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Data Descriptor

NJN: A Dataset for the Normal and Jaundiced Newborns

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Abstract: Jaundice is a common condition for newborns, and its complications can be severe and cause permanent damage to the patient's brain if no action is taken at its early stages. Current methods for jaundice detection are invasive, which include collecting blood samples from the patient, which can be painful and stressful and may cause some complications. Alternatively, a non-invasive approach can be used to diagnose jaundice through image-processing and artificial intelligence (AI) techniques, requiring a database of infant images to achieve a high-accuracy diagnosis. This data article provides a collection of newborn images, called NJN, with various birthweight and skin tones, with ages ranging from 2 to 8 days, and an excel sheet file in CSV format for the values of RGB and YCrCb channels and the status for each raw which is freely accessible at (https://sites.google.com/view/neonataljaundice). It also provides Python code for data testing using different AI techniques. Thus, this article offers a unique resource for all AI researchers to train their AI system and develop algorithms to help neonatal intensive care unit (NICU) healthcare specialists monitor neonates and provide fast, real-time, non-invasive, and accurate jaundice diagnosis.

Keywords: Jaundice; Hyperbilirubinemia; skin color analysis; NICU; artificial intelligence (AI) techniques.

1. Summary

The sclera of the eye and body skin discoloration to yellow are the main apparent symptoms of neonatal jaundice [1]. Jaundice is caused due to high levels of bilirubin in the patient's blood due to premature liver, known as hyperbilirubinemia [2]. The severity of hyperbilirubinemia classifies it as one of the top causes of newborns' mortality and permanent disorders causes. As statistics implied, over a decade ago, hyperbilirubinemia caused 114000 deaths and 75000 brain dysfunction in newborns [3]. Diagnosis of hyperbilirubinemia can be achieved by collecting blood samples from the patient, and this specific test is called Total Serum Bilirubin (TSB) [4]. This type of test causes stress and discomfort to the patient since it is an invasive method; hence, a non-invasive way is preferred. Transcutaneous Bilirubin (TcB) is a non-invasive technique for bilirubin calculation [5]; however, this method is not available in all healthcare institutes [6].

Researchers started implementing image-processing techniques for diagnosing jaundice more than two decades ago. In 2009, a study by Leartveravat [7] attempted to calculate bilirubin levels for 61 neonates with jaundice non-invasively by analyzing their images taken by a digital camera using the CMYK calculation method. The researcher calculated the CMYK components manually using photoshop and estimated the bilirubin levels by subtracting values of M from Y components. After implementing Pearson's product-moment and linear regression methods, they discovered a significant correlation between bilirubin levels measured using TSB and the Y-M value. This method was the start of many attempts to diagnose jaundice using non-invasive techniques despite being an approximation method lacking precision. The researchers Mansour et al. [8] attempted to diagnose hyperbilirubinemia or jaundice using color detection. They used images from a

random database of infant monitoring from the google website. They picked the pictures from the image acquisition toolbox in Matlab of normal and jaundiced infants with different lighting environments and capturing angles. They used the YCrCb color space method to exclude the Y component, which represents the luminance, and the CrCb component, which represents the chrominance due to being stored in different channels. Then, standard deviation, mean, and kurtosis methods were used to compare the skin colors of normal and jaundiced infants. Munkholm et al. [9] proposed TcB measurement from images taken with a dermatoscopy attached to iPhone 6 camera with a Wratten No. 11 filter placed in between. Pearson's correlation coefficient was used to evaluate the relation between intensity and TSB levels. Regardless of their results, they were able to collect a total of 64 infant images only. Another study by Endang et al. [10] proposed a system used in estimating the risk zone for jaundiced neonates based on skin color analysis. They used a digital camera for capturing newborn images. They collected 120 images only and performed multiple techniques to acquire values of RGB, HSV, and YCbCr color spaces and used them as input parameters for modeling and validation of linear regression. They achieved 67% accuracy. On the other hand, Padidar et al. [11] proposed a method for jaundice detection using a mobile application for Android. The results were promising, although they managed to collect only 113 infant images. Ayden et al. [12] used AI as a classifier was made in 2016. They used only 80 images of infants; half were for normal infants, and the other half were for jaundiced ones, all taken by a smartphone camera. They used an image segmentation technique to achieve color balance using an 8-colored card put on a specific area of the baby's skin for calibration. Afterward, they used color map transformation and feature extraction on the baby's skin color and the calibration card in RGB, YCrCb, and LAB color space. Then, kNN (k-Nearest Neighbour) and SVR (Support Vector Regression) algorithms were applied to the acquired data to estimate the bilirubin levels. These results show better quality results with less processing time using AI techniques.Recently, Hashim et al. [13] attempted to use image-processing methods for diagnosing jaundice. They used only two manikins and 20 images of infants due to the unavailability of more neonate images.

All previous works mentioned used infant images of no more than 120 due to the difficulty and scarceness of obtaining such images. This data article provides 670 neonate images, which acts as a valuable source of data for developing studies in jaundice detection and AI techniques to assist medical staff in the NICU in diagnosing jaundice accurately and non-invasively quickly.

2. Data Description

This dataset article provides images of newborns taken in the NICU at Al-Elwiya Maternity Teaching Hospital in Al Rusafa, Baghdad, Iraq. It is a hospital specializing in obstetrics and gynecology; therefore, all infants are considered aseptic. This data comprises normal and jaundiced infant images from different angles and lighting environments. Thus, collecting as many images as possible helps increase the accuracy. The collected data includes 670 infant images (560 normal and 200 jaundiced) with 1000 × 1000 resolution, all in jpg format. The images were taken by an iPhone 11 pro max 12 MP camera. The dataset is composed of three folders: normal neonate images, jaundiced neonate images, and an excel sheet file in CSV (Comma delimited) format that contains the RGB and YCrCb channel values in addition to the status of each row values, either "1" for normal, or "2" for jaundiced. The classification of NJN data and specification table are shown in Figure 1 and Table 1, respectively.

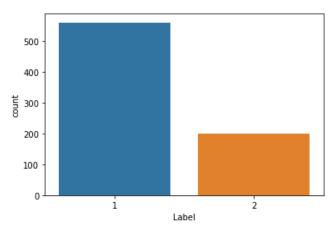


Figure 1. The classification of NJN data where "1" for normal, or "2" for jaundiced newborns.

Table 1. Specification Table.

Task	Description			
Beneficiaries	Biomedical Engineers and Computer Science researchers.			
Specific subject area	AI for neonatal jaundice and skin diseases.			
Type of data	Images and excel sheet in CSV format for RGB and YCrCb channel values			
	and the status of each row.			
How data were acquired	Images were taken with an iPhone 11 pro max camera.			
Data format	Jpg format.			
Parameters for data collection	Images were taken from different angles and lighting conditions.			
Description of data collection	Images were collected from the NICU for 500 aseptic normal and jaun-			
	diced neonates.			
Data source location	NICU ward in Al-Elwiya Maternity Teaching Hospital in Al Rusafa,			
	Baghdad, Iraq.			
Data accessibility	The dataset is freely accessible at (https://sites.google.com/view/neona-			
	<u>taljaundice</u>).			

3. Methods

2.1. Ethics Considerations

The data was collected from about 600 newborns aged between 2 to 6 days with different skin tones and weights. All infant image data were collected from Al-Elwiya Maternity Teaching Hospital in Al Rusafa, Baghdad, Iraq, all according to the Declaration of Helsinki guidelines (Finland 1964) with the clearance ethics granted by the research committee in Al Rusafa Directorate of Health, Iraqi Ministry of Health and Environment, Baghdad, Iraq (Protocol number: 2022019) and written approval of the legal guardian for each infant.

2.2. Data Evaluation

The experimental assessment was carried out using the Python program (version 3.9) in the Spyder integrated development environment (IDE) (version 5.2.2) from the Anaconda3-Navigator. To evaluate the collected data, the color intensity values of RGB and YCbCr obtained from the selected ROI from each infant have been collected and placed on an excel file (train.csv). The evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix, were used for evaluating the data based on three AI techniques, including K-Nearest Neighbors (KNN)[13], Random Forest (RF) [14] and eXtreme Gradient Boosting (XGboost) [15]. All these techniques used 80% of the data for training and 20% for testing and provided the weighted average of the above metrics, as shown in Table 2.

Table 2. Data evaluation based on different AI techniques.

Technique	Accuracy	Precision	Recall	F1-score
KNN	95.4%	96%	95%	96%
RF	97.3%	97%	97%	97%
XGboot	98.6%	99%	99%	99%

From Table 2, we have observed that XGboot has the best accuracy amongst all the techniques used in this work, with an accuracy of 98.6%, and KNN having the least accuracy of 95.4%.

The visualization of the confusion matrix from three AI techniques is shown in Figure 2 having the number of instances of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

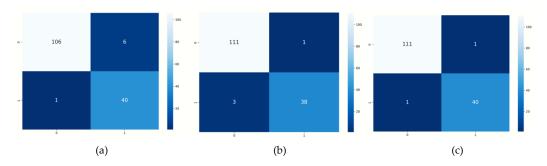


Figure 2. The confusion matrix using (a) KNN, (b) RF, and (c) XGboot technique.

4. User Notes

- Images of normal and jaundiced neonates are scarce online and not easily accessible.
- Healthcare professional developers working in the AI field can benefit from this
 data
- Other researchers in biomedical engineering and computer science can also use the provided images in skin color analysis for neonates to diagnose jaundice or other skin conditions.
- Provided images comprise 560 normal and 200 jaundiced infants.
- The images are in jpg format with 1000×1000 resolution.
- An excel sheet in CSV (comma delimited) format that contains RGB and YCbCr channel values for all the provided images.

Supplementary Materials: The following supporting information can be downloaded at: https://sites.google.com/view/neonataljaundice.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: https://sites.google.com/view/neonataljaundice

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