ICIC Express Letters
Volume **19**, Number **4**, April **2025**
ICIC International ©2025 ISSN 1881-803X
pp. **393–401**

IMPROVING ACCURACY THROUGH COLORMAP MODIFICATION IN ANALYZING ELECTROCARDIOGRAM SIGNALS WITH COMBINATION OF WAVELET TECHNIQUES AND DEEP LEARNING NETWORKS

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Received April 2024; accepted July 2024

Abstract. *Color stands as one of the primary critical variables of visual information. Selecting the best possible colormap relies on both the specific analytical objective and the careful consideration of suitable 2D color schemes. Colormap was employed to classify electrocardiogram signals using images generated from Continuous Wavelet Transform. The findings from previous research suggest that the selection of a colormap affects the accuracy of electrocardiogram classification. The issue lies in determining the most suitable colormap to attain highest level of accuracy. This research examines the importance of colormap in creating scalograms to enhance classification accuracy using Continuous Wavelet Transform and selects deep learning networks for electrocardiogram signals representing Arrhythmia, Congestive Heart Failure, and Normal Sinus Rhythm. The simulation results demonstrate that by modifying the colormap can lead to varying optimization, ranging from 59.375% to 96.875%. Additionally, when we create transitioning from a monochromatic white to two-color progression colormap schemes, such as those represented in the RGB color cube diagram, there was a notable increase in accuracy. The costumed colormap, namely myw2m(128) pixels, remarkably boosts the accuracy from 59.375% to a perfect 100%.*
Keywords: Neural network, Classification, AlexNet, RGB color cube, Heartbeat

DOI: 10.24507/icicel.19.04.393

1. **Introduction.** Deep learning has found to be extensive application across various fields for tasks such as classification and prediction. The utilization of deep neural networks, such as in automatic gray image from grayscale to colored images and in the integration of different modalities by merging depth maps with color images, illustrates the innovation of deep neural networks [1,2]. However, more innovative solution is needed for improving image analysis. Automatic color adjustment in landscape images based on color mapping demonstrates the potential for realistic image reproduction. Moreover, the evaluation of pseudo-coloring algorithms in myocardial perfusion imaging reveals superiority of specific color maps in enhancing image quality [3,4]. In medical task, deep learning significantly impacts the precision of classification of images. Utilizing deep learning technique is essential, as in diagnose leukemia in blood cells employs pre-processed images for feature extraction by pre-trained network [5]. This method underscores the importance of pre-trained network in understanding color influences on image analysis. The application of pre-trained AlexNet in ECG signal processing has been a focal point in research efforts. Several studies have investigated the use of AlexNet to enhance the analysis and classification of ECG signals [6,7]. The motivation of this research is to gain a deeper understanding of colormaps and establish a direct connection involving images, their color compositions, and their accuracy by leveraging basic models of pre-trained networks of AlexNet. We have developed seven progression colormaps by ourselves according to RGB color cube to improve accuracy. Considering this, contribution of this study focuses on highlighting how colormaps variations impact the accuracy of ECG signals classification. The rest of this paper is organized as follows. Section 2 presents our method. Section 3 provides result and discussion, and then Section 4 gives conclusion.

2. **Methodology.** This study aims to improve accuracy particularly for ECG signals and to outline the importance of colormap in the scalogram to enhance classification using Continuous Wavelet Transform (CWT) and Convolutional Neural Network (CNN) techniques, utilizing simple pre-trained network models. Certainly, no colormap can perfectly meet all needs. This allows data scientists not only to discover the most suitable option for a specific duty but also to directly apply the same colormap in further visualization tools.

2.1. **Data description.** ECG data was collected from three dissimilar groups: individuals diagnosed with cardiac Arrhythmia (ARR), individuals suffering from Congestive Heart Failure (CHF), and individuals exhibiting Normal Sinus Rhythms (NSR). A total of 162 ECG recordings were obtained from three PhysioNet databases: the MIT-BIH Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database, and The BIDMC Congestive Heart Failure Database. More precisely, the data comprises 96 individuals with Arrhythmia, 30 individuals with Congestive Heart Failure, and 36 individuals with Normal Sinus Rhythms. The ECG data is organized as a structure array containing two components: data and labels. The data field is a matrix of size 162×65536, where each row represents an ECG recording sampled at 128 hertz. The labels consist of a 162×1 cell array containing single diagnostic labels corresponding to each row of data [8-10].

The objective is to train a classifier capable of distinguishing connections to ARR, CHF, and NSR using different MATLAB built-in colormaps, analyze and measure the accuracy.

2.2. **Research design.** The proposed method is designed to systematically vary color maps and their pixel configurations to determine their impact on classification performance, with a focus on distinguishing among three classes: Arrhythmia (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR). The steps are specifically designed to examine how colormap choice influences the classification accuracy using data from PhysioNet databases. The research steps are outlined as follows.

Step 1. Simulate transfer learning.

1) Apply transfer learning using AlexNet where the last three layers of the network are adapted for classifying into three categories: ARR, CHF, and NSR.
2) Record the accuracy.
3) Select other colormap and repeat steps 1) and 2) again.
4) Modify the pixels of colormap, yet again go over as step 3).
5) Run the simulation for 18 colormap with pixels variation of (16), (32), (64), (128), (256) pixel.
6) Sort out the accuracy according to the outcome of the simulation.
7) Look for fluctuations in results and organize them into different categories, and then provide explanations based on these categories.

Step 2. Analyze the ECG signals by examining each signal individually through their corresponding images. Here the novelty of this paper is presented in creating new colormap. We create seven colormap by ourselves in which we modify the type of white colormap and transform it into two color progression scheme based on RGB color cube before running transfer learning simulation again as in Step 1.

Step 3. Conclude based on analysis. Analyzing image involves processing its components and extracting information.

3. Result and Discussion.

3.1. **Step 1.** Figure 1 illustrates the simulation process employing a modified version of AlexNet across 18 predefined colormaps, with 5 varying pixel each, resulting in a total of 90 simulations. The accuracy, as indicated by the simulation outcomes, is depicted in Table 1. The result of accuracy demonstrates fluctuation based on colormap and pixel, exhibiting random variations, which can be categorized into three groups as 1) the lowest, 2) the

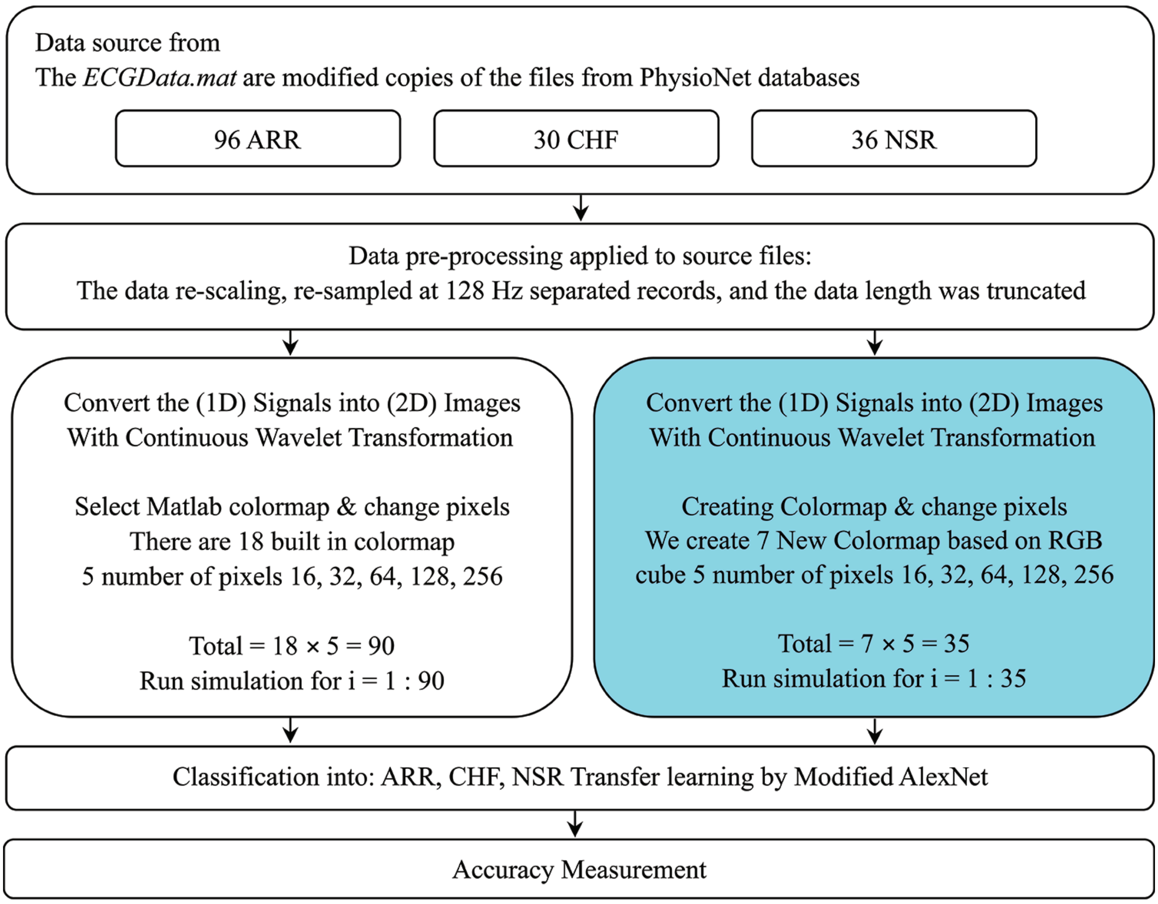


FIGURE 1. Simulation steps of transfer learning

Table 1. Accuracy result of transfer learning by modified AlexNet

No	Name of colormap	Accuracy by various number of pixels				
		Pixels = 16	Pixels = 32	Pixels = 64	Pixels = 128	Pixels = 256
1	white	0.59375	0.59375	0.59375	0.59375	0.59375
2	flag	0.87500	0.90625	0.87500	0.90625	0.84375
3	prism	0.87500	0.84375	0.87500	0.87500	0.87500
4	colorcube	0.90625	0.90625	0.93750	0.90625	0.84375
5	lines	0.90625	0.90625	0.87500	0.87500	0.84375
6	pink	0.78125	0.93750	0.93750	0.96875	0.96875
7	copper	0.81250	0.93750	0.96875	0.93750	0.96875
8	bone	0.81250	0.96875	0.90625	0.96875	0.96875
9	gray	0.81250	0.96875	0.90625	0.96875	0.96875
10	winter	0.87500	0.93750	0.90625	0.93750	0.93750
11	autumn	0.90625	0.96875	0.87500	0.84375	0.93750
12	summer	0.81250	0.90625	0.93750	0.93750	0.96875
13	spring	0.84375	1.00000	0.96875	0.93750	0.93750
14	cool	0.87500	0.90625	0.93750	0.96875	0.90625
15	hot	0.90625	0.96875	0.93750	0.90625	0.90625
16	hsv	0.87500	0.96875	0.93750	0.96875	0.96875
17	jet	0.93750	0.93750	0.96875	0.93750	1.00000
18	parula	0.90625	0.96875	0.93750	0.93750	0.93750

highest, and 3) the fluctuates. The lowest accuracy is colormap named *white*: 0.59375 (59.375%) and it stays the same value for (16), (32), (64), (128) and (256) number of pixels. While the maximum accuracy is given by *spring(32)* and *jet(256)* in which it reaches 1.0 or 100% accuracy. On the other hand, group accuracy is fluctuated from 0.78125 to 0.96875 (78.125%-96.875%) for any other colormap and pixel. Additional details regarding the colormap characteristics of the lowest and highest accuracy groups could be explored using the MATLAB colormap editor. The colormap associated with the lowest accuracy group, represented by the color white adopts the monochromatic scheme with RGB triplets for its 64 pixels, namely *white(64)*. The color corresponding to the highest accuracy group, namely *spring(32)* pixel, comprises two colors: magenta and yellow, represented by RGB triplets. This configuration is then identified as magenta to yellow progression scheme. In the case of the colormap type *jet(256)*, it encompasses six distinct colors ranging from dark blue to cyan, and then transitioning to dark red. This configuration, characterized by RGB triplets across 256 pixels, is referred to as a diverging progression scheme. The lowest accuracy outcome associated with a monochromatic colormap exhibits a single color spanning from the beginning to the end, resulting in the lowest accuracy. Conversely, progression color smoothly transitions from one hue to another. The arrangement of colors is contingent upon the number of RGB triplets, which is typically determined by the default settings in MATLAB for generating such sequences.

3.2. **Step 2.** Analyze the ECG signals. As outlined in the data descriptions, each of the data recordings comprises 65536 samples, making it conducive for thorough signal analysis and study. After converting the 1D signal into 2D using Continuous Wavelet Transform (CWT), the signals initially consisting of 65536 samples, are transformed into images with dimensions of 227×227. These transformed images are referred to as scalograms. In Figure 2 and Figure 3, the ARR image corresponds to the data from the 1st row, the CHF image originates from the 97th row, and the NSR image is derived from the 127th row of the recording [11,12].

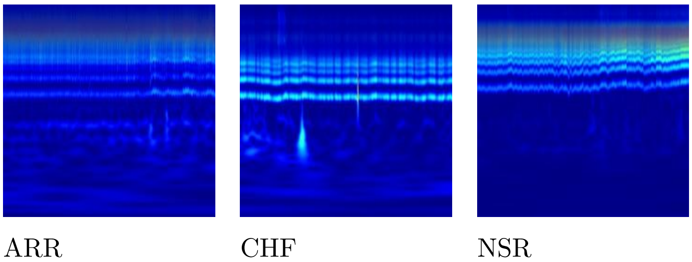


Figure 2. (color online) Scalogram type *jet(256)*

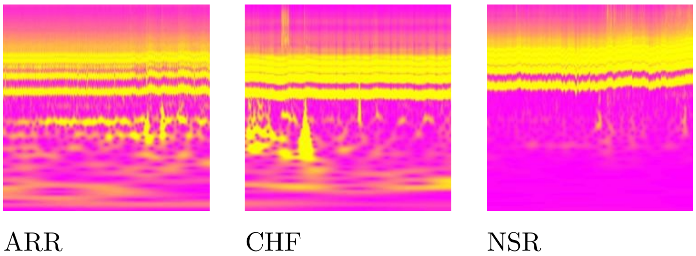


Figure 3. (color online) Scalogram type *spring(32)*

There are a total of 162 images, comprising 96 images representing ARR, 30 images depicting CHF, and 36 images showcasing NSR. The colormap types *jet(256)* and *spring(32)* yield the highest level of accuracy.

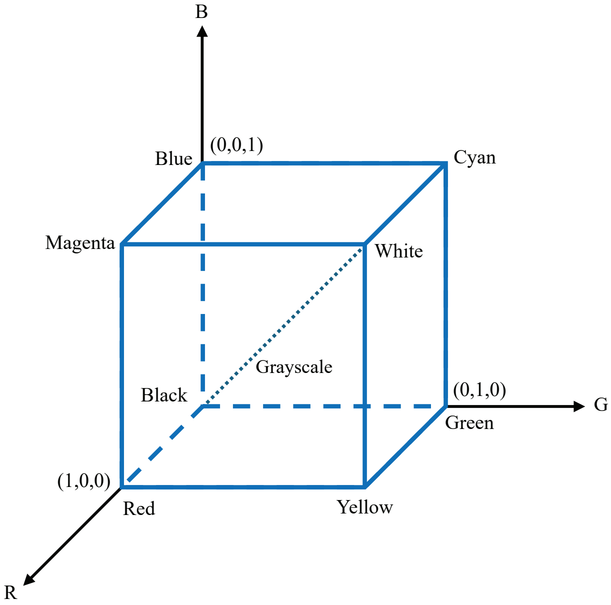
These images are utilized for training and testing in transfer learning to categorize the conditions of ARR, CHF, and NSR. The images are divided, with 80% allocated for training purposes as well as the remaining 20% for testing and validation. Transfer learning offers a quicker with simpler alternative compared to training a Convolutional Neural Network (CNN) from scratch. Training a CNN from the beginning necessitates millions of input images, extensive computational resources, also substantial training time, as well as high-speed and efficient computer hardware [13-15].

The scalogram is generated in the time versus frequency domain, where each element encompasses a large number of pixels. Intensity of the images in scalogram can analyzed by histogram. This visualization displays specific brightness values on the horizontal axis and the corresponding number of pixels in the image on the vertical axis.

The novelty of this paper lies in the creation of colormaps as depicted in Figure 1. Specifically, we have developed seven progression colormaps by ourselves. Given that the colormap type *spring(32)* is characterized by a two-color progression scheme, the lowest group represented by monochromatic white colormap will be modified using linear interpolation method similar to type *spring(32)*. This process will result a new colormap, converting it into a two-color progression scheme following schematic representation of the RGB color cube illustrated in Figure 4.

The initial point of the progression moves from the white corner to any other corner of the RGB color cube, following the steps outlined in Figure 5. The progressions include white to red, white to green, white to blue, white to black, white to yellow, white to cyan, and white to magenta, each represented by 64 pixels as depicted in Figure 6. Each progression scheme is further adjusted using pixels of 16, 32, 64, 128, and 256. Those seven new colormaps with two-color progression schemes are ready for utilization in the transfer learning simulation.

The steps involved in transfer learning remain identical to those depicted in Figure 1, with the only difference being the replacement of the colormap with our new colormap featuring as two-color progression scheme. There are 35 simulations. Before the modification of the monochromatic scheme, the accuracy was approximately 0.59375 (59.375%), but



RGB triplets value for common color

Color	*RGB triplets*
Yellow	[1 1 0]
Magenta	[1 0 1]
Cyan	[0 1 1]
Red	[1 0 0]
Green	[0 1 0]
Blue	[0 0 1]
White	[1 1 1]
Black	[0 0 0]

FIGURE 4. Schematic of RGB color cube

Generate n points (pixels) linearly spaced values in three columns vectors correspond to Red Green Blue (RGB) triplets that will make colormap.
The equal spacing between the points is (x2-x1)/(n-1)

↓

Set the RGB triplets as "**new colormap**" using get current figure (gcf)

↓

Run simulation with "**new colormap**"

FIGURE 5. Procedure of generating new colormap based on RGB cube

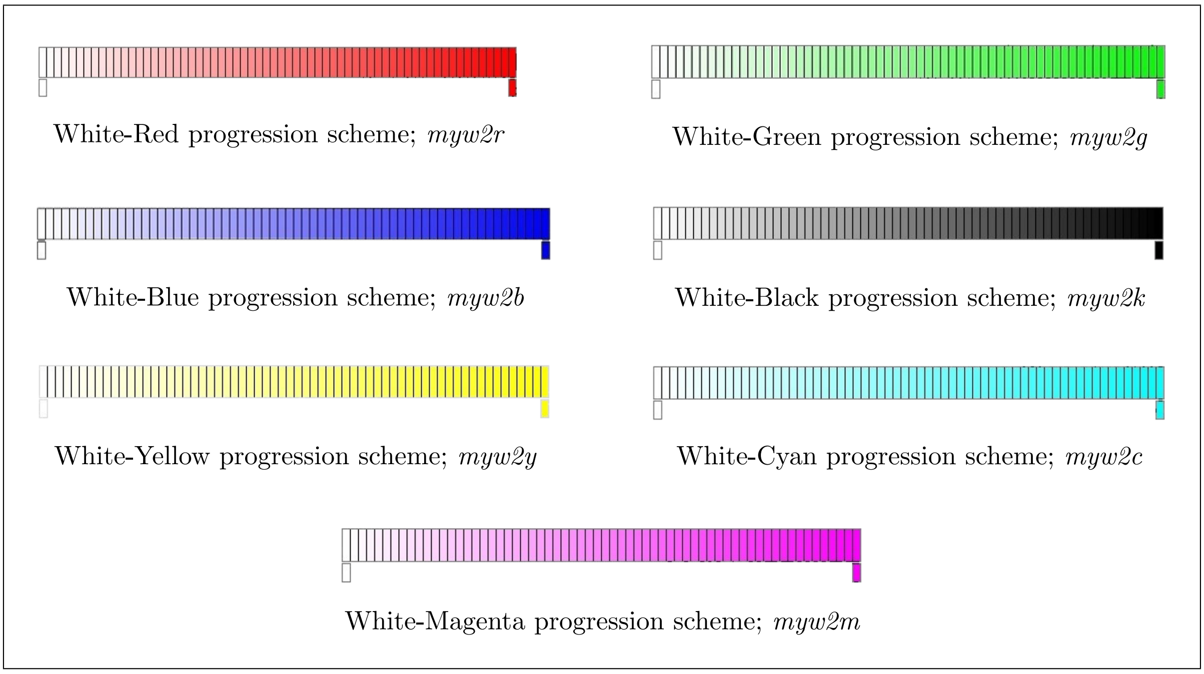
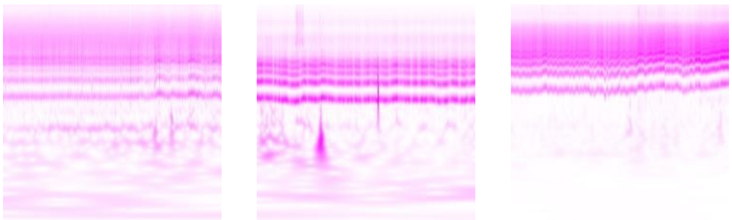


FIGURE 6. (color online) Modified of two color progression scheme

after the modification, it increased, randomly fluctuating to at least 0.84375 (84.375%), as reported in Table 2. This phenomenon is attributed to the intensity of the image and the brightness of the pixels, which are directly linked to the RGB triplet matrix. It is evident that the accuracy has been notably improved. The effectiveness of the modified colormap with a two-color progression scheme is exemplified by the modified colormap type white to magenta, namely *myw2m(128)* pixel, which achieves the highest accuracy in the simulation, reaching a perfect 1.0 or 100%. Indeed, this outcome is directly linked to the intensity of the image and the brightness, as determined by the RGB color cube.

Table 2. Accuracy result of modified two color progression schemes

Modified name	Two color progression	Accuracy by various number of pixels				
		Pixels = 16	Pixels = 32	Pixels = 64	Pixels = 128	Pixels = 256
myw2r	White-Red	0.93750	0.96875	0.96875	0.93750	0.93750
myw2g	White-Green	0.84375	0.93750	0.96875	0.93750	0.90625
myw2b	White-Blue	0.90625	0.93750	0.96875	0.96875	0.90625
myw2k	White-Black	0.90625	0.90625	0.93750	0.96875	0.93750
myw2y	White-Yellow	0.84375	0.84375	0.84375	0.87500	0.84375
myw2c	White-Cyan	0.87500	0.90625	0.93750	0.90625	0.90625
myw2m	White-Magenta	0.87500	0.93750	0.96875	1.00000	0.96875



ARR CHF NSR

Figure 7. (color online) Scalogram of modified colormap *myw2m(128)*

Figure 8. Training progress *white(128)*

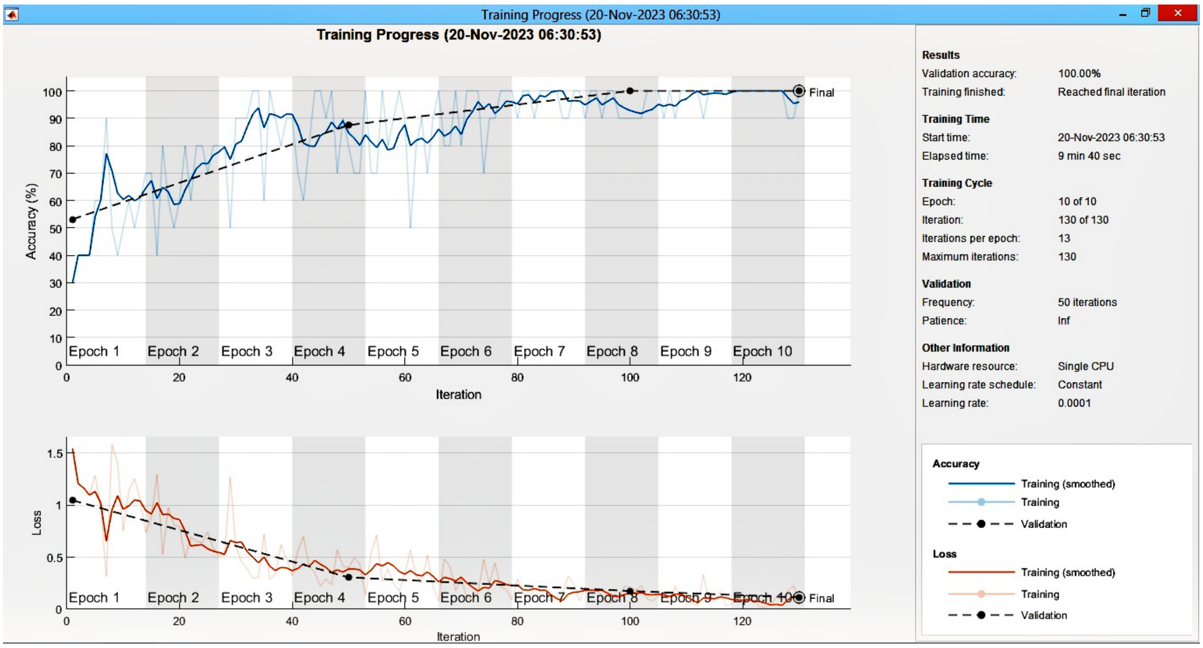


FIGURE 9. Training progress *myw2m(128)*

Type *white(128)* Type *myw2m(128)*

FIGURE 10. Confusion matrix

3.3. **Step 3.** Conclude based on the analysis. The fluctuations in accuracy presented in Table 2 can be classified into two distinct groups, namely 1) the highest, and 2) the fluctuates. The maximum accuracy is attained by the *myw2m(128)* at 1.0 or 100% precisely. The remaining accuracies range from 0.84375 to 0.96875 (84.375%-96.875%), fluctuating within this range. The result clearly demonstrates that the modification of the colormap from monochromatic to two-color progression schemes has optimized the accuracy results. To gain a better understanding of the accuracy improvement resulting from the modification of the colormap, a visual comparison is presented. Figure 7 depicts the scalogram of the modified type *myw2m(128)*, while Figure 8 and Figure 9 offer graphical comparisons between the monochromatic scheme *white(128)* and the modified two-color progression scheme, specifically white to magenta progression of type *myw2m(128)*. These figures depict the training progress results of the deep learning model, with Figure 10 showing the confusion matrix which says that the type *white(128)* classifies the CHF and NSR wrongly while the type *myw2m(128)* could classify correctly, 19 ARR, 6 CHF and 7 NSR, respectively.

4. **Conclusions.** The significance of colormaps in improving accuracy by Continuous Wavelet Transform (CWT) and Convolutional Neural Network (CNN) is highlighted in this paper, particularly utilizing transfer learning of AlexNet. The findings indicate that optimizing classification accuracy can be achieved by modified colormaps and varying pixels. Furthermore, the study reveals that modifying the monochromatic scheme into a two-color progression, can significantly impact the accuracy results, increasing them from 0.59375 (59.375%) to a maximum of 1.0 or 100%. Certainly, this phenomenon is closely linked to the image intensity and brightness of the pixels. We suggest further studies to explore other potential modifications and also mathematical validations to enhance robustness of the findings.

Acknowledgment. This study is a collaborative effort supported by research departments of Universitas Muhammadiyah Makassar, Universitas Atma Jaya Makassar, UIN Alauddin Makassar and Universitas Patompo. Many thanks to people who have directly or indirectly contributed to the completion of this research.

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