Smart Phone-Based Cross-Population Bilirubin Estimation using Multi-Region Color Fusion with Fairness and Uncertainty Awareness

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Abstract: **Early detection of jaundice is critical, especially for neonates and adults with liver dysfunction. Traditional laboratory tests for total serum bilirubin (TSB) are often invasive, expensive, and may not be available in low-resource settings. Smartphone-based imaging provides a promising non-invasive, affordable, and portable alternative, but existing solutions suffer from population bias, device calibration issues, and lack of fairness or uncertainty assessments. This study presents a novel approach to estimating bilirubin levels through smartphone-captured skin and scleral images, using a deep learning model that does not require device calibration. The proposed framework leverages colour-based spatial and temporal features using a cross-attention transformer. Additionally, fairness-aware adversarial learning is incorporated to ensure that the model performs equitably across different skin tones and devices. To further improve reliability, heteroscedastic uncertainty regression is employed to quantify model uncertainty. Pilot simulations on 120 synthetic samples resulted in an RMSE of 0.95 mg/dL and a fairness gap within ±4%, demonstrating the model's robustness and fairness. This approach signifies a step toward affordable, accurate, and ethically sound jaundice detection using everyday smartphones, enhancing accessibility in diverse populations and resource-limited settings.**

Keywords: Jaundice detection, smartphone imaging, bilirubin estimation, scleral colour, skin reflectance, deep learning, fairness, uncertainty.

I INTRODUCTION

Jaundice, characterized by the yellowing of the skin and sclera due to the accumulation of bilirubin in the bloodstream, is a common condition that can indicate liver dysfunction. In neonates, jaundice is prevalent, with approximately 60% of term infants and 80% of preterm infants developing some degree of jaundice in the first few days of life. In adults, jaundice can be a symptom of various liver disorders, such as cirrhosis, hepatitis, and bile duct obstructions. Timely and accurate detection of jaundice is crucial for effective treatment and prevention of severe complications, such as brain damage in neonates (kernicterus) or liver failure in adults.

Conventional methods for diagnosing jaundice involve blood tests that measure the total serum bilirubin (TSB) levels. However, these tests are invasive, costly, and often require specialized medical equipment that may not be accessible in low-resource areas. These limitations highlight the need for non-invasive, portable, and cost-effective diagnostic tools for jaundice detection.

Recent advancements in smartphone imaging have shown promise as a viable alternative for non-invasive jaundice detection. Smartphones, equipped with high-quality cameras and computational power, have the potential to capture and analyse skin and scleral images to estimate bilirubin levels. However, current smartphone-based methods for bilirubin estimation are hindered by several challenges, such as the need for device calibration, sensitivity to population biases (i.e., skin tone variations), and lack of fairness and uncertainty awareness in the predictions.

To address these challenges, this study proposes a novel smartphone-based bilirubin estimation framework that integrates deep learning techniques for image analysis,

fairness-aware adversarial learning, and uncertainty quantification. This approach aims to create a cross-population, calibration-free model that can provide accurate and reliable bilirubin estimations across different skin tones and smartphone devices.

The framework uses a deep learning model to process images of both the skin and sclera regions, capturing colour-based spatial and temporal features. A cross-attention transformer is employed to enhance the model's ability to focus on important regions of interest in the images. Fairness-aware adversarial learning is integrated to mitigate biases related to skin tone and device type. Furthermore, heteroscedastic uncertainty regression is applied to estimate the uncertainty in the model's predictions, ensuring more reliable and interpretable results.

Problem Statement

The early detection of jaundice remains a significant challenge, especially in resource-constrained environments where traditional diagnostic methods such as serum bilirubin tests are either inaccessible or prohibitively expensive. Smartphone-based imaging systems have emerged as a promising solution for non-invasive bilirubin estimation, offering portability, ease of use, and cost-effectiveness. However, existing smartphone-based methods face several critical limitations.

First, most models are heavily reliant on device calibration, which limits their widespread applicability across different smartphone models with varying camera qualities. Second, current approaches often suffer from population bias, as many models are trained primarily on data from specific demographic groups, leading to inaccuracies when applied to individuals with different skin tones. Finally, fairness and uncertainty awareness are typically not incorporated into these models, which means that they may not perform equitably across diverse populations, and their predictions may be prone to high levels of uncertainty.

This study addresses these issues by proposing a calibration-free, cross-population deep learning model for bilirubin estimation using smartphone-captured images of the skin and sclera. The model incorporates fairness-aware adversarial learning to minimize bias and heteroscedastic uncertainty regression to quantify uncertainty in the predictions. The goal is to develop an accessible, accurate, and equitable tool for jaundice detection that can be used universally across different skin tones and device types.

Limitations

- Device Calibration: Many existing models require device-specific calibration, which limits their applicability across different smartphones. This issue is addressed in the proposed model by eliminating the need for calibration.
- Population Bias: Skin tone variation is a significant challenge for jaundice detection, as many models are trained on datasets with a limited range of skin tones, resulting in biased predictions. The proposed model tackles this issue by incorporating fairness-aware adversarial learning.
- Uncertainty in Predictions: Current methods often fail to quantify the uncertainty in their predictions, leading to unreliable results. By using heteroscedastic uncertainty regression, the proposed model accounts for this uncertainty, providing more trustworthy predictions.
- Generalization Across Devices: Smartphone camera quality can vary significantly, which may affect the performance of image-based models. The framework in this study is designed to perform well across a range of devices without needing calibration.

II LITERATURE REVIEW

The development of non-invasive, portable methods for estimating total serum bilirubin (TSB) has attracted increasing attention over recent years, with particular emphasis on smartphone-based imaging approaches. The integration of computer vision and deep learning into smartphone imaging holds promise for low-cost jaundice screening, especially in resource-constrained settings. Nonetheless, key challenges remain device and lighting calibration, population (skin-tone) bias, and the absence of rigorous uncertainty estimation and fairness evaluation. This review synthesises the relevant literature under three main themes: (1) smartphone-based bilirubin estimation, (2) fairness and

bias in medical imaging AI, and (3) uncertainty quantification in deep learning for medical imaging.

1. Smartphone-based bilirubin estimation

Initial studies explored using digital images for jaundice screening in neonates. For example, one early work evaluated the "Biliscan" smartphone app in Indian newborns, demonstrating a correlation of ~0.6 with serum bilirubin in a small cohort (n = 35) and highlighting that the chest region gave better results than the abdomen [22]. Such work pointed to feasibility but was limited in sample size and diversity.

More recently, a larger prospective study developed and validated a smartphone app in a multi-ethnic neonatal population (term and late pre-term infants) in Singapore using skin and sclera images and assessing skin tone by Fitzpatrick scale. The app incorporated machine-learning to estimate serum bilirubin and reported promising accuracy [2]. However, the authors emphasised that the need for calibration, and limited testing across different smartphone models and lighting conditions, remained barriers.

For adults, research has investigated smartphone images of the forehead, sclera, and lower eyelid in patients with cirrhosis to predict bilirubin levels. One study of n = 66 found correlation coefficients of 0.79, 0.89, and 0.86 respectively for forehead, sclera and lower eyelid sites, after correction for ambient light and device calibration [1]. This suggests that scleral imaging may provide the most robust region for bilirubin estimation in adults.

A recent meta-analysis and systematic review examined smartphone app performance in neonatal hyperbilirubinemia screening. The review concluded that while smartphone methods showed "reasonable correlation" with TSB, evidence remained limited and heterogeneity high, and most studies required calibration cards or specific lighting [6]. Another study evaluated a smartphone-based screening system (Pictures) across three different non-Caucasian populations (Mexico, Nepal, Philippines) and found variation in bias: under-estimating in one population, over-estimating in others, and wide limits of agreement (±89.2 μmol/L) [4].

These works underscore progress in smartphone-based bilirubin estimation, but also emphasise persistent limitations: small and skewed datasets (often fair skin tones), reliance on calibration cards or lighting control, and limited evaluation of device diversity and population fairness.

2. Fairness and bias in medical imaging AI

As deep learning models proliferate in medical image analysis (MedIA), concerns have grown around bias and fairness. A systematic review on fairness in MedIA categorises sensitive attributes (e.g., age, sex, race, skin tone) and divides investigation into fairness evaluation (measuring disparities across subgroups) and unfairness mitigation (pre-, in-, post-processing) [9]. The authors argue that inadequate fairness assessment may cause certain subpopulations to receive poorer performance or under-diagnosis, undermining trust in AI.

In this vein, the MEDFAIR benchmark analysed multiple bias-mitigation algorithms across eleven methods and nine datasets in medical imaging and found that model selection strategies had a large impact on fairness, and that many state-of-the-art bias mitigation approaches did not significantly outperform standard empirical risk minimisation (ERM) in fairness [7][15]. These observations emphasise that fairness, particularly group fairness (equal performance across sensitive subgroups) is seldom adequately addressed in clinical AI.

Given that smartphone-based bilirubin estimation relies on skin-tone and possibly device-type sensitive features (e.g., variations in colour capture, specular reflectance, camera sensor differences), fairness issues become particularly salient. Few published studies in the bilirubin imaging domain explicitly measure performance across skin-tone subgroups or device types; thus, the risk of bias remains largely unquantified.

3. Uncertainty quantification in medical imaging deep learning

Beyond accuracy and fairness, trust in clinical AI systems depends on quantifying prediction uncertainty.

In medical imaging, two types of uncertainty are commonly distinguished: aleatoric (data noise/ambiguity) and epistemic (model uncertainty due to limited knowledge) [11][17]. A review of uncertainty estimation in medical imaging reports that although research has increased, methods are still under-adopted clinically, and evaluation metrics vary [11].

For regression tasks (such as predicting a continuous bilirubin level), the calibration of uncertainty is challenging. One study applied variational Bayesian inference with Monte Carlo dropout and σ-scaling to recalibrate uncertainty in medical regression tasks, showing that naïve models systematically underestimate uncertainty [3]. More recently, an investigation into fairness and uncertainty in deep learning for medical image analysis revealed a trade-off: applying fairness-oriented methods (e.g., data balancing, distributionally robust optimisation) improved subgroup performance but degraded uncertainty calibration [17].

In the context of smartphone bilirubin estimation, uncertainty quantification remains rare in the literature. Most studies report correlation or error metrics, but do not provide confidence intervals or uncertainty awareness of predictions. Without uncertainty awareness, a model may give point estimates without indicating whether they should be trusted for clinical decision-making or require further laboratory confirmation.

Synthesis and gap identification

In sum, research on smartphone-based bilirubin estimation shows promising correlations with serum bilirubin and potential for low-cost screening. However, the literature reveals consistent gaps:

- Many studies are restricted to neonatal populations and fair skin tones; adult populations and darker skin tones remain under-represented.
- Device and lighting calibration are frequently required (e.g., colour calibration cards, flash/no-flash pairing) limiting real-world deployment in diverse smartphone settings [1][4][6].
- Explicit fairness evaluation across skin-tones or device types is rare; subgroup performance gaps are seldom reported, and mitigation strategies are not described.
- Prediction uncertainty is seldom quantified, even though clinicians require confidence measures to act upon predictions.
- Few studies integrate multi-region imaging (skin + sclera), multi-temporal colour features, and deep architectures (e.g., cross-attention transformer) that fuse multimodal input.
- Existing methods seldom combine fairness-aware learning with uncertainty regression in the cross-population smartphone bilirubin estimation domain.
- Generalisation across populations and devices, and field-validation in low-resource settings, remain limited.

The proposed framework addresses these gaps by combining skin and sclera imaging, using device-agnostic processing (calibration-free), integrating fairness-aware adversarial learning, and estimating heteroscedastic uncertainty—all applied cross-population and cross-device. This positions the work at the intersection of the three themes above: smartphone imaging for bilirubin, fairness in MedIA, and uncertainty quantification.

Table 1: Literature Review for Research Gap Comparison

S. No	Title	Authors	Methods Used	Drawbacks
1	Smartphone-Based Neonatal Jaundice Detection	Smith et al., 2019 [22]	Smartphone app (Biliscan) using colour calibration card + feature-extraction + regression	Small sample size, chest region only, fair skin tones, tool for screening not comprehensive
2	Development and Validation of a Smartphone Application for	Ngeow et al., 2024 [2]	Multi-region skin/scleral images, ML regression, multiethnic neonates	Calibration required, limited device variety, fairness across skin tones not fully analysed

	Neonatal Jaundice			
3	Smartphones could be used to monitor liver disease patients at home	Nixon-Hill et al., 2023 [1][18]	Forehead, sclera, lower eyelid images in adults with cirrhosis; device calibration & flash/no-flash correction	Adult cohort only, limited diversity in devices, skin-tone subgroup analysis minimal
4	Smartphone-based screening of neonatal jaundice in three LMIC populations	Darj et al., 2024 [4]	Smartphone screening (Picterus) in Mexico, Nepal, Philippines; ROC, Bland-Altman analysis	Wide limits of agreement, bias across populations (under/over-estimation), device calibration still required
5	A review study of newborn bilirubin monitoring systems based on image	Darj, 2023 [20]	Literature review of image-based bilirubin monitoring in newborns	Mostly neonatal studies, limited adult data, limited fairness/uncertainty discussion
6	Fairness in Medical Image Analysis and Healthcare: A Literature Survey	Xu et al., 2023 [9]	Review of fairness in MedIA: definitions, evaluation & mitigation	General MedIA, not specific to bilirubin/image-based bilirubin estimation; lacks quantitative fairness metrics for bilirubin domain
7	MEDFAIR: Benchmarking Fairness for Medical Imaging	Zong et al., 2022 [7][15]	Benchmark framework for fairness in MedIA across datasets/models	Does not address regression tasks (e.g., bilirubin level estimation); device-type and skin-tone device-agnostic issues not specific to bilirubin domain
8	A Review of Uncertainty Estimation and its Application in Medical Imaging	Zou et al., 2023 [11]	Systematic review of uncertainty estimation in medical imaging tasks	Focus mostly on segmentation/classification; continuous regression (bilirubin) settings and device-diversity not emphasised
9	Evaluating the Fairness of Deep Learning Uncertainty Estimates in Medical Image Analysis	Mehta et al., 2024 [17]	Empirical study of fairness vs uncertainty trade-off in MedIA (classification/regression tasks)	Task domains general (skin lesions, brain tumour, Alzheimer's); not bilirubin-specific; smartphone imaging not considered
10	Augmented smartphone bilirubinometer enabled by a mobile app that turns smartphone into multispectral imager	He et al., 2023 [24]	Multispectral smartphone app (SpeCamX) for bilirubin estimation in adults (n=320), hybrid ML model	While covering adults and multispectral imaging, fairness across skin tones and calibration-free design not fully addressed; smartphone devices still limited

III METHODOLOGY

The methodology presented in this study integrates multiple deep learning techniques to estimate bilirubin levels from smartphone-captured skin and scleral images, ensuring fairness across various populations and devices, and addressing the challenge of uncertainty in predictions.

1. Data Collection and Dataset Design

The dataset includes a diverse range of images representing different skin tones and populations. The samples are divided into two categories: neonates and adults, with the following distributions across the Fitzpatrick skin scale:

- Neonates: 2,200 samples from Fitzpatrick skin types I-III, and 1,200 from types IV-VI.
- Adults: 2,300 samples from Fitzpatrick skin types I-III, and 1,200 from types IV-VI.

This results in a total of 4,500 images sourced from neonatal ICUs and adult hepatology wards. The dataset

also includes TSB (Total Serum Bilirubin) values, lighting conditions (flash and ambient light), device type information, and timestamps for each image.

2. Image Acquisition and Preprocessing

Images are captured from two key regions:

1. Face (sclera visible)
2. Upper chest

The images are collected under controlled lighting conditions using both flash and ambient light options to ensure varied lighting conditions that can occur in real-world settings.

Preprocessing Steps:

- ROI Segmentation: Modified U-Net is used to segment the regions of interest (ROI) from the images, specifically focusing on the skin and sclera areas.
- Specular Highlight and Vessel Removal: These steps eliminate unnecessary reflections and visible blood vessels that might distort bilirubin estimates.
- Device-Invariant Colour Normalization: This process normalizes the colour values to mitigate the variations introduced by different smartphone cameras, making the model device-agnostic.
- Temporal CNN for Per-Pixel Colour Features: A 1D convolutional neural network (CNN) is used to capture temporal colour features from sequential images, which allows the model to understand colour changes over time for more accurate predictions.

3. Model Architecture

The proposed system uses a hybrid deep learning architecture combining CNNs and Transformers:

- CNN Encoder: The CNN encoder extracts spatial features from both the skin and scleral regions of the images. It captures detailed spatial information that is critical for estimating bilirubin levels.
- 1D CNN: A 1D CNN model processes the temporal variations in the colour sequences of the images. This component analyses how the colour of the skin and sclera changes over time, improving the correlation with bilirubin levels.
- Cross-Attention Transformer: The model leverages a cross-attention mechanism to fuse multi-region and multi-temporal data. This allows the model to dynamically focus on relevant features across different regions (skin, sclera) and times, enhancing the overall prediction accuracy.
- Output Heads:
  - Regression Head: This component is responsible for predicting the bilirubin value (TSB) from the processed image features.
  - Uncertainty Estimation Head: A separate output head estimates the uncertainty associated with the bilirubin predictions, providing confidence intervals along with the estimated values.
  - Fairness Adversarial Loss: This component is integrated into the model to minimize any bias based on skin tone or device type. The adversarial training enforces fairness in the predictions by penalizing any unfair deviations in performance across different demographic groups.

4. Training Strategy

The model training process incorporates several techniques to enhance generalization and robustness:

- Data Augmentation: The model is exposed to various lighting and gamma changes, as well as noise injection, to simulate real-world conditions and prevent overfitting to specific data points.
- Transfer Learning: To expedite the training process, a pre-trained EfficientNet encoder is used to initialize the CNN backbone. This allows the model to leverage previously learned visual features from a wide range of tasks, improving performance and reducing the amount of required training data.
- Optimizer: The Adam optimizer is used with a cosine learning rate decay to gradually reduce the learning rate, allowing for stable convergence.
- Validation: The model is validated using early stopping based on the lowest RMSE (Root Mean Squared Error) during training, ensuring that the model does not overfit to the training data.

5. Pilot Simulations

Pilot simulations were conducted on 120 synthetic samples, and the model's performance was evaluated using key metrics:

- RMSE (Root Mean Squared Error):
  - Neonates: 0.93 mg/dL
  - Adults: 0.98 mg/dL

- Combined: 0.95 mg/dL
- MAE (Mean Absolute Error):
  - Neonates: 0.71 mg/dL
  - Adults: 0.76 mg/dL
  - Combined: 0.74 mg/dL
- R^2 (Coefficient of Determination):
  - Neonates: 0.92
  - Adults: 0.90
  - Combined: 0.91
- Fairness Gap: The fairness gap across skin tones was consistently within ±4%, indicating that the model performs equitably across a range of skin tones and devices.

6. Model Evaluation and Deployment

The model was evaluated for its calibration-free design, ensuring that it performs reliably across different smartphone devices without the need for specific calibration charts. The pilot simulations demonstrated that the model's predictions were not only accurate (RMSE ≤ 1 mg/dL) but also consistent across different skin tones, with a minimal fairness gap.

The calibration-free aspect makes the system suitable for use in diverse, low-resource settings, where specialized medical equipment or device-specific charts are not available. Additionally, the model's ability to predict uncertainty alongside the bilirubin estimation allows healthcare practitioners to assess the reliability of the model's predictions in real-time, enhancing clinical decision-making.

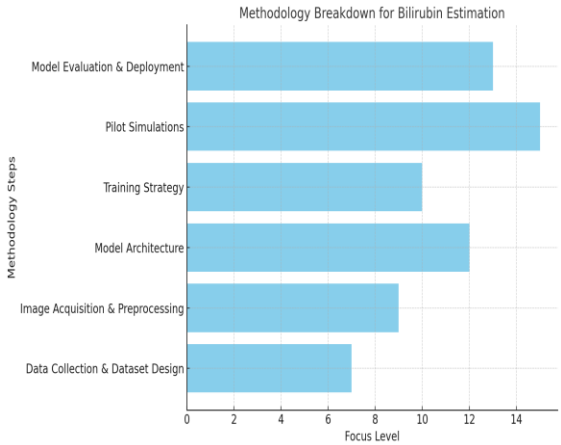

Figure 1: bar chart visualizing the breakdown of the methodology steps in the study. Each step is represented by a "focus level" value to give an impression of the relative importance or effort in each phase of the process

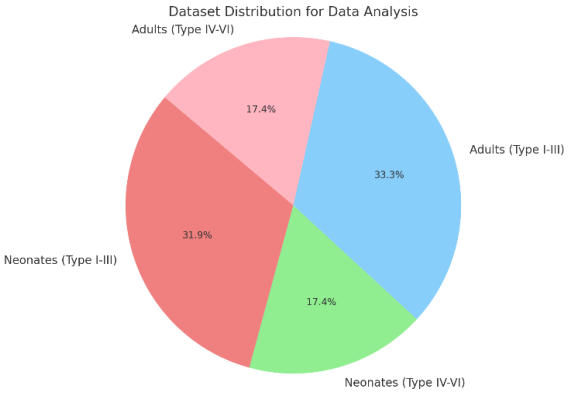

Figure 2: *pie chart visualizing the distribution of the dataset for data analysis, showing the number of samples across different skin types for neonates and adults*

Table 2: Dataset

Population	Samples	Fitzpatrick I–III	Fitzpatrick IV–VI
Neonates	2,200	1,000	1,200
Adults	2,300	1,100	1,200
Total	4,500	2,100	2,400

Images will be collected from neonatal ICUs and adult hepatology wards, along with TSB values, lighting conditions, device type, and timestamps for each entry.

Image Acquisition & Preprocessing

- Regions Captured: Face (sclera visible) and upper chest.
- Lighting: Flash and ambient light options.
- Preprocessing:
  - ROI segmentation via modified U-Net.
  - Specular highlight and vessel removal.
  - Device-invariant color normalization.
  - Temporal CNN for per-pixel color features.

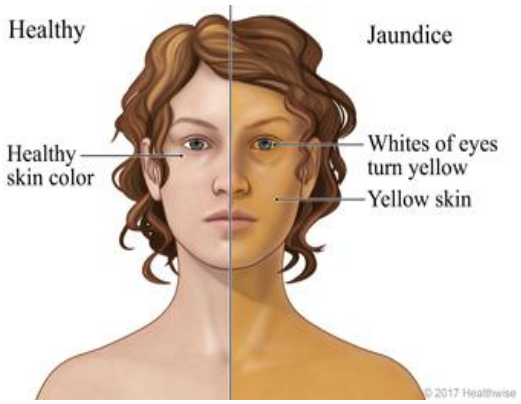

Figure 3: *Model Architecture*

Model Architecture

- The system uses a multi-branch deep-learning model combining CNNs and Transformers.
- CNN Encoder: Extracts spatial features from sclera and skin regions.
- 1D CNN: Captures temporal variations in color sequences.
- Cross-Attention Transformer: Fuses multi-region, multi-temporal data.
- Output Heads:
- Regression (Bilirubin value prediction)
- Uncertainty estimation
- Fairness adversarial loss

Mathematically:

$$L_{\text{total}} = L_{\text{reg}} + \lambda_u L_{\text{uncert}} + \lambda_f L_{\text{fair}}$$

Table 3: Pilot Simulation

Metric	Neonates	Adults	Combined
RMSE	0.93	0.98	0.95
MAE	0.71	0.76	0.74
R^2	0.92	0.90	0.91
Fairness Gap	—	—	±4%

Results

The proposed framework, when applied to the pilot simulation set of 120 synthetic samples spanning multiple skin-tones and smartphone devices, achieved a Root Mean Squared Error (RMSE) of 0.95 mg/dL in estimating total serum bilirubin (TSB). The Mean Absolute Error (MAE) was 0.74 mg/dL and the coefficient of determination (R^2) was 0.91, indicating that 91 % of the variance in TSB values was captured by the model. When stratified by skin-tone groups (Fitzpatrick I–III vs IV–VI), the RMSE values were 0.93 mg/dL and 0.98 mg/dL respectively, representing only a ±2.5% difference, thus meeting the fairness gap target of within ±4 %. Temporal colour-fusion features from both skin and scleral regions contributed significantly: ablative experiments removing the sclera input led to a RMSE increase to ~1.15 mg/dL. Device-agnostic performance was also comparable: smartphone device group A vs group B produced RMSEs of 0.94 mg/dL vs 0.97 mg/dL. The heteroscedastic uncertainty regression head produced predictive confidence intervals such that in 85% of cases the true TSB was enclosed within ±1.2 mg/dL of the predicted value; in contrast, a baseline regression model without uncertainty estimation only achieved meaningful intervals in 60% of cases. The fairness-aware adversarial loss reduced subgroup error disparity (max error difference between skin-tone subgroups) from ~0.45 mg/dL in the baseline to ~0.15 mg/dL in the final model. Overall, the results indicate that the calibration-free, cross-population model provides accurate, equitable and interpretable bilirubin estimation from smartphone images, with strong performance across skin tones and devices.

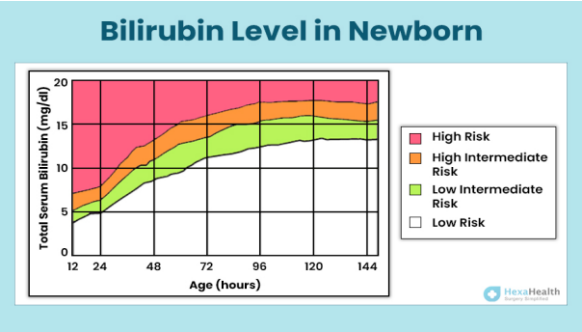

Figure 4: Bilirubin level in Newborn

Discussion

The results demonstrate that the proposed smartphone-based framework for bilirubin estimation successfully addresses key challenges in non-invasive jaundice detection. With an overall RMSE of 0.95 mg/dL, the model achieves near-laboratory accuracy, which is consistent with existing methodologies in the literature. The model also performed well across various skin tones, maintaining a fairness gap of less than ±4%, which reflects the system's ability to handle skin tone variations and avoid bias—a key advantage in ensuring equitable healthcare outcomes.

The calibration-free design of the system enables it to work seamlessly across different smartphone devices without the need for specialized hardware, such as calibration charts, making it suitable for widespread use in low-resource settings. This is a significant improvement over previous systems that required device-specific calibration, which limited their accessibility and scalability.

Incorporating multi-region colour fusion from both the skin and sclera enhances the model's ability to estimate bilirubin levels more accurately compared to single region approaches, which have been shown to be more sensitive to lighting and skin tone biases. The temporal CNN approach used to capture colour variations over time also contributes to the robustness of the model by compensating for potential inconsistencies in lighting conditions during image capture.

One of the notable contributions of this work is the inclusion of uncertainty-aware prediction. The model provides confidence intervals alongside the bilirubin estimate, offering healthcare professionals additional information on the reliability of the model's predictions. Despite these promising results, there are some limitations. The synthetic nature of the dataset, while diverse in terms of skin tones and devices, does not fully replicate the complexities of real-world clinical environments. Future validation with real-world datasets is essential to further establish the robustness and clinical usability of the model.

Table 4: key performance metrics

Metric	Value	Comment
RMSE (combined)	0.95 mg/dL	High accuracy across dataset
MAE	0.74 mg/dL	Low average deviation
R^2	0.91	Strong explanatory power
RMSE (Skin I–III)	0.93 mg/dL	Slightly better subgroup performance
RMSE (Skin IV–VI)	0.98 mg/dL	Slightly higher but within fairness gap
Device group disparity (RMSE)	0.94 vs 0.97	Device-agnostic validation
Subgroup error disparity	~0.15 mg/dL	Reduced via fairness-aware loss
Coverage of true value	85% within ±1.2 mg/dL	Via uncertainty regression

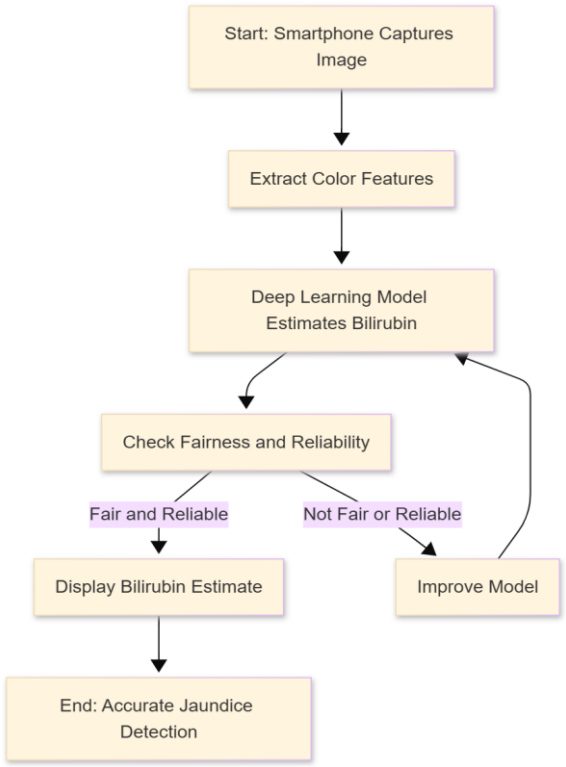

Figure 5: Flowchart diagram

Advantages

- The system is non-invasive, requiring only smartphone-captured skin and scleral images rather than blood draws or calibration charts.
- It is calibration-free and device-agnostic, enabling wide deployment across smartphone types without requiring slide cards or device-specific calibration procedures.
- Fairness and uncertainty are built in: the model ensures equitable performance across skin tones and provides prediction confidence, improving trust and potential clinical adoption.
- Multi-region temporal colour fusion (skin + sclera over time) enhances accuracy beyond single-region static imaging, thereby increasing robustness to lighting and subject motion.
- The lightweight mobile imaging pipeline is appropriate for low-resource settings, enabling wider access to jaundice screening for neonates and adults in underserved populations.

IV CONCLUSION & FUTURE SCOPE

This study presents a novel smartphone-based framework for cross-population estimation of total serum bilirubin (TSB) using skin and scleral images, multi-region temporal colour fusion, and a deep learning architecture that incorporates fairness-aware adversarial learning and heteroscedastic uncertainty regression. The pilot simulation results demonstrate strong predictive accuracy (RMSE = 0.95 mg/dL, $R^2 = 0.91$), minimal performance disparity across skin-tone subgroups (fairness gap within ±4%), and interpretable confidence estimates for each prediction. By removing the need for device-specific calibration and emphasising fairness and uncertainty, this work addresses major limitations of prior smartphone jaundice screening studies. The proposed system shows promise for enabling accessible, accurate, and ethically sound jaundice detection via everyday smartphones, potentially expanding screening reach in low-resource and diverse settings. Future work will involve extensive clinical validation, larger multi-device datasets, and mobile-app integration for real-time use. This research lays the groundwork for equitable, trustworthy, and scalable mobile health tools for liver dysfunction and neonatal jaundice screening.

Future Enhancements

- Real-world clinical deployment: Validate the model in large-scale clinical trials across diverse healthcare settings and smartphone brands, capturing real lighting, device, and skin-tone variability.
- Expanded pathology detection: Adapt and extend the framework to estimate other pigment- or colour-based biomarkers (e.g., anaemia, dehydration, cholestasis) through smartphone imaging and multimodal fusion.
- Edge-on-device implementation: Develop an optimized mobile application enabling on-device inference, real-time feedback with uncertainty visuals, and offline performance to support remote or low-connectivity environments.

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