Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 8, S. 204-218, 5, 2024

Araştırma Makalesi

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 8, pp. 204-218, 5, 2024

Research Article

https://as-proceeding.com/index.php/ijanser
ISSN: 2980-0811

Non-invasive Methods for Diagnosing Jaundice in Newborns: A Review

Banan K. Abdulkader*, Mazin H.Aziz [2]

[1]*Computer Engineer, University of Mousl, IRAQ*
[2]*Computer Engineer, University of Mousl, IRAQ*

bananaldabbagh99@gmail.com

(Received: 15 June 2024, Accepted: 27 June 2024)

(3rd International Conference on Frontiers in Academic Research ICFAR 2024, June 15-16, 2024)

ATIF/REFERENCE: Abdulkader, B. K. & Aziz, M. H. (2024). Non-invasive Methods for Diagnosing Jaundice in Newborns: A Review. *International Journal of Advanced Natural Sciences and Engineering Researches*, 8(5), 204-218.

Abstract – Neonatal jaundice, characterized by the manifestation of yellowing in the skin and eyes as a result of augmented levels of bilirubin, presents a substantial peril to the well-being and duration of life in neonates, conceivably influencing their comprehensive health and longevity. Its early onset, typically within the initial days, demands prompt attention, especially when it arises physiologically on the second or third day. Elevated bilirubin, stemming from red blood cell breakdown, presents a challenge for newborns as they struggle to naturally eliminate this pigment. Left untreated, jaundice can lead to severe outcomes like kernicterus, causing irreversible brain damage due to heightened bilirubin levels. This study aims to comprehensively assess various non-invasive frameworks for identifying neonatal jaundice. The review scrutinizes innovative, non-invasive approaches, comparing methods based on clinical data to predict serum bilirubin levels. Challenges in using machine learning for jaundice detection are also highlighted. Non-invasive methods have shown remarkable success across diagnostic, supportive, research, and clinical domains in managing neonatal jaundice. This ongoing exploration sets the stage for improved neonatal care, underscoring the importance of timely diagnosis and intervention to prevent enduring neurological damage resulting from acute bilirubin encephalopathy. The conclusions drawn from this research hold great importance, as they emphasize the possibility of non-invasive methods to revolutionize neonatal healthcare, guaranteeing a safer and more efficient approach to monitoring and treating jaundice in infants.

Keywords – Neonatal jaundice, Machine Learning, bilirubin, Total Serum Bilirubin, Transcutaneous Bilirubin.

I. Introduction

Neonatal jaundice, a widely recognized condition in neonates, has been a focal point of comprehensive investigation and technological research in recent times. Thus, there has been a consistent effort to formulate novel approaches for the timely identification and management of this prevalent ailment. The earliest recorded instance of Neonatal Jaundice can be traced back to the historical literature "Ein Regiment der Kinder," penned by the Metlinger in 1473, as mentioned by A. Chakraborty et al. [1]. Approximately 60% of neonates born at full term and 80% of those born preterm encounter icterus within the initial week of their lives, whereas 10% of neonates who are breastfed experience jaundice within four weeks [2].

Neonatal jaundice, distinguished by a yellow hue, emerges due to elevated concentrations of bilirubin in the circulatory system. Factors like gestational duration, weight, asphyxia [3], urinary tract infection [4], congenital anemia, parental blood group disparities, metabolic imbalances, and breastfeeding transition can also contribute to jaundice [5]. The early identification of jaundice is increasingly facilitated through the utilization of image-processing technology. This advanced engineering approach involves capturing visual data of an infant's skin and/or scleral areas and subjecting it to sophisticated algorithms designed to recognize specific characteristics associated with jaundice. This innovative methodology holds significant potential for rapidly and non-invasively diagnosing this potentially severe condition. By leveraging image processing capabilities, engineers have formulated creative strategies for detecting jaundice in its initial stages. These methods employ cameras to capture digital images of infants' skin, which are then subjected to computational analysis. Through intricate algorithms, precise quantitative features related to jaundice are extracted and evaluated, enabling early intervention and improving the overall well-being of newborns [6].

The preference for non-invasive methods for managing low bilirubin levels is guided by the aim of minimizing risk and discomfort, while the urgency of addressing critical situations justifies the potential exploration of invasive techniques. The choice of approach is dictated by the spectrum of bilirubin levels. Gentle, non-invasive methods provide valuable insights and minimize stress for infants with mild jaundice, whereas in acute cases, the swift and targeted action of invasive procedures may be the sole recourse for safeguarding their health [7]. Understanding the full extent of jaundice involves dealing with different ways to diagnose it, mainly divided into invasive and non-invasive methods. Checking total serum bilirubin (TSB) by taking a blood sample is the most accurate way to confirm high bilirubin levels. However, this method relies on specialized staff and is invasive, which might not be ideal for delicate newborns. That's why it's important to explore less intrusive ways to diagnose jaundice [7]. A promising advancement in neonatal care is the transcutaneous bilirubinometer (TCB). It offers a safe, affordable, and easily accessible alternative to invasive blood tests. TCB uses light passing through the skin to give a precise and convenient estimate of bilirubin levels. This significantly improves monitoring newborns and overcomes the limitations of invasive testing [8].

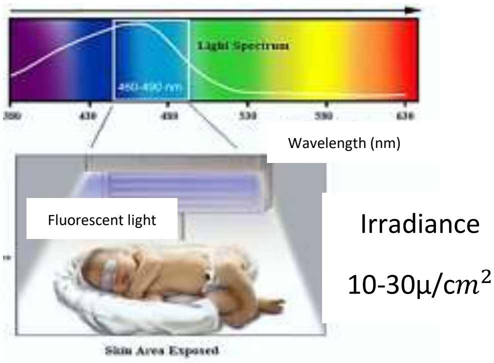

Figure1. Light spectrum and the effective range for phototherapy [18].

The widespread use of TCB devices in wealthier countries highlights their effectiveness in preventing the harmful effects of severe neonatal hyperbilirubinemia [9]. However, it's crucial to consider the accuracy and consistency of TCB measurements, as different devices may show variations in their readings [10]. Despite these advancements, it's widely accepted that all invasive methods are painful for newborns, carry a higher risk of infection at the sampling site, and cause anxiety for parents [11]. In contrast, TCB was specifically designed for non-invasive assessment and indirectly measures the level of bilirubin in the body [12].

To ascertain whether an infant should receive appropriate medical interventions such as phototherapy and exchange transfusions, healthcare professionals utilize specialized graphs, such as the Bhutani nomogram, which takes into account the newborn's age, gestational weeks, and bilirubin level. Hyperbilirubinemia is characterized as aggregate bilirubin (TB) greater than the 95th percentile on the hour-specific Bhutani nomogram [13]. In newborn infants, a bilirubin level exceeding 85 μmol/l (5 mg/dL) indicates the presence of clinical jaundice, whereas, in adults, a level of 34 μmol/l (2 mg/dL) would indicate icteric jaundice in newborn infants. The dermal icterus initially manifests on the face of the newborn and then progresses downward to the trunk and extremities as the bilirubin level rises. [14]. Phototherapy represents itself as a highly efficacious therapeutic modality for neonatal jaundice, acknowledged for its remarkable effectiveness in the management of this clinical entity. The initial investigation into the utilization of phototherapy was published over two decades ago [15]. The primary objective of phototherapy is to mitigate or halt the escalation of circulating bilirubin levels. This can be achieved by utilizing light energy to modify the structure and configuration of bilirubin, thereby allowing it to be converted into molecules that can be excreted even in cases of inadequate regular conjugation [16]. Only those wavelengths that are absorbed by bilirubin and can penetrate through tissue possess a phototherapeutic effect. Consequently, the intensity and wavelengths of the employed light significantly influence the rate of development of bilirubin photoproducts. Taking these considerations into account, utilizing a light source emitting wavelengths within the blue spectrum (460–490 nm) proves to be the most efficient approach to managing hyperbilirubinemia, as shown in Fig. 1 [17]. Nonetheless, jaundiced infants who do not respond to phototherapy or exhibit extreme hyperbilirubinemia upon diagnosis are subjected to more invasive and serious treatment methods, such as exchange transfusion.

II. Machine Learning

Machine learning, a subset of artificial intelligence, involves training machines to learn from data and improve their performance without explicit programming. It functions by utilizing data to detect patterns, make determinations, and acquire knowledge from said determinations. Instead of depending on predetermined equations, machine learning algorithms directly acquire knowledge from the data using computational methods. As the quantity of learning examples increases, the algorithms progressively enhance their abilities [19]. There are various techniques in machine learning, such as supervised, unsupervised, and reinforcement learning [20]. These machine learning techniques find application across diverse fields, including healthcare, offering improved diagnostic accuracy and decision-making capabilities [19], [21]. Machine learning is currently being employed to identify infant jaundice through a range of different methodologies. One of these methodologies includes utilizing the camera of a smartphone to capture images of infants, which are subsequently processed through the utilization of algorithms such as face detection, skin detection, and colour map transformation. Quantitative characteristics are derived from the processed images, subsequently employing machine learning techniques like Support Vector Machine (SVM) and ensemble regression. These models aim to differentiate between infants affected by jaundice and those classified as normal [22]. An alternative methodology encompasses the examination of aggregated information from a diverse array of determinants, including the type of blood possessed by the mother, the age of the mother, the duration of pregnancy until delivery, and the approximate weight of the newborn. By employing models grounded in the principles of machine learning, it becomes possible to evaluate the probability of neonatal jaundice and subsequently classify infants as either low-risk or high-risk [22].

III. Previous Works

R. Karim et al. [23] conducted a study on research that explored the detection and identification of jaundice in infants using machine learning and image processing. The studies mentioned in their research are as follows: concentrating on the skin as a bodily component A. Gupta et al. [22], A. Althnian et al. [24].

In the study [22], they used data on babies with and without jaundice from King Khalid University, applying the MLP, SVM, DT, and RF techniques. Recall, accuracy, and precision were 64.39%, 64.77%, and 67.39%, respectively, according to the data. However, when the linear, lasso, KNN, and SVR methods were used in a study [24], different findings regarding bilirubin levels were found. The actual value was approximately 15, with a predicted value of approximately 15.8.

Alternatively, as noted by S. B. Munkholm et al. [25], Padidar et al. [26] concentrated on the skin of the forehead. In the investigation, a linear regression model was employed [25]. The study employed 64 images from Aalborg University Hospital; the findings indicated that the specificity was 62%, the blue sensitivity was 90%, the green sensitivity was 100%, and the specificity was 60%. By using a regression approach, on the other hand, the study [26] produced better findings than the prior study. Utilizing a wider image collection with sensitivity = 68% and specificity = 92.3%, they collected 113 images from the hospitals in Hafez and Shoushtari.

In the study of S. Ali et al. [27], and A. Kumar et al. [28], the targeted areas were the sternum and forehead skin. The study [27] employed techniques such as KNN, LARS, LARS-Lasso Elastic Net, SVR, and RF. The study utilized 100 images collected from the University of Washington. The results showed a linear correlation of 0.84 with total serum bilirubin (TSB) and a mean error of 2 mg/dl. On the other hand, a study [28] utilized the matching technique and collected a set of serum bilirubin samples. The researchers considered accomplished a relationship result that outperformed the past investigation, with a relationship esteem of 0.93.

In studies [22], [29], [30], [31], [32] the focus on the region of examination was the eye. In the study by F. Outlaw et al. [29], the regression technique was employed, utilizing 86 images from the London UCH Neonatal Unit. T. S. Leung et al. [30] presented in their paper 110 images taken from College London Hospital. Meanwhile, study 48 utilized the Jaundice Eye Color Index, Scleral-Conjunctival Bilirubin, and SCBxy model with 51 images from UCL Hospital using linear regression. Both studies [30], [32] yielded equal results with a correlation of 0.75, surpassing the study [29], which provided a correlation of 0.71. In a study by M. R. Rizvi et al. [31], the diazo method with dichloroaniline (DCA) was utilized for 100 images from King Khalid Hospital, resulting in a sensitivity of 90% and a specificity of 75.6%. Study 25 employed MLP, SVM, DT, and RF techniques for data collected from King Khalid University, including images of healthy and jaundiced newborns. The results showed accuracy of 73.53%, precision of 74.64%, and recall of 73.36%.

In the research by F. Outlaw et al. [33], the focus was on the abdomen and skin, and the methods employed were KNN and SVM. The study utilized a set of images collected from Firat University, yielding a KNN accuracy of 85% and an SVM accuracy of 75%.

Regression analysis was used by J. A. Taylor et al. [35] and S. Swarna et al. [34]. The targeted areas in [34] were the sternum and abdomen skin, with images sourced from India and China (35 images). The results showed a correlation of 0.6 for the sternum. On the other hand, the study [35] concentrated solely on the sternum skin, using a dataset of 350 images from different races in the US. The outcomes indicated a sensitivity of 84.6% and a specificity of 75%.

The skin of the arms, forehead, palms, and soles were the main subjects of the research by J. Castro-Ramoset et al. [36]. After using the SVM technique on twenty Mexican baby images, the results displayed a 71.8% sensitivity and a 78.8% specificity.

For the skin on the face, arms, feet, and central torso, linear regression was used, as reported by W. Y. Hsu and H. C. Cheng [37]. A 92.5% accuracy rate was attained by the study, which used 196 photos from Firat University.

The KNN approach was used for the facial skin in the study by M. N. Mansor et al. [38]. 120 photos were taken and used from Google Infant Monitoring. The outcome of the examination yielded an accuracy rate falling within the spectrum of 90% to 96%.

IV. METHODOLOGIES OF NEONATAL JAUNDICE DETECTION

In 2013, M. N. Mansor et al. [38] developed an independent system for detecting jaundice by targeting the skin area, as shown in Fig. 2. Subsequently, they carried out health validation tests to differentiate the skin color of newborns afflicted with jaundice from those with normal skin tones. This system was based on the KNN classifier, utilizing 120 images specifically targeting the face skin. The results indicated an accuracy of 90%. The paper concentrates on integrating pre-processing and a skin color detection method for jaundice detection. However, it does not furnish numerical data regarding the method's accuracy.

In 2014, L. De Greef et al. [39] introduced the Bilicam application, which was presented at a relatively affordable price with a specific focus on the sternum and forehead regions, as shown in Fig. 3. The images were captured through a smartphone camera, with pictures taken at the University of Washington Medical Center (UWMC) and Roosevelt Pediatric Care Center using the application. A color calibration card was placed on the child's chest, and photos were taken both with and without flash. The primary objectives of this paper were to balance the image's color, extract intensities of various reflected wavelengths, and analyze the chromatic and achromatic properties of the skin. Furthermore, the paper aimed to estimate bilirubin levels using machine learning.

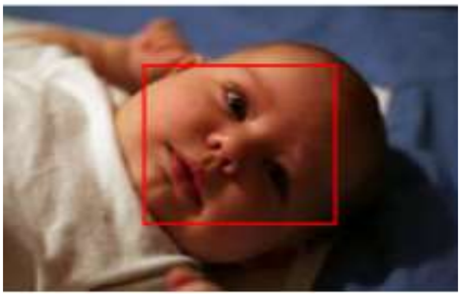

Figure 2. The Face Skin target [38].

Figure 4. Bilcam Application in use targeting sternum and forehead Regions [39].

Figure 3. Padidar et al. android application focusing on forehead skin region [26].

the drawback of this study is that various brands and models of smartphones feature different cameras, lenses, filters, and color corrections, which may impact the collected data. The diversity of the dataset used in BiliCam is limited, as more than half of the participants are of Caucasian descent. Gathering data from a wide array of participants who represent different ethnicities is of utmost importance.

In 2019, P. Padidar et al. [26] developed an Android application for jaundice detection, specifically targeting the infant's forehead region, as shown in Fig. 4. The study included 113 newborns gathered from two healthcare centers in Iran. This paper relied on a smartphone, a color calibration card, and a magnification microscope with a 100x zoom. Images of the infant's forehead were captured within 5 minutes of measuring bilirubin levels by specialists to ensure accuracy. The average RGB values for the forehead images and color calibration card were then calculated and transformed into color parameters, saturation, and intensity (HSI) using machine learning and regression techniques for analysis. The estimated sensitivities are 68% and 82% for TSB values less than 10 mg/dl and 15 mg/dl respectively. The estimated specificity is 92% and 100% for TSB values less than 10mg/dl and 15mg/dl respectively.The research did not consider newborns who underwent phototherapy, potentially restricting the generalizability of the results to this specific group.

In 2020, W. Hashim et al. [18] proposed the use of a digital camera as a color-based screening tool. The system captures images and analyzes them to detect and estimate jaundice, as shown in Fig. 5. The study involved two infants, one diagnosed with jaundice and the other without. The blue component (B) from the RGB color space and the Cb channels from the YCbCr color space were used as the main components for yellowness detection. The region of interest (ROI) was manually selected using MATLAB to provide interesting skin data. The average value of the brightness pixel for each component within the selected ROI was extracted using specific equations. The Arduino Nano microcontroller was used to turn the UV therapy on or off, depending on the detected TCB level. The proposed system has some problems, such as manual selection of ROI, light sensitivity, background color, and a limited number of samples. A. Aune et al. [40] conducted a prospective cross-sectional study in two hospitals in Norway. The study included 302 newborns from St. Olav and Akershus. In St. Olav, images were obtained under uniform lighting conditions with two lamps placed 60 cm apart on each side of the infant, resulting in four images: three using flash from specified distances (20, 30, 40 cm) and one without flash from a distance of 40 cm. In Akershus, six images were captured using a smartphone – three with flash and three without – all at an equal distance of 30 cm. The images were color-calibrated using a color card, and bilirubin estimates were made for each image. The final estimation used in the analysis was the average bilirubin estimate from flash and non-flash images. The study evaluated the relationship between smartphone estimates and total serum bilirubin (TSB) and transcutaneous bilirubin (TcB) using Pearson's correlation. A physics-based simulation model was employed to estimate bilirubin levels from smartphone images. The correlations between bilirubin estimates from images and TSB and TcB results were assessed. The correlation between the smartphone predictions and TSB was assessed using Pearson's r, resulting in a value of 0.84 for the entire sample. The correlation between image predictions and TcB was 0.81. The sensitivity of detecting severe jaundice (over 250 µmol/L) achieved 100%, with a specificity of 69%.

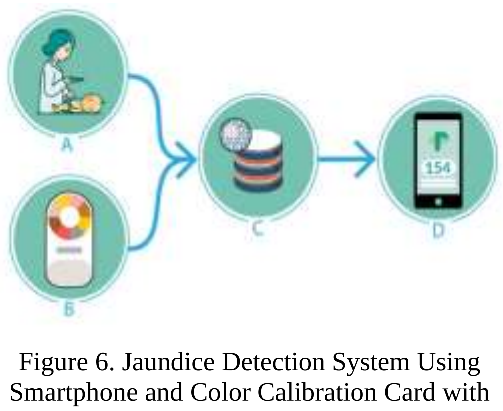

Figure 6. Jaundice Detection System Using Smartphone and Color Calibration Card with Image Processing and Classification [40].

Figure 5. The 30 points on the baby's body were utilized by Hardalaç et al. for jaundice level prediction [42].

In 2021, S. Lingaldinna et al. [41] conducted a study primarily focused on investigating the correlation between blood bilirubin levels and bilirubin measurements obtained using the Biliscan application. They utilized scatter plots and Bland-Altman analysis. The secondary objective was to assess the sensitivity of Biliscan in identifying neonates with high TSB values. They captured images of the infant's skin in the chest area using an iPhone 6 for 143 newborns. The images were collected at a tertiary care center Hyderabad, India. The images were taken with the assistance of a color calibration card specific to the Biliscan application. The color calibration card was employed to balance skin color under varying lighting conditions. The results showed that the mean serum sample was 11.9 g/dl, compared to 13.1 g/dl derived from the smartphone application. The correlation coefficient stood at 0.6, demonstrating a strong sensitivity of 90% for detecting elevated serum bilirubin levels. The research solely involved newborns from a lone tertiary care facility in Hyderabad, India, potentially restricting the applicability of the results.

F. Hardalaç et al. [42] were to develop a mobile support system utilizing non-invasive image processing methods for the classification and early detection of neonatal jaundice. The research focused on devising an algorithm capable of functioning on a mobile device with limited camera and processing capabilities. The proposed method utilized a simple regression curve to estimate bilirubin levels, avoiding the need for complex mathematical operations in morphological image processing methods. A total of 196 images were used, comprising 61 images representing severe jaundice, 95 with mild jaundice, and 40 for testing purposes. Thirty points on the baby's body were identified, as shown in Fig. 6. The regional mean of RGB values (a total of 42 RGB values) was then calculated. The Multiple Linear Regression Line Calculation algorithm, based on 156 baby data points, was employed for classification, followed by MLR.

A prediction test was conducted on 40 data test images, including 20 with bilirubin levels less than 10 mg/dl and 20 with levels greater than 20 mg/dl. The MLR findings showed that 18 out of 20 samples were correctly recognized with levels below 10 mg/dl, whereas 19 out of 20 were accurately categorized with levels exceeding 10 mg/dl. The system attained an accuracy of 92.5% in classification. The dataset utilized in the research comprised a modest number of participants. The investigation concentrated on creating an algorithm suitable for a mobile device equipped with basic camera and processor capabilities, potentially constraining the intricacy and precision of the employed image processing methods.

Figure 7. Sample image of the dataset that was used by Rahayu et al [43].

A. Althnian et al. [22] aimed to create a non-invasive diagnostic tool for neonatal jaundice using a smartphone camera. The researchers adopted a blind transfer learning approach based on eye and skin images, as shown in Fig. 7, comparing the performance of traditional machine learning models with transfer learning. Images were collected using a Samsung Galaxy S7 with the child awake, and a calibration card was placed on the chest. Although initially 100 images were collected, some were excluded, resulting in a final count of 68 images, including 44 males and 24 females. Out of the participants, 44 were identified with jaundice, while 24 were not, ranging in age from birth to five days. The research team employed machine learning models like MLP, SVM, DT, and RF, assessing their effectiveness compared to transfer learning. The classification was based on two groups: those affected and those unaffected. Occurrences, where the general serum bilirubin (TSB) outperformed 11.9 mg/dl, were classified as jaundice, whereas those underneath this edge were categorized as non-jaundiced. The results were derived using measurements such as accuracy, precision, recall, F-score, and area under the curve (AUC). The discoveries have shown that transfer learning gives way better execution with skin pictures, whereas MLP predominantly comes about with eye highlights. The study was conducted on a relatively small sample size of data.

In the study conducted by E. P. Rahayu et al. [43], the primary objective was to introduce a web-based digital image processing method for the early detection of jaundice in infants based on their skin complexion. This observational research was conducted in a high-risk prenatal ward, involving 30 infants. The proposed method encompasses four phases of jaundice detection: initial image collection, as shown in Fig. 8, and complexion detection, followed by RGB digital image processing and Euclidean distance measurement. The third phase includes the application of a web-based information system and the last phase centers on verifying the accuracy of the system. The determination of bilirubin levels is achieved through the Euclidean approximate distance of RGB values obtained from both the infants' complexion and color calibration cards. This method employs Euclidean distance to assess similarities in color between infants' skin and color calibration cards. The research findings reveal a significant correlation (0.93596) between Euclidean distance and the bilirubin level of infants, showcasing a web-based digital image processing accuracy of 90%. Furthermore, the system accuracy validation demonstrates a noteworthy 90% accuracy in diagnosing hyperbilirubin jaundice cases.

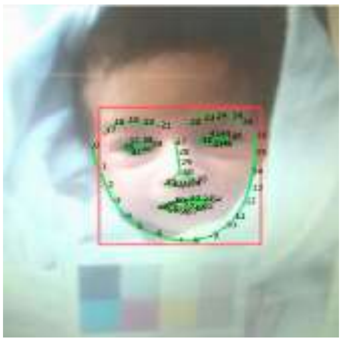

Figure 8.Eye and skin detection using face key points [22].

In 2022, M. S. Jarjees et al. [44] created and deployed a smart system to monitor neonatal jaundice by employing transfer learning from convolutional neural networks (CNN) and Raspberry Pi. The system is designed to estimate bilirubin levels in newborns non-invasively through digital images taken with smartphones and artificial neural networks (ANN) A total of 145 images of newborns were captured from Ibn Al-Atheer Hospital and Al-Khansaa Hospital in Mosul. The classification included three classes: "normal" for healthy infants (50 images), "low" (TSB1)" for infants with bilirubin levels between 3-9mg/dl, and "high" (TSB2) for infants with bilirubin levels between 10-16 mg/dl. The training process involved 70% of the images, while the remaining 30% were reserved for testing. The research involved data capture, preprocessing (which included image resizing and data augmentation), and image classification. Transfer learning was utilized by employing pre-trained Convolutional Neural Network (CNN) models, such as "VGG16," "VGG19," "ResNet50," "EfficientNet B0," and "EfficientNet B7."Among these models, ResNet50 exhibited the highest accuracy, reaching 84.091%, surpassing other algorithms in jaundice classification.

M. Dwi Anggraeni et al. [45] have ingeniously developed an uncomplicated approach for detecting neonatal hyperbilirubinemia through the utilization of chest images captured by a smartphone. A total of 31 newborns were included in the examination, selected randomly. The newborns' birth weights varied between 1526 and 3900 grams, and their gestational age spanned from 31 to 41 weeks. Hospital evaluations indicated blood bilirubin levels ranging from 11 to 25.9 mg/dL, with an average concentration of 16.6 mg/dL. The method involved capturing images of the newborns' chests using a smartphone camera. Subsequently, ImageJ software was utilized to analyze the images by extracting color intensity. The intensity of color in the chest images was subsequently compared to the blood bilirubin levels determined by the standard hospital procedure. The research demonstrated a noteworthy correlation between the derived blue color intensity from the images and the blood bilirubin concentration, underscoring the potential application of smartphone-captured chest images in screening for neonatal hyperbilirubinemia.

S. Dissaneevate et al. [46] created a mobile computer-aided diagnosis (mCADx) tool designed for the detection of neonatal hyperbilirubinemia in newborns through the utilization of digital image processing and data mining methods. The investigators gathered and analyzed image data from 178 infant subjects exhibiting varying levels of jaundice severity. The severity of the condition was evaluated based on blood test results annotated by medical experts. The dataset underwent exploration using digital image processing and data mining techniques, which included decision trees, k k-nearest neighbor, and the Conventional Neural Network. The findings were thoroughly compared and discussed. The classification results revealed that the conventional neural network (CNN) demonstrated the utmost accuracy, as evidenced by the values of 0.8099, 0.9251, and 0.8086. The study delved into the constraints of comparing classification performances with a non-invasive screening device for neonatal hyperbilirubinemia employing special light beam generators, in contrast to their research utilizing only smart devices. The limitations and potential future avenues for research were also addressed, although specific details were not provided.

In 2023, A. A. Al-Naji et al. [47] established a dataset encompassing images of both normal and jaundiced newborns. This dataset functions as a reference for identifying jaundice and implementing artificial intelligence (AI) methods to facilitate the precise and non-invasive diagnosis of jaundice in newborns. Comprising a total of 670 neonatal images, the dataset comprises 560 images of normal infants and 200 images of jaundiced infants. An accompanying Excel sheet in CSV format is included in the dataset, providing RGB and YCrCb channel values along with an indication of the status of each image, specifying whether it is normal or jaundiced. The image acquisition took advantage of the iPhone 11 Pro Max 12 MP camera. Data collection transpired at a hospital in Baghdad, Iraq, with infants aged between 2 to 6 days employed to assess the dataset using three AI techniques: K-Nearest Neighbors (KNN), Random Forest (RF), and Extreme Gradient Boosting (XGboost). Each technique was used for training 80% of the data and testing 20%.XGboost demonstrated the highest accuracy, achieving an accuracy rate of 98.6%, with KNN exhibiting the lowest accuracy at 95.4%.

A. Yaseen Abdulrazzak et al. [2] created a computer-assisted system employing a random forest algorithm to automatically identify jaundice in newborns. The goal of the system is to diagnose neonatal jaundice or hyperbilirubinemia through the analysis and detection of color alterations in the infant's skin. The study involved 374 healthy infants and 137 infants diagnosed with jaundice. Two types of data were utilized: a set of 100 images obtained from the internet and a second set consisting of 400 images from a hospital in Baghdad, Al Rusafa. The infants' ages ranged from two to six days, encompassing diverse skin tones and weights. The researcher initially captured images of the newborns using the iPhone 11 Pro Max camera. Afterward, the system identified the skin area, determined the region of interest (ROI), analyzed skin color, created histograms for RGB and YCbCr channels, compared the outcomes using the Random Forest (RF) algorithm, and presented the final result. These processes were executed through MATLAB. If jaundice was detected, a UV lamp was activated, and if the infant was deemed normal, the lamp remained inactive. The training utilized 75% of the data, leaving the remaining proportion for testing. The random forest algorithm achieved an impressive accuracy of 98.4375%. The study's outcomes are encouraging, presenting opportunities for the implementation of monitoring applications in various medical disease detections with a notably high degree of accuracy.

H. V. S. L. Inamanamelluri et al. [48], the researcher aimed to employ a binary spring search algorithm (BSSA) with machine learning for the classification of jaundice symptoms in newborn infants. The study utilized both real-time and benchmark datasets, employing targeted methods to identify jaundice in infants. The proposed approach involves utilizing BSSA to categorize jaundice cases and employing the XGBoost classifier to automatically grade histopathology images for mitotic activity. The study's findings suggest that early diagnosis facilitated by AI-based applications, like the proposed method, holds promise for identifying jaundice in newborns. The method is characterized by its simplicity in implementation, requiring no specialized skills, and incurring minimal costs. Furthermore, the study underscored the significance of choosing pertinent features in the training of classifiers and accentuated the impact of employing image processing methods in predicting neonatal hyperbilirubinemia The study also utilized standard performance metrics like accuracy, sensitivity, and specificity for evaluating predictions.

F. T. Z. Khanam et al. [49] endeavored to develop a neonatal jaundice detection system that is both non-invasive and contactless. This was achieved by utilizing skin color analysis and machine learning techniques presented through a user-friendly graphical interface (GUI). The primary aim of the study was to facilitate early detection of jaundice in infants without the need for invasive procedures or expensive equipment. The researchers employed a dataset comprising 511 images of infants, which were classified into two categories: normal and jaundiced. These images were employed as the training data for the jaundice detection model. The proposed approach involves the automated selection of a region of interest (ROI) from an infant's image, which has been captured using a digital camera. The skin color within the selected ROI was then analyzed in both RGB and YCbCr color spaces. To determine the necessity of treatment, an integration of the random forest (RF) algorithm, a machine learning algorithm, was used to classify whether the infant had jaundice or was in a normal condition. The research systematically assessed different machine learning algorithms, finding that the random forest algorithm exhibited superior cross-validation performance. It demonstrated significant F1 score, recall, accuracy, and precision. The experimental results strongly support the potential of the suggested jaundice detection system as a non-invasive method for clinical applications. The empirical results yielded substantial evidence regarding the potential of the proposed jaundice detection system as a non-invasive technique for clinical applications.

E. Zarehpour et al. [50] aimed to create a smartphone-based screening tool named BiliBin for the identification of neonatal hyperbilirubinemia resulting from elevated bilirubin levels in newborns. The dataset utilized in this investigation comprised 446 samples extracted from the sternum skin of newborns across four medical centers in Iran. The outlined approach encompasses four key phases: data collection, data preprocessing, feature extraction, and jaundice estimation through machine learning regression. A regression model based on machine learning is trained on the image dataset to predict the bilirubin levels. The findings indicate that, when contrasted with total serum bilirubin (TSB) values established as the reference standard, this approach generates bilirubin forecasts characterized by an average absolute error of 1.807 and a correlation coefficient of 0.701.

Table 1 presents a comparative analysis of different studies on non-invasive bilirubin detection for neonatal jaundice utilizing a color calibration card, while Table 2 focuses on similar studies that do not incorporate the use of a color calibration card.

V. Machine Learning Challenges in Jaundice Detection

Machine learning has the potential to identify infant jaundice, but challenges include affordability, availability, and precise models. Transcutaneous bilirubinometers are financially restrictive and geographically scarce, and further optimization and refinement are needed [51], [52]. Machine learning algorithms must consider various factors like bilirubin levels, weight, gestational age, and hours since birth to accurately forecast jaundice severity [53]. Despite these obstacles, overcoming these challenges is crucial for effectively utilizing machine learning in diagnosing jaundice.

VI. CONCLUSION

The identification of neonatal jaundice, a commonly observed problem in premature infants and breastfed newborns, is presently being investigated through the utilization of non-intrusive techniques that encompass image analysis and the application of artificial intelligence (AI). This advancement is a transformative shift in the healthcare sector, offering cost-effective, objective, and less intrusive methods. However, challenges such as technology accessibility, accuracy, and considering multiple variables influencing jaundice severity persist. Machine learning has the potential to predict jaundice severity, but affordable and accessible detection technologies and robust models are essential. Successful integration and widespread adoption of AI-driven non-invasive techniques in neonatal healthcare will depend on surmounting technology availability challenges and enhancing machine learning models to accommodate various variables. Continued research and innovation in AI-driven approaches hold the potential to revolutionize neonatal healthcare, ensuring better outcomes and care for newborns worldwide.

Table 1. Comparison of non-invasive bilirubin assessment methods for detecting and classifying jaundice in newborns with a color calibration card.

Ref	Data sets	Body Part	Sensor and hardware	Age	Technique	Results	Class
[26]	113	Forehead skin	Smartphone with 100X zoom microscope clip	2 to 9 days	ML and regression techniques	- A 68% sensitivity and 92.3% specificity (TCB <10 mg/dL). - A 82% sensitivity and 100% specificity (TCB <15 mg/dL).	2
[22]	68	Eyes' sclera and forehead skin	Smartphone camera	0 to 5 days	-DTL VGG-16 -MLP, SVM, DT, RF	TL model performed the best with skin images, while traditional models achieved the best performance with eyes and fused features.	2
[42]	196	Head, arms, middle body, and feet	Smartphone camera	N/A	MISO regression model	Accuracy 92.5%	3
[43]	30	Full body	Smartphone camera	3 to 14 days	KNN	Accuracy 90%	3
[46]	178	Abdomen skin	Smartphone camera And mCADx	4.15-1.93 days.	DT, KNN, and CNN	Accuracy 96.88% and 98.44% where CNN has the best	3
[40]	302	Sternum skin	Smartphone camera	up to 15 days	Simulation model	Sensitivity of 100% and Specificity of 69% for (TSB > 250 µmol/L).	EBL
[41]	143	Chest skin	Smartphone camera	2 to 4 days	Different algorithms	Sensitivity =90% & Negative predictive value =95%	EBL
[54]	31	Forehead skin	Smartphone camera	31 to 41 weeks	Simple regression analysis	High level of correlation in the intensity of the blue color	EBL
[50]	446	Sternum skin	Smartphone camera	2 to 4 weeks	ML regression model	MAE= 1.807	EBL

ML: Machine Learning.

DTL: Deep transfer learning.

MISO: Multiple Input Single Output.

DT: Decision Trees.

MAE: Mean Absolute Error.

EBL: Estimating Bilirubin Levels.

Table 2.Comparison of non-invasive bilirubin assessment methods for detecting and classifying jaundice in newborns without a color calibration card.

Ref	Dataset	Body Part	Sensor and hardware	Age	Technique	Results	Classes
[38]	120	Face skin	Images were taken from the NET	18 hours to 3 days	- Statistical features derived from texture images - KNN classifier employed for classification	Accuracy 90%	2

[18]	12	Skin region	Digital camera and Arduino Nano	Below 30 weeks	Color comparison	Very high detection rate for the skin state	2
[47]	670	Skin region	Smartphone camera	2 to 6 days	KNN , RF and XGboost	- XGboot Accuracy 98.6%. - KNN Accuracy 95.4%.	2
[2]	511	Skin region	Smartphone, Digital camera and Arduino Uno	2 to 6 days	RF	Accuracy 98.4375%.	2
[49]	50	Skin region	Camera	3 to14 days	RF K-Means Linear Regression	Accuracy 99.2%,.	2
[44]	145	Foreh-ead and Abdo-men skin	Smartphones and Raspberry Pi4	One day to several weeks	VGG16, VGG19 ,ResNet50, EfficientNet B0 and B7). DL with fine-tuning	ResNet50 Accuracy 84.091%	3
[48]	125	Skin region	N/A	N/A	BSSA, DT, RF, NB, KNN, SVM, and XGBoost.	Accuracy 98%,	2

SVM: Support Vector Machine. **RF**: Random Forest.

XGboost: Extreme Gradient Boosting. **BSSA**: Binary Spring Search Algorithm.

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