Biliary Atresia Detection Using Color Clustering and Nearest Neighbor Classification: A User Interactive Approach

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***Abstract*—Biliary Atresia (BA) refers to a disease that mostly affects newborns by partially obstructing the bile ducts from the liver to the intestines, causing the trapped bile to damage the liver itself and often resulting in the need for a transplant. To detect BA, expert personell (e.g., pediatricians) or non-experts (e.g., the parents) usually analyze the color of the feces with the help of a reference stool color card. To automate this process, some approaches in the literature proposed smartphone apps enabling the parents to capture an image of the feces, select a point of the image to analyze, and compare it with the stool color card. However, such approaches consider only the local pixel chosen for matching and are therefore highly dependent on the position chosen by the user, who may choose a non-significant pixel to perform the analysis. In this work, we propose the first method in the literature for BA detection that considers a color-based segmentation and a nearest neighbor classification. Differently than the approaches in the literature, the color segmentation clusters the image in different areas based on the color and permits to automatically and robustly consider the corresponding cluster, and not only the local pixel, to perform the classification. Results on a database captured in uncontrolled conditions show the validity of the approach.**

***Index Terms*—Biliary Atresia (BA), Image Processing, Nearest Neighbor (NN)**

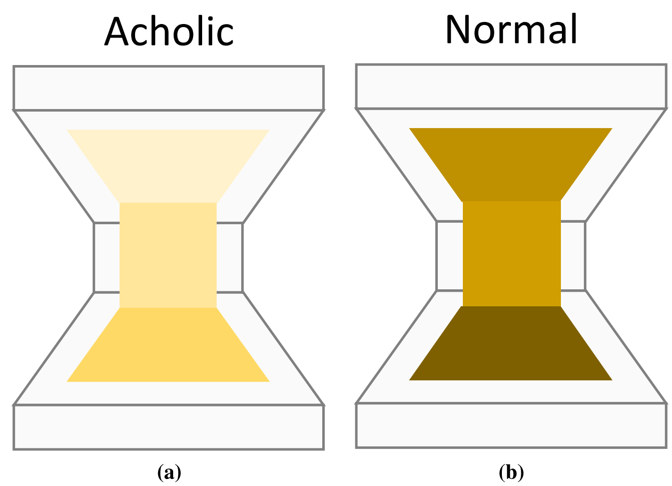

Fig. 1: Biliary Atresia (BA) is usually detected by analyzing the color of the feces in newborns. The Figure shows color examples of diapers with Acholic feces (a) that have a paler color with respect to normal feces (b) and can be associated with the presence of BA*.

I. Introduction

Biliary Atresia (BA) is a disease that affects newborns and consists in a partial obstruction of the bile ducts from the liver into the intestines, resulting in the bile being trapped inside the liver and eventually damaging the liver itself. To cure BA, in many cases it is necessary to perform a liver transplant. However, if BA is not properly detected at an early stage, it may have fatal consequences [1].

The detection of BA is often performed by analyzing the color of the feces in newborn: the occurrence of pale (acholic) feces is correlated with the presence of BA and can be used to detect it in a timely manner (Fig. 1). Such color analysis can be performed by expert personnel (e.g., a pediatrician) or even by non-expert individuals (e.g., the parents of the newborn) by looking up a stool color card that lists several colors for normal feces and several colors for acholic feces. By matching the color of the feces with the closest color present in the stool card, it is possible to perform a preliminary diagnosis of BA [2]. The introduction of stool color cards made possible to perform a diagnosis of BA in a greater number of situations and resulted in less transplants and fatalities [3].

Currently, the detection of BA is in most cases performed manually, either by expert or non-expert personnel, with the help of stool color cards. In some cases, the stool color card

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*We strongly discourage the use of the images in this paper for diagnostic or different activities than the purpose of image processing.

can be accessed by an app on a smartphone, which can perform a color comparison with the feces just by taking a picture using the smartphone itself, therefore further increasing the simplicity in the diagnosis [4]. However, the method described in [1] is currently the only algorithmic approach for BA detection that considers color analysis and image processing. In fact, the use of computer-based methods for such detection is still considered an emerging field [5], despite the field of medical imaging based on image processing and machine learning being increasingly studied [6]–[8]. In particular, the work proposed in [1] describes a local approach for BA detection, in which the method asks the user to select a certain pixel of the image and then matches it against the stool color card to determine whether the feces are normal or acholic. However, such approach uses only local information and is therefore highly dependent on the position chosen by the user, that may not correspond to the most significant area of the image. In fact, reflections and shadows are commonly present in user-captured images: if the user selects one of such areas, the results may be misleading. For example, a shadowed region of the image may resemble the color of normal feces, with the result of a missed detection.

To overcome the disadvantages of current methods in the literature using only local information, in this work we propose the first user-interactive approach for BA detection based on color segmentation and nearest neighbor (1-NN in the following) classification[†]. Differently than [1], our approach performs an automated color-based segmentation of the image in different color clusters, so that when the user selects a region of the image, our method automatically and robustly considers the corresponding cluster, and not only the local pixel, to perform the classification using a 1-NN classifier*. Results on a database of images captured in uncontrolled conditions using a smartphone show promising results.

The paper is structured as follows. Section II introduces the relevant literature review. Section III describes the proposed method. Section IV presents the experimental results. Finally, Section V contains the conclusions and future works.

II. Related Works

The method proposed in [1] describes the only algorithmic (non-medical) approach so far for the detection of BA. The approach realizes a semi-automated way for detecting BA based on the stool color card [2], by introducing a smarthphone app that lets the user take an image of the feces and select a significant part of the image. The app then matches the color of the selected pixel against a library of reference colors. The reference colors corresponding to acholic feces are taken from the stool color card, while the colors corresponding to normal feces are computed by averaging the colors of several images manually labeled by pediatricians.

The work introduced in [4] improves on the concept proposed in [1] by introducing a different way of color comparison. In fact, the work analyzes how the image saturation in the Hue Saturation Value (HSV) color space is more correlated with the presence of BA, with respect to the Red Green Blue (RGB) color space.

To the best of our knowledge, there are no algorithmic approaches in the literature for BA detection that consider a color-based segmentation of the image, with the purpose of selecting the most significant region of the image in a robust way.

III. Methodology

This Section describes the proposed methodology for the detection of BA using images of the feces captured in uncontrolled conditions using smartphones. The method is semi-automated in the sense that it considers a partial user interaction to achieve the best results, and is based on a color-based segmentation, a color-based feature extraction, and a 1-NN classification. The method consists in the following steps: *A)* color segmentation; *B)* user selection; *C)* feature extraction; *D)* classification. Fig. 2 outlines the proposed approach.

A. Color Segmentation

We consider an image I with size $W \times H$, depicting the feces of the newborn. After a min-max normalization of I, we perform a color segmentation using the K-Means clustering algorithm [9], with the clusters initialized with random centers. As a result, we obtain K clusters, with each cluster i represented in a label image L with the same size $W \times H$ as I and with integer values $L(x, y) \in \{i : 1, 2, \ldots, K\}$, describing the cluster in which each pixels (x, y) belongs.

B. User Selection

We observe that the K-Means clustering algorithm is effective at separating the color components of the image and at differentiating the background, the foreground, and the regions of the image with non-ideal illumination (e.g., shadowed regions, reflections). However, it is not trivial to automatically select which of the K color clusters corresponds to the significant part of the image. For example, a shadowed region of an image with acholic feces may appear as feces with normal color, due to the darker tone caused by the shadow.

To compensate for the issue of automatically selecting the correct color cluster, in our methodology we adopt a user-interactive and semi-automated approach, in which the user selects the significant part of the image. Then, we match the user selection –in the form of a pixel location– to the correct color cluster and use the corresponding mask to segment I. It is possible to divide the method for selecting the cluster in four steps:

1) We show I to the user and ask to select a location of the image (x_u, y_u) belonging in the area to analyze. Intuitively, the user is likely to select a point of the foreground without shadows or reflections.
2) We construct a mask M_u centered in (x_u, y_u) and with size $W_{M,u} \times H_{M,u}$.
3) We select the cluster i having the largest overlapping area with M_u (Fig. 3). We consider the mask M_u instead of

[†]The source code is available at: https://iebil.di.unimi.it/avb/index.htm

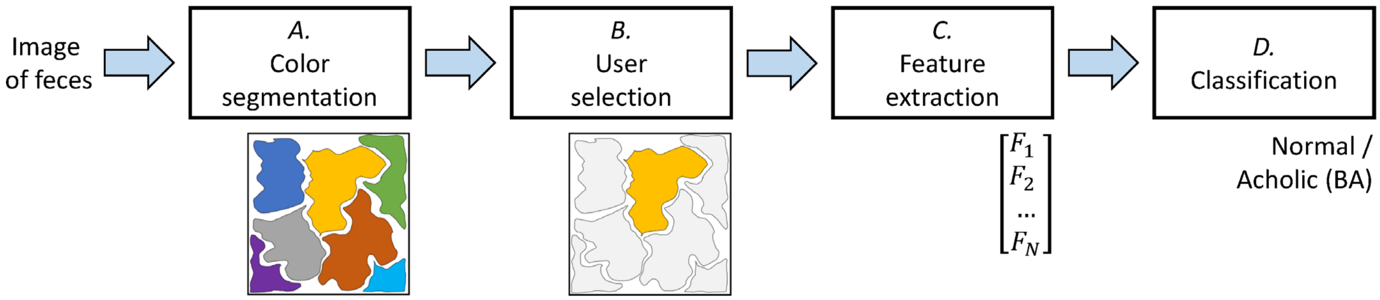
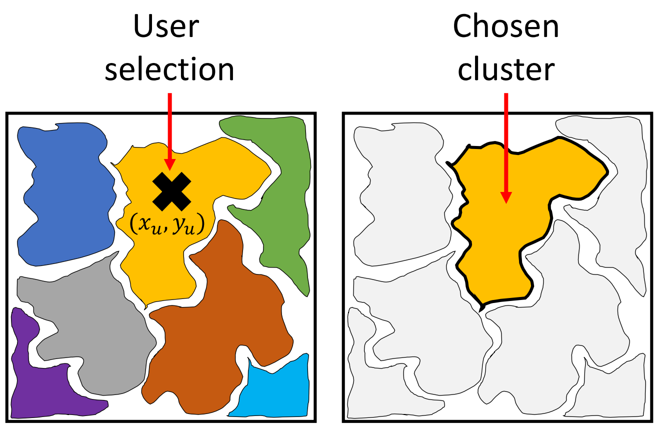


Fig. 2: Outline of the proposed methodology. First, the image of the feces is segmented using color-based approach, then the user is asked to select the most significant color cluster. We extract the features from the corresponding cluster, and lastly we use them to perform the classification of the feces as normal or acholic (possible Biliary Atresia (BA)*.



(a) (b)

Fig. 3: After segmenting the image using the K-Means color clustering algorithm, the user selects the significant part of the image (a). Then, we match the user selection –in the form of the pixel location (x_u, y_u)– to the correct color cluster (b). The corresponding mask M_i describes the region of the image I to analyze*.

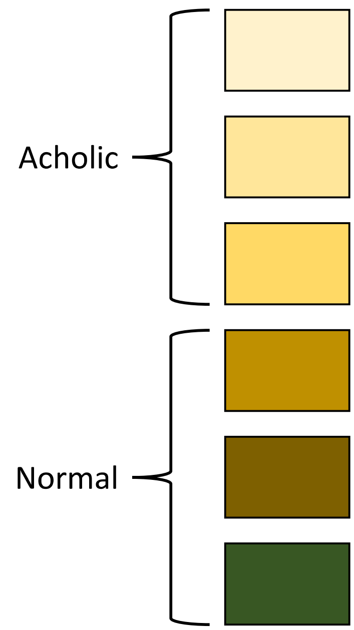


Fig. 4: Example of stool color card. The card lists different possible colors for each case (Acholic or Normal)*.

the single pixel (x_u, y_u) to avoid the user selecting a pixel belonging to a different cluster that he/she intended. For example, it is possible for the user to select a pixel while having a certain area of the image in mind, while failing to see that a particular pixel may describe a small non-ideal area (e.g., a shadow) encircled in the area to analyze and therefore belonging to a different cluster than what the user meant to select.

4) We obtain the segmentation mask M_i by considering the chosen cluster i and we perform a morphological processing by applying a closing operation followed by an opening operation [10]. Then, we select only the largest connected component.

Lastly, we segment I with M_i, obtaining the image I_i describing the region of the image to analyze.

C. Feature Extraction

From I_i, we extract a feature vector $\mathbf{f}$ consisting in the average values along the RGB channels and the average values along the YUV channels. In particular, we consider the following features:

- $\mathbf{f}(1)$: $\mathrm{mean}\,(I_{i,R})$;
- $\mathbf{f}(2)$: $\mathrm{mean}\,(I_{i,G})$;
- $\mathbf{f}(3)$: $\mathrm{mean}\,(I_{i,B})$;
- $\mathbf{f}(4)$: $\mathrm{mean}\,(I_{i,Y})$;
- $\mathbf{f}(5)$: $\mathrm{mean}\,(I_{i,U})$;
- $\mathbf{f}(6)$: $\mathrm{mean}\,(I_{i,V})$,

where $\mathrm{mean}()$ denotes the two-dimensional average operation. We apply the feature extraction step on all the images $\{I\}$, obtaining F_{test}.

We perform a similar feature extraction operation from the different images of the stool color card [2] (Fig. 4). In this case, we apply the feature extraction step directly on the images, as they only contain the foreground. As a result, we obtain F_{train}.

TABLE I: RESULTS OF THE CLASSIFICATION FOR EACH IMAGE WHEN CONSIDERING THE CLASSES "ACHOLIC" OR "NORMAL".

Image N.	**Output**	**Label**
1	Acholic	Acholic
2	Normal	Normal
3	Normal	Normal
4	Acholic	Acholic
5	Normal	Normal
6	Normal	Normal
7	Acholic	Acholic
8	Normal	Normal
Total accuracy: 100%		

TABLE II: RESULTS OF THE CLASSIFICATION FOR EACH IMAGE WHEN CONSIDERING THE SUBCLASSES "ACHOLIC 1", "ACHOLIC 2", "ACHOLIC 3", "NORMAL 4", "NORMAL 5", "NORMAL 6", "NORMAL 7".

Image N.	**Output**	**Label**
1	Acholic 3	Acholic 3
2	Normal 6	Normal 6
3	Normal 7	Normal 7
4	Acholic 3	Acholic 3
5	Normal 7	Normal 7
6	Normal 6	Normal 5
7	Acholic 3	Acholic 2
8	Normal 6	Normal 6
Total accuracy: 75.0%		

TABLE III: AVERAGE TIME REQUIRED IN THE PROPOSED APPROACH, FOR COLOR SEGMENTATION, FEATURE EXTRACTION, AND CLASSIFICATION.

Step	**Average Time [s]**
Color segmentation	2.52
Feature extraction	0.13
Classification	0.11
Total average: 2.76 s	

D. Classification

To perform the classification, we consider a 1-NN classifier that, for each feature vector $\mathbf{f}$ in F_{test}, looks for the closest sample in F_{train}. The output of the classification is then the label corresponding to the closest sample. In this work, we considered as a distance metric the Euclidean distance. The 1-NN has no parameters and does not require a training procedure [11].

IV. EXPERIMENTAL RESULTS

A. Database

We consider a database composed of 8 images, each captured in uncontrolled conditions using a smartphone camera. The images are in RGB color format and have size $W \times H = 1000 \times 1000$. Each image is then labeled by an expert pediatrician as either "Acholic" or "Normal". Moreover, each acholic image is further classified into a subclass: "Acholic 1", "Acholic 2", or "Acholic 3", while each normal image is further classified as "Normal 4", "Normal 5", "Normal 6" or "Normal 7", following the subclasses indicated in the stool color card described in [2].

B. Accuracy

We apply the proposed method on all the images in the database, considering $K = 5$ clusters in the color segmentation phase (Section III-A) and a mask M_u with size $W_{M,u} \times H_{M,u} = 60 \times 60$ in the user selection phase (Section III-B).

Table I shows the results of the classification for each image when considering the labels "Acholic" or "Normal". From the Table, it is possible to observe that the proposed method achieves a 100% classification accuracy. Moreover, Table II shows the results of the classification for each image when considering also the subclasses. In this case, a lower accuracy is obtained, however the limited amount of available images does not permit to consider a more complex feature space or train more complex classification models.

C. Computational Time

Table III reports the average time required for color segmentation, feature extraction, and classification. We did not report the time for user selection since it is highly variable and dependent more on the user than the implementation. From the table, it is possible to observe that the color segmentation is the step with the most computational complexity.

D. Used Parameters and Sensitivity Analysis

We chose the value of the parameter K by varying it in the range $[1, 10]$ and considered the value $K = 5$ that enabled to obtain the greatest classification accuracy. Similarly, we chose $W_{M,u}, H_{M,u}$ by varying them in the range $[20, 100]$ and considered the value $W_{M,u} = H_{M,u} = 60$.

To perform a sensitivity analysis, we varied the values of parameters $K, W_{M,u}, H_{M,u}$ by ± 20 %. When considering the classes "Acholic" or "Normal", we did not observe a significant variation in the accuracy. When considering the subclasses "Acholic 1", "Acholic 2", "Acholic 3", "Normal 4", "Normal 5", "Normal 6", "Normal 7", we observed in the worst case a $\approx 10\%$ decrease in accuracy.

V. Conclusions

In this paper, we proposed the first method for the detection of Biliary Atresia (BA) that uses a color segmentation and nearest neighbor (1-NN) classification, applied on images of feces captured using a smartphone in uncontrolled conditions. Differently than the other methods in the literature, our approach uses a color clustering to robustly separate the foreground regions from the background, shadows, and reflections. Moreover, we consider a cluster selection scheme that robustly incorporates the user input to extract only the significant area of the image. We perform the classification using a nearest neighbor (1-NN) classifier and the images extracted from the reference stool color card in the literature. The results on a database captured in-house show the validity of our approach. Future works will consider databases with a larger number of images and more complex classification models.

References

[1] A. Franciscovich, D. Vaidya, J. Doyle, J. Bolinger, M. Capdevila, M. Rice, L. Hancock, T. Mahr, and D. Mogul, "PoopMD, a mobile health application, accurately identifies infant acholic stools," *PLoS One*, vol. 10, no. 7, 2015.

[2] S.-M. Chen, M.-H. Chang, J.-C. Du, C.-C. Lin, A.-C. Chen, H.-C. Lee, B.-H. Lau, Y.-J. Yang, T.-C. Wu, C.-H. Chu, M.-W. Lai, H.-L. Chen, and the Taiwan Infant Stool Color Card Study Group, "Screening for biliary atresia by infant stool color card in Taiwan," *Pediatrics*, vol. 117, no. 4, pp. 1147–1154, 04 2006.

[3] T.-H. Lien, M.-H. Chang, J.-F. Wu, H.-L. Chen, H.-C. Lee, A.-C. Chen, M.-M. Tiao, T.-C. Wu, Y.-J. Yang, C.-C. Lin, M.-W. Lai, H.-Y. Hsu, Y.-H. Ni, and the Taiwan Infant Stool Color Card Study Group, "Effects of the infant stool color card screening program on 5-year outcome of biliary atresia in Taiwan," *Hepatology*, vol. 53, no. 1, pp. 202–208, 2011.

[4] Z. Shen, S. Zheng, R. Dong, and G. Chen, "Saturation of stool color in HSV color model is a promising objective parameter for screening biliary atresia," *Journal of Pediatric Surgery*, vol. 51, no. 12, pp. 2091–2094, 2016.

[5] U. Lendahl, V. C. Lui, P. H. Chung, and P. K. Tam, "Biliary atresia – emerging diagnostic and therapy opportunities," *eBioMedicine*, vol. 74, p. 103689, 2021.

[6] A. Genovese, M. S. Hosseini, V. Piuri, K. N. Plataniotis, and F. Scotti, "Acute lymphoblastic leukemia detection based on adaptive unsharpening and deep learning," in *Proc. of the 2021 IEEE Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP)*, 2021, pp. 1205–1209.

[7] ——, "Histopathological transfer learning for acute lymphoblastic leukemia detection," in *Proc. of the 2021 IEEE Int. Conf. on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, 2021, pp. 1–6.

[8] F. Rundo, A. Genovese, R. Leotta, F. Scotti, V. Piuri, and S. Battiato, "Advanced 3D deep non-local embedded system for self-augmented X-Ray-based COVID-19 assessment," in *Proc. of the 2021 IEEE/CVF Int. Conf. on Computer Vision Workshops (ICCVW)*, 2021, pp. 423–432.

[9] E. W. Forgy, "Cluster analysis of multivariate data : efficiency versus interpretability of classifications," *Biometrics*, vol. 21, pp. 768–769, 1965.

[10] R. C. Gonzalez and R. E. Woods, *Digital image processing*. Upper Saddle River, N.J.: Prentice Hall, 2008.

[11] A. K. Jain, R. P. W. Duin, and J. Mao, "Statistical pattern recognition: a review," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 1, pp. 4–37, January 2000.