Anemic Blood Detection and Color Constancy Algorithm using CNNs

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***Abstract*— Here, we propose an algorithm for Anemic Blood Detection using Hough-Circle Transform and intensity mapping. Convolutional Neural Networks were used classification and also in order to recognise the same color of images, invariant to illumination color (color constancy).**

I. INTRODUCTION

Today bio-imaging provides many state of the art methods in the field of medicine[1].Anemia arises from deficiency of iron intake that affects many people across the world especially in developing countries. Hence the need arises for detection of anemia, which was previously attempted by various sources[2][3][4]. One of the main problems in medical-image processing is processing images taken under varying illuminations. So the aim of a color constancy algorithm is to correct for the effect of illuminant color. Color constancy algorithms can be either Statistical Based Algorithms or Learning Based Algorithms.

- **Statistical based algorithms** which are based on the assumptions about the distribution of colors in the image
- **Learning based algorithms** which estimate illumination using a model that is learned on the training data

Here we use a learning based color constancy algorithm using CNNs which proves to be more reliable in terms of robustness and accuracy.

II. COLOR CONSTANCY RELATED WORK

A camera set up which takes images under uniform illumination was designed, and to over come the challenges it presented we used basic color constancy algorithms initially.

A. Grey World Algorithm

Based on the assumption made by the Grey World Algorithm that the average reflectance in the scene is achromatic,illumination color is estimated as the average color of all pixels in the image. Later, the image is corrected after finding out the intensity of the illuminating color.

B. White Patch Algorithm

White patch algorithm assumes that for each color channel there is at least one pixel in the image with maximal reflection of the illumination source light for that channel and when these maximal reflections are brought together they form the color of the illumination source.

III. PREPROCESSING

Color constancy is one of the prominent pre-processing steps in bio-medical image processing. Before running color constancy algorithm, the series of images used in the process of anemic blood detection are gone through other pre-processing steps which are explained one by one and images are attached after application of each of the pre-processing steps:

A. Gamma Correction

Since all the images used in our data set were non-linear γ != 1 in nature, gamma correction of $\gamma = 1.7$ was applied to linearize the dataset.

$$s = c * r^{\gamma}$$

where c and γ are positive constants with which r and s are mapped as shown in the above equation

B. Image Resizing and Cropping

The background was cropped and only the template for blood detection was made sure to be present for further processing. Final Image size range is around 510x510 pixels.

C. Global Histogram Stretching

An image enhancement technique known as Global Histogram Stretching was used to increase the possible range of image intensities. Using the lower and upper ranges of image intensities of the datasets global histogram stretching is calculated as

$$s = (r - c)(b - a/d - c) + a$$

Here, in the above equation c and d are lower and upper ranges of input images in the dataset. a and b are 0 and 255 which are typical intensity ranges of a pixel.

D. Feature Standardisation

Feature Standradisation is computed as x^1 where

$$x^1 = (x - mean)/\sigma$$

where $mean$ represents the average of all the pixel intensities of the selected input image. (in generic case $mean$ represents the mean of the feature vector. σ represents standard deviation from all the pixels.

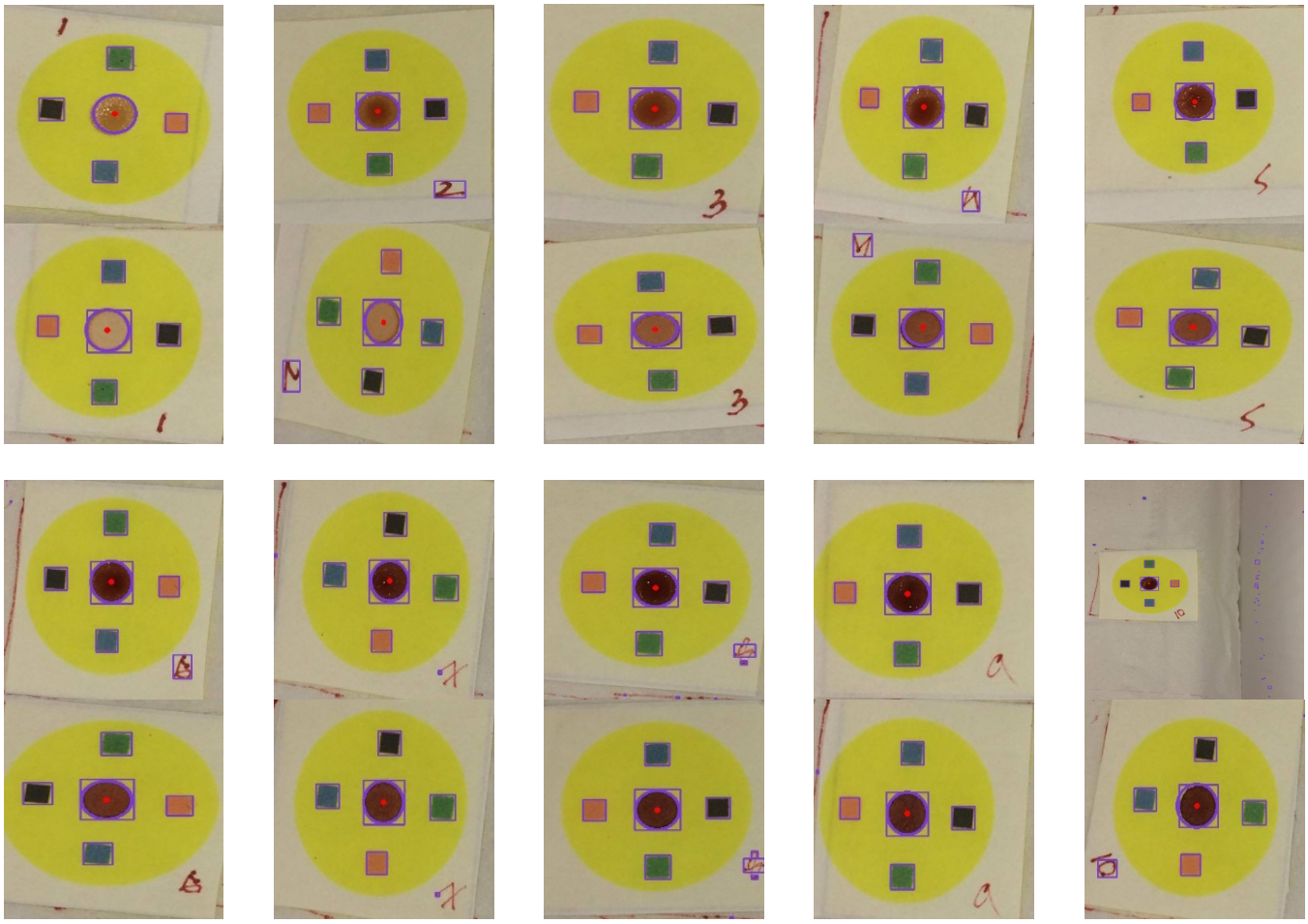

Fig. 1. This image represents the anemic levels from 1-10, taken from the created blood samples; First row represents 1-5 anemic blood levels and third row represents 6-10 levels. Second row represents the same corresponding 1-5 blood levels but after a certain time frame. Second row represents the same corresponding 6-10 blood levels but after a certain time frame.

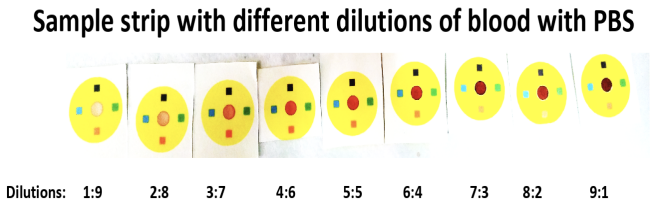

Fig. 2. Sample strip

IV. METHODOLOGY

A. Preparation of Dataset

An exclusive strip was created for the exact purpose of anemic blood detection. It was observed that 5 ul of sample is required to form uniform spreading in the sample loading zone and different quantity of blood is giving different intensity of colour, hence need to fix the amount of blood loaded in the strip.

As shown in the figure 2, 5 ul of sample is loaded in each sample zone. It is observed that gradation of colour is obtained with dilution representing anemic blood levels. Now the primary requirement is a controlled environment for clicking the picture to eliminate differences obtained with lighting and distance. The 3D printed samples were used for further image processing and detection steps.

B. Blood Detection

This is the main part of this process. The 3D printed sample is stained with samples of created blood with various levels of dilution that represents various levels of anemia. Here we use hough circle detection for detecting the circle from the sample. And the boundary squares that are surrounding the circle are detected using active contours and polynomial approximation. The images were taken under different time frames. This can be seen from Figure 1. It was observed that there are slight difference in intensities in between the same samples that are apart in time. The results are summarised for this in table 1. Hence there is requirement of color constancy algorithm for this particular problem setting. Hence we went for basic color constancy algorithms like Grey World and White Patch Algorithm which did not prove to be as effective. Hence we moved to color constancy using CNNs.

Level	B	G	R	B after time t1	G after time t1	R after time t1
1	74.86	101.61	153.18	107.71	124.18	166.65
2	49.92	60.38	115.68	83.49	96.38	146.69
3	49.69	52.86	111.10	72.39	77.47	136.27
4	49.12	48.25	107.80	62.57	61.29	119.01
5	49.15	47.64	105.17	63.37	61.37	119.57
6	42.86	34.61	88.06	53.73	49.45	104.05
7	44.14	33.47	83.70	52.03	45.22	96.82
8	41.01	28.82	73.78	47.46	38.19	83.59
9	42.83	30.46	77.27	50.63	40.30	87.38
10	44.66	33.26	78.36	49.06	39.09	82.77

TABLE I

BGR INTENSITIES BEFORE AND AFTER TIME T1

V. COLOR CONSTANCY ALGORITHM

A. PreProcessing

The pre-processing steps are discussed in the above sections. In fact color constancy is itself the primary pre-processing step involved in this problem of blood detection since active contours and hough circle transform are affected by the illumination under which images are taken.

B. CNN Architecture

CNNs have been very well studied have been known to out perform many other Machine Learning Algorithm in case of object recognition, detection, and various other computer vision applications. CNN utilize the spatial information unlike other algorithms, in order to reduce the overall complexity.Smaller problems can make CNN expensive to train, whereas for larger problems CNNs are more feasible than other algorithms as the complexity of other algorithms grows faster. CNNs learn to extract more high-level features. Each conventional filter scans scans the entire image to produce an output map. CNN learns more meaningful features compared to other methods. If a feature translates, output map will reflect that so CNN will recognise the feature no matter where it is located. Pooling in CNN allows the feature to move around relative to each other. Convolutional neural networks have advantage over neural network in the aspect that, it uses less weights when compared to ordinary neural nets. Since generally in images pixels nearby are more correlated to each other than pixels far away and there is no use of connecting each and every pixel of the image(that is we do not need to connect each and every neuron in one layer to every neuron in the next layer effectively decreasing the number of weights needed to be learnt). These are the exact traits required to solve the problem at hand and hence CNN works effectively better in this situation. Hence we use CNN to estimate the color of light source The network consist of 5 layers

- **Input layer**
- **Convolutional layer** : Its parameters consist of a set of learnable filters. Dot product is computed between the filter and a part of image(a X a X 3) and a 2-D output is obtained for each filter. Stacking many filters results in 3-D output.
- **Max-pooling layer** : It reduces the dimensionality of the feature map. It divides the feature map into non-overlapping rectangles and outputs the mean value from each patch(mean pooling).It reduces the computational complexity, storage-requirement and controls overfitting.
- **Fully connected layer** : It maps every neuron to every neuron in the previous layer.By adding FC layer, high-level featured data can be flattened and connected to the output layer.
- **Output layer**

The way the algorithm is able to adjust its filter values is through a process called back propagation. As an image passes through the different layers, the algorithm tries to learn a set of features in each of these layers, like edges and curves in the CONV layer, high level features in the next layer and so on for facial recognition An image is passed through the network in the forward pass, and when we get the output(not reasonable since all the weights are randomly initialized), we calculate the loss function which is a function of the weights. To get the optimum value of weights, this loss function must be minimised and this is done using gradient descent algorithm. Here we differentiate the function with respect to the weights and obtain the minimum. Now we want to find out which weights contributed most to the loss and adjust them so that the loss decreases. For achieving this after computing the derivative we perform weight update.

C. Training and Testing

Two different datasets were used for the purpose of training. Shi-Gehler dataset which contains 568 images and SFU which contains 11,346 images out of which 500 are selected for training and testing. Equal distribution between datasets is selected inorder not to over fit the model with respect to any particular dataset. The parameters include batch size for cross validation in this case which is 100, epochs is 15, learning rate 0.5 and weight decay parameter 0.0054, momentum of 0.7.

D. Experimental Setup and Results

This CNN architecture consists of one input layer, one CONV layer, one POOL layer, two fullt connected layers and one output layer. After training and testing the datasets, the ground truths are tested form the results obtained from the CNN model. The error measure used here is angular error which is defined as

$$Error = (e^T * e / ||e^T|| * ||e||)$$

The results for selected five of the output images are presented in figure 3, after using color constancy, and the intensity representations.

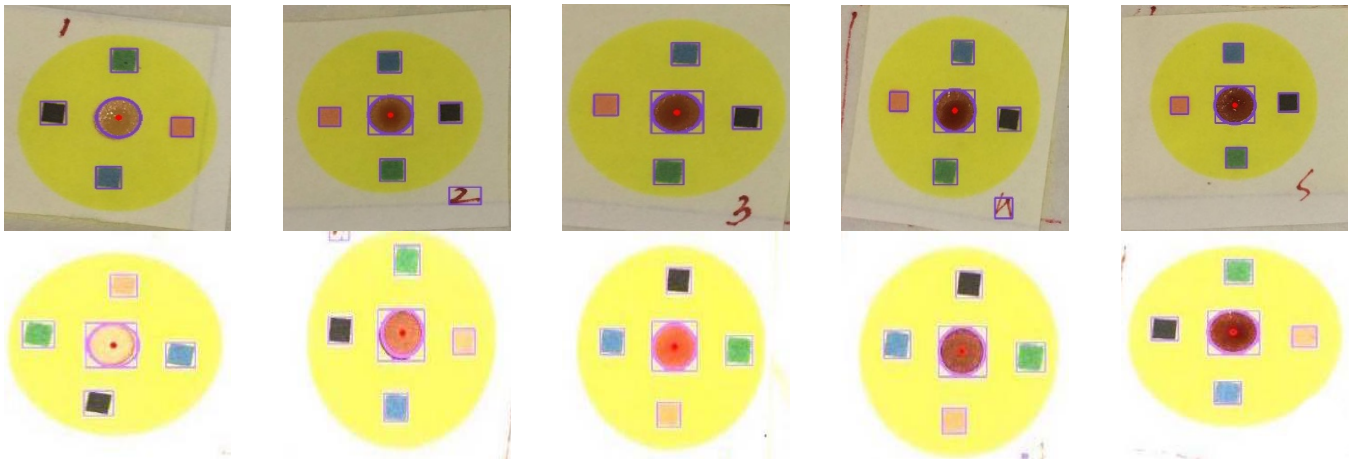

Fig. 3. Color images with anemic levels from 1 - 5 and their color constant images.

VI. CONCLUSIONS

Here the intensities of the blood color images are accurately measured and matched after color constancy algorithm is applied.

REFERENCES

[1] Miller, Jeffery L. Iron deficiency anemia: a common and curable disease. Cold Spring Harbor perspectives in medicine vol. 3,7 a011866. 1 Jul. 2013.

[2] Mohammed Khalaf, Abir Jaafar Hussain, Omar Alafandi, Dhiya Al-Jumeily, Mohamed Alloghani, Mahmood Alsaadi, Omar A. Dawood, Dhafar Hamed Abd, Intelligent Computing Theories and Application, vol. 11644, pp. 580, 2019.

[3] Xu M, Papageorgiou DP, Abidi SZ, Dao M, Zhao H, Karniadakis GE (2017) A deep convolutional neural network for classification of red blood cells in sickle cell anemia. PLoS Comput Biol 13(10): e1005746.

[4] A. Tamir et al., "Detection of anemia from image of the anterior conjunctiva of the eye by image processing and thresholding," 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Dhaka, 2017, pp. 697-701.