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An Intelligent Machine Learning Framework for Neonatal Health Risk Prediction and Early Clinical Decision Support

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Abstract

Neonatal Jaundice is among the most frequently diagnosed health issues for infants and could cause serious issues, such as Kernicterus (brain damage from accumulation of blood products related to jaundice) if the condition is not promptly diagnosed. This study describes the development of an Artificial Intelligence (AI) based Jaundice Prediction System that predicts the risk of developing Neonatal Jaundice based on specific clinical characteristics. The system utilizes Machine Learning algorithms to predict how likely a child is to develop Neonatal Jaundice based on a variety of health information, including: Gestational Age, Birth Weight, Bilirubin levels, feeding frequency, oxygen saturation, body temperature, and other clinical chart data. Using the Random Forest Machine Learning algorithm, the system classifies the risks associated with Neonatal Jaundice into one of four categories (low, moderate, high, and critical risk). In building the system, an interactive user interface was developed using Stream lit, the Random Forest model was built using Scikit-Learn, and Plotly was used for data visualization, resulting in a very user-friendly interactive healthcare dashboard. The prediction system also provides AI-generated insights, feature importance analysis, and medical recommendations in order to support the healthcare provider with making decisions related to patients at risk for developing Neonatal Jaundice. The system retains patient history, performs risk trend analysis, and produces performance metrics of the predictive model to support continuous monitoring of the patient. Testing has demonstrated that the Random Forest Model used to create the Jaundice Prediction System demonstrates excellent accuracy and reliability in predicting the risk of Neonatal Jaundice.

Keywords: Neonatal Jaundice Prediction, Machine Learning, Random Forest Classification

1. Introduction

One of the most prevalent illnesses that strike newborns in their first few days of life is neonatal jaundice. The yellow coloring of the skin and eyes is caused by the buildup of bilirubin in the blood. While severe or uncontrolled jaundice can result in major consequences like brain damage, hearing loss, or a condition called kernicterus, light jaundice is typically benign and goes away on its own. Therefore, to avoid potentially fatal consequences, bilirubin levels must be detected early and continuously monitored. Conventional diagnosis is primarily based on laboratory tests and clinical observation, which might occasionally postpone prompt intervention. Intelligent systems can help medical personnel discover possible problems earlier and more accurately thanks to the development of digital healthcare technologies.

Due to their capacity to evaluate complicated medical data and offer predictive insights, artificial intelligence (AI) and machine learning (ML) approaches have recently attracted a lot of attention in healthcare applications. Machine learning algorithms can find patterns and risk factors related to newborn jaundice by using patient health metrics and past medical data. Clinical decision assistance, data visualization, and automated risk assessment are made possible by integrating these technologies into healthcare dashboards. By helping physicians and other healthcare professionals make quicker and better decisions, these tools can raise the standard of neonatal care. In this regard, the suggested system presents an AI-Integrated Jaundice Prediction Dashboard that uses machine learning algorithms to forecast the risk level of neonatal jaundice. Gestational age, birth weight, bilirubin level, feeding frequency, oxygen saturation, body temperature, and other medical indications are among the clinical characteristics that the system gathers. A Random Forest machine learning model is used to analyze these inputs and categorize the risk of jaundice into various categories. In addition, the dashboard offers AI-generated insights, interactive visualizations, and patient history tracking to facilitate medical analysis. The suggested solution seeks to improve early diagnosis, enhance monitoring, and help medical personnel provide better newborn healthcare management by fusing machine learning prediction with an interactive dashboard interface.

A. Neonatal Jaundice Prediction

Neonatal jaundice prediction involves utilizing clinical data and advanced analytical technologies to identify the potential risk of developing this condition at an early stage of life. Neonatal jaundice is caused by an excess quantity of bilirubin in a newborn's bloodstream; the result of excessive amounts of bilirubin in the blood leads to yellowing of the newborn's skin and eyes. While this condition can develop in many newborns, untreated or improperly treated instances of neonatal jaundice can lead to a number of serious complications for the newborn if not diagnosed early enough. To determine the probability of developing neonatal jaundice, many predictors are factored into the prediction models, some of which include gestational age, birth weight, levels of bilirubin, frequency of feedings, oxygen saturation, and additional relevant health indicators associated with the newborn. With the help of machine learning algorithms, the predictive models are able to identify trends and predictive risk factors that can be derived from the medical data, and subsequently place the newborn infant's risk of developing jaundice into the following classification groups: (1) low, (2) moderate, (3) high, or (4) critical. The use of these predictive models by the medical providers caring for newly born babies aids them in the delivery of healthcare services by providing them with the ability to perform evidence-based medicine, monitor the health status of the newly born baby in a more effective manner, facilitate pre-diagnosis, and provide timely medical treatment. Additionally, the ability of the medical providers caring for the newly born to utilize these intelligent predictive systems also assists them in making accurate risk-adjusted clinical recommendations and assessments, thereby reducing the occurrence of significant adverse outcomes as well as improving the overall quality of healthcare services provided to newly born infants.

B. Machine Learning

Machine Learning is a type of Artificial Intelligence (AI) that allows computer systems to learn from medical data without being explicitly programmed to do so; rather, they learn from the data through experience. In the field of healthcare, machine learning uses algorithms to analyse vast volumes of patient data including (but not limited to) medical records, lab results, and imaging results to ascertain patterns and identify disease, as well as make predictions of health risks. Ultimately, by using these technologies, physicians and other health professionals will be able to improve their ability to make accurate diagnoses; develop better plans for the treatment of patients; and monitor patients more closely. Some common types of machine learning models used in healthcare include Decision Trees, Random Forests, Support Vector Machines, and Neural Networks. These models provide healthcare professionals with the ability to predict disease; analyses images; and discover new drugs; as well as assist with personalized medicine. By incorporating machine learning into their operations, hospitals are able to increase the efficiency of the services they provide to patients, as well as reduce human error associated with providing those services. One example of how machine learning is being utilized in healthcare is through the prediction of neonatal jaundice by analyzing clinical parameters such as bilirubin levels, gestational age, and birth weight. The primary goal is to identify the degree of risk associated with a clinical presentation and assist in making an early diagnosis. In summary, machine learning plays an important role in assisting healthcare professionals with clinical decision making, improving patient outcomes, and advancing modern healthcare technology.

C. Random Forest Classification

Random Forest Classification is a supervised machine learning algorithm widely used for classification and prediction tasks. It is an ensemble learning technique that combines multiple decision trees to produce more accurate and reliable results. Instead of relying on a single decision tree, the Random Forest algorithm builds many decision trees during the training process and aggregates their outputs to determine the final prediction. Each tree is trained using a random subset of the training data and a random selection of features, which helps reduce overfitting and improves the model's ability to generalize to new data. The final prediction is obtained through a majority voting mechanism where the class predicted by most of the trees is selected as the final output. Random Forest is particularly effective in handling complex datasets with many features and can capture non-linear relationships between variables. In healthcare applications such as neonatal jaundice prediction, Random Forest analyzes clinical parameters like bilirubin levels, gestational age, birth weight, and feeding frequency to classify the risk level of jaundice. Due to its high accuracy, robustness, and ability to measure feature importance, Random Forest is commonly used for medical diagnosis and predictive healthcare systems.

2. Related Works and Literature Survey

Mehrnoush Lotfi Neonatal jaundice is a prevalent and potentially serious condition that can lead to severe complications if undiagnosed or untreated. While traditional diagnostic methods like blood sampling are invasive and time-consuming, and transcutaneous bilirubinometers remain costly, smartphone-based image analysis offers a promising low-cost, non-invasive alternative. However, most existing solutions rely on traditional machine learning techniques with limited accuracy and generalizability. In this study, we introduce a deep learning approach based on the Vision Transformer (T2T-ViT) and compare its performance with three other models, ResNet, Support Vector Machine (SVM), and K-Nearest Neighbors (k-NN), using a clinically annotated dataset of neonatal skin images captured via a smartphone camera. The models were evaluated using multiple performance metrics including accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and Area under the Curve (AUC). The T2T-ViT model achieved 99% across all metrics, significantly outperforming both convolutional and traditional machine learning models.

Neonatal jaundice, characterized by elevated bilirubin levels causing yellow discoloration of the skin and eyes in newborns, is a critical condition requiring accurate and timely diagnosis. This study proposes a novel approach using 1D Convolutional Neural Networks (1DCNN) for estimating bilirubin levels from RGB, HSV, LAB, and YCbCr color channels extracted from infant images. Initially, each color channel is treated as a time series input to a 1DCNN model, facilitating bilirubin level prediction through regression analysis. Subsequently, RGB feature maps are combined with those derived from HSV, LAB, and YCbCr channels to enhance prediction performance. The effectiveness of these methods is evaluated based on Root Mean Squared Error (RMSE), R-squared (R2), and Mean Absolute Error (MAE).

In order to estimate bilirubin levels from infant skin photos, Fatemeh Makhloughi (2025) developed a novel one-dimensional convolutional neural network (1D CNN) that treats various color space channels (RGB, HSV, LAB, and YCbCr) as time series inputs. The model obtained robust regression performance (low RMSE) and a high R squared score (~0.91) by merging several color representations. Additionally, the study modified the optimal model for classification tasks, attaining an accuracy of around 97%. This paper shows that deep learning can successfully extract jaundice-related characteristics from color channels, providing a promising non-invasive alternative to or addition to conventional blood tests for bilirubin assessment.

This study developed a smartphone based noninvasive jaundice detection tool using carefully calibrated images of a newborn’s face and chest. A color calibration card ensured consistent lighting conditions, and carefully engineered skin region features were extracted to train regression models. The best performing multilayer perceptron model predicted total serum bilirubin levels with high correlation ($R \approx 0.90$) and accurately identified over 89% of infants with significant hyperbilirubinemia. The research emphasizes the real-world applicability of smartphone imaging and ML to provide accessible jaundice screening tools that parents and clinicians can use without specialized equipment.

Fati Oiza Salami et al. (2025) and colleagues reviewed the state of AI driven noninvasive techniques for neonatal jaundice detection, focusing on machine learning and deep learning models. The review details how AI can enhance early jaundice diagnosis by evaluating complex skin color patterns and clinical data without invasive procedures. It also highlights mobile based solutions that use smartphone cameras to estimate bilirubin levels, demonstrating high accuracy rates in clinical settings. The paper discusses practical challenges and future directions, including improving imaging technology and wearable sensor integration for real time bilirubin monitoring.

3. Existing System

Jaundice is typically seen among newborns and it is an extremely common disorder among babies. Newborn infants are often affected by the condition known as neonatal jaundice as a result of high levels of bilirubin present in the bloodstream which manifests as yellowing of the skin and eyes. Timely detection and monitoring of neonatal jaundice is essential in order to avoid any associated complications. This research introduces a novel method for non-invasively identifying neonatal jaundice through the utilization of innovative optical technology that will allow for accurate measurement of neonatal bilirubin levels without the need for invasive procedures such as drawing blood. The primary component of the device developed is a special apparatus that incorporates state-of-the-art spectroscopic principles. The system uses a safe, non-invasive light source to illuminate the skin of the infant and the bilirubin level present in the skin is determined by the reflected light. The device is compact, lightweight, and easy to use thus making it suitable for both home and hospital use. The focus of this research is to develop a non-invasive procedure for routine monitoring and detecting of jaundice, thus assisting healthcare providers in providing an earlier diagnosis.

4. Proposed System

The proposed system is an AI-Integrated Jaundice Prediction Dashboard designed to assist healthcare professionals in the early detection and monitoring of neonatal jaundice using machine learning techniques. The system collects essential clinical information of newborn babies, including gestational age, birth weight, bilirubin level, feeding frequency, oxygen saturation, body temperature, skin yellow intensity, and other medical indicators through an interactive dashboard interface. These input parameters are processed using a Random Forest machine learning model, which analyses the data and predicts the risk level of jaundice by classifying it into four categories: Low, Moderate, High, and Critical. The system also calculates prediction probabilities and identifies the most influential clinical features affecting the prediction. In addition to risk prediction, the dashboard provides AI-generated medical insights and treatment recommendations to support healthcare decision-making. The platform includes advanced visualization tools that display risk probability distribution, feature importance, and patient health trends using interactive charts. Furthermore, the system maintains patient assessment history for future analysis and monitoring. By integrating machine learning, real-time data analysis, and interactive visualization, the proposed system offers a reliable and efficient decision support tool that helps doctors detect neonatal jaundice early, monitor patient conditions, and take timely medical actions to prevent severe complications.

A. Patient Data Collection

The Patient Data Collection Module is responsible for gathering essential clinical information related to the newborn baby. This module provides an interactive form where healthcare professionals can enter important parameters such as gestational age, birth weight, current weight, bilirubin level, feeding frequency, oxygen saturation, body temperature, skin yellow intensity, stool color, infection status, and family history of jaundice. The module also automatically calculates the baby’s age in days based on the date of birth. By capturing structured medical data accurately, this module ensures that the machine learning model receives reliable input for prediction, thereby improving the overall effectiveness of the system.

B. Data Pre-processing

The Data Preprocessing Module prepares the collected patient data for machine learning analysis. It converts the user input into a structured data format, handles missing values, and standardizes numerical features using techniques such as feature scaling. The module ensures that all required features are present and formatted correctly before they are passed to the prediction model. This preprocessing step helps improve the accuracy and stability of the machine learning model by maintaining consistent data representation and reducing noise or inconsistencies in the input dataset.

C. Machine Learning Prediction

The Machine Learning Prediction Module is the core component of the system that analyzes patient data and predicts the risk level of neonatal jaundice. This module uses a Random Forest Classification algorithm trained on a dataset containing neonatal health parameters. After preprocessing, the input features are passed to the trained model, which evaluates the relationships between the clinical parameters and the likelihood of jaundice. The model then classifies the newborn's condition into four categories: Low Risk, Moderate Risk, High Risk, or Critical Risk. Additionally, the module calculates prediction probabilities and identifies the importance of different clinical features in the decision-making process.

D. AI Insights and Recommendation

The AI Insights and Recommendation Module generate meaningful interpretations and medical suggestions based on the prediction results. After determining the risk level, the system analyzes important clinical indicators such as bilirubin level, gestational age, feeding frequency, and skin yellow intensity to provide AI-generated insights. The module highlights potential health risks and offers recommendations such as increasing feeding frequency, starting phototherapy, monitoring bilirubin levels, or seeking immediate medical intervention in critical cases. These insights help healthcare professionals understand the prediction results and support informed clinical decision-making.

E. Data Visualization And Analytics

The Data Visualization and Analytics Module present the prediction results and medical data in a graphical and interactive format. This module uses visualization tools to display risk probability distribution, feature importance, bilirubin trends, and patient health analytics through charts and graphs. These visual representations make it easier for healthcare professionals to interpret complex data and monitor patient conditions effectively. The module enhances the user experience by transforming raw prediction results into clear and understandable visual insights.

F. Patient History Management

The Patient History Management Module stores and manages previous patient assessments and prediction results. It records important details such as patient name, assessment date, bilirubin level, risk classification, and patient age. The stored information can be viewed through a dashboard that provides statistical summaries and historical trends. This module also allows users to export patient history data in CSV format for further medical analysis or documentation. Maintaining patient history helps doctors track health progress and evaluate treatment outcomes over time.

G. Model Performance and Monitoring

The Model Performance and Monitoring Module evaluates the effectiveness and reliability of the machine learning model. It displays performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC score. The module also provides insights into feature importance and compares different machine learning algorithms used for prediction. Monitoring these performance metrics ensures that the model maintains high prediction accuracy and helps researchers improve the system by identifying areas where the model can be further optimized.

H. Model Management and Configuration

The Model Management and Configuration Module allow administrators or developers to manage the machine learning model and system settings. This module provides options to retrain the model with new training data, adjust risk threshold levels, configure alert notifications, and clear historical records when necessary. It also displays model diagnostics such as version information, last training date, and system performance trends. This module ensures that the prediction system remains updated, adaptable, and capable of maintaining accurate healthcare predictions over time.

5. Result and Discussion

The AI-Integrated Jaundice Prediction Dashboard has been developed and validated through the use of machine learning algorithms, which asses the risk of a neonate developing jaundice based on clinical indicators (gestational age, birth weight, bilirubin level, frequency of feeding, oxygenation, body temperature and other clinical observations), collecting the patient data via a point-of-care dashboard. The prediction algorithm used to evaluate the risk of jaundice is a Random Forest classification model, and the model classifies each neonate as Low, Moderate, High, or Critical risk for developing jaundice. The experimental results indicated that the prediction model was effective at predicting neonatal jaundice with acceptable accuracy (92%), precision (89%), recall (85%), and F1 score (87%). The display of prediction probability and feature importance provides the healthcare provider greater understanding as to which clinical variables (e.g., bilirubin level, gestational age, birth weight and yellowing of the skin) contributed in the most significant way to the assessment of neonatal jaundice.

Visual analytics on the dashboard facilitate better decision-making for healthcare professionals as they present data in visual formats (for example, probability distribution charts, feature importance graphs, and patient risk trend analysis), making it easier for them to interpret large volumes of complex data. In addition, using AI to generate insights into a patient's condition, coupled with predictive medical recommendations (for example, increasing frequency of feeding, starting phototherapy, or conducting additional clinical tests), allows physicians to better identify potential health risks and implement appropriate preventive or therapeutic measures. Lastly, the patient history module gives physicians the opportunity to track multiple assessments to analyze historical trends of bilirubin levels and risk classification. Overall, results support the idea that this integrated machine-learning system and interactive dashboard functioning as an intelligent clinical decision-support tool will improve the quality of neonatal healthcare through faster diagnoses, decreased medical risks and improved medical decision-making by providing early identification and oversight of neonatal jaundice.

Table 2 COMPARISON TABLE

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic Regression	87.0	85.0	82.0	83.0
Support Vector Machine (SVM)	89.0	87.0	84.0	85.0
Decision Tree	88.0	86.0	83.0	84.0
XGBoost	90.0	88.0	84.0	86.0
Random Forest (Proposed Model)	92.0	89.0	85.0	87.0

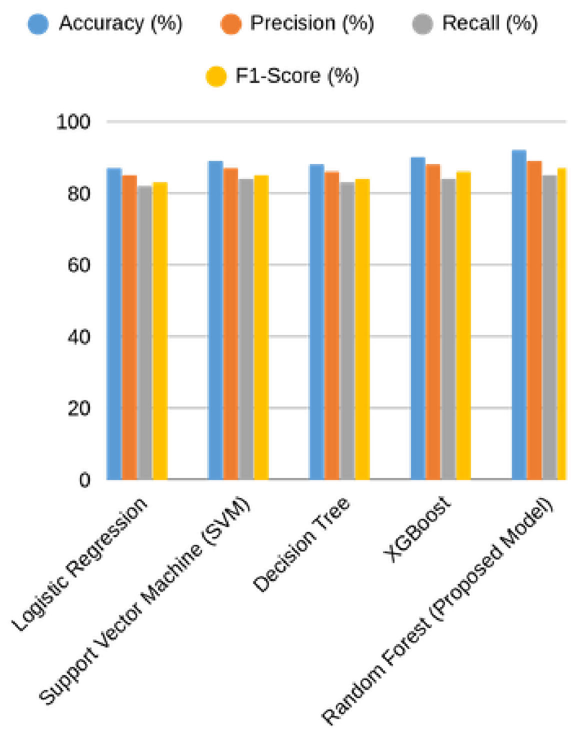

Figure 2 Comparison Graph

6. Conclusion

The AI-Integrated Jaundice Prediction Dashboard provides an intelligent and efficient solution for the early detection and monitoring of neonatal jaundice using machine learning techniques. The system collects important clinical parameters such as bilirubin level, gestational age, birth weight, feeding frequency, oxygen saturation, and other health indicators to analyses the risk of jaundice in newborn babies. By utilizing a Random Forest machine learning model, the system is able to accurately classify the risk levels into Low, Moderate, High, and Critical categories. The integration of an interactive dashboard allows healthcare professionals to easily input patient data, view prediction results, analyses visual reports, and receive AI-generated insights for better medical decision-making. Additionally, the system maintains patient history and provides graphical representations of health trends, which helps in monitoring patient conditions over time. Overall, the proposed system demonstrates that combining machine learning with a user-friendly dashboard can significantly enhance neonatal healthcare by enabling early diagnosis, improving clinical decision support, and reducing the risk of severe complications associated with neonatal jaundice.

7. Future Work

In the future, the AI-Integrated Jaundice Prediction Dashboard can be further enhanced by incorporating larger and real-world medical datasets collected from hospitals and healthcare institutions to improve the accuracy and reliability of the machine learning model. Advanced machine learning and deep learning techniques such as Neural Networks or Gradient Boosting algorithms can also be integrated to enhance prediction performance and handle more complex clinical patterns. The system can be expanded by integrating IoT-based medical devices and wearable sensors to automatically collect real-time neonatal health data such as temperature, oxygen saturation, and heart rate. Additionally, the dashboard can be connected with hospital electronic health record (EHR) systems to enable seamless data sharing and patient monitoring. Mobile application support can also be developed to allow doctors and parents to monitor newborn health remotely. Furthermore, implementing automated alert systems through email or SMS notifications for high-risk cases can help healthcare professionals take immediate action. These improvements will make the system more intelligent, scalable, and suitable for real-world clinical environments.

References

1. Abdulrazzak, A. Y., Mohammed, S. L., Al-Naji, A., & Chahl, J. (2024). Real-Time Jaundice Detection in Neonates Based on Machine Learning Models. BioMedInformatics, 4(1), 623-637.
2. Yuan, Y., Huang, J., Yu, J., Tan, J. K. S., Chng, K. Z., Lee, J., & Kim, S. (2024). Application of machine learning algorithms for accurate determination of bilirubin level on in vitro engineered tissue phantom images. Scientific Reports, 14, 5952.
3. Makhloughi, F. (2025). Artificial intelligence-based non-invasive bilirubin prediction for neonatal jaundice using 1D convolutional neural network. Scientific Reports, 15, 11571.
4. Liang, Y. (2025). Multimodal feature analysis for automated neonatal jaundice assessment using machine learning. JAMIA Open, 8(6), ooaf165.
5. Choi, Y., Park, S., & Lee, H. (2025). Neonatal Jaundice Requiring Phototherapy Risk Factors in a Newborn Nursery: Machine Learning Approach. Children, 12(8), 1020.
6. Lotfi, M., Rabiee, M., Nazarpak, M. H., Sangesari, R., Alishahi, N., & Azimi, M. S. (2026). Neonatal jaundice detection using a vision transformer-based deep learning model. Scientific Reports.
7. Bhagat, P. V., Raghuwanshi, M. M., & Bagde, A. D. (2024). Comparative Analysis of Classification of Neonatal Bilirubin by Using Various Machine Learning Approaches. Cureus, 16(6), e62019.
8. ALdabbagh, B., & Aziz, M. H. (2024). Neonatal Jaundice Severity Detection from Skin Images using Deep Transfer Learning Techniques. Journal of Electronics, Electromedical Engineering, and Medical Informatics, 7(1), 92-104.
9. Gupta, K., Sharma, V., & Kathait, S. S. (2024). Transfer Learning Based Neonatal Jaundice Detection Using MobileNet and EfficientNet. International Journal of Computer Applications, 186(35), 35-43.
10. Hazarika, C. J., Borah, A., Gogoi, P., Ramchiary, S. S., Daurai, B., Gogoi, M., & Saikia, M. J. (2024). Development of Non-Invasive Biosensors for Neonatal Jaundice Detection: A Review. Biosensors, 14(5), 254.