors use three popular convolutional neural architectures: ResNet, MobileNet, and Inception-V3. All three were originally pre-trained using the ImageNet data set. This data set is one of the most used data set to pre-train convolutional neural networks for image classification tasks, and it contains 1.2 million RGB images divided into 1000 classes.

Once the pre-trained CNN architectures are established, the authors define the new image classification problem to perform. So, this problem is basically to classify, in two possible classes, a data set of images of cats and dogs. This data set contains 25000 images represented in the RGB color space. So, for the experiment, the authors perform this classification task using this data set in the original RGB color space, and after that, the authors perform the same task again for other color spaces.

So, the color spaces used to represent the data set are RGB and LAB, which are examples of Device-dependent and Device-independent color spaces respectively. Also, in order to explore how much each component of LAB Color Space affects the learning transfer, the authors simulate three other color spaces. Those color spaces are: LLL, AAA, and BBB, which are the three repeated components of the LAB Color Space.

In the results, the authors found that each one of the three CNN architectures obtains different accuracy levels in different color spaces. For example, in the case of ResNet architecture, the model obtains a slightly better performance in the RGB color space, compared with the LAB, LLL, AAA, and BBB color spaces. While, in the case of MobileNet, the same level of accuracy is reached using the five color spaces. This is interesting because even using just the LLL, AAA, or BBB color spaces (each one representing one LAB component) the same accuracy as using the RGB or LAB color spaces is reached. Finally, the Inception-V3 architecture obtained the most interesting result because, in this case, the RGB color space reaches a low accuracy compared to all the other color spaces. That means that even the LLL, AAA, or BBB color spaces obtain better results than the original RGB color space.

The authors conclude that these accuracy differences could be due to the differences in the internal architecture and functioning of each convolutional neural network. Because, for example, some architectures are much deeper than others and therefore they become more specialized in handling the color space in which they were originally pre-trained. Also, they assume that some CNN architectures perform the classification based mostly on spatial characteristics, rather than fine color details. Finally, as future works, they propose that it would be very interesting to perform this type of comparison using other architectures, data sets, and color spaces.

3.2 Shreyank Gowda, and Chun Yuan. (2019)

In this research [8], the authors explore the influence of different color spaces on convolutional neural networks to perform image multi-class classification. Also, they propose a novel CNN architecture for image classification which processes images represented in seven different color spaces at the same time.

In order to do so, first, the authors implement a simple CNN architecture and perform multiclass classification using CIFAR-10 Data Set (In RGB Color Space). Then, this is repeated using the other 6 color spaces, which are: YIQ, LAB, HSV, YUV, YCbCr, and HED. After that, they compared the classification accuracy obtained using each color space. So, through confusion matrixes, they found that some color spaces improve the classification accuracy of some classes in particular.

So, based on that, they propose a novel CNN architecture for image classification that uses seven different color spaces, at the same time, to classify a particular image. This new architecture, named ColorNet, is composed of seven independent DenseNets that process the images dataset in different color spaces. Then, the output of those seven DenseNets is combined using a final dense layer which gives the final classification result. The authors also mention that due to the redundancy produced by introducing the same image in seven color spaces, the original DenseNet architecture can be modified to reduce the number of parameters and thus to avoid a computational overhead.

In the results, the architecture proposed by the authors obtains slightly better accuracy than the traditional CNN architectures that use images represented just in the RGB color space. Also, due to the reduced number of parameters to adjust during training, they mention that the efficiency of this architecture is slightly better than other complex CNN architectures with many hidden layers and parameters.

3.3 Wilson Castro, et al. (2019)

In this work [5], the authors implement four machine learning techniques, combined with three different color spaces, in order to compare and determine which machine learning technique and color space are the best to classify fruit images according to their ripeness level.

The data set used in this work contains 925 images of Cape Gooseberry Fruit. This data set was labeled into 7 different ripeness levels by human experts. Also, some image pre-processing techniques, such as image segmentation and enhancement, were applied to the original data set. Finally, the resultant enhanced image data set, which is represented in the RGB color space, was transformed to HSV and LAB color spaces. So, these three image data sets will be used to train and test four image classification approaches.

So, the machine learning approaches that have been implemented and compared in this work are Artificial Neural Networks (ANN), K-nearest Neighbors (KNN), Decision Trees (DT), and Support Vector Machines (SVM). With respect to the ANN Image Classification Method, which is relevant to this literature review work, the specific architecture used is the Radial Basis Function Artificial Neural Network (RBF-ANN). This type of ANN architecture is an improvement of the standard ANN because it allows for faster learning and convergence. So, all these machine learning approaches were individually trained using the three-color spaces mentioned before, and the performances were analyzed.

In the results, the authors found out that the models that reached the best accuracy were: ANN and SVM. Also, they noticed that the precision of both models is very sensitive to the color space used during the training phase. For this reason, both models reached a very high accuracy in the CIELAB color space, but a very low accuracy in the other color spaces.

3.4 Vanessa Buhrmester, et al. (2019)

In this work [4], the authors explore two principal ideas about image classification using CNN. First, they try to understand the behavior of CNN architectures when there is a color space transformation in the input images data set. Second, they explored which are the color spaces more prone (and less prone) against image disturbances, for example, noise or blur. In both cases, they try to calculate the accuracy difference performing image classification, using different types of data set. In this way, they try to find the color space that leads to better classification accuracy and that has more robustness against disturbances.

So, they use four different image data sets: PersonFinder, FlickrScene, CIFAR-10, and CIFAR-100. The first data set contains 15876 RGB images labeled in two classes, person and background. The second data set contains 10000 RGB landscape images labeled in four classes: desert, forest, snow, and urban. Finally, the third and fourth are both well-known data sets for image classification, each one contains 60000 RGB images of different objects divided into 10 and 100 classes respectively.

Now, for the first part of this project, they perform color space transformation in the four original image data sets. So, they obtain five different versions: RGB, HSV, HSI, YUV, and YIQ. After that, for the second part, they create the disturbed versions of those data sets through the addition of Gaussian Noise and Gaussian Blur. Then, with each version of those data sets, they train a simple CNN architecture, which is formed by two convolutional-pooling layers pairs. Finally, they analyzed and compared the accuracy obtained in each case.

So, in the results, they conclude that the color space information is very important in image classification using CNN. In fact, they found that in some data sets, especially with a large number of classes, the accuracy of classification could be very different if we change the original color space. For example, in the CIFAR-100 data set, the model with the best accuracy was trained with RGB Color Space. Instead, in the FlickrScene data set, the YIQ color space outperformed the other implemented spaces. They also conclude that HSV is the less robust color space against image disturbances, and they also mention that the Luminance component itself, present in some color spaces, is very robust against this type of disturbances.

3.5 Parham Khojasteh, et al. (2018)

In this work [13], the authors compare the performance of different color spaces during the detection of exudates through retinal image classification using CNN. Also, they perform a Principal Component Analysis (PCA) to generate the eigenchannels of each color space used, and they measure the accuracy with those color spaces versions. Finally, they propose a novel color space, formed by the combination of different components of different color spaces, which leads to high accuracy in this retinal image analysis.

The data set used in this work is a fusion of two publicly available image data set: DIARETDB1 and e-Ophtha. They contain RGB images of the retina which were manually labeled in two independent classes: Exudate and Non-Exudate. After that, this image data set was converted into two other color spaces: LUV and HSI. Finally, a PCA Analysis was applied to those color spaces obtaining the PCA versions: PCA-RGB, PCA-LUV, and PCA-HSI.

After training a simple convolutional neural network using six color spaces versions, the authors obtained that the HSI space reaches the highest accuracy level with 97.62%. And the second-best color space was PCA-RGB with a 96% accuracy level. Also, they found out that the second component of each PCA color space version shows a higher contrast between exudate and non-exudate image regions. With these results, the author proposes a new color space formed by the combination of HSI and PCA-RGB color spaces. This new three-channel color space, called "PHS", combines the second channel of PCA-RGB with the Hue and Saturation channels of the HSI Color Space. So, using this new color space, the classification model achieves higher accuracy than all previously tested models.

In the end, the authors conclude that the selection of a specific color space is a very important factor for image classification using CNN, especially in the retinal image analysis. They also demonstrate that it is possible to form a new three-channel color space, from the combination of individual components from other spaces, which can lead to better accuracy in image classification. Finally, as future works, they propose to carry out these experiments on other types of medical images, in order to improve the precision of current image classification systems based on convolutional neural networks.

3.6 Sachin Rajan, et al. (2018)

In this research [25], a pre-trained convolutional neural network is implemented to classify a scene image data set. This data set is converted to different color spaces and intensity plane representations. The objective of the authors is to find out which color space or intensity plane leads to obtain the highest accuracy in performing this particular image classification task.

With respect to the color spaces used, the authors analyze the effect of 4 different color spaces: RGB, HSV, CIELAB, and YCbCr. Also, they analyze 4 intensity planes obtained from the color spaces mentioned before. These intensity planes are V Plane, L Plane, Y Plane, and RGB2Gray obtained from HSV, CIELAB, YCbCr, and RGB color spaces respectively.

The experiment was implemented using the Oliva Torralba (OT) data set which contains 2688 RGB Images (256x256 pixels in size) of outside scenes. This data set is divided into 8 different classes: Open Country, Coast, Forest, Highway, Inside City, Street, Mountain, and Tall Building. For this experiment, the image data set is divided into 1888 images for training, and 800 images for testing. Finally, all these images are converted to obtain the versions in 4 different color spaces and 4 intensity planes mentioned before.

So, the convolutional neural network architecture used in this work is called Places205-CNN. This is a pre-trained CNN used to classify scene images. In this work, the CNN does not perform the classification by itself, but this is used just as a feature extractor. In this way, the CNN process the input images obtaining a feature map which will be processed later by another simple classification method. So, for this part, the authors implement two final classification methods, which are: Random Forest, and Extra Tree Classifiers.

In the results, the authors realized that each of the eight classes is classified better or worse than others in a specific color space or intensity plane. In this way, they conclude that there is no unique color space (or intensity plane) that obtains the perfect accuracy for all the classes at the same time. Finally, they conclude that choosing a determined color space is very important for image classification since if we ignore this, it can have a negative impact on the general accuracy of this type of task.

3.7 Jiasong Wu, et al. (2017)

In this work [28], the authors implement a PCANet-SVM to perform image classification using three different data sets and using different color spaces. So, the main objective is to find the color space which leads to the best accuracy performing these image classification tasks.

The three data sets that the authors use are CURet Texture Dataset, UC Merced Land Use Dataset, and Georgia Tech Face Dataset. So, the first data set contains images of surfaces of 61 different materials classes, where each class contains 92 images in RGB color space. The second data set contains satellite image sections of an urban map, which is divided into 21 classes with 100 images per class. The last data set, Georgia Tech Face Dataset, contains images of faces of 50 people, with 15 images for each person.

So, after defining and converting those three data sets into different color spaces (such as CIELAB, HSV, HSI, YUV, etc), the proposed PCANet-SVM architecture was implemented. This architecture consists of two fundamental parts. The first part is the PCANet Convolutional Neural Network which works as a feature extractor of input images. The second part is the Support Vector Machine (SVM) which receives the features extracted in the first part and gives us the final classification result.

At the final, the authors conclude that, in most cases, the best color spaces to perform image classification using PCANet Convolutional Neural Network are: YUV and YIQ color spaces. Also, they found that the use of Hue-Saturation Color Spaces, which are HSV, HSL, and HSI, produces very poor image classification performance compared with other color spaces.

3.8 Comparison Table

In Table 1, a comparison of the main aspects of the seven scientific articles reviewed is presented. This table describes the specific image classification task, including the number of classes. Also, the type of ANN architecture is mentioned. And finally, the color spaces used in each article are detailed.

Table 1. Comparison table of the reviewed scientific articles

Article	Author	Image Classification Task	Number of Classes	ANN Architecture	Color Space Used
The Effect of Color Channel Representations on the Transferability of Convolutional Neural Networks. (2019)	Javier Diaz-Cely, et al.	Cat/Dog Image Classification.	2	1)InceptionV3 + FC-ANN 2)ResNet + FC-ANN 3)MobileNet + FC-ANN	RGB, LAB, LLL, AAA, BBB.
ColorNet: Investigating the importance of color spaces for image classification. (2019)	Shreyank Gowda, and Chun Yuan.	Objects and Animals Images Classification. (CIFAR-10)	10	ColorNet, (7 DenseNets Fusion)	RGB, YIQ, LAB, HSV, YUV, YCbCr, HED
Using machine learning techniques and different color spaces for the classification of Cape gooseberry (Physalis peruviana L.) fruits according to ripeness level. (2019)	Wilson Castro, et al.	Fruit Images Classification According Ripeness Level	7	RBF-ANN	RGB, HSV, LAB.
Evaluating the Impact of Color Information in Deep Neural Networks. (2019)	Vanessa Buhrmester, et al.	1) Person/Background Image Classification 2) Landscape Image Classification 3) CIFAR-10 4) CIFAR-100.	2, 4, 10, 100	Simple CNN	RGB, HSV, HSI, YUV, YIQ
A novel color space of fundus images for automatic exudates detection. (2018)	Parham Khojasteh, et al.	Exudate/Non-Exudates Retinal Images Classification	2	Simple CNN	Color Spaces: RGB, LUV, HSI. PCA Transformations: PCA-RGB, PCA-LUV, PCA-HSI
Dependency of Various Color and Intensity Planes on CNN Based Image Classification. (2018)	Sachin Rajan, et al.	Outside Scene Images Classification.	8	Places205-CNN + RF/ET.	Color Spaces: RGB, HSV, LAB, YCbCr. Intensity Planes: RGB2Gray, L Plane, V Plane, Y Plane
PCANet for Color Image Classification in Various Color Spaces. (2017)	Jiasong Wu, et al.	1) Texture Image Classification 2) Urban Areas Image Classification 3) Face Image Classification	61,21,50	PCANet + SVM, (PCANet is used as a feature extractor)	RGB, YUV, YIQ, YPbPr, YCbCr, YDbDr, HSI, HSV, HSL, CIEXYZ, CIELCH, CIELAB.

4 Conclusions

In this work, we have reviewed some relevant research articles about the importance of color spaces for image classification using ANN. So, we have explored the behavior of different ANN-based image classification architectures when different data sets are represented in different color spaces.

In this way, through this literature review, we have explored the use and effectiveness of different color spaces when performing image classification tasks. Although the RGB color space is the most used space to perform these types of tasks, we were able to verify that the use of other color spaces, such as HSV or YUV, can lead to better classification accuracy. Furthermore, the effectiveness of new proposed color spaces, such as “PHS” which is a combination of different color spaces, was reviewed in this work.

Also, through the scientific articles reviewed in this paper, we have explored different ANN-based image classification architectures. So, we have reviewed from relatively simple ANNs, such as an RBF-ANN, to more complex ANNs architectures, such as DenseNet, PCANet, InceptionV3, among others. Also, in some articles, we were able to review new architectures such as ColorNet, which exploits the potential of combining different color spaces to improve the general image classification accuracy.

So, we not only reviewed different methods of classifying images in different color spaces, but we also reviewed their performance in different contexts of classifying images. Since, in the reviewed articles, the authors used different data sets to carry out different image classification applications. Applications such as face classification, medical image classification, fruit classification, among others. Each one of these applications being of great importance today for the field of industry and research.

Thus, after evaluating these articles, we have been able to confirm that the use of different color spaces can lead to an increase, or decrease, in the overall ANN-based image classification accuracy. Thus, certain architectures show great accuracy when trained with images in a given color space, while the same architectures show much lower accuracy when using other color spaces. Finally, we were able to observe that some classes, within the same dataset, are likely to be classified more accurately than the rest of the classes when using a specific color space.

For future works, all the authors agree that it would be good to implement these types of comparisons using other image data sets and applications. Also, the authors agree that it would be good to test the influence of color spaces in new types of ANN architectures, in order to improve the general accuracy when performing image classification tasks.

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