Maternal-Fetal Dynamics: Navigating the Intersection for Predicting Low Birth Weight

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Abstract:

This study addresses the critical need for predicting low birth weight during pregnancy to identify infants at risk of health complications. The research focuses on developing a simple and effective method by analyzing various maternal factors, including age, weight gain during pregnancy, and medical history. A reliable prediction model was created, allowing healthcare providers to identify women at a higher risk of giving birth to a low-weight baby early in pregnancy. The implementation of this model enables targeted interventions and personalized care, leading to improved outcomes for both mothers and their newborns. This approach enhances the daily practices of healthcare providers, ensuring proactive measures for at-risk pregnancies and contributing to overall maternal and infant well-being.

Keywords: Low birth weight Prediction,Proactive measures,Maternal and infant well-being.

1.Introduction:

The critical challenge of predicting low birth weight during pregnancy to identify infants at risk of health complications, the study focuses on developing a straightforward and efficient method by examining various maternal factors, including age, weight gain during pregnancy, and medical history. Through this investigation, a reliable prediction model is crafted, empowering healthcare providers to pinpoint women at a heightened risk of delivering a low-weight baby early in their pregnancy journey.Implementing this predictive tool allows healthcare professionals to initiate targeted interventions and deliver personalized care, leading to better outcomes for both mothers and their newborns.By enabling healthcare practitioners to take preventative actions for pregnancies that are at risk, this strategy seeks to improve their everyday practices and make a crucial contribution to the general well-being of mothers and infants. The model is a useful tool in the continuous endeavour to enhance the health outcomes of expectant mothers and their unborn children because of its simplicity and efficacy, which provide healthcare practitioners with applicable insights.

Fundamentally, the model is saying it means a lot to find out right on time in the event that a child may be brought into the world with a low weight. Along these lines, specialists can step in and help in time. They need to watch out for how the mother is doing during pregnancy and utilize straightforward checks to get any issues from the beginning. The principal point is to bring down the possibilities of children being conceived excessively little and having medical conditions, ensuring infants from one side of the planet to the other have a superior beginning throughout everyday life.

2.Literature Survey:

Silva Awor et al. (2022) [2]employed Logistic Regression and various predictors to screen for Low Birth Weight in Gulu, Uganda. Key predictors include gravidity, education level, serum ALT/GGT levels, lymphocyte count, placental location, and end-diastolic notch, aiding identification of at-risk pregnant women in prenatal clinics. The study provides valuable insights for targeted interventions in low-resource settings.

Liu et al. (2022) [4] conducted a literature review on interpretable machine learning for birth weight prediction. They utilized eight supervised models, including Linear Regression and Support Vector Machines, assessing model accuracy with root mean squared error via cross-validation. The study offers insights into interpretable machine learning applications, emphasizing robustness through rigorous validation.

Khan et al. (2022) [22]showcased the application of multiple ML algorithms for birth weight estimation in the UAE, incorporating Linear Regression, Support Vector Machines, Random Forests, K Nearest Neighbors, Artificial Neural Networks, and ensemble methods like AdaBoost. Utilizing a blend of maternal characteristics, prenatal factors, and environmental variables, these algorithms significantly improved the accuracy of birth weight estimation. The study offers a comprehensive exploration of diverse machine learning approaches in this context.

Arayeshgari et al. (2023)[26] reviewed literature showcasing diverse ML algorithms like Decision Trees, Random Forests, Support Vector Machines, K-Nearest Neighbors, Artificial Neural Networks, Logistic Regression, and ensemble methods such as AdaBoost and gradient boosting for LBW prediction. These classifiers consistently outperformed traditional statistical models, exhibiting higher accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve.

3.Overview of Existing System:

The Logistic Regression model is a key element in the existing system that helps determine whether a baby is considered Low Birth Weight or not. Using a variety of maternal parameters, this predictive model is trained and tested so that it can generate well-informed predictions based on the input.

Important elements pertaining to the mother's health, medical background, and demographic data are among the components taken into account by the model. Through the utilization of these characteristics, the Logistic Regression model evaluates the probability of Low Birth Weight in each unique instance, providing significant understanding into possible health hazards for infants. By using such a predictive model, medical professionals can make more educated judgments and advance our understanding of the factors impacting birth weight outcomes.

4.Proposed System

This research addresses the crucial need to predict low birth weight during pregnancy, aiming to identify infants at risk of health complications. The focus is on developing a predictive model utilizing a decision tree algorithm in machine learning. The model intricately examines vital maternal factors, including age, weight gain, and medical history, presenting a straightforward yet potent approach. Through the implementation of this system, early identification of at-risk pregnancies becomes possible, allowing for targeted interventions and personalized care. The resulting reliable prediction model empowers healthcare providers to proactively identify women at a higher risk of delivering a low-weight baby in the early stages of pregnancy. This proactive approach contributes to improved outcomes for both mothers and newborns. The proposed system's use of a decision tree algorithm enhances daily healthcare practices, ensuring timely measures for pregnancies at risk and positively impacting overall maternal and infant well-being.

5.System Architecture:

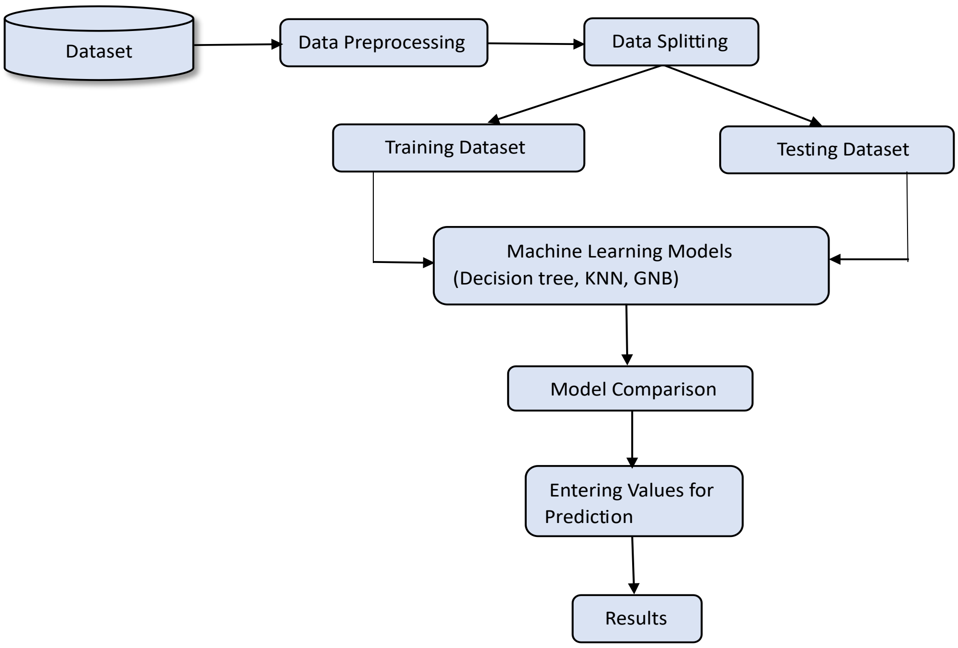

Fig.5.1. System Architecture

In the system architecture, the dataset undergoes processing, including the segmentation into training and testing sets. Machine learning models are then employed to predict mental and fetal values based on user-input data, with the results presented on the prediction page.

6.Results and Discussions

The figures presented are utilized for forecasting the occurrence of low-birth-weight problems. In Figure 2, users can input various parameters related to the pregnant women's conditions. Based on these inputs, the system generates messages to provide feedback or information to the user regarding the potential risks or outcomes associated with the entered values.

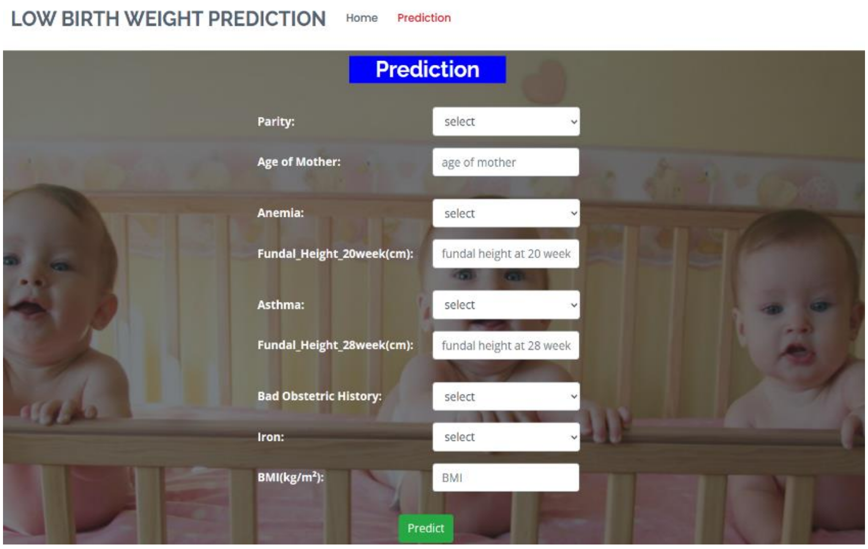

Fig.6.1.Prediction Page

Users provide inputs on this page, prompting the system to generate predictions based on their input, fostering an interactive and dynamicexperience.

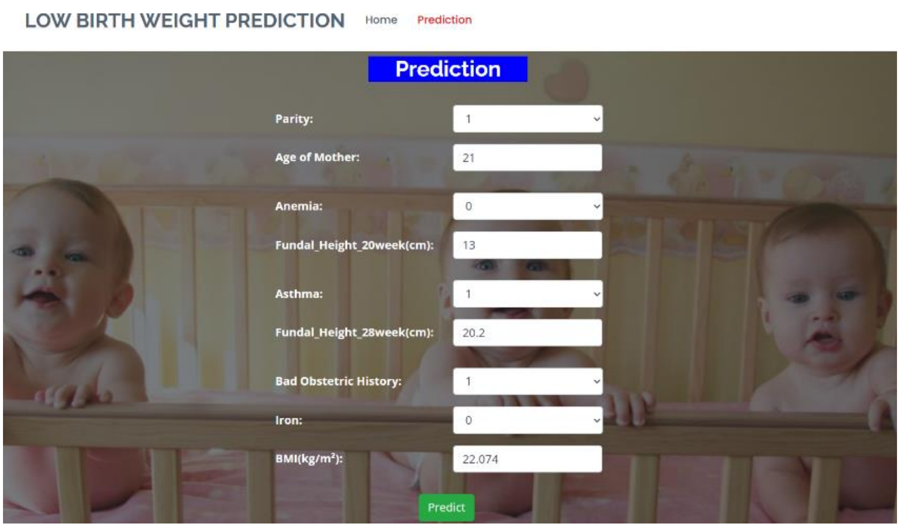

Fig.6.2.Entering Input's

Users input specific values related to pregnancy, enabling the system to generate predictions for the baby's birth weight, enhancing personalized guidance in the anticipation of a newborn's arrival.

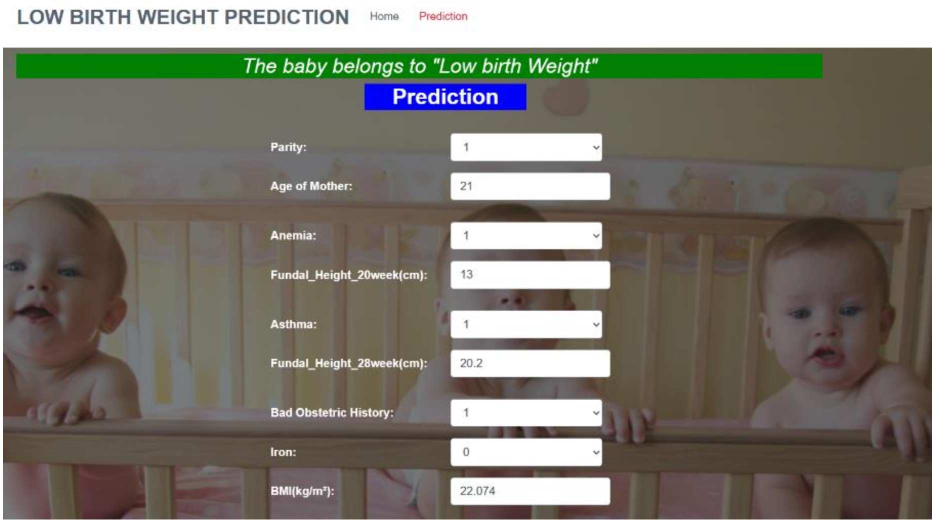

Fig.6.3.output Page

Finally, the system conveys the outcome resembling a message format, detailing whether the baby's weight aligns with the norm or not, utilizing diverse expressions for clarity and precision.

6.1. Table: Result Comparison

Models	Accuracy(%)
Decision Tree	91.13
K-Nearest Neighbour	75.36
Gaussian Naïve Bayes	73.39

Observations revealed that among K-Nearest Neighbor, Decision Tree Classifier, and Gaussian Naïve Bayes, the Decision Tree Classifier exhibited superior performance with an accuracy score of 91.13%. In contrast, K-Nearest Neighbor achieved a score of 75.36%, while Gaussian Naïve Bayes achieved 73.39%. This underscores the notable proficiency of the Decision Tree Classifier in achieving higher accuracy compared to the other algorithms.

7.Conclusion and Future Scope

In this specific application, an AI model was created to discover whether a child falls into the Low-Birth-Weight class. Eminently, while contrasting the presentation of K-Closest Neighbor, Choice Tree Classifier, and Gaussian Innocent Bayes, the Choice Tree Classifier arose as the top-performing model, showing a predominant precision score of 91.13%. Conversely, K-Closest

Neighbor accomplished a score of 75.36%, and Gaussian Credulous Bayes accomplished 73.39%. Future undertakings might include leading extra near investigations to recognize factors affecting Low Birth Weight cases. The ongoing framework is widely prepared on marked datasets, introducing a chance for development to unlabeled information. Also, there is potential for improving expectation execution through the joining of Gathering Learning methods in the framework's turn of events.

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