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RESEARCH ARTICLE - ENGINEERING

Computer-Aid System for Automated Jaundice Detection

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Abstract

At the beginning of their lives, newborns may have a widespread condition known as Jaundice or Hyperbilirubinemia. High levels of bilirubin in the blood are the primary cause of jaundice. Severe cases of jaundice may cause acute bilirubin encephalopathy due to the toxicity of bilirubin to the cells of the brain, which may lead to kernicterus. Kernicterus causes several symptoms, including a permanent upward look, loss of hearing, and repetitive and uncontrolled movements. Therefore, diagnosing this condition at the appropriate time helps to prevent chronic effects. In this study, jaundice or hyperbilirubinemia is diagnosed using a computer vision system based on a random forest algorithm. The system comprises a digital HD camera, a computer device with a Matlab application installed to analyze and detect the skin color changes of the infant, and an Arduino Uno microcontroller to control an LED ultraviolet light. A set of neonate images were collected to train the random forest algorithm, including 374 for normal and 137 for jaundiced infants. |The experimental results using the random forest algorithm for classification reached an accuracy of 98.4375%. The results of this study are promising and open doors for new monitoring applications in various medical diseases detection with a high degree of accuracy.

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1. Introduction

The first clinical symptom of infant jaundice is the change of color of the eyes and skin to yellow. It is a prevalent condition, especially for premature newborns and breastfeeding children [1]. The leading cause of neonatal jaundice is the incomplete growth of the neonate's liver, thus, making it unable to rid the body of the excess bilirubin. Furthermore, in some cases, neonatal jaundice can be a resulting symptom due to another existing disease [2]. Studies show that one of the top three reasons for newborn mortality was jaundice. A decade ago, statistics showed that 114000 children died from jaundice, which could have been avoided if proper treatment had been provided. Additionally, 75000 children have brain dysfunction because of complications of jaundice [3]. In some severe cases, hyperbilirubinemia can cause acute bilirubin encephalopathy due to the toxicity of bilirubin to the brain cells, which may lead to brain trauma and then to kernicterus. Kernicterus causes several symptoms, such as permanent upward look, loss of hearing, and repetitive and uncontrolled movements. Therefore, diagnosing and treating this condition at the appropriate time helps to prevent chronic effects. Statistics showed that the highest rates of morbidity and mortality in the world due to neonatal jaundice and its complications occur in developing countries [4]. One way to identify the risk of developing bilirubin encephalopathy in a neonate is by testing the blood of the patient for Total Serum Bilirubin (TSB) [5]. TSB is calculated by using a spectrophotometer to examine the serum and plasma [6]. These tests are considered invasive and hence cause pain and stress for the patient since it includes taking samples of blood from them. Alternatively, a non-invasive technique, such as Transcutaneous Bilirubin (TcB), is preferred for bilirubinemia detection [7]. However, this type of test is not available in all healthcare institutions [8].

The earliest studies regarding the implementation of image-processing techniques to diagnose neonatal jaundice were made by some researchers in 2009 [9]. They tried to calculate the level of bilirubin for sixty-one newborn patients non-invasively. Images for the patients taken by a digital camera were manually analyzed to measure the CMYK components and manually adjusted using Photoshop. The actual value of the bilirubin level is found when subtracting the value of the M component from the value of the Y component. Pearson's product-moment and linear regression methods were used to evaluate the correlation between the total serum bilirubin and the Y-M value. The researchers discovered that there was a considerable correlation between the value of serum bilirubin levels and that obtained from analyzing the images. Regardless of being an approximation method lacking precision, it was considered the birth of a new non-invasive method for diagnosing neonatal jaundice [9]. Another study by Mansour et al. [10] proposed diagnosing infants with hyperbilirubinemia employing a color detection method. Images were picked from a collection library of patients' and nonpatients' images with different lighting conditions, capturing angles and distances using the image acquisition toolbox in Matlab. Due to the advantage of storing Chroma (CrCb) and luminance (Y) in different channels, the YCrCb color space method was preferred due to being appropriate for analyzing images with various lighting conditions. Since its probability of false detection, the researchers neglected the luminance (Y) component. Afterward, certain features were applied, for instance, mean, standard

Nomenclature

TSB	Total Serum Bilirubin	TcB	Transcutaneous Bilirubin
CMYK	Cyan, Magenta, Yellow, and Key (black)	RGB	Red Green Blue
YCrCb	Luminance Chrominance	k-NN	k-Nearest Neighbour
GUI	Graphic User Interface	ROI	Region of interest
LAB	L: Lightness, A: green-red colors, B: blue-yellow colors		

deviation, skewness, kurtosis, energy, and entropy, to complete the process of comparing the skin colors of normal and hyperbilirubinemia infants. These findings concluded that kurtosis gave higher values than other features. In 2013, the same researchers developed their study [11] using the k-NN (k-Nearest Neighbour) algorithm to classify the infant images, whether they were normal or jaundiced. This method was proposed to act as a supporting factor for a better and more effective technique for jaundice detection and treatment. A study by Aydin et al. [12] used 40 images of normal and 40 images of jaundiced babies captured by a smartphone camera; the smartphone was Samsung Galaxy Alpha equipped with a twelve-megapixel camera. The first step of this study was a color balance which was achieved by an image segmentation technique. The researchers used an 8-colored card on the infant's skin for calibration purposes. The main focus was on specific essential regions of interest, while the unnecessary areas were neglected, thus keeping the images unaffected by external lighting conditions. In the second step, the infant's skin color and the calibration card features were extracted in RGB, YCbCr, and Lab color spaces using colormap transformations and feature extraction. The third stage was the regressions of machine learning, which was accomplished by collecting the data from the second stage and applying it to the k-NN (k-Nearest Neighbour) and the SVR (Support Vector Regression) algorithms. The last stage of this study was the evaluation of the bilirubin levels by data from the regression process. The resulting estimations show that this study provides better quality results with a shorter processing time. The increasing need for higher accuracy jaundice detection techniques led to seeking new approaches to get more efficient results. In 2021, Hashim et al. [13] proposed a computer vision system to diagnose neonatal jaundice using Graphic User Interface (GUI). Their proposed system consisted of four main parts, skin color analysis, ROI selection, color range selection, and the practical part that includes a digital camera and a microcontroller. The classifier used in their study is the '*if*' and '*else if*' built-in commands in the Matlab application. The results were accurate at some level; however, the system required specific lighting conditions to function correctly, in addition to the manual ROI selection. Later that year, they took their study further and applied multiple image processing techniques in their proposed system for detecting and diagnosing jaundice in newborn babies using computer vision [14], in which they overcame the ROI selection obstacle. However, the changes in light conditions and skin tone were not considered in their study. Artificial Intelligence has become an essential technique to detect other diseases like breast cancer, skin cancer, cervical cancer, and many more in the medical field. A study by Chaudhary et al. [15] suggested the implementation of artificial intelligence by using random forest algorithm for detecting breast cancer. The main objective was to create a prediction model to evaluate breast cancer, whether malignant or benign. They used 569 breast cancer patients with 31 parameters. Three hundred fifty-seven patients were benign, and the rest 212 were malignant. The results show that random forest algorithm presented experimental results with 98.6% accuracy. For skin cancer, Luu et al. [16] proposed a study to distinguish three types of skin cancer from normal skin tissue using random forest algorithm as a classifier with 16 parameters for 32 skin tissue types. The algorithm achieved 93% accuracy in classifying four types of skin tissue: normal, basal cell carcinoma, squamous cell carcinoma, and melanoma. Therefore, this study aims to design a computer vision system based on an artificial intelligence technique using affordable, cost-effective, durable and ample components, where light conditions and skin tones are the main considerations.

The remainder of this paper will be as follows: Section 2 describes the methods and materials of the proposed system, including data collection, experimental setup and system design. Section 3 demonstrates the experimental results obtained using the random forest algorithm, and finally, section 5 discusses the conclusion and future work directions.

2. Materials and Methods

2.1. Data Collection

The proposed study requires data from confirmed infants of jaundice and normal infants to train the random forest algorithm. The required training data is simply a collection of two groups of images, one group for normal neonates and the other for jaundiced neonates. The more samples collected, the more accurate the result will be. The first set of images, which includes 100 images, was downloaded from the internet; the second set consists of 411 images that was acquired from Al-Elwiya Maternity Teaching Hospital in Baghdad, Al Rusafa. These infants are between 2 to 6 days with different skin tones and birth weights. This study was performed under the Declaration of Helsinki guidelines (Finland 1964) and after having the written parental approvals with full clarification about the study, in addition to acquiring the ethical clearance granted by the research committee in Al Rusafa Directorate of Health, Ministry of Health and Environment, Baghdad, Iraq (Protocol number: 2022019).

2.2. Experimental Setup

The proposed system comprises a smartphone camera (iphone 11 pro max with 12 MP camera was used in this study), a computer device with Matlab application installed to analyze and detect the skin color of the infant under investigation, and an Arduino Uno microcontroller to control an LED ultraviolet light. Matlab is chosen in this study because it is used for teaching the basics of programming languages to engineering and students. It reduces the time for students learning programming by 50 %[17]. It is also considered user-friendly to beginning programers and encourages experimenting with computational concepts [18]. The camera provides a high resolution of 1080 × 1920 pixels and 16 megapixels for stationary images. The Matlab application used to run the code for processing the image feed is version R2021b. The microcontroller used is Arduino Uno to manage and control the desired actions after the image processing completes the diagnosis, as shown in Fig. 1. An image of a neonate under investigation inside the incubator in the NICU is taken by a human using a smartphone camera, then the image is imported to a computer device and processed by Matlab application, if the result was "jaundice", the microcontroller that is connected to the computer device will turn on the UV lamp via a triggering circuit, and if the result was "normal", the lamp remains off.

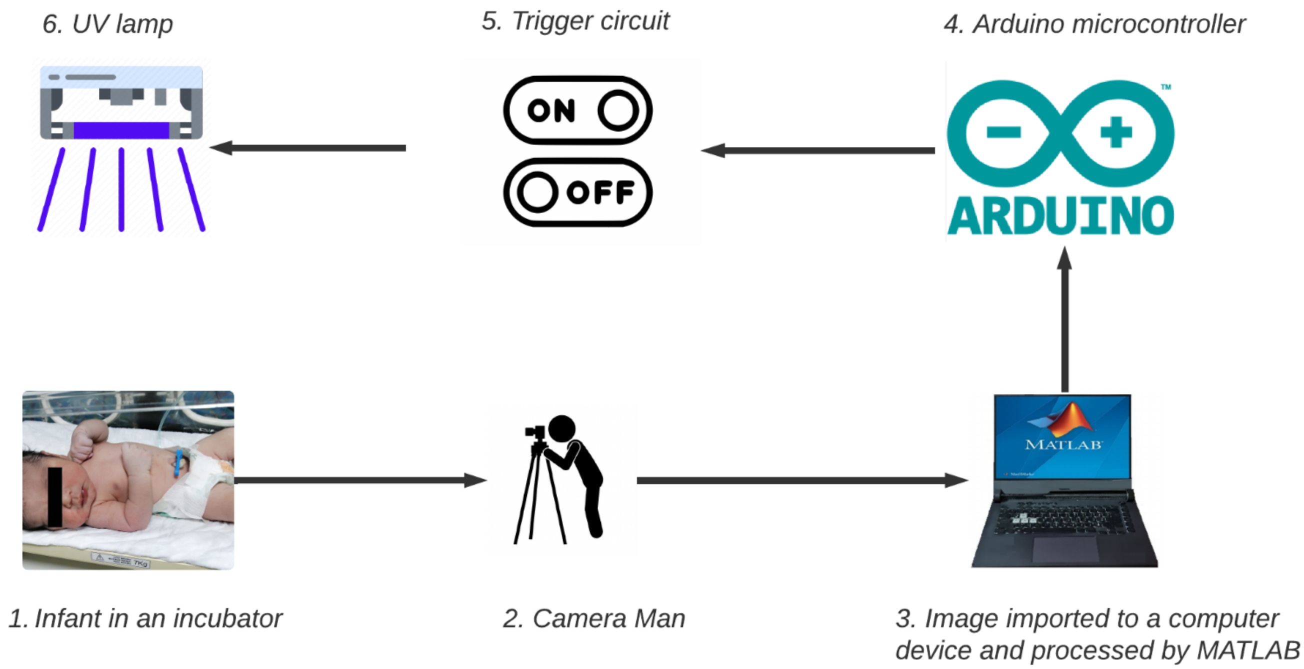

Fig. 1. System design of the proposed study

2.3. System Design

2.3.1. Image Analysis

Several techniques were used in this system to extract and analyze the essential features of the image. These techniques include, skin detection, skin color analysis, image histogram for RGB and YCrCb channels, and Random Forest algorithm as a classifier. Fig. 2 illustrates the general overview of the system.

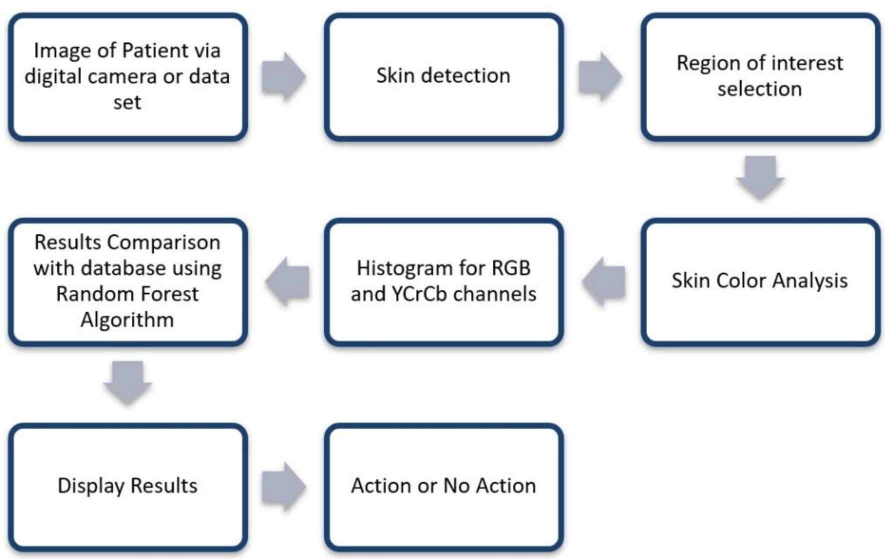

Fig. 2. The general block diagram of the proposed system

The method used for diagnosing jaundice in this study is by analyzing one of its significant symptoms: the patient's skin color. The essential parameter in the process of detecting skin pixels is skin color. But due to the skin tone and lighting variations, it is not the sole factor in determining the final judgment for the patient's status under study. Skin detection is based on RGB, YCbCr color models since the color-based approach is the most optimum method to detect skin pixel due to its short processing time [19].

The proposed system uses Matlab application in skin detection for input images based on three techniques, color space transformation, thresholding, and image processing. The proposed system uses Matlab application in skin detection for input images based on three techniques, color space transformation, thresholding, and image processing. The process starts by converting the acquired image of the infant from the RGB color model to LAB color model where "L" represents the brightness, "A" represents the green-red colors, and "B" represents the blue-yellow colors since LAB color space identifies each color regardless of how it is being displayed. Image conversion to LAB color space is considered the simplest conversion since it does not depend on specific settings, and it does not involve decision making. After the RGB to LAB conversion, a threshold in gray level and binary is applied to each LAB channel based on pixel intensity. Thresholding algorithms compare the threshold values with the grayscale image resulting in a binary image. If the input pixel intensity had a greater value than the threshold, the output is white (foreground); other than that, the output is black (background). This thresholding technique (Otsu's Thresholding) is used due to its ability to categorize each pixel without depending on its neighboring pixel and to get a binary image [20]. Since the output image from the previous processes is binary, meaning all values are set to zeros and ones, all desired pixels are set to one, while the rest will be set to zero and neglected by applying a specific filter of erosion. The outcome of the filter is an image for skin only and smooth around the edges, thus choosing the ROI that contains the skin only. After acquiring the image of the neonate under investigation and imported to the computer device, the skin areas are selected manually. Figs. 3 and 4 illustrate the ROI selection for two different infants.

Fig. 3. ROI selection for infant 1

Fig. 4. ROI selection for infant 2

After acquiring the part of the image containing the skin only, skin color analysis was then applied to deal with pixel analysis based on significant color models: RGB and YCbCr, where RGB is the red, green, and blue, and YCbCr is the luminance chrominance. Based on test results of jaundiced infant images, the blue channel is the most vivid channel for yellow color detection compared to the rest channels [21]. Therefore, this study depends mainly on the B and Cb channels and their comparison with the predefined threshold values to detect jaundice.

2.3.2. Artificial Intelligence based on Random Forest

The Random Forest algorithm is an artificial intelligence technique that provides efficient and optimum performance in recognizing patterns [22]. This proposed system relies on the Bagging method to form 100 decision trees, and from the result obtained from the predictors of each decision tree, it makes voting to reach the final prediction, either "1" for normal or "2" for jaundice for this proposed system. The command "fitensemble" in Matlab is used to achieve this function. Fig. 5 illustrates the process of random forest algorithm.

The acquired B and Cb channel values discussed in the previous section are compared to threshold values using the Random Forest algorithm. If the values of these two channels obtained from the infant under test exceed the threshold values, the patient is considered normal; otherwise, the patient is considered jaundiced. The outcome of this classification will provide the patient's diagnosis, and the microcontroller will turn ON or OFF the UV lamp that is placed above the infant based on this diagnosis.

2.3.3. Evaluation metrics

Since the result of this study is a binary categorization, the samples will be classified into two categories: positive and negative. If the training and testing results are both True, then it is called true positives (TP). If the training and testing results are false, they are called true negatives (TN). If the training was true and the testing was false negatives (FN). Finally, if the training was false and the testing was true, it is called false positive (FP). The following equations give the evaluation metrics:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$sensitivity = \frac{TP}{TP+FN} \tag{2}$$

$$specificity = \frac{TN}{TN+FN} \quad (3)$$

$$percision = \frac{TP}{TP+FP} \quad (4)$$

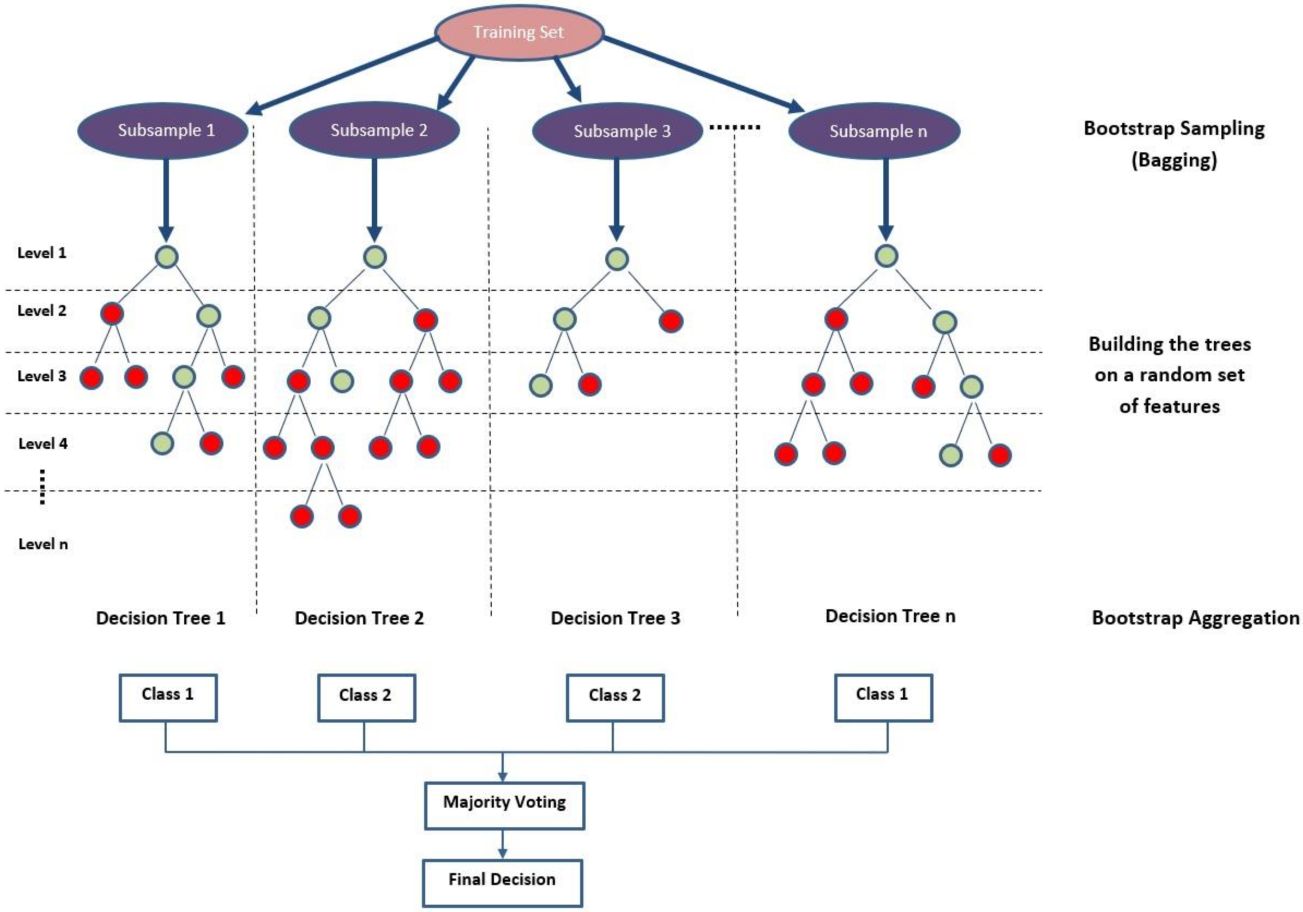

Fig. 5 Random Forest algorithm process

3. Experimental Results and Discussion

The proposed study analyzes images obtained from sources mentioned in section 2.1. The images were analyzed using a Matlab graphic user interface (GUI) with a random forest algorithm. Afterward, the values of the channels and the decision of the random forest algorithm were displayed and collected in an excel sheet. Figs. 6 and 7 show that all RGB and YCrCb channels are listed, the RGB histogram, the infant condition, and the state of the UV lights for each test.

The same procedure was done to all of the collected images, and their channels and infants' status results were collected in an excel sheet saved in CSV format. Table 1 lists a sample of the collected images with RGB and YCbCr channel values for total 511 infant images under different light environment with their classification where class 1 represents normal; class 2 represents jaundice. These values are all stored in an excel sheet in CSV (comma delimited) format.

The total result status for all the collected images is shown as a chart in Fig. 8. The blue bar represents the total number of normal babies, while the orange represents the total number of jaundiced babies.

75% of the collected results were used for training and 25% for testing. The results of the confusion matrix calculations from the random forest algorithm for the 25% testing images can be seen in Fig. 9, where "0" represents class 1, and "1" represents class 2, the obtained accuracy was 98.4375%, and the precision, recall, and f1-score for 89 normal infants' images was 99%, and the precision, recall, and f1-score for 39 jaundice infants' images was 97%.

Although the random forest algorithm provides the highest accuracy among other techniques, it requires more input data to train the algorithm for the highest accuracy possible. This process is achieved by analyzing each input image and collecting the RGB YCrCb channel values individually in an excel sheet. This process takes a fair amount of time and workforce.

Fig. 6. GUI panel for a normal infant 1

Fig. 7. GUI panel for a jaundiced infant

Table 1. A sample of analytical results of the collected infant images

R	G	B	Y	Cb	Cr	class
237.7732	190.7482	175.6426	190.4242	114.4127	149.7785	1
233.5075	198.4393	174.4094	193.1304	112.094	145.4485	1
175.8973	124.1336	88.3874	132.3992	104.4951	153.2263	2
208.6625	171.2744	160.6501	171.6802	117.8507	145.0839	1
206.1056	132.3889	116.6028	147.0972	110.3417	161.4889	1
241.1192	173.8192	110.4	176.3038	89.9038	162.1038	2

198.3578	132.6595	128.6422	146.4009	116.6573	157.2629	1
233.5771	196.2726	178.9398	192.4944	115.1203	145.8139	1
205.6296	136.0095	115.3342	148.6625	108.6082	160.0518	1
252.9928	180.7412	125.635	184.3699	93.0248	163.6874	2
186.4159	156.0291	147.9612	157.0496	119.8804	142.0032	1

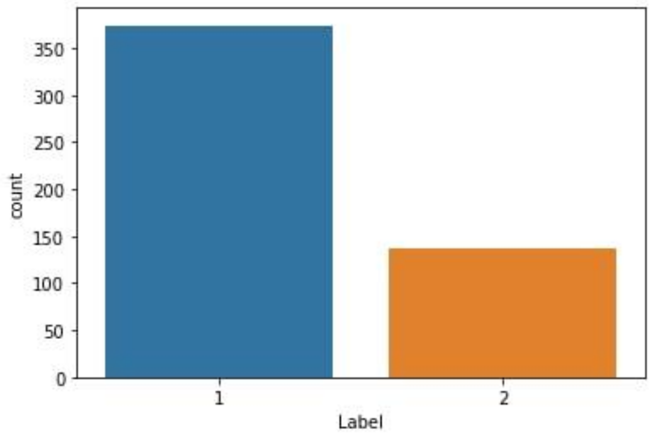

Fig. 8. The total results of the image classification chart

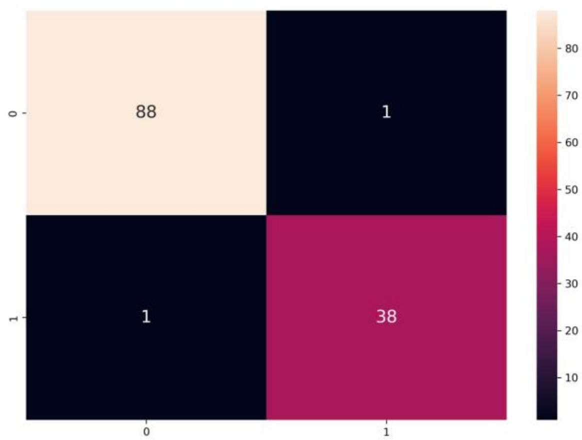

Fig. 9. The confusion matrix of the collected data

4. Conclusion

Since neonatal jaundice is a common disease for newborns, its complications may cause damage to the brain; thus, it is necessary to diagnose and detect this disease as soon as possible. Current methods use invasive approaches to calculate the total serum bilirubin for the infant, which causes pain and discomfort to the baby. However, computer-assistive technologies were used as an alternative way to diagnose jaundice non-invasively. This proposed system used artificial intelligence to make the jaundice detection, hence applying the random forest algorithm as the classifier to detect jaundice under different light conditions and skin tones. This method has proven to give higher accuracy rates than other medical applications with similar approaches using other artificial intelligence techniques and without needing an 8-colored card as calibration in addition to providing control of the operation of a UV lamp used for treating jaundiced infants. Therefore, the more images of normal and jaundiced infants are gathered, the more accurate the diagnosis will be since the algorithm's training will include more RGB and YCbCr channel values and thus makes the prediction more accurate. This study used a total sum of 511 infant images and based on the study results, an accuracy of 98.4375% was obtained. However, this applies to a specific region of the world that is where the images were collected and does not work successfully with all human races and skin colors. And thus, more images with different skin tones from all over the world are required to overcome this issue. The image gathering is ongoing and an approach to collect more from different regions of the world, in addition to an attempt to develop a real-time system for jaundice detection based on this study methods are considered as a future work for this study.

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