

Non-Invasive Neonatal Jaundice Detection Using Image Processing and Machine Learning

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ABSTRACT

Neonatal hyperbilirubinemia, marked by elevated bilirubin levels, can lead to jaundice and severe complications if untreated. Conventional diagnosis involves invasive blood sampling, which is time-intensive and stressful for newborns. This study presents a non-invasive bilirubin estimation method using image processing, offering a faster, more accessible alternative. Key steps include skin detection, region of interest (ROI) extraction, and conversion to the YCbCr color space to enhance sensitivity to bilirubin-induced color shifts, especially in the Cb channel. Machine learning algorithms: K-Nearest Neighbors (k-NN), Random Forest (RF), and XGBoost, were evaluated, with XGBoost achieving 98% accuracy and the lowest mean squared error (MSE). This approach enables rapid jaundice detection, reducing reliance on repeated blood tests. Its integration into clinical practices and home-based monitoring systems offers the potential for early diagnosis and timely intervention, significantly improving neonatal healthcare outcomes.

Keywords: Neonatal hyperbilirubinemia, Image Processing, XGBoost

1 INTRODUCTION

Neonatal jaundice is a common condition affecting approximately 60% of term and 80% of preterm infants in their first week of life. It occurs when the liver is not yet fully developed to efficiently process bilirubin, a yellow byproduct of red blood cell breakdown. When bilirubin levels become elevated (a condition called hyperbilirubinemia), it causes a yellow discoloration of the skin and eyes, which can be distressing for both the baby and parents. While mild jaundice in newborns often resolves on its own, elevated bilirubin levels can be harmful and may lead to serious neurological complications like kernicterus if not treated promptly [1][2]. Traditionally, jaundice is managed through frequent blood tests to monitor bilirubin levels—an approach that can be invasive and distressing for infants. Treatment typically involves hospital-based phototherapy, where the baby is placed under blue light to help break down bilirubin in the skin. However, repeated hospital visits and the need for specialized equipment can be difficult for families, especially in low-resource settings or where healthcare access is limited.

To address these challenges, researchers have focused on developing non-invasive methods for both detecting and treating jaundice. One promising technique uses image processing to analyze skin color and estimate bilirubin levels. This method begins with skin detection, where color-based segmentation isolates skin regions in neonatal images. Then, regions of interest (ROIs)—such as the forehead or



chest—are extracted to focus on areas most indicative of bilirubin concentration, reducing background noise. Next, color space transformation enhances sensitivity to jaundice-related color changes by converting images from RGB to YCbCr or LAB formats [3]. This transformation helps separate color channels, making subtle variations more noticeable. Finally, feature extraction calculates quantitative metrics like the mean and standard deviation of pixel values within the ROI. These features are compiled into datasets used to train machine learning models such as Random Forest, k-NN, and XGBoost. Among these, XGBoost has shown superior performance, making it the preferred model for classifying neonatal jaundice. These algorithms analyze patterns in the image data to predict bilirubin levels with high accuracy and determine whether medical intervention is needed.

The core issue this project tackles is the reliance on invasive, hospital-based methods for monitoring and treating neonatal jaundice. Blood sampling, while effective, can be painful for infants and burdensome for parents—especially when frequent testing is required. The proposed solution offers a non-invasive, real-time monitoring system that uses skin color analysis through image processing, reducing the need for blood tests and making the process more comfortable and accessible. Many previous studies have emphasized non-invasive detection methods that eliminate the need for painful sampling. These approaches often rely on cameras or mobile devices to analyze skin color, offering a cost-effective alternative to traditional blood tests. This is particularly useful for frequent monitoring without causing discomfort to newborns. Several studies, including [4], highlight the importance of using widely available tools like smartphones and digital cameras, making the technology more accessible in low-resource settings. These methods have the potential to democratize jaundice screening in remote areas.

However, a common limitation across these studies is the dependence on high-quality images captured under consistent lighting. Variations in lighting, camera resolution, and angle can affect the accuracy of color-based jaundice detection. These external factors may introduce noise and reduce reliability. Another study [5] explores the central role of color detection in estimating bilirubin levels from neonatal skin images. It examines various image processing techniques that analyze color changes associated with jaundice. By using color spaces such as RGB and YCbCr, the study demonstrates how these methods can isolate and quantify skin tone variations linked to elevated bilirubin levels. This marks a shift from traditional diagnostics toward non-invasive and efficient monitoring systems. The use of color space transformation to separate luminance and chrominance components improves detection accuracy and helps mitigate lighting variability issues common in RGB-based analysis. Still, the study faces limitations, including sensitivity to lighting conditions and potential bias in datasets. If the images used do not represent a wide range of skin tones, the algorithm’s effectiveness may be compromised—especially for infants with darker skin. Additionally, reliance on fixed thresholds for color detection may reduce adaptability.

Hashim et al. [4] used skin color analysis as an image-processing tool to diagnose jaundice. Their system overcame location-specific limitations by implementing a robust skin detection mechanism that wasn't confined to areas like the face or sclera. It utilized the Cb channel of the YCbCr color space to assess skin color, minimizing the impact of ambient lighting. The system also featured a configurable threshold for diagnosis, allowing users to set bilirubin levels for phototherapy while maintaining high accuracy at a low cost. However, the study was limited by a small dataset—only two manikins and 20 infant images—and didn't account for lighting conditions. Moreover, it relied on basic MATLAB commands like "if" and "elseif" instead of machine learning models, which restricted performance when input data fell outside predefined ranges.

In early 2023, researchers attempted to diagnose jaundice using a random forest-based machine learning model. They collected 411 images of both healthy and jaundiced infants and developed a MATLAB-based graphical user interface (GUI) to detect jaundice from still images. While the results were promising, the study lacked comparative analysis with other models and required manual image transfer for processing. The researchers later developed three models—k-NN, RF, and XGBoost—and compared their performance. The study used MATLAB GUI, which required the MATLAB application to run, and did not include external hardware or live testing [6]. A subsequent study proposed a jaundice detection application using various machine learning models, including SVM, k-NN, RF, and XGBoost, based on collected data. Among these, XGBoost delivered the highest accuracy [7].

The goal of this study is to develop a non-invasive bilirubin detection system that uses advanced image processing and color analysis. By enabling real-time monitoring and accurate estimation of bilirubin levels, the system aims to support doctors in managing neonatal jaundice more effectively and improve healthcare outcomes for newborns.

2 MATERIALS AND METHODS

The block diagram given in the figure 1 illustrates the pre-processing stages involved in a system designed to detect jaundice and estimate bilirubin levels. The process begins with Image Capture, where an image of the patient's skin or sclera is acquired. ROI extraction then isolates the region of interest (e.g., the sclera) from the captured image. Colour Space Transformation converts the image from the standard RGB color space to a more suitable color space (e.g., YCbCr) for analysis. Feature extraction extracts relevant features from the transformed image, such as color intensity and texture information. These extracted features are then used to train a machine learning algorithm on a training dataset containing images with known jaundice and bilirubin levels. This trained model can then be used to detect jaundice and estimate bilirubin level in new images, potentially aiding in the diagnosis and monitoring of jaundice.

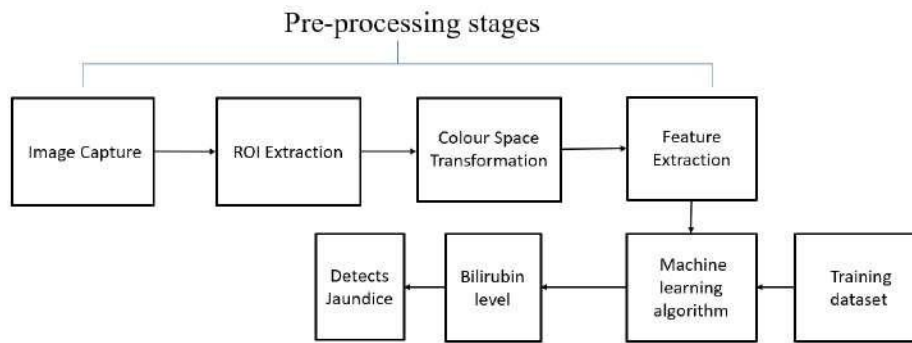


Fig 1: Block diagram for Bilirubin detection from neonate's image.

2.1 IMAGE ACQUISITION

Image acquisition plays a vital role in accurately estimating bilirubin levels through image processing. The quality of the captured image directly influences the reliability of the analysis. Typically, high-resolution digital cameras or smartphones are used to photograph the neonate's skin, with a resolution of 1000×1000 pixels considered ideal. This resolution strikes a balance between image clarity and manageable file size, enabling the detection of subtle skin color changes linked to jaundice. Clear and detailed images are essential for precise bilirubin estimation. To facilitate further analysis, images are usually saved in common formats such as PNG or JPG, which are compatible with most processing tools and allow for easy manipulation during subsequent steps [6]. The fig 2 provides the image acquisition process of an infant



Fig 2: Image acquisition of the infant.

2.2 Skin Detection

Skin detection is a foundational step in the proposed system and serves as the most effective mechanism for identifying jaundice-related features. While skin pixels are the primary focus, the wide range of human skin tones means that detection cannot rely on color alone. Various techniques are employed to ensure accurate identification of skin regions [7]. This stage is carried out using three key processes: region of interest (ROI) extraction, color space transformation, and feature extraction [8][12].

2.3 Region of Interest (ROI) Extraction

ROI extraction helps eliminate irrelevant areas—such as the eyes, nostrils, mouth, clothing, and background—that could interfere with the color analysis essential for jaundice detection. The process unfolds in three main steps:

1. **Face Detection using HOG and SVM** The system uses the Dlib library's Histogram of Oriented Gradients (HOG) combined with a linear Support Vector Machine (SVM) to detect the infant's face. This method is chosen over more complex CNN-based detectors due to its faster processing speed. Since infants are typically positioned close to the camera, their facial features are clearly captured, making the HOG-SVM model an efficient choice.
2. **Facial Landmark Detection** Once the face is detected, the next step involves identifying 68 facial landmarks using a pre-trained model from the Dlib library. These landmarks map out key facial features such as the jawline, eyebrows, eyes, nose, and lips. This geometric structure is essential for isolating specific regions of the face for focused analysis.
3. **Forehead ROI Selection using Landmark-Based Approach** The final step targets the forehead as the region of interest. This area is selected because it offers a consistent and stable surface for detecting subtle skin color changes associated with jaundice. Accurate analysis of this region enhances the reliability of bilirubin estimation.

2.4 Colour Space Transformation

Transforming the image into a different color space is a crucial step in detecting bilirubin levels through skin color analysis. Jaundice presents as a yellowish tint in the skin, and analyzing specific color components helps identify this change. Raw RGB values are often affected by lighting and shadows, which can distort results. To minimize these effects, the image is converted from the RGB color space to YCbCr. This transformation is performed using a linear mapping of RGB values into YCbCr components. The YCbCr color space separates luminance (Y) from chrominance (Cb and Cr), allowing for better isolation of color information relevant to jaundice detection. Specifically, the B and Cb channels from both RGB and YCbCr are used to detect yellow tones in the skin, which are indicative of elevated bilirubin levels [11]. Fig 3 provides the colour transformed image.



Fig 3: Color transformed image[9].

2.5 Feature Extraction

Feature extraction is a key step in analyzing neonatal images for bilirubin detection. Its purpose is to isolate specific characteristics from the skin that correlate with bilirubin levels, enabling accurate assessment of jaundice in newborns. In this process, mean values are calculated for each color channel in both the RGB and YCbCr color spaces. These calculations yield six distinct features—three from each color space—which serve as the foundation for further analysis [8][10].

2.5.1 Application of Machine Learning Algorithm

Machine learning plays a central role in enhancing non-invasive jaundice detection, with XGBoost emerging as the most effective model. The process begins with a labeled dataset of neonatal skin images, categorized as either jaundiced or normal. To ensure robust performance, the dataset is split—70% for training and 30% for testing—allowing the model to learn and generalize effectively. The algorithm focuses on patterns in the Cb channel, which closely correlate with bilirubin levels. A diverse and balanced dataset, captured under controlled lighting conditions, further improves the model's reliability.

XGBoost stands out among other algorithms like Random Forest and k-NN due to its ability to handle complex, non-linear relationships between skin color and bilirubin concentration. This makes it particularly effective in detecting subtle differences in skin tone. In the study, XGBoost achieved a classification accuracy of 98.6% in distinguishing between jaundiced and non-jaundiced infants, highlighting its precision and reliability in neonatal jaundice detection [8][10].

3 RESULTS AND DISCUSSION

The integration of image processing and machine learning offers a non-invasive approach to estimating bilirubin levels in neonates. High-resolution skin images are analyzed in the YCbCr color space, with emphasis on the Cb channel to extract meaningful color features. These features, paired with known bilirubin values, are used to train an XGBoost regression model. The model's performance is evaluated using Mean Squared Error (MSE), and it effectively classifies infants as "Jaundiced" or "Not Jaundiced" based on a set threshold, such as 10 mg/dL.

Implemented in the Spyder environment, this method supports rapid and accessible jaundice screening. Its compatibility with telemedicine and mobile health platforms makes it a practical tool for early diagnosis, especially in settings where traditional blood tests may not be feasible [8][10]. Table 1 provides the estimated bilirubin levels and classification results for infant images.

Table 1: Estimated Bilirubin Levels and Classification Results for Infant Images

INFANT IMAGES	BILIRUBIN LEVEL	CONDITION
1	13.25 mg/dL	Jaundice
2	12.25 mg/dL	Jaundice
3	15.60 mg/dL	Jaundice
4	12.13 mg/dL	Jaundice
5	4.60 mg/dL	Normal
6	6.10 mg/dL	Normal
7	7.10 mg/dL	Normal
8	4.60 mg/dL	Normal
9	12.75 mg/dL	Jaundice
10	10.72 mg/dL	Jaundice

The table summarizes estimated bilirubin levels for a set of infant images, along with their corresponding classification as either "Jaundiced" or "Normal." Jaundice is typically diagnosed when bilirubin levels exceed a threshold of 10 mg/dL, while lower levels are considered within the normal range.



Fig 4: Infant with Jaundice condition

The fig 4 provides an image of an infant with an estimated bilirubin level of 12.75 mg/dL, which places the infant in the "Jaundiced" category. This elevated level indicates a higher concentration of bilirubin—

a yellow pigment produced during the breakdown of red blood cells. When bilirubin accumulates beyond safe limits, as seen in this case, it can signal that the infant's body is struggling to process and eliminate it effectively. Such levels warrant timely medical attention, as untreated jaundice can pose risks of neurological complications.



Fig 5: Infant with normal condition

Fig 5 provides image of a tested infant with an estimated bilirubin level of 6.75 mg/dL, which is below the commonly accepted jaundice threshold of 10 mg/dL. This value indicates that the infant's bilirubin concentration remains within a safe range and does not suggest a need for medical intervention. The image processing and machine learning system accurately classified the condition as "Normal," confirming that the infant is not experiencing elevated bilirubin levels. As a result, no phototherapy or specialized treatment is required, and routine monitoring can continue without concern for immediate action.

3.1 Performance evaluation

XGBoost demonstrates superior performance compared to k-NN and Random Forest, achieving an outstanding accuracy of 98.6% and a near-perfect precision of 99%. This indicates that nearly every jaundice case flagged by XGBoost is a true positive, underscoring its reliability and diagnostic precision in neonatal jaundice detection. Its advanced boosting mechanism effectively reduces both false positives and false negatives—an essential feature in medical diagnostics where accuracy is paramount. Table 2 summarizes the comparative performance of the algorithms.

Table 2: Performance evaluation of Algorithms

Algorithms	Accuracy	Precision
K-NN	95.4%	96%
Random Forest	97.3%	97%
XG Boost	98.6%	99%

4. CONCLUSION

This study underscores the potential of combining image processing and machine learning to develop a reliable, non-invasive method for estimating bilirubin levels in neonates—offering a novel solution for managing neonatal jaundice. By leveraging high-resolution images and applying targeted color space transformations, particularly isolating features in the Cb channel of the YCbCr color space, the system effectively detects subtle skin tone variations associated with bilirubin concentration. The XGBoost regression model, trained on a 70:30 dataset split, exhibited strong predictive accuracy with a low mean squared error (MSE), affirming its clinical applicability. This approach shows promise for early and accessible jaundice screening, especially in resource-constrained environments where smartphone-based imaging could enhance portability and scalability. Future improvements may focus on optimizing performance across varied skin tones and lighting conditions, paving the way for real-time implementation. Overall, the integration of image processing and machine learning presents a transformative step toward efficient and timely neonatal jaundice detection.

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REFERENCES

- [1] S. Mitra and J. Rennie, “Neonatal jaundice: aetiology, diagnosis and treatment,” *Br. J. Hosp. Med.*, vol. 78, no. 12, pp. 699–704, 2017.
- [2] U. Abiha, D. S. Banerjee, and S. Mandal, “Demystifying non-invasive approaches for screening jaundice in low resource settings: a review,” *Front. Pediatr.*, vol. 11, p. 1292678, 2023.
- [3] S. Kolkur, D. Kalbande, P. Shimpi, C. Bapat, and J. Jatakia, “Human skin detection using RGB, HSV and YCbCr color models,” *arXiv preprint arXiv:1708.02694*, 2017.
- [4] A. Hashim, A. Al-Naji, I. A. Al-Rayahi, M. Alkhaled, and J. Chahl, “Neonatal jaundice detection using a computer vision system,” *Designs*, vol. 5, no. 4, p. 63, 2021.
- [5] M. N. Mansor et al., “Jaundice in new-born monitoring using color detection method,” *Procedia Eng.*, vol. 29, pp. 1631–1635, 2012.
- [6] Y. Abdulrazzak, S. L. Mohammed, and A. Al-Naji, “NJN: A dataset for the normal and jaundiced newborns,” *BioMedInformatics*, vol. 3, no. 3, pp. 543–552, 2023.
- [7] Y. Abdulrazzak, S. L. Mohammed, A. Al-Naji, and J. Chahl, “Real-time jaundice detection in neonates based on machine learning models,” *BioMedInformatics*, vol. 4, no. 1, pp. 623–637, 2024.
- [8] F. T.-Z. Khanam, A. Al-Naji, A. G. Perera, D. Wang, and J. Chahl, “Non-invasive and non-contact automatic jaundice detection of infants based on random forest,” *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.*, vol. 11, no. 6, pp. 2516–2529, 2023.
- [9] S. Nihila et al., “Detection of jaundice in neonates using artificial intelligence,” in **Soft Computing: Theories and Applications: Proc. SoCTA 2020*, Vol. 2*, Springer, 2021, pp. 431–443.
- [10] W. Hashim, A. Al-Naji, I. A. Al-Rayahi, and M. Oudah, “Computer vision for jaundice detection in neonates using graphic user interface,” in *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 1105, no. 1, IOP Publishing, 2021, p. 012076.
- [11] A. Y. Abdulrazzak, S. L. Mohammed, A. Al-Naji, and J. Chahl, “Computer-aid system for automated jaundice detection,” *J. Tech.*, vol. 5, no. 1, pp. 8–15, 2023.
- [12] N. Mansor, S. Yaacob, H. Muthusamy, and S. Nisha, “PCA-based feature extraction and k-NN algorithm for early jaundice detection,” *System*, vol. 1, no. 1, pp. 25–29, 2011.