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AI-Driven Neo-Maternal Diagnosis: A Machine Learning Framework for Early Maternal and Neonatal Risk Prediction

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ABSTRACT- Neo-maternal diagnosis is concerned with recognizing health-related problems in pregnant women and newborn infants at an early stage. The growing availability of analytical tools and clinical data has led to increased use of machine learning methods in studies related to maternal and neonatal care. These methods are mainly used to support disease detection, outcome estimation, and clinical judgment. This review summarizes previous studies that have employed machine learning for neo-maternal diagnosis, focusing on the methods used, the nature of the data, and the results obtained. The paper also discusses the major difficulties, practical limitations, and possible areas for future investigation in the development of dependable and understandable diagnostic systems to improve maternal and neonatal health care.

KEYWORDS- Neo-Maternal Diagnosis, Machine Learning, Maternal-Fetal Health, Predictive Analytics, Preeclampsia, Gestational Diabetes, Healthcare Automation, Preterm Birth.

I. INTRODUCTION

Maternal and child health is one of the several important markers of health progress in a society. And despite the advances that science has made in medicine, many mothers and babies remain at serious risk during their pregnancies and deliveries. The risk of these complications can be reduced considerably with early identification of problems like preeclampsia, gestational diabetes, anemia and preterm labor. In most cases, these diseases can be detected when the symptoms become serious which you will not have any chance for preventive treatment

The rise of artificial intelligence (AI) and machine learning (ML) in health has introduced new opportunities for analyzing complex biomedical data and revealing disease patterns that may not be discovered using traditional methodologies. When the system processes a large amount of data from mother and foetus, ML algorithms are capable of predicting future complications and aiding doctors with clinical decisions by providing individualized suggestions to each patient. Conventional diagnostic tools commonly depend on manual information assimilation, e.g., reading ultrasound reports, blood parameters and vital signs, which may be time-consuming and prone to human error. On the other hand, the ML based diagnostic systems can be designed to perform automated analysis of data with applications of algorithms like Random Forest (RF), Support Vector Machine (SVM), XG Boost and Logistic Regression to uncover subtle patterns. Such models improve the accuracy and efficiency of clinical predictions. The use of Explainable AI (XAI) frameworks such as SHAP13 and LIME14 ensure interpretability in the predictions which enable clinicians to have insight on how particular factors impact outcomes.

II. RELATED WORK

Anjali Sharma et al. implemented a machine learning model for predicting high-risk pregnancies using maternal data such as age, blood pressure, glucose, and hemoglobin levels. The study compared Logistic Regression, Random Forest, and SVM models, concluding that Random Forest achieved the highest accuracy in early risk prediction [1].

Priya and R. Suresh proposed a maternal health monitoring system that leverages Artificial Neural Networks (ANN) to predict pregnancy complications like gestational diabetes and preeclampsia. Their model demonstrated improved reliability by combining clinical and lifestyle data [2].

Ritu Gupta et al developed a Clinical Decision Support System (CDSS) for maternal–fetal risk detection using Decision Tree and K-Nearest Neighbors (KNN) classifiers. Their model assists healthcare professionals in making fast and data-driven diagnostic decisions [3].

S. Deepa and A. Kumar presented an ensemble learning approach combining Gradient Boosting and Random Forest for detecting hypertension and anemia in pregnant women. The hybrid model outperformed single algorithms in precision and recall metrics [4].

P. Bhattacharya et al. investigated the role of Explainable AI (XAI) techniques in maternal diagnosis. Using SHAP and LIME for feature interpretability, their study improved transparency in machine learning predictions, enabling clinicians to trust model outputs [5].

M. Lakshmi and T. Rajesh built a predictive analytics model using the XGBoost algorithm to identify early signs of gestational diabetes. The model was trained on clinical datasets and achieved high accuracy through optimized hyper parameters [6].

A. Thomas and S. Fernandes explored neural network–based pregnancy risk prediction using multiple physiological parameters. Their deep-learning framework adapted over time, reducing false negatives in maternal condition predictions [7].
K. Patel and J. Kaur implemented a hybrid CNN–RNN model for analyzing ultrasound scan data and predicting fetal health anomalies. The network effectively processed sequential image data for real-time diagnosis support [8].
Dr. P. Meenakshi and N. Prabhu utilized machine learning–based regression models to predict fetal weight and birth outcomes. Their results suggested that data-driven models can outperform conventional clinical estimation methods [9].
R. Naik and G. Hegde introduced an IoT-enabled maternal monitoring system integrated with ML algorithms. The system collected sensor-based data in real-time and used Decision Tree classification for anomaly detection in maternal vitals [10].
S. Rao et al. proposed an adaptive healthcare system for neonatal health prediction using deep learning models. Their approach analyzed patterns from neonatal intensive care unit (NICU) datasets to forecast potential health issues [11].
A. Dutta and B. Sen worked on maternal mortality reduction through predictive modeling using Logistic Regression and Random Forest. Their research emphasized the importance of dataset balance and interpretability in life-critical domains [12].
N. Shree and D. Verma developed a cloud-integrated maternal diagnostic tool that supports remote healthcare delivery. The model uses predictive learning to provide early alerts for at-risk pregnancies in rural areas [13].
K. Raj and P. Sharma demonstrated that transfer learning models like ResNet-50 and MobileNet can effectively analyze maternal ultrasound images to detect abnormalities. Their CNN-based approach achieved significant improvement in diagnostic precision [14].
M. Jain et al. created a machine learning pipeline combining data preprocessing, feature selection, and ensemble classification for pregnancy outcome prediction. The system achieved a balanced accuracy across diverse patient demographics [15].
T. Varghese and L. Menon introduced an interpretable diagnostic model that merges Bayesian networks with decision trees. This hybrid system offered probabilistic insights into pregnancy risks, aiding clinical understanding [16].
H. Iqbal and F. Ahmad explored sentiment and behavioral data analysis from maternal health surveys. Using natural language processing (NLP) with ML classifiers, the study identified emotional stress patterns linked to high-risk pregnancies [17].
R. Banerjee et al. proposed a fetal health classification model using the Cardiotocography dataset and Support Vector Machine. Their findings showed that SVM provided superior classification results compared to Naive Bayes and Decision Trees [18].
S. Krishnan and P. Gupta emphasized predictive modeling for neonatal mortality using ensemble ML methods. Their system combined Logistic Regression and Random Forest to produce stable and interpretable predictions of neonatal health risks [19].
V. Ramesh and S. Nandhini designed a prediction model using Support Vector Machines (SVM) to classify maternal health conditions. The model used features from real-world hospital data and showed high sensitivity in identifying preterm birth risks [20].

III. PROBLEM FORMULATION

Maternal and newborn health issues still create big problems worldwide, causing lots of illness and death during pregnancy and just after birth. Problems like high blood pressure in moms, diabetes while pregnant, early delivery, poor baby growth, or infections in infants need quick spotting so bad effects don't happen. Still, old-school diagnosis uses hands-on checks, doctor guesses, and lab work - methods that take time, feel uncertain, and sometimes mess up.
That delay means care comes late, more stays in hospitals, particularly where expert doctors are hard to reach. Even though tons of mom-and-baby health info now comes from digital files, body trackers, and live monitors, current checklist-style tools struggle to make sense of messy, layered data. So, we really need smart, self-running tools that use learning algorithms to give fast and precise results. These kinds of systems might help doctors act sooner, catch problems earlier, and boost health chances for both mom and baby.

A. Objectives of the Proposed System

The following are the Objectives of the proposed Neo Maternal Diagnosis project, each designed to overcome existing limitations in traditional maternal and neonatal risk detection by leveraging AI-driven analysis, automated prediction models, and advanced clinical decision-support techniques:

- Build machine learning tools that spot serious pregnancy issues - like preeclampsia or early labor - not just list them. Instead of waiting, catch warning signs sooner through patterns in data. Try out methods such as Random Forest or XGBoost; they work well when trained right. These models learn from past cases, so predictions get sharper over time. SVM can help too, especially with tricky boundaries between normal and risky outcomes.
- Improve early neonatal assessment by designing ML algorithms that detect complications like neonatal sepsis, respiratory distress, and low birth weight. Use vital signs, biochemical markers, and clinical history for real-time risk alerts.
- Pre-process and optimize maternal–foetal datasets through missing-value handling, outlier removal, and feature engineering. Apply normalization techniques to enhance model performance, accuracy, and overall stability.
- Ensure interpretability of ML models using explainable AI tools like SHAP and LIME. Provide clear reasoning behind predictions to support healthcare professionals in clinical decision-making.
- Integrate ML diagnostics into clinical workflows through an automated decision support system linked with EMRs and mobile apps. Enable real-time alerts and personalized treatment recommendations for mothers and newborns.
- Explore continuous-learning AI systems that update models with new maternal health data. Maintain long-

term accuracy, personalization, and adaptability across various clinical environments.

IV. METHODOLOGY AND ARCHITECTURE

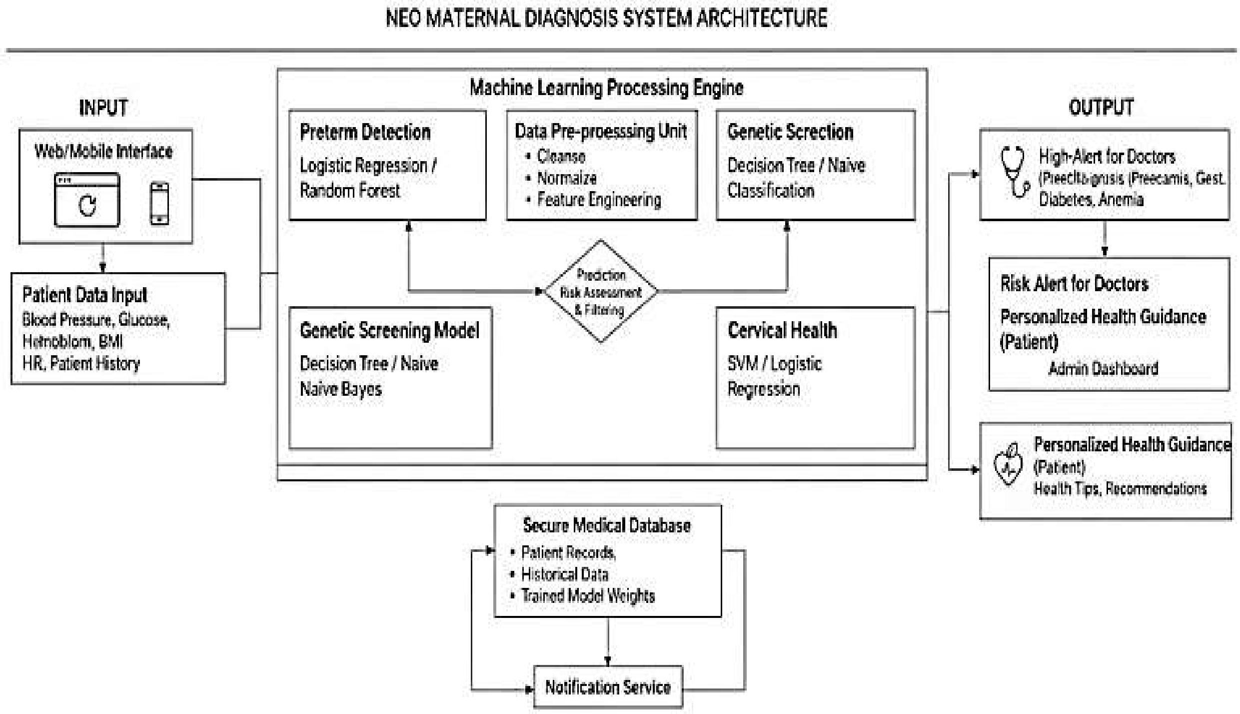

Figure 1: System architecture of the proposed system

Figure 1 shows how the new pregnancy check system is built. This setup uses several connected parts working at once to catch mom and baby health issues sooner. Instead of just one piece doing all the work, it mixes raw data cleanup with smart prediction tools made from past cases. A helpful chat feature gives instant feedback, tailored tips, or alerts med
staff when things look off. All pieces run together smoothly so moms get faster, clearer advice during their care journey. The Neo-Maternal Diagnosis setup uses several machine learning parts to help spot pregnancy risks early while giving instant health tips. People use a phone app or website to enter mom's health details - like vital signs, symptoms, and daily habits. That data moves over to the ML Engine, which runs smart models checking for issues like early labor, blood sugar problems, low iron, or inherited conditions. Just before analysis, the raw info gets cleaned up, adjusted, and turned into usable features so the predictions stay accurate. The system checks risk levels while offering custom feedback. During crises, a live map tool helps people find close medical help. A built-in assistant boosts engagement - giving advice, sharing wellness hints, or explaining results from the analysis. Altogether, it supports constant tracking, solid forecasts, and easier access to care for pregnant women.

IV. ALGORITHMS

- Logistic Regression: Used for binary and multiclass classification problems to determine risk levels such as low, medium, or high.
- Use Case: Predicts whether a pregnant woman falls under a high-risk category based on parameters like blood pressure and glucose level.
- Decision Tree Classifier: Constructs a tree-like model for decision-making by splitting data into feature-based branches.
- Use Case: Helps classify maternal conditions (e.g., anemia, preeclampsia) based on clinical test results.
- Random Forest: An ensemble of multiple decision trees that improves prediction accuracy and reduces over fitting.
- Use Case: Provides robust maternal health risk predictions by combining outputs from several models.
- Support Vector Machine (SVM): Identifies optimal boundaries between classes for accurate classification in high-dimensional data.
- Use Case: Detects complex medical patterns, such as early symptoms of gestational diabetes or hypertension.
- K-Nearest Neighbors (KNN): Classifies new samples based on similarity to previously known data points. Use case: Compare a patient's data with existing cases to identify matching risk trends.
- Naïve Bayes: A probabilistic algorithm based on Bayes' theorem, suitable for categorical data.
- Use Case: Predicts maternal conditions using categorical inputs like symptom descriptions or survey responses.
- XGBoost (Extreme Gradient Boosting): A highly efficient boosting algorithm that improves accuracy through gradient-based optimization.
- Use Case: Used for final diagnosis scoring to generate the most accurate maternal health predictions.

V. RESULTS

The following section presents snapshots of the developed Forensic Face Sketch Construction and Recognition system (Figure 2 to Figure 10). Figure 2 serves as the entry point of the system, offering users a simple and welcoming interface. It provides quick access to major features such as registration, login, and diagnostic tools.

Figure 3 is the landing page and the landing page gives users an overview of the application and guides them toward key modules. It ensures smooth navigation by highlighting important system functionalities.

Figure 4 shows new users to securely enter personal and medical details required for diagnosis. It ensures accurate data collection, which forms the foundation for reliable machine-learning predictions.

Figure 5 shows the login interface enables authenticated access to the system for patients and healthcare professionals. It ensures data privacy and secure usage through validated credentials.

Figure 6 is the dashboard page, the dashboard provides a centralized view of system features, patient updates, and diagnostic shortcuts. It helps users efficiently access health records, predictions, and alerts in a structured layout.

Figure 7 displays a comprehensive list of patient details and medical history in an organized format. It supports clinicians by offering quick access to vital information for decision-making.

Figure 8, the preterm detection interface analyses maternal health data to assess early-delivery risks. It presents prediction results clearly to assist doctors in initiating preventive care.

Figure 9 displays Cervical Health Details Page; this page presents cervical health indicators and diagnostic insights relevant to pregnancy wellness. It helps identify abnormalities early by summarizing important clinical parameters.

Figure 10, the genetic screening interface evaluates hereditary risk factors using machine-learning analysis. It provides clear visual indicators to assist in early identification of genetic complications.

Figure 11 shows the graph compares the accuracy of four machine-learning models used in the Neo-Maternal Diagnosis system. XGBoost and Random Forest show the highest performance, indicating their strong predictive capability for maternal risk detection.

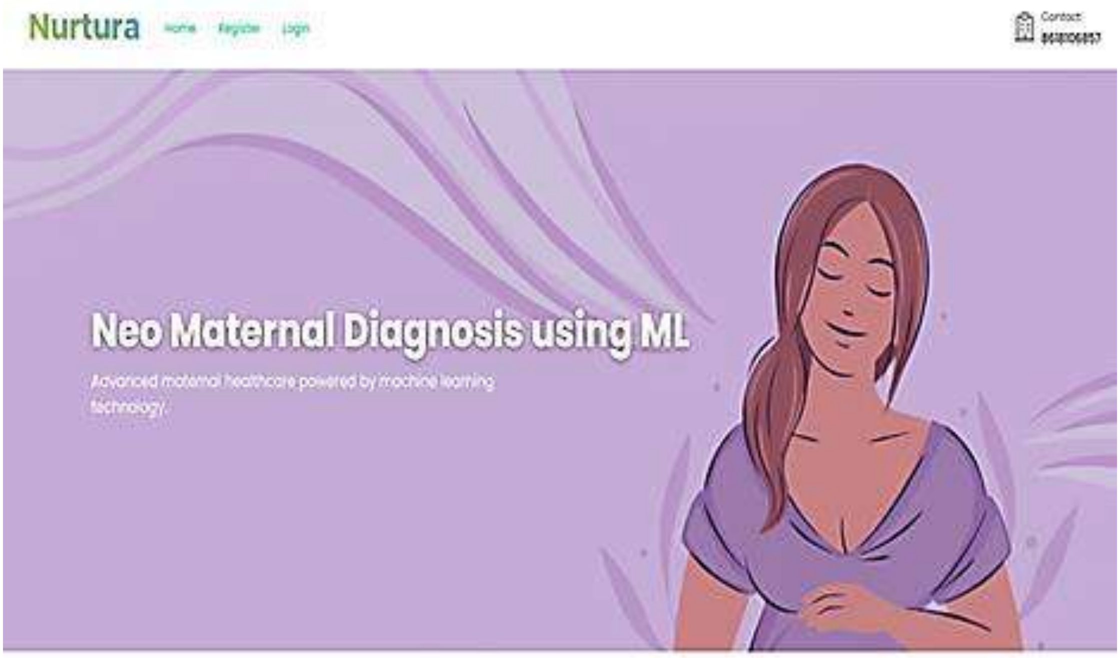

Figure 2: Home page

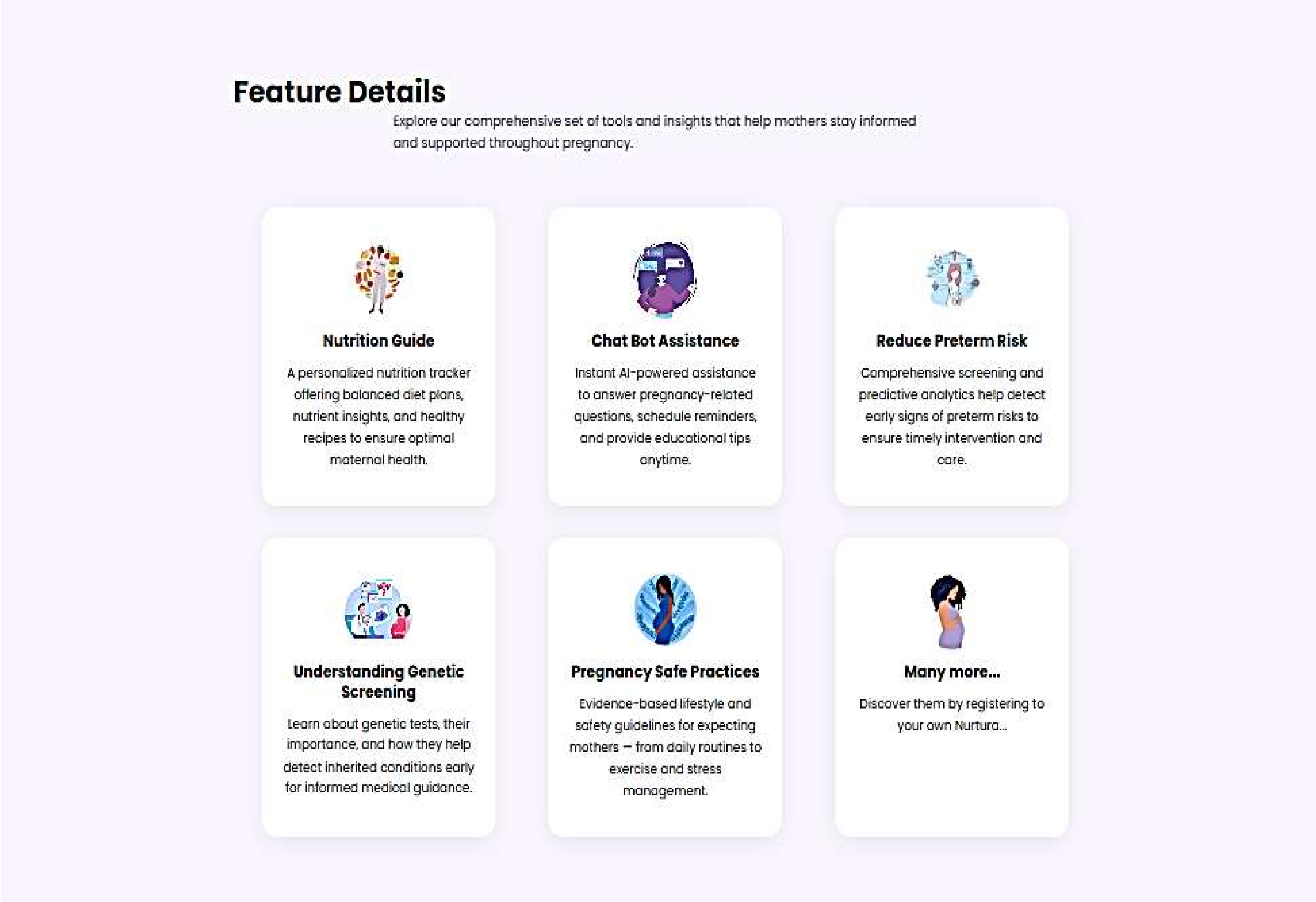

Figure 3: Landing page

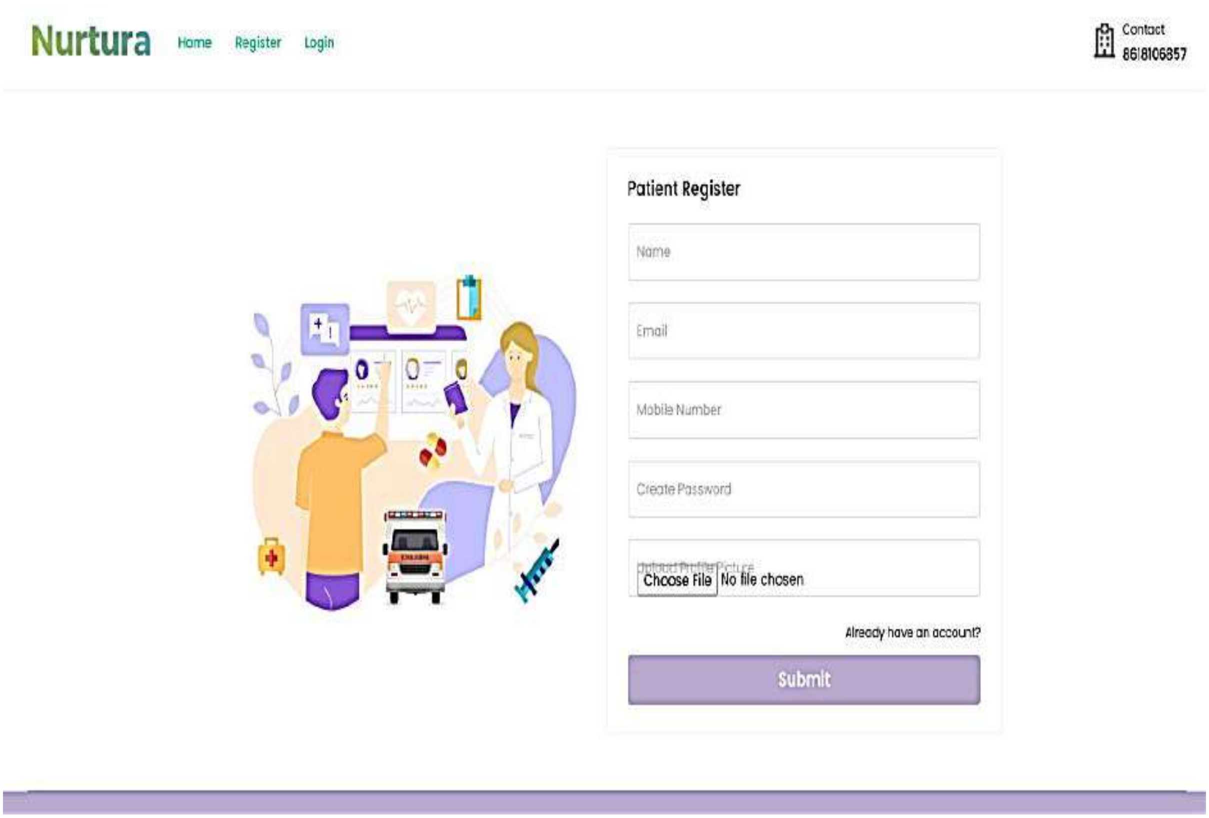

Figure 4: Patient registration page

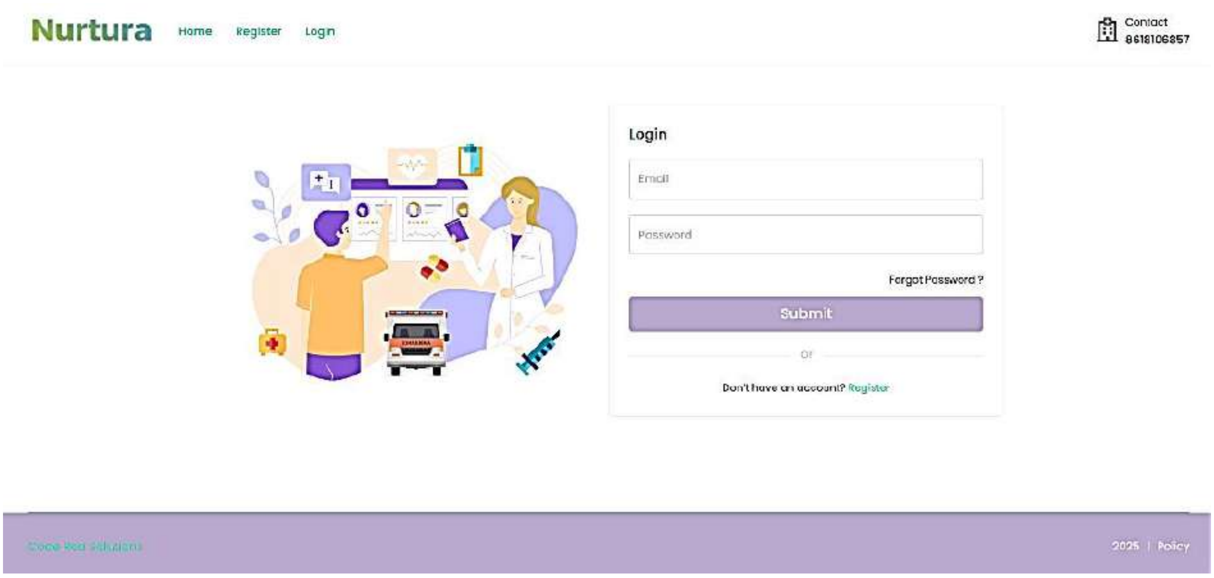

Figure 5: Login page

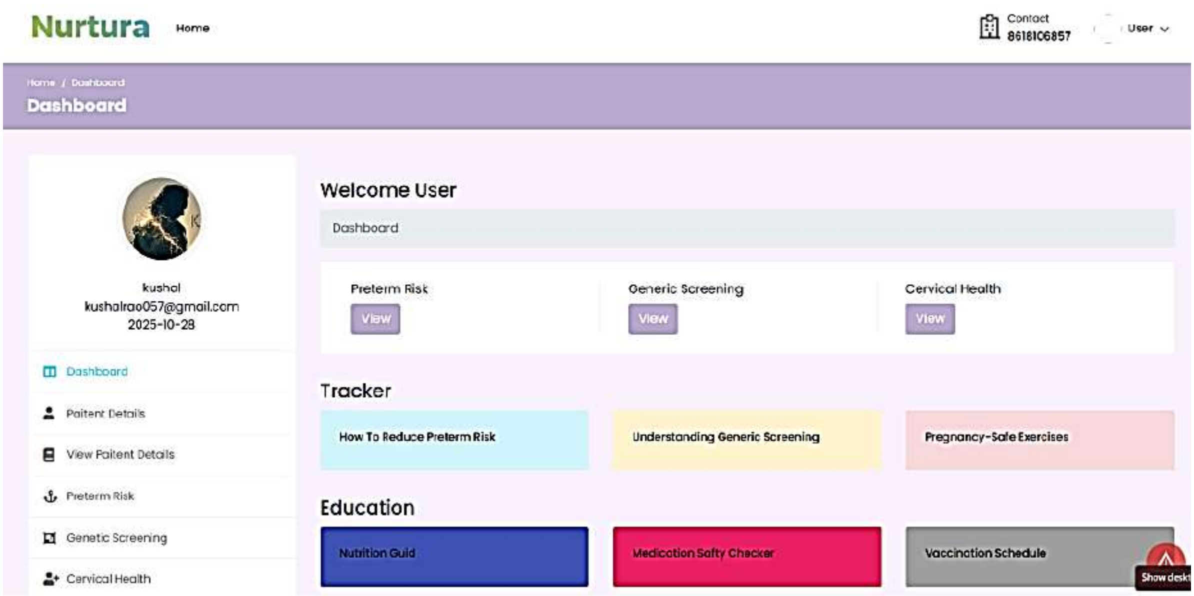

Figure 6: Dashboard page of the interface

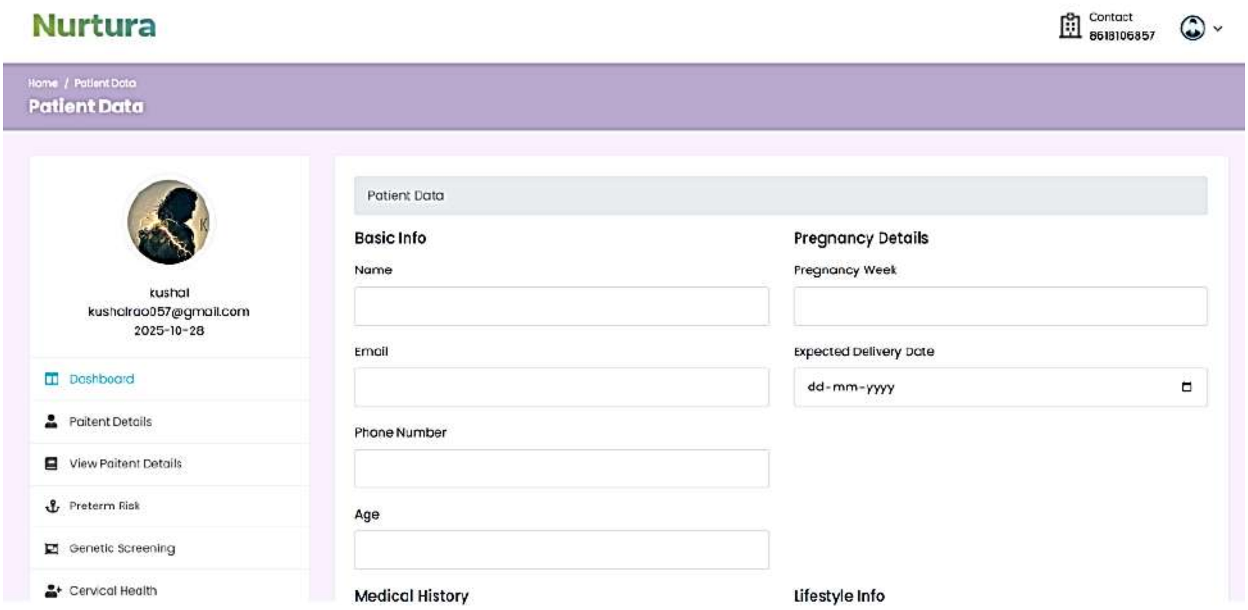

Figure 7: Patient Data page

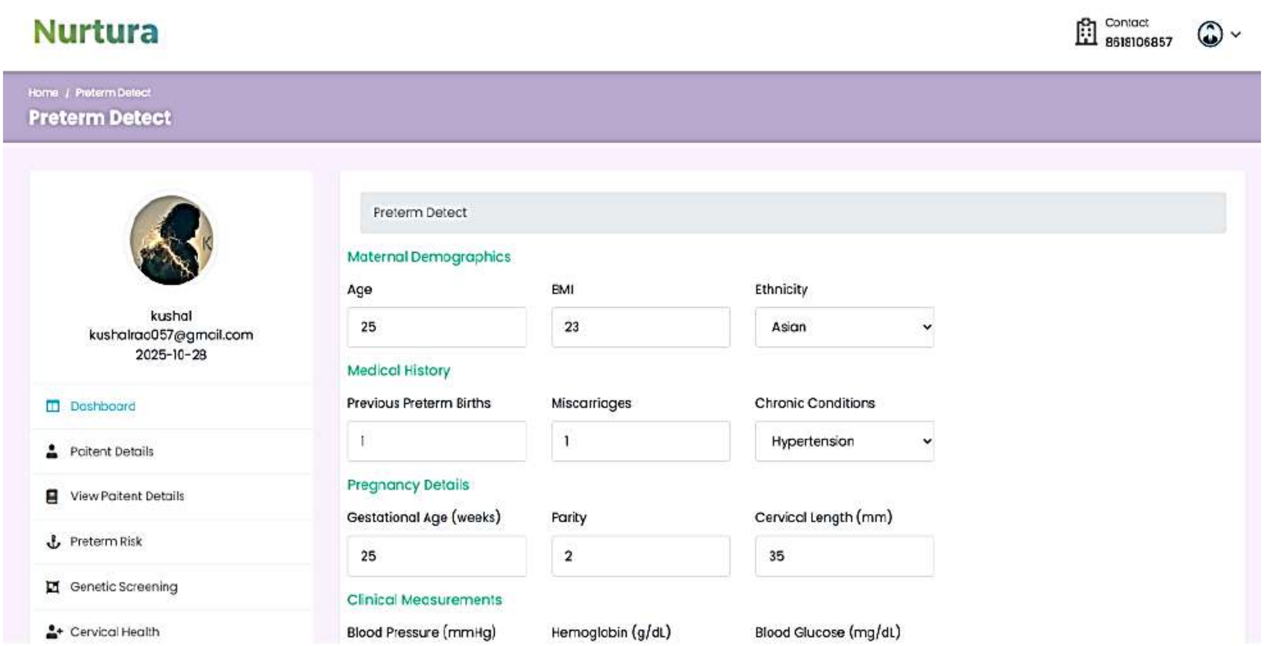

Figure 8: Preterm detect page

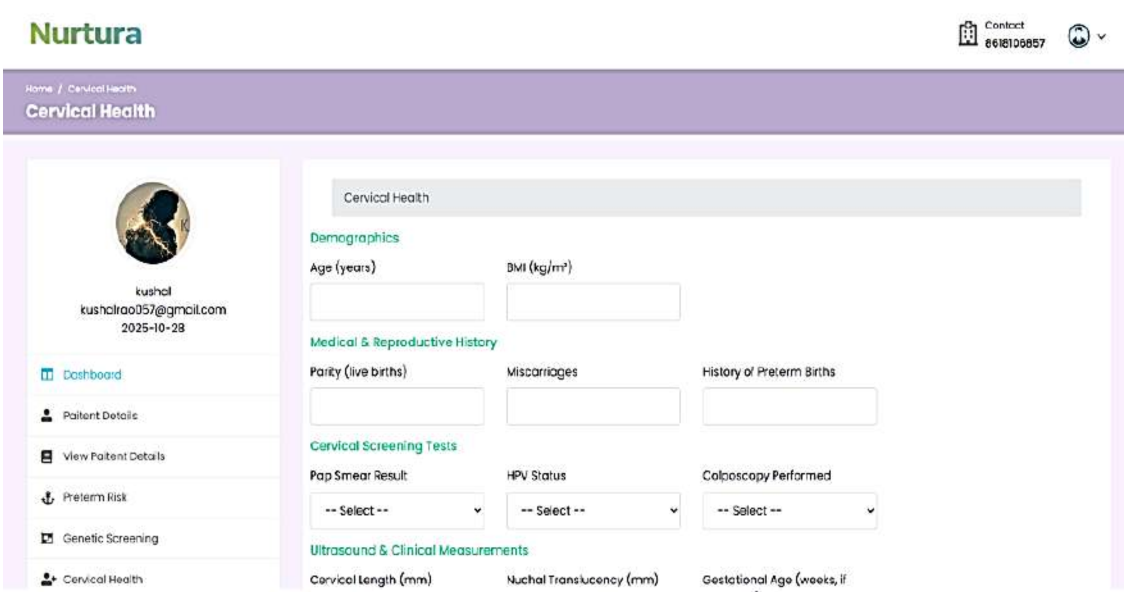

Figure 9: Cervical health details

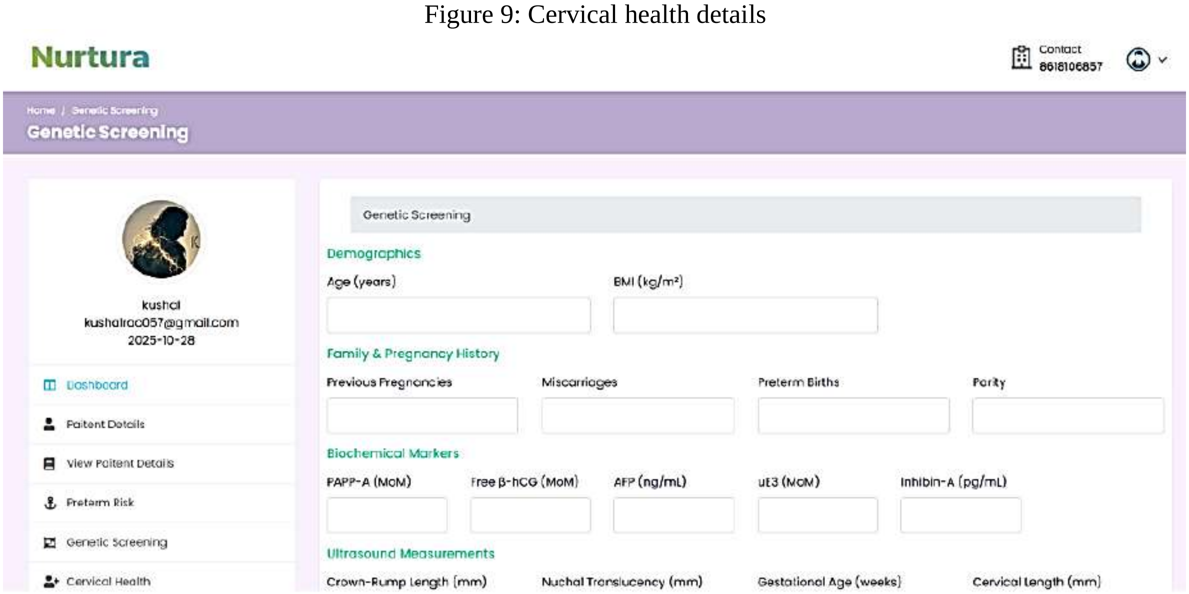

Figure 10: Genetic screening page

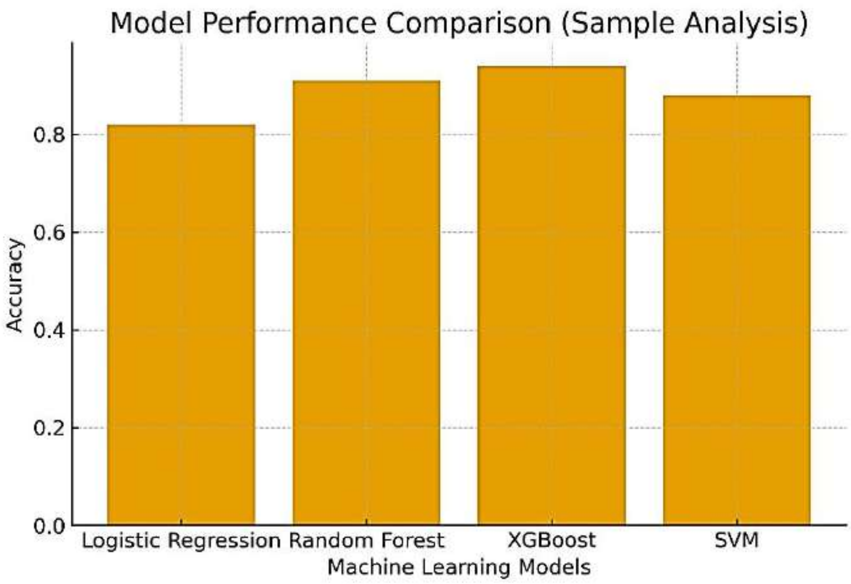

Figure 11: Graphical representation of model performance comparison

VI. RESULTS

The Neo-Maternal Diagnosis setup shows how machine learning can change mom and baby care by spotting risks early, predicting outcomes, while giving tailored help. Instead of just traditional methods, it uses smart tools like Logistic Regression, Random Forest, or XGBoost paired with a responsive chatbot - helping moms stay involved and assessed quickly. This model doesn't simply boost diagnosis precision - it connects tech use with real-world access, especially where resources are tight. With clear data patterns and models people can understand, it gives doctors and pregnant women better info to act on. In short, this research highlights how AI might lead to healthier pregnancies, faster responses when needed, plus fairer care for all moms.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] Sharma, S. Arakeri, R. Kanungo, and S. Pagi, "Hematological changes in platelet apheresis donors: An observational study," *Cureus*, vol. 16, no. 11, p. e73907, Nov. 2024. Available from: https://tinyurl.com/ydp4e582

[2] R. Haripriya, M. Suresh, and C. B. Vinutha, "A hybrid routing algorithm using artificial neural network and swarm intelligence for wireless sensor networks," *J. Neonatal Surg.* [Internet], vol. 14, no. 27S, pp. 757–768, May 2025.

[3] R. P. Singh *et al*., "Exploring neural network approaches for Alzheimer's disease detection: An analysis of RNN and CNN performance," in *Proc. 2024 Int. Conf. Communication, Computer Sciences and Engineering (IC3SE)*, Gautam Buddha Nagar, India, 2024, pp. 1028–1033. Available from: https://ieeexplore.ieee.org/abstract/document/10593216

[4] S. Rinesh, S. Deepa, R. T. Nandan, R. S. Sachin, S. V. Thamil, R. Akash, M. Arun, C. Prajitha, and A. P. Senthil Kumar, "Prediction and classification of solar photovoltaic power generation using extreme gradient boosting regression model," *Int. J. Low-Carbon Technol.*, vol. 19, pp. 2420–2430, 2024. Available from: https://doi.org/10.1093/ijlct/ctae197

[5] J. Li, X. Liu, S. He, and Y. Ren, "Interpretable machine learning for predicting adverse pregnancy outcomes in gestational diabetes: Retrospective cohort study," *JMIR Med. Inform.*, vol. 13, p. e71539, 2025. Available from: https://medinform.jmir.org/2025/1/e71539

[6] X. Hu *et al*., "Prediction model for gestational diabetes mellitus using the XGBoost algorithm," *Front. Endocrinol. (Lausanne)*, 2023. Available from: https://doi.org/10.3389/fendo.2023.1105062

[7] M. Alzubaidi *et al*., "Toward deep observation: Survey on AI for fetal growth monitoring via ultrasound and deep learning," *iScience*, 2022. Available from: https://www.cell.com/iscience/fulltext/S2589-0042(22)00985-3

[8] X. Ouyang *et al*., "Multi-modal AI for embryo grading and pregnancy prediction," *Ann. Biomed. Eng.*, 2025. Available from: https://link.springer.com/article/10.1007/s10439-025-03865-1

[9] S. Meenakshi, M. Suganthi, and P. Suresh Kumar, "An approach for automatic detection of fetal gestational age at the third trimester using kidney length and biparietal diameter," *Soft Comput.*, vol. 23, no. 8, 2019. Available from: https://doi.org/10.1007/s00500-019-03913-8

[10] K. Sooda *et al*., "Android monitor for maternity care using cloud and IoT," 2017.

[11] S. Das, R. Dutta, S. B. P. A., B. Roy, and P. Ghosh, "A machine learning approach to predict NICU units in hospital by developing smart e-healthcare system," in *Proc. 2023 3rd Int. Conf. Pervasive Computing and Social Networking (ICPCSN)*, Salem, India, 2023, pp. 199–204. Available from: https://ieeexplore.ieee.org/abstract/document/10266092

[12] M. Dutta, S. Ghosh, and Z. Husain, *Maternal and Child Health in India: Networks and Information Diffusion*, 1st ed. New Delhi, India: Routledge India, 2024. Available from: https://doi.org/10.4324/9781003499251

[13] Verma *et al*., "Near-miss obstetric events and maternal deaths in a rural tertiary care center in North India," *Cureus*, vol. 12, no. 12, 2020. Available from: https://tinyurl.com/4w8e37k5

[14] R. Ranjan *et al*., "Comparative analysis of ultrasound and MRI in diagnosing uterine fibroids: A cross-sectional study," *Eur. J. Cardiovasc. Med.*, vol. 14, no. 3, 2024. Available from: https://tinyurl.com/5572phc4

[15] Jain and D. Zongker, "Feature selection: Evaluation, application, and small sample performance," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 19, no. 2, pp. 153–158, 2002. Available from: https://ieeexplore.ieee.org/abstract/document/574797

[16] H. Wang *et al*., "Efficacy and safety of dihydropyridine calcium channel blockers for primary hypertension: A Bayesian network meta-analysis," *Curr. Hypertens. Rev.*, vol. 21, no. 2, pp. 117–128, 2025. Available from: https://doi.org/10.2174/0115734021357729250214090452

[17] G. Ahmad, S. Saima, *et al*., "Sensing and artificial intelligent maternal-infant health care systems: A review," *Sensors*, vol. 22, no. 12, p. 4362, 2022. Available from: https://doi.org/10.3390/s22124362

[18] J. Banerjee *et al*., "Haemoglobin level at birth is associated with short-term outcomes and mortality in preterm infants," *BMC Med.*, vol. 13, no. 1, p. 16, 2015. Available from: https://link.springer.com/article/10.1186/s12916-014-0247-6

[19] R. Dandona *et al*., "Subnational mapping of under-5 and neonatal mortality trends in India: The Global Burden of Disease Study 2000–17," *Lancet*, vol. 395, no. 10237, pp. 1640–1658, 2020. Available from: https://tinyurl.com/yc54xmjk

[20] R. S. Nandhini and R. Lakshmanan, "A novel ensemble learning approach for fault detection of sensor data in cyber-physical system," *J. Intell. Fuzzy Syst.*, vol. 45, no. 6, pp. 12111–12112, 2023. Available from: https://doi.org/10.3233/JIFS-235809

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