A detailed evaluation of colour representations for image recognition

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Data Analytics

Senthilnathan Balamurugan
Student ID: X21193371

School of Computing
National College of Ireland

Supervisor: Dr Giovani Estrada

National College of Ireland
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A detailed evaluation of colour representations for image recognition

Senthilnathan Balamurugan
X21193371

Abstract

The investigation of colour channels as a key element impacting classification accuracy has drawn a lot of attention in the field of image classification. The encoding of colour information in images, which is essential for communicating visual content, is a critical part of image recognition. This study offers a thorough and methodical assessment of different color representations for image recognition tasks. Through a methodical investigation of numerous colour modes, including RGB, grayscale, and individual colour channels, the study discovers broad results with value for both academic and practical applications.The model using only the Red and Green colour channels is found to be the most successful in reliably differentiating between awake and drowsy states in a thorough review of drowsiness detection methods. This amazing discovery challenges popular opinion and highlights how effective some colour modes are in improving accuracy. The results of this study provide substantial insight on the advantages and disadvantages of various color representations for image classification tasks.

1 Introduction

1.1 Colour

Accurate object classification and pattern recognition are crucial in the fields of machine learning. Since colour is a key characteristic of human vision, visual information has historically been important in the classification process. However, research into the function and effects of colour representation in machine learning systems is currently underway. A powerful characteristic that offers detailed information about objects and scenes is colour. It enriches the human visual experience by communicating semantic meanings and assisting in object recognition. Colour representation plays a crucial role in the training of machine learning models since it greatly affects the model's capacity to identify and distinguish between distinct classes. Image identification and computer vision can benefit greatly from an understanding of how colour representation affects classification Velastegui and Pedersen (2021). Researchers can get knowledge that can progress a variety of practical applications by examining the effects of various colour representations on classification accuracy and performance.

1.2 Colour in image processing

The selection of colour space is one component of colour representation that researchers often examine. There are various ways to encode colour information, including using colour spaces like RGB (Red-Green-Blue), HSV (Hue-Saturation-Value), or LAB (Lightness-A, Green-Red, Blue-Yellow) Velastegui and Pedersen (2021). Each colour space has its own benefits and drawbacks that can affect how well it can distinguish between various object types. Investigating how various colour spaces affect classification might aid in determining which representations are more effective for a given job. Additionally, colour representation has an impact that extends beyond the selection of colour space. Accurate categorization can be impacted by variables like colour normalization, colour quantization, and colour constancy approaches. These methods are designed to lessen fluctuations in lighting, colour intensity, and other environmental elements that could affect how colours are perceived. Algorithms and models can be improved by comprehending how various pre processing methods affect categorization Sachin et al. (2018). In this research we will be examining the various colour modes by splitting the colour space of RGB.

1.3 Research Question

How does colour representation influence the classification accuracy for drowsiness detection?

1.4 Proposed Technique

By conducting various experiments on drowsiness classification dataset, We will explore various colour channel modes and preprocessing to determine the impact of colour representation on classification results. For researchers, professionals, and developers involved in computer vision, image identification, and machine learning, our discoveries can be a significant source of information. Ultimately, this research aims to advance our knowledge of the importance of colour representation in classification tasks and pave the way for more precise and reliable machine learning algorithms that can better leverage the potential of colour information.

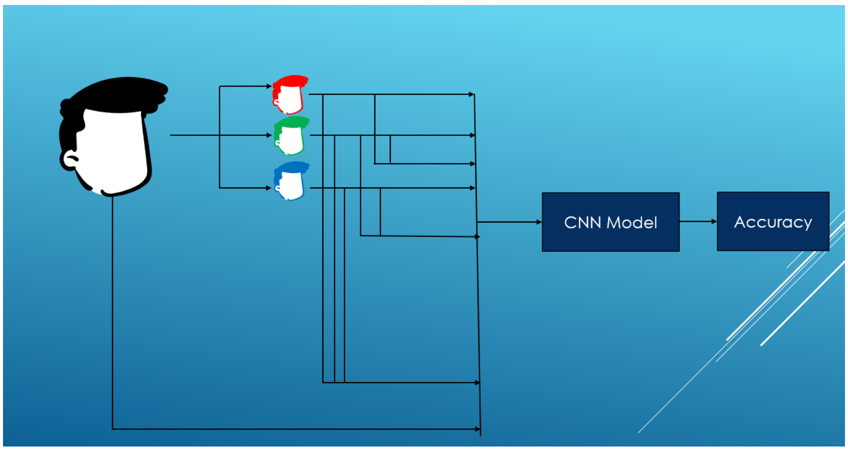

Figure 1: Overview

The overview of this research is shown in Figure 1 The image input given for the CNN Model is divided into different colour channel and sent to determine the accuracy.

The overall structure of the research paper will be provided in this area, and it will be covered in more detail in the sections that follow.

Section 2 : This section of a project provides a comprehensive overview of the existing research on the influence of colour representation and drowsiness detection.

Section 3 : This section provides the in depth details about the methodology followed with different subsections.

Section 4 : This section covers the design specifications of the research.

Section 5 : In this section the implementation of the methodology is explained.

Section 6 : This section outlines the results and experiments done to gather the results.

Section 7 : The final section covers the conclusion and the potential future works.

2 Related Work

2.1 Drowsiness Detection

Road safety is seriously compromised by drowsy driving, which causes many collisions and fatalities around the world. The researchers Al-madani et al. (2021) recognize the serious issue of driver fatigue contributing to traffic accidents and offer a non-intrusive, inexpensive method that uses facial landmarks to detect probable tiredness in drivers. The suggested method analyzes the driver's eye movement and yawning to detect tiredness and warn the driver. The system makes use of dlib and openCV to recognize facial landmarks in real-time. The experiment's approach, which entails selecting a sample of individuals and using webcam streams to record their eye movement and yawning, is thoroughly explained. In order to assess the efficiency and dependability of the suggested system, the experiment's results are contrasted with those from previous investigations. The study's results show great promise for identifying driver drowsiness with high accuracy.

The study contains some restrictions, despite the system's advantages. The lack of information from the authors regarding the dataset size employed in the experiment raises doubts about the validity and generalizability of the study.The study's conclusions, which are based on a small number of participants, might not apply to the wider public. Furthermore, the report did not explain how the system will handle erroneous positives or false negatives, which reduces the system's dependability. The system's performance in various weather and illumination scenarios was also not covered, which might have an impact on how well it performs on the road.

In conclusion, the authors offer an inexpensive, non-intrusive solution to the issue of driver drowsiness with their suggested approach. To assess the study's applicability and generalizability for deployment in the real world, its advantages and disadvantages must be balanced. Future research can concentrate on overcoming the restrictions and applying the system to bigger datasets to see how well it performs in various weather and illumination scenarios.

To identify driver fatigue, a study on the use of machine learning algorithms to detect driver drowsiness was conducted. The goal of this research is to increase road safety by more effectively and precisely identifying drowsy driving. The authors suggest a system that employs a machine learning algorithm and heart rate variability (HRV) to identify weariness.According to the study, it is important to recognize driver drowsiness because it raises the likelihood of accidents. Although earlier research in the area has made encouraging progress, there are still a number of issues that need to be resolved within the current systems to guarantee road safety. The authors Gopinath et al. (2022) advise improving the HRV-based approach, which has demonstrated tremendous potential in spotting anomalies while driving. For instance, HRV can be seen in facial and head movements.

The study concludes with a potential method for detecting driver fatigue that is based on an HRV-based system and a machine learning algorithm. The method has the potential to increase road safety by more precisely identifying weariness, enhancing reaction times, and lowering the probability of accidents. Given that they only tested 34 drivers, which is one of the paper's limitations, there is still room for additional testing and system validation. Additionally, despite claims to the contrary in the paper, the system is said to be cost-effective without any supporting calculations. But given how crucial it is to identify driver drowsiness and work toward safer roadways, this study is still important to take into account.

A further study done by Baby Shamini et al. (2022) used a computer vision-based technique to identify driver fatigue and drowsiness in order to stop traffic accidents. Webcam facial recognition, eye tracking, and image processing are all used in the proposed system to find, locate, and identify facial expressions. When the system determines that the driver is drowsy, a loud alarm or signal is issued to notify them. The paper highlights how driver fatigue and drowsiness are increasingly to blame for traffic accidents, which has become a key problem for global road safety. There have been a number of relevant studies on drowsiness detection, however it is still difficult to recognize fatigued drivers. The suggested system accurately detects and tracks driver fatigue and drowsiness using image and video processing, facial feature extraction, and machine learning techniques.

The proposed system architecture and its underlying operating principle are presented in the paper. Driver drowsiness is detected, tracked, and alerted using a webcam, OpenCV, and an alarm system. The dashboard is connected to the webcam in front of the driver's face, and an image-based program there continuously keeps track of the driver's eyes and facial expressions. The driver's face and eyes are identified and detected by the image processing algorithm to check for signs of fatigue. An alarm signal tells the driver to avoid accidents when the drowsiness count surpasses the set limit of parameters. On the basis of trials and analyses of comparable studies, the system's performance was assessed. The findings demonstrated that the suggested system accurately monitors and identifies driver fatigue and drowsiness, then alerts the driver with an alarm signal to prevent accidents. In conclusion, the suggested technique is a successful way to prevent traffic accidents brought on by fatigued and drowsy drivers. The technology provides a discreet, economical solution that is simple to use. Future studies might concentrate on enhancing the system's functionality and assessing its efficacy in a real-time driving situation. The research suggests using the suggested technique to stop car accidents brought on by fatigued and drowsy drivers.

A Real-Time Drowsiness Detection System (RT-DDS) for drivers employing traditional Computer Vision applications is suggested by an additional study. The device uses the blink rate, eye closure, and yawning to gauge the driver's level of exhaustion and drowsiness. With the ultimate goal of minimizing the incidence of sleep-related traffic accidents, the suggested system intends to provide a quick and simple way for identifying intoxication while driving. By employing established computer vision applications to identify driver fatigue and drowsiness in real-time, the proposed RT-DDS makes a substantial contribution to minimizing traffic accidents.

The suggested solution entails keeping a camera on and taking pictures of the driver's face utilizing Haar Cascade Classifiers and pre-existing characteristics for facial landmark detection. The system calculates metrics like the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) for each frame, and an alarm is set off if the EAR and MAR values are higher than the corresponding threshold values Garg (2020). The study done by Baby Shamini et al. (2022) on computer vision based technique to identify driver fatigue and drowsiness takes into account only the Eye Aspect Ratio.

When the elements of eye blinking and yawning are combined, the method achieves 100% accuracy. The suggested technique is a straightforward but efficient solution to identify driver fatigue because it requires less computational effort than current approaches. The use of typical computer vision programs to quickly identify drowsiness is one of this study's advantages. The suggested methodology makes the best possible use of currently available technologies to offer an acceptable solution to a critical issue. The suggested system's simplicity also makes it simple to integrate into already-existing equipment, offering a practical solution to lessen the amount of sleep-related traffic accidents. The use of just blink rate, eye closure, and yawning as sleepiness indicators is one of this work's shortcomings. Blood pressure and pulse rate are not taken into account, nor are other variables that could cause sleep-related accidents. High-resolution cameras are also needed by the suggested system, which may not be practical for all vehicles.

2.2 Role of Colour channels in Image classification

To determine the accuracy while employing various Colour spaces, research was conducted on the effectiveness of various Colour spaces in convolutional neural network (CNN)-based medical images Khan et al. (2022). The authors Velastegui and Pedersen (2021) used an AlexNet CNN to classify colon tissue images to detect tumors using several Colour spaces, including RGB, XYZ, CIELAB, HSV, and YCbCr. They tested the models and analyzed the results to determine which Colour spaces gave the best accuracy in performing this medical image classification task.

The researchers Velastegui and Pedersen (2021) discovered that while no single Colour space can accurately categorize all classes, some Colour spaces can do so for different classes. Additionally, they discovered that the initial RGB space did not produce the best categorization accuracy. Instead, adopting the CIELAB Castro et al. (2019) Colour space yielded the maximum classification accuracy in both the overall case and the tumor case. Additionally, the researchers looked into how Colour spaces affected the transfer learning capabilities of CNNs and discovered that different CNN designs achieve varying degrees of accuracy in various Colour spaces. They came to the conclusion that the impact of picking one Colour space over others is crucial for classifying images.

Positively, the study offers insightful information on the best Colour space to employ for categorizing medical images, which might increase the precision of automated systems and lessen the demand for knowledgeable physicians. Researchers and practitioners in the field of medical image analysis can benefit from the study's findings of how Colour spaces affect CNN transfer learning and alternative CNN designs. The fact that the study only looked at one CNN architecture and one dataset is one of its drawbacks. The results might not apply to other CNN architectures and medical picture datasets as a result. The size of the dataset, the number of training epochs, and the choice of optimizer are other variables that may have an impact on the accuracy of medical picture classification but were not examined in this work.

Challenge-response authentication is a sort of security technique used in CAPTCHA (Completely Automated Public Turing Test to Tell Computers and Humans Apart). By requesting that you pass a brief test to demonstrate that you are a real person and not a computer trying to access a password-protected account, CAPTCHA helps protect you from spam and password decryption. [1] A method of recognizing dynamic character sequences in text CAPTCHAs using convolutional neural networks trained with a special loss function. The authors present their experimental findings that were derived from the text CAPTCHA data set from the social media site VKontakte (Russian online social media and networking website) in order to investigate the effects of individual Colour channels and their linear combination on the final quality of the models.The researchers Ishkov and Terekhov (2022) emphasizes the value of Colour diversity in CAPTCHA patterns and proposes that gauging the quality of text CAPTCHA production by taking into account the balance of the Colour channels.

The use of convolutional neural networks trained with a specific loss function to recognize dynamic character sequences in text CAPTCHAs is a useful aspect of the paper.The authors illustrate how this strategy might help safeguard Internet assets from automated Internet bots and lower the resource needs for model training without sacrificing recognition quality. The authors also demonstrate how taking into account the balance of the Colour channels and the significance of Colour diversity in CAPTCHA patterns can estimate the quality of text CAPTCHA creation.

On the other hand, the research paper primarily focused on the use of convolutional neural networks and did not explore other alternatives to recognizing dynamic letter sequences in text CAPTCHAs, such as auditory CAPTCHAs or touch CAPTCHAs. The study did not evaluate the suggested strategy on different data sets to confirm the model's capacity to generalize, and it only used one data set from a social media website.Additionally, the study did not compare the proposed method with other cutting-edge approaches, which might have revealed more information about the proposed method's effectiveness.

The study explores colour image segmentation using a combinatory strategy of masking, filtering, and thresholding while exploiting the tristimuli of the RGB Colour model. According to the researchers, while Colour photos lack segmentation methods, gray images do. In order to create an output image that is well-enhanced, they therefore suggest a new segmentation method that involves extracting the RGB image's Colour channels. The technique combines fuzzy membership functions to produce a mask based on RGB values to scan the image with a variety of combinations.The authors Kumar and Thiagarasu (2017) tests with channel separation and trapezoidal membership functions with 2x2 masks showed encouraging results. Additionally, they evaluated the efficacy of the suggested strategy with other literature-based approaches, concluding that integrating multiple techniques results in more potent segmentation than utilizing a single approach. Given that several sorts of outcomes based on RGB can be obtained, the authors suggested altering the masking qualities. This increases window widths and improves the clarity of images.

[1] http://support.google.com

3 Methodology

The data gathering, data preprocessing, model creation, and model evaluation makes up the methodology of this study.

3.1 Data Collection

For this study, a dataset for drowsiness detection taken from an open source library. [2] Two sets of image data—one for training and the other for testing—are included in the dataset. Both the sets of data contains four classes of images which are open eyes, closed eyes, yawn and no yawn. The dataset taken was a balanced dataset.

3.2 Data Preprocessing

The *ImageDataGenerator* library was used to help with the data preprocessing. The library preprocesses the photos using a lambda function. The batch size was set at 128. By dividing each pixel value by 255, the image data are then rescaled to have pixel values in the range [0, 1].With a maximum zoom of 20%, the zoom range is employed to randomly zoom the photos. This will increase the dataset's diversity and help the model generalize more effectively. The amount of training data that should be set aside for validation is specified. In this research, 10% of the training data will be used for validation and 90% for training. The target size for the images are set as 256,256 which indicates that all the images will be resized to the defined pixels. Class mode is defined as Categorical which denotes that the data labels are presented in a categorical way. It denotes one-hot encoding of the labels, with each class represented by a binary vector.

3.2.1 Lambda Function For Extracting Different colour Models

A lambda function was defined to extract only defined channels of the images and discard the other channels. The resulting image was store as grayscale. The models were then created using different types of input colour channels which are as follows -
RGB, Grayscale, Red, Green, Blue, Red and Green, Green and Blue, Red and Blue

3.3 Model Architecture

The Keras Sequential API was used to define a convolutional neural network model with four classes. A 2D convolutional layer with 32 filters of size (3, 3) serves as the model's first layer. Rectified Linear Unit (ReLU) is the activation function employed in this convolutional layer and is represented by activation='relu'. A max-pooling layer (MaxPooling2D) with a pool size of (2, 2) is added after the convolutional layer. By picking the highest value in each 2x2 zone, max-pooling decreases the spatial dimensions of the feature maps. It introduces some translation invariance and aids in reducing the computing complexity of the model. Using the same padding and ReLU activation function, the model adds a second convolutional layer with 64 filters of size (3, 3). From the representations that were acquired in the preceding layer, this layer continues to learn higher-level characteristics and patterns. Another max-pooling layer with a pool size of (2, 2) is implemented after the second convolutional layer to further minimize the spatial

[2] `https://www.kaggle.com/datasets/serenaraju/yawn-eye-dataset-new/code`

dimensions. The third layer is added again with the same features as the previous two layers but with 128 filters. A flattening layer is added before the output of the final max-pooling layer is sent to the fully connected layers. In order to be fed into the fully linked layers, the flattening layer transforms the 3D tensor output from the preceding layer into a 1D vector. Furthermore, The first dense layer is added, the ReLU activation function is applied by the first dense layer, which has 32 neurons. On the basis of the features discovered by the convolutional layers, this layer adds a nonlinearity to the model and carries out high-level feature extraction and combining.

The output layer, the last layer, has as many neurons (4 in my research problem) as there are classes in the classification task. The activation function here is softmax because this is a multi-class classification task. In order to describe the probability that each input belongs to one of the classes, softmax activation transforms the raw model outputs into probabilities. The total of the probability for each class is 1. Convolutional layers, max-pooling layers, and a fully connected layer make up the overall model architecture, which is intended to learn and extract hierarchical characteristics from the input images. An output layer that forecasts the probability distribution over the four classes for each input image completes the architecture.

The architecture of the model is shown in Figure 2

3.4 Model Evaluation

In order to create training and testing sets, a labeled dataset with images representing the four classes (closed eyes, open eyes, no yawn, and yawn) was gathered. The drowsiness classification dataset was used in the study to determine the accuracy for various colour modes. The batch size of 128 is used to load the dataset. The data is then transformed into various colour modes for the input layer which are RGB, Grayscale, Red, Green, Blue, Red and Green, Blue and Green, Red and Blue for the input layer. A standard CNN model was created as discussed previously in the model architecture section 3.3. The loss function used is categorical entropy which is the suitable function for multi class classification and the adam optimizer was used. Accuracy was defined as the metrics to be tracked during the training of the model. The model is then trained with various colour modes to find the effect of colour modes in classification.Post training, visualization was used to evaluate the model's accuracy and loss on the training and testing datasets. The variations in loss and accuracy over training epochs were plotted. A separate test set was also used to evaluate the trained model, and the test loss and test accuracy were provided as indicators of the model's effectiveness on different colour modes.

4 Design Specification

4.1 Framework and Libraries

The Keras framework, a high-level neural networks API that can operate on top of several backends, including TensorFlow, is used in the implementation.To describe the architecture and preprocess the data, the necessary Keras components are imported, including Sequential, Conv2D, MaxPooling2D, Dense, Flatten, Dropout, and ImageDataGenerator.

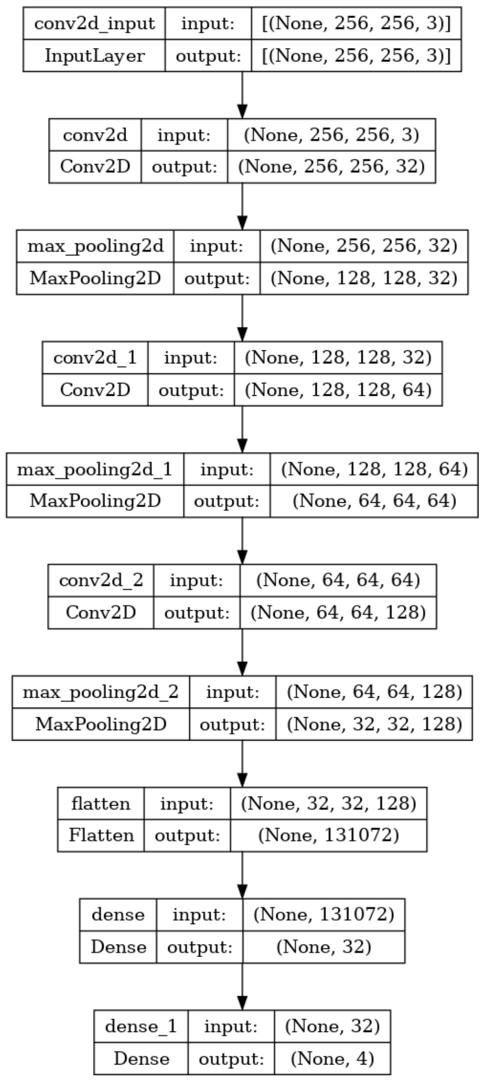

Figure 2: Model Architecture

4.2 Convolutional Neural Network (CNN) Architecture

Convolutional Neural Networks (CNNs), a subset of deep learning models that are efficient for image classification tasks, is the main technique used.Multiple convolutional and pooling layers are included in the architecture, which is followed by fully linked layers.Convolutional operations are applied by convolutional layers on the input images to extract features.Downsampling is used by MaxPooling layers to minimize spatial dimensions while preserving significant information.

4.3 Data Augmentation

The ImageDataGenerator class from Keras is used to apply data augmentation.To improve the model's capacity to extrapolate from sparse data, methods such as horizontal flipping (horizontal flip), rescaling (rescale), and zooming (zoom range) are employed.To extract only certain channels from the images and ignore the rest, a lambda function was created. The final image was stored in grayscale which will be given as input for the model.

5 Implementation

For this study, a computer equipped with AMD Ryzen 9 5900HX with Radeon Graphics and 16GB of RAM, was employed to effectively train the neural network. Software tools included the programming language Python, the deep learning framework Keras, and TensorFlow as Keras' backend. Python is the core language used for implementing the project. The dataset is loaded as training and testing sets. Different colour modes, including RGB, Grayscale, Red, Green, Blue, RedGreen, RedBlue, and GreenBlue, are applied to the images in the dataset. CNN is used to develop classification models for each colour representation. CNN model was found to be the best model for image classification tasks, hence it was used. Then the various colour modes are used to build and train models. Performance indicators like accuracy and loss are used to assess trained models. These metrics help in quantifying the classification performance. These metrics were chosen as the evaluation metrics since the dataset was a balanced dataset. Comparisons are made between the classification accuracy of each colour representation. The output of all the models are visualized using matplotlib to represent the comparison of the classification accuracy.

The dataset is gathered using the *os* function and the preprocessing is done using the *ImageDataGenerator* function.

The four classes are visually represented as shown in Figure 3.

The dataset is then split into different colour channels for the input layer of the CNN Model. A standard CNN model is created with the same layers, optimizer and Epochs. The input layer is changed in each model as per the colour channel. The accuracy of the different colour channels are noted for further evaluation and comparison.

6 Evaluation

The experiments in the following list were run, and the results were evaluated using the evaluation metrics such as accuracy and loss. Accuracy is a calculation of correctly

Figure 3: Visual representation of four classes of dataset

predicted instances out of total instances. Its a common metric used for predicting balanced dataset. Loss measures the discrepancy between the true labels for each image in a dataset and the anticipated probabilities. It gives an indication of how closely the model's predictions correspond to the actual labels.

Accuracy and loss was chosen as the evaluation metrics because - Accuracy serves as an obvious measure of how well the model is handling the classification task. The precise predictions for each class in the dataset are also taken into account. The model's efficacy for each individual class is revealed via loss. If the model has difficulty correctly classifying a specific class, it has a high loss for that class. The results of each experiment are thoroughly discussed below.

6.1 Experiment 1

The first experiment was done without splitting the colour channels. Grayscale and RGB colour modes were taken as input channel for the CNN model with 10 epochs. RGB colour channel had 3 layers of input whereas grayscale colour channel was given as 1 layer of input. The accuracy that was obtained was RGB colour channel was 82.90% and for grayscale 81.98%

6.2 Experiment 2

The next experiment was done by splitting the colour channel as Red, Green, Blue, Red and Green, Red and Blue, Blue and Green. The rest of the channel were made as null values when extracting single or double channel from the RGB layer. The results obtained with the different colour channel are shown in Table 1.The model with the green channel has the highest accuracy of 89.83% followed by the model with RedGreen channel of 89.14%. The Red and Green colour channel had the minimum loss of 25.75% which makes it the best model.

Table 1: Accuracy of various colour channels

Colour Mode	Accuracy	Loss
RGB	82.90	35.21
Grayscale	81.98	37.11
Red	82.44	37.34
Green	89.83	28.75
Blue	87.99	27.93
Red and Green	89.14	25.75
Red and Blue	87.06	26.19
Green and Blue	89.14	28.04

6.3 Experiment 3

The next experiment was done by taking the values of division of R/G , G/B, and B/R.The models built with these channels as input layers were getting a high percentage of loss as shown in Table 2

Table 2: Accuracy of various colour channels

Colour Mode	Accuracy	Loss
Red/Green	79.31	49
Green/Blue	77.93	47
Blue/Red	81.37	38

6.4 Experiment 4

The final experiment was done as similar to the 6.2 but with an increased number of epochs of 30. The results obtained were promising and was proving to be the best models for this experiment. We can see in the Table 3 the accuracy and loss comparison between different colour channels.
Accuracy Comparison: Across various colour settings, the accuracy of drowsiness detection varied significantly. The model with only Red and Green channels produced the highest accuracy of 96.69% followed by Red and Blue channel producing the accuracy of 95.61%. Also the loss for the model with only Red and Green channel was the lowest with 08.36% followed by Red and Blue channel with the loss of 13.60%.

6.5 Discussion

Investigating the impact of various colour representations on classification accuracy was the study's main goal. The CNN classification models were used to assess a number of colour modes, including RGB, Grayscale, Red, Green, Blue, Red and Green, Red and Blue, and Green and Blue. To discover the best colour channel in the image recognition process, various tests were conducted. The most pertinent conclusions are as follows:

The CNN model created with 30 epochs in the final experiment 6.4 had the highest accuracy among all the tests that were conducted. The input layer given as single or double channel and making the other channels as null values has significantly reduced

Table 3: Accuracy of various colour channels

Colour Mode	**Accuracy**	**Loss**
RGB	94.68	15.54
Grayscale	90.53	23.45
Red	94.45	19.58
Green	92.37	25.26
Blue	95.37	17.96
Red and Green	96.69	08.36
Red and Blue	95.61	13.60
Green and Blue	91.68	23.48

the loss compared to giving the input layer as division of R/G and so on as discussed in 6.3

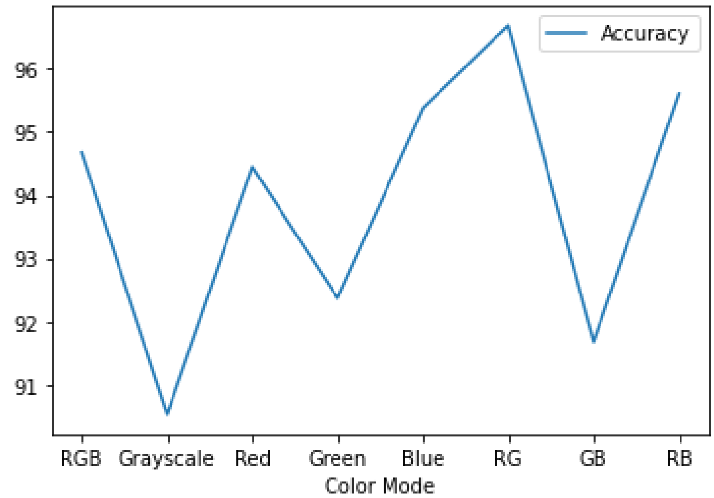

Figure 4: Accuracy

Figure 4 displays the accuracy line graph for each of the tested colour modes in 6.4

Figure 5 displays the loss line graph for each of the tested colour modes in 6.4

Figure 6 depicts the accuracy and loss of the best suited model with Red and Green colour channel.

6.6 Discussion

The study advances the field by empirically showing how the accuracy of drowsiness detection is strongly impacted by colour representation.It emphasizes the value of taking into account information from many colour channels in order to detect drowsiness accurately, outperforming information from individual colour channels.When planning future experiments incorporating image-based classification tasks, researchers should take these findings into account.

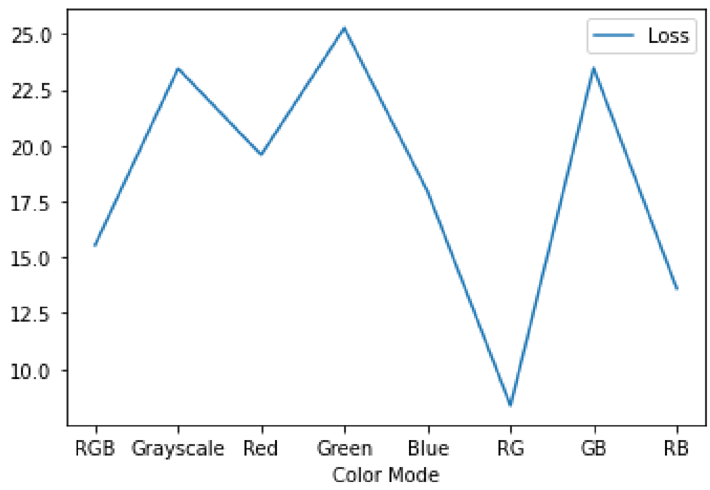

Figure 5: Loss

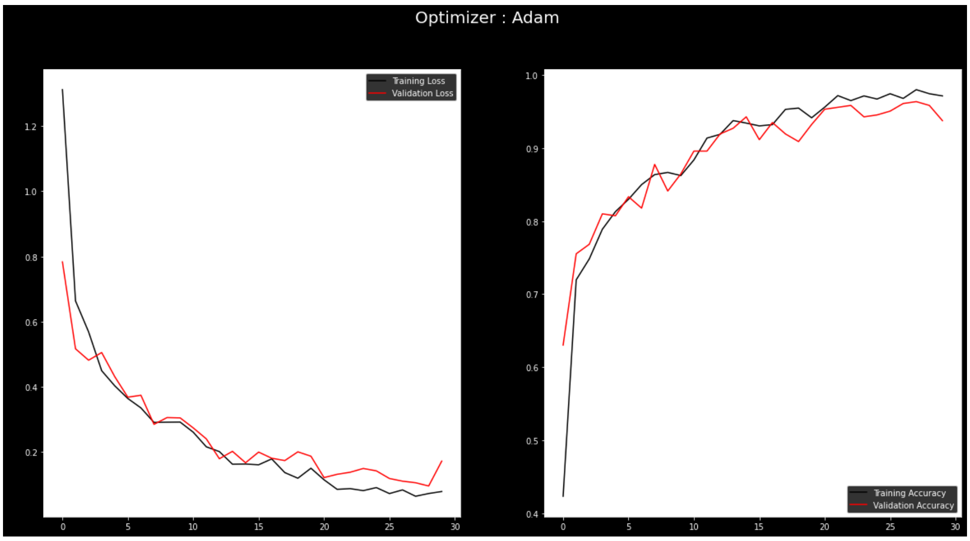

Figure 6: Accuracy and Loss of Red and Green Channel

6.7 Practitioner Implications

Redgreen and RedBlue colour modes should be prioritized by professionals creating drowsiness detection systems because they have been demonstrated to be accurate.This information can help ensure accurate drowsiness detection in practical applications like driver monitoring systems by guiding the choice of colour modes. This also enables faster data processing by using only two colour channels not three.

7 Conclusion and Future Work

The purpose of this study was to examine how colour representation affects classification accuracy for a dataset for drowsiness detection. After conducting various experiments with different input layers and different model architectures, It is concluded that the model with Red and Green colour channel had the highest accuracy and lowest loss. By utilizing these colour modes, drowsiness-related symptoms may be detected more precisely and successfully. Also, using only two colour channels, the model runs more quickly. One of the limitations of this study is that the results rely on the drowsiness dataset that was used. Because image quality, variety, and noise might vary, different datasets may produce different results.By underlining the significance of colour modes, the study adds to the collection of knowledge in the field of image classification. By examining additional aspects of accuracy, such as lighting conditions, preprocessing methods, and complex algorithms for machine learning, researchers may expand on this study.

In conclusion, the research has relevance for both current and future research in image classification. Both practitioners and researchers can benefit from its methodological rigor and useful findings. Although the study has several limitations, it nonetheless makes a significant addition to the subject and provides a foundation for future research and improvement.

8 Acknowledgement

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