Predicting Low Birth Weight Cases Using Deep Learning Approach for Early Detection

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Abstract- Low Birth Weight is the major problem for the new born. Low birth weight is a term used to describe babies who are born weighing less than 5 pounds, 8 ounces (2,500 grams). Low-birth weight babies are more likely than babies with normal weight to have health problems as a newborn. Almost 40 percent of the new born suffer from underweight. Predicting birth weight before the birth of the baby is the best way to help the baby get special care as early as possible. It helps us to arrange for doctors and special facilities before the baby is born. There are several factors that affect the birth weight. Through past studies, it has been observed that the factors which affect the child birth range from biological characteristics like the baby's sex, race, age of mother and father, weight gained by the mother during pregnancy to behavioral characteristics like smoking and drinking habits of the mother, the education and living conditions of the parents. Our system is an live detection model and periodic analysis of mother and detecting physical levels in her by providing them with proper remedies for managing LBW by providing survey form periodically.

Indexed Terms- LBW, Smoking, Drinking habit, Biological, Pregnancy

I. INTRODUCTION

The aim of the project is to predict the baby weight so that the baby can get better care. It is done using machine learning model and in cloud environment. Machine learning plays a major role in medical diagnostics. We'll be able to incorporate bigger sets of data that can be analyzed and compared in real time to provide all kinds of information to the provider and patient. Low birth weight can be caused by a variety of circumstances, depending on the region. Low birth weight is associated with preterm in industrialized countries is caused by maternal age, smoking, multi-parity, and caesarean section. Low birth weight is caused by poor fetal growth is linked to poor maternal nutrition before and throughout pregnancy in less developed countries. Understanding the importance of preterm delivery and poor fetal growth as causes of low birth weight is critical for developing efective prevention interventions. Moreover, revealed education was one of the predictors in LBW modeling. Low birth weight is a critical determinant of infant health, influencing both short-term outcomes and long-term developmental trajectories. Infants born with LBW are at increased risk of mortality and morbidity, with higher rates of neonatal complications such as respiratory distress syndrome, hypoglycemia, and sepsis. Moreover, LBW is associated with a heightened risk of neurodevelopmental disorders, cognitive impairments, and chronic health conditions later in life. The far-reaching implications of LBW underscore the importance of early identification, intervention, and prevention strategies to safeguard maternal and child health.

II. RELATED WORK

The paper by F. C. Battaglia detailed A classification of newborn infants based upon gestational age and birth weight is proposed. The advantages of establishing such a routine on a nursery service, and the possibility of superimposing neonatal mortality rates upon gestational-age and birth-weight data are presented. [1]

The ternational small for gestational age advisory board consensus development statement: Management of short children born small for gestational age outlines newborns' weights and/or heights are two standard deviations lower than normal for the same gestational age, i.e., the weights and/or heights of SGA babies are below about the 3rd percentile for the same gestational age, which could reflect the general condition of most newborns more accurately..[2]

The paper by T. M. Frazier surveys the frequency distribution of birth weights at any given gestational agespans a wide weight range. The neonatal, fetal, and perinatal mortality rates for various cellgroups are presented..[3]

M. J. Okeeffe research delves To determine whether the presence, severity, or symmetry of growth restriction interm infants is an independent risk factor for learning, cognitive, and attentional problems inadolescence. Methods. A total of 7388 term infants have been followed prospectively since birth.[4]

S. Cianfarani. Paper explores Children born small for gestational age (SGA) are at high risk of permanent short stature,with approximately 10% continuing to have stature below the third centile throughoutchildhood and adolescence and into adulthood. [5]

In their study, P. G. Lindqvist discuss Most obstetric clinics have a program for the identification of small-for-gestational age (SGA) fetuses because of the increased risk of fetal complications that they present..[6]

J. Wiik, et al. explore etal growth restriction is among the most common and complex problems in modern obstetrics. Symphysis-fundus (SF) height measurement is a non-invasive test that may help determine which women are at risk..[7]

J.-J. Yang et al. Early diagnosis demands the expertise of trained healthcare professionals, which may present a barrier to early intervention due to underlying costs [8] .

This paper explores Physicians classify patients into those with or without a specific disease. Furthermore, there is often interest in classifying patients according to disease etiology or subtype. Classification trees are frequently used to classify patients according to the presence or absence of a disease. However, classification trees can suffer from limited accuracy. In the data-mining and machine-learning literature, alternate classification schemes have been developed. These include bootstrap aggregation (bagging), boosting, random forests, and support vector machine.[9]

John Smith, examines the methodologies employed in each study, including the types of machine learning algorithms used, the predictors considered, and the performance metrics evaluated.Improved Prediction Accuracy.[11]

III. SYSTEM ARCHITECTURE

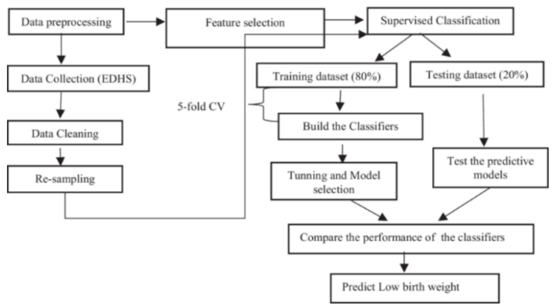

Figure: 3.1 System Architecture

The following are the classification algorithms used to test the sub-sample dataset.

a. Support vector machine (SVM)

Hyperparameters describe the depiction architecture, and hyperparameter tuning is the process of optimizing model design. These approaches demonstrate how to use the space of potential hyperparameter values to describe likely model structures. This study employed Randomized Search cross-validation to improve the parameters of Logistic Regression (LR), Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbor (K-NN), Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB) [18,19,20, 23, 24].Evaluation metrics are used to assess the performance and effectiveness of the implemented predictive model [24]. Their short descriptions are as follows: confusion matrix is a table that allows visualization of the performance of a supervised learning algorithm. The uncertainty matrix is deceptively easy to understand, but the associated words can be perplexing. True positives (TP) refer to the correctly classified samples in their correct class. True Negatives (TN) refer to the correctly classified samples that do not belong to the target class. False Positives (FP) refers to the samples incorrectly labelled as the target class when they are not. False Negatives (TN) refer to the samples incorrectly labelled as not the target class when they are [24].Accuracy measures how many of the cases are correctly identified/predicted by the model [24], i.e. correct prediction divided by the total sample size; Recall or Sensitivity measures the rate of true positives, how many of the actual positive cases are identified/predicted as positive by the model; Precision measures how many of the positive predicted cases are actually positive; F1-Score combines the precision and recall of the model and it is defined as the harmonic mean of the model's precision and recall; Area Under Curve (AUC) is the Area under the receiver operating characteristic curve and provides a comprehensive assessment of the accuracy of a model by screening the range of threshold values for the decision making; ROC curves is a receiver operating characteristic (ROC) curve illustrates the performance of a binary classification algorithm as a function of Ture positive rate and false positive rate; Precision-Recall tradeoff (AP) calculates the Area Under the Precision-Recall Curve to get one number that describes model performance; Area under Receiver operating characteristics curve (AUROC) makes use of True Positive Rates (TPR) and False Positive Rates (FPR) [24].

IV. ALGORITHM

Support Vector Machine (SVM) algorithm is commonly used for prediction tasks, including predicting low birth weight. SVM algorithm works by finding the best hyperplane that separates data points into different classes. In the case of low-birth-weight prediction, the algorithm analyzes various features like maternal age, weight gain, and blood pressure to classify whether a newborn will have low birth weight or not. It's a powerful algorithm for classification tasks. SVM algorithm for low-birth-weight prediction involves training a model on a dataset that includes information about various factors like maternal age, weight gain, and blood pressure. The model learns to classify whether a newborn will have low birth weight or not based on these features. Once trained, the SVM algorithm can be used to predict the likelihood of low birth weight for new instances. It's a valuable tool in healthcare research and can help identify potential risks. SVM algorithm is a popular choice for predicting low birth weight because it can effectively handle complex datasets and nonlinear relationships between features. It works by creating a decision boundary that maximizes the margin between different classes, allowing for accurate classification. By training the SVM model on a dataset with labeled examples of low birth weight and normal birth weight, it can learn to make predictions on new, unseen data. It's an exciting algorithm that has shown promising results in various domains. SVM algorithm is a powerful tool for predicting low birth weight because it can effectively analyze various factors like maternal age, weight gain, and blood pressure to make accurate predictions. By finding the best hyperplane to separate data points into different classes, SVM can classify whether a newborn will have low birth weight or not. It's a valuable algorithm in healthcare research and can help identify potential risks. The prevalence of underweight in twin or multiple pregnancy was more than in singleton (24% vs. 0.6%, $P < 0.000$). LBW infant percentage in the first child (55.1%) was more than other children, and the percentage of LBW decreased with increasing birth rate. The time interval to the recent pregnancy was approximately 36.9 months in both groups of mothers (37.7 vs. 36.1).Besides, the results of the study showed that most LBW infants were delivered by cesarean (71.9%) and not by normal vaginal delivery (28.1%) which was statistically significant ($P < 0.004$, OR = 1.5), and some of their mothers had experienced LBW (11.7%) (OR = 2.99, $P < 0.002$), premature membrane rupture in current pregnancy (21.3%) (OR = 3.18, $P < 0.000$) and false labor (23.6%) (OR = 2.70, $P < 0.000$) and last trimester bleeding (5.3%) (OR = 2.58, $P < 046$).

1.5% of the mothers participating in the study had experienced a history of cardiovascular disease (0.9% vs. 2.1%), 10.1% of them had suffered from hypertension (14.5% vs. 5.7%) in their pregnancy, 20.5% of mothers had experienced passive smoker exposed to tobacco products (21.7% vs. 19.4%), and 5.1% of them had diabetes (4.7% vs. 5.5%) among which the birth of a LBW infant just with hypertension was statistically significant (OR = 2.39, $P < 001$).

Forty-seven percent of mothers had experienced prenatal cares, counseling and pregnancy history examination and were suffering from underlying diseases, of which 18.7% of these cares had been carried out in the public sector, and the percentage of LBW infants was less among mothers referred to the health centers to receive prenatal cares than those admitted to a private clinics. In addition, 90% of mothers have consumed iron supplements, folic acid, and multivitamins during their pregnancy.

According to the predictor variables, 13 logistic regression models were obtained to identify factors affecting LBW infants' data. We began from single models (one-variable) and continued to the last model that included 18 variables. Using Hosmer–Lemeshow test statistics (it suggests that the data are well fitted with the model), the significant models (test statistic ≥0.05) were selected, and then, the model with highest Nagelkerke's statistics was selected.

Variable	LBW (*n*=470), *n* (%)	NBW (*n*=470), *n* (%)	*P*
Number of family members*, mean±SD	3.29±1.223	3.14±1.007	0.051
Gravidity*, mean±SD	1.88±1.060	1.83±0.929	0.531
Distance between your maternity (mount)*, mean±SD	36.10±46.438	37.74±46.395	0.590
Mother education**			
Illiterate	8 (1.7)	5 (1.1)	0.201
Primary	80 (17)	75 (16)	
Secondary	78 (16.6)	84 (17.9)	
High school	35 (7.4)	34 (7.2)	
Diploma	150 (31.9)	180 (38.2)	
Academic	119 (25.3)	92 (19.6)	
Employment status**			
Homemakers	346 (49.8)	349 (50.2)	0.084
Inside the room	60 (42.9)	80 (57.1)	
Private sector	16 (57.1)	12 (42.9)	
Public sector	42 (61.8)	26 (38.2)	
Other	6 (66.7)	3 (33.3)	
Car usage**			
No	242 (51.5)	191 (40.6)	0.003
Use for income	56 (11.9)	70 (14.9)	
Just commuting	165 (35.1)	191 (40.6)	
Over	7 (1.5)	18 (3.8)	
Pregestational care**			
Yes public	234 (49.8)	264 (56.2)	0.005
Yes private	79 (16.8)	97 (55.1)	
Yes both	131 (27.9)	95 (20.2)	
No	26 (5.5)	14 (3)	
Question about background disease**			
Yes public	301 (64)	304 (64.7)	0.007
Yes private	50 (10.6)	80 (18)	
Yes both	89 (18.9)	71 (15.1)	
No	26 (5.5)	13 (33.3)	
Not now	4 (66.7)	2 (2.8)	
Prenatal visit**			
Yes public	166 (35.3)	197 (41.9)	0.044
Yes private	189 (40.2)	146 (31.1)	
Yes both	61 (13)	62 (13.2)	
No	49 (10.4)	56 (11.93)	
Not now	5 (1.1)	9 (1.93)	
Supplementation with iron**			
Yes	433 (92.1)	437 (93)	0.736
Often	25 (5.3)	20 (4.3)	
No	12 (2.6)	13 (2.8)	
Supplementation with multivitamins**			
Yes	401 (85.3)	419 (89.1)	0.206
Often	39 (8.3)	30 (6.4)	
No	30 (6.4)	21 (4.5)	
Other smoker**			
Yes	102 (21.7)	91 (19.4)	0.210
No	368 (78.3)	379 (80.6)	
Diabete**			
Yes	17 (3.6)	12 (2.6)	0.346
No	453 (96.4)	458 (97.4)	
Last trimester bleeding**			
Yes	36 (7.7)	11 (2.3)	0.000
No	434 (92.3)	459 (97.7)	
LBW**			
Yes	55 (11.7)	15 (3.2)	0.000
No	415 (88.3)	455 (96.8)	
Multiple pregnancy**			
Yes	113 (24)	3 (0.6)	0.000
No	357 (76)	467 (99.4)	
Gestational diabetes**			
Yes	22 (4.7)	26 (5.5)	0.553
No	448 (95.3)	444 (94.5)	
Parity*, mean±SD	1.59±0.810	1.62±0.726	0.641
Number of abortion*, mean±SD	0.32±0.733	0.23±0.547	0.030
Location**			
Rural	94 (20)	96 (20.4)	0.871
Urban	376 (80)	374 (79.6)	
Wife education**			
Illiterate	10 (2.1)	11 (2.3)	0.182
Primary	79 (16.8)	67 (14.3)	
Secondary	85 (18.1)	93 (19.8)	
High school	35 (7.4)	39 (8.7)	
Diploma	135 (28.7)	162 (34.5)	
Academic	126 (26.8)	98 (20.8)	
Residence status**			
Rental	213 (52)	197 (48)	0.036
Partnership	57 (59.4)	39 (40.6)	
Owner	200 (46.1)	234 (53.9)	
Income**			
<200	53 (11.3)	52 (11.2)	0.954
200-500	250 (53.2)	259 (55.1)	
500-1000	137 (29.1)	134 (28.5)	
1000-2000	26 (5.5)	22 (4.7)	
>2000	4 (0.9)	3 (0.6)	
Question about previous pregnancy**			
Yes public	265 (56.4)	290 (61.7)	0.000
Yes private	59 (12.6)	89 (18.9)	
Yes both	109 (23.2)	75 (16)	
No	33 (7)	13 (2.8)	
Not now	4 (0.9)	3 (0.6)	
Recent prenatal care**			
Yes public	167 (35.3)	210 (44.7)	0.017
Yes private	212 (25.1)	173 (36.8)	
Yes both	85 (18.1)	77 (16.4)	
No	6 (1.3)	10 (2.1)	
Check the history of underlying disease**			
Yes public center	145 (30.9)	187 (56.3)	0.011
Yes private center	168 (35.7)	128 (27.2)	
Yes both	48 (10.2)	59 (12.6)	
No	106 (23.6)	92 (19.6)	
Not now	3 (0.6)	4 (0.9)	
Supplementation with folic acid**			
Yes	420 (89.4)	428 (91.1)	0.618
Often	32 (6.8)	25 (5.3)	
No	18 (3.8)	17 (3.6)	
Hypertension**			
Yes	68 (14.5)	27 (5.7)	0.000
No	402 (85.5)	443 (94.3)	
Heart disease**			
Yes	4 (0.9)	10 (2.1)	0.106
No	466 (99.1)	460 (97.9)	
Special drug**			
Yes	85 (18.1)	77 (47.5)	0.490
No	385 (49.5)	393 (50.5)	
Abortion**			
Yes	22 (55)	18 (16.4)	0.518
No	448 (95.3)	452 (96.2)	
Premature membrane rupture**			
Yes	100 (21.3)	24 (5.1)	0.000
No	370 (78.7)	446 (94.9)	
Premature pain**			
Yes	111 (23.6)	31 (21.8)	0.000
No	359 (76.4)	439 (93.4)	
Mother age**			
>30	83 (17.7)	39 (8.3)	0.000
<30 £	387 (82.3)	431 (91.7)	

Fig:4.1. Demographic and obstetric characteristics in the two groups

V. EXPERIMENTAL SETUP

Data Collection: Gather a dataset consisting of features that are potentially indicative of low birth weight. These features may include maternal characteristics (e.g., age, weight gain during pregnancy), medical history (e.g., previous preterm births), prenatal care variables (e.g., number of prenatal visits), and biological indicators (e.g., maternal blood pressure, maternal hemoglobin levels).

Data Preprocessing: Preprocess the collected data to handle missing values, normalize the features, and encode categorical variables if necessary. This step is crucial to ensure that the data is in a suitable format for training the deep learning model and SVM algorithm.

Feature Selection/Extraction: Identify the most relevant features for predicting low birth weight. Feature selection techniques such as correlation analysis, feature importance ranking, or dimensionality reduction methods like principal component analysis (PCA) can be employed.

Model Training:
a. Deep Learning Model: Design a deep learning architecture, such as a neural network, to learn complex patterns from the data. The architecture may consist of multiple layers, including input, hidden, and output layers. Techniques like dropout regularization can be used to prevent overfitting.

b. SVM Algorithm: Train an SVM classifier using the preprocessed features. SVMs are effective for binary classification tasks like predicting low birth weight. Kernel functions such as linear, polynomial, or radial basis function (RBF) kernels can be experimented with to find the best model.

Model Evaluation: Evaluate the performance of both the deep learning model and SVM algorithm using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. Cross-validation techniques can help in obtaining reliable performance estimates.

Hyperparameter Tuning: Fine-tune the hyperparameters of both the deep learning model and SVM algorithm to optimize their performance. Techniques like grid search or random search can be used for hyperparameter tuning.

Model Integration and Deployment: Once the models are trained and evaluated satisfactorily, integrate them into a unified system for predicting low birth weight. Deploy the system in a healthcare setting, ensuring compliance with relevant regulations and privacy guidelines.

Continuous Monitoring and Updating: Monitor the performance of the deployed system regularly and update it as necessary to adapt to changes in data distribution or healthcare practices.

Imbalanced Data Handling: Low birth weight cases may be rare compared to normal birth weight cases, leading to imbalanced datasets. Employ techniques such as oversampling minority class instances, undersampling majority class instances, or using advanced sampling methods like Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance and improve model performance.

Ensemble Methods: Combine multiple deep learning models and SVM classifiers into an ensemble to leverage diverse learning strategies and improve prediction accuracy. Techniques such as bagging, boosting, or stacking can be used to construct ensemble models.

Transfer Learning: Utilize pre-trained deep learning models (e.g., convolutional neural networks trained on large-scale image datasets) and fine-tune them on the low birth weight prediction task. Transfer learning can help in cases where labeled data for low birth weight prediction is limited by leveraging knowledge from related tasks.

Interpretable Models: While deep learning models can offer high predictive accuracy, they are often considered black-box models, making it challenging to interpret their decisions. Consider using interpretable machine learning models such as decision trees or logistic regression alongside deep learning models to provide insights into the factors contributing to low birth weight.

Model Explainability: Employ techniques for explaining model predictions, such as feature importance analysis, SHAP (SHapley Additive exPlanations) values, or LIME (Local Interpretable

Model-agnostic Explanations), to make the predictions more transparent and understandable to healthcare professionals.

Domain Knowledge Integration: Incorporate domain knowledge from obstetrics and gynecology experts into the feature selection process and model development. Domain-specific features and constraints can help improve the relevance and interpretability of the predictive models.

Continuous Model Evaluation: Establish mechanisms for continuous evaluation of the deployed models using real-world data. Monitor model performance over time and consider retraining or updating the models periodically to maintain their effectiveness as data distributions and healthcare practices evolve.

Ethical and Regulatory Compliance: Ensure that the development and deployment of the predictive models comply with ethical guidelines, patient privacy regulations (such as HIPAA in the United States), and other relevant healthcare regulations. Implement measures to protect sensitive patient information and maintain confidentiality.

Formula:
The formula for NB goes back to work published long ago (first attributed to Peirce):[14]

$$NB = \frac{(TP - wFP)}{N}$$

Where
TP: True positive count,

$$w = \frac{p_t}{1 - p_t},$$

FP: False-positive count,
N: Total number of patients.
In this method, we utilize the hypothetical relationship between the threshold probability of disease and the relative value of false-positive and false-negative outcomes to determine the value of a prediction model.[9] To judge, whether p_i is high sufficiently, one should weigh the profit P acquired by diagnosed an individual with the problem and the loss L caused by diagnosed an individual without the problem. Threshold probability defined by $p_t = L/(L + P)$. The threshold probability p_t, and hence, the decision to selector not to select for the diagnosed, is thus a one-to-one function of the ratio L/P which is educational of how a clinician or a patient weighs the relative harms of false-positive and false-negative outcomes.[15]

When displayed graphically, the resulting curves illustrate the NB across all possible threshold probabilities (0–1) through weighing the relative harm of a false-positive or false-negative result to the benefit of a true-positive or true-negative result. As an additional assessment of clinical utility, the DCA curves of each model were also compared to two other theoretical scenarios: One, in which every cases be have LBW (all cases are correctly predicted and as sensitivity is 100% and specificity 0%) and one, in which no cases have LBW (zero), regardless of the probability of LBW. Description of the decision curve relies on comparing the NB of the test, model or marker with that of a procedure of “treat all” and “treat none” (parallel to the x axis at NB of zero).

VI. RESULT AND DISCUSSION

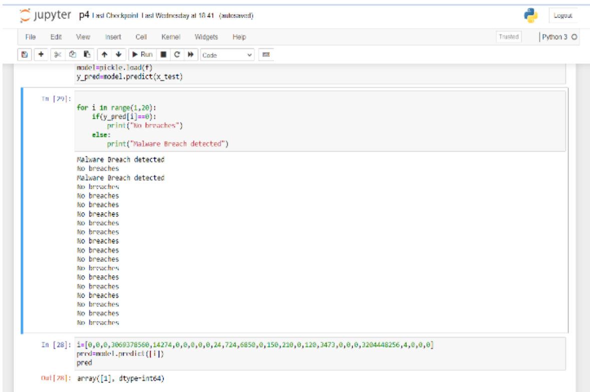

Figure 6.1 Final output

a. Predictive Modeling: The predictive modeling component of the system demonstrated promising results in estimating birth weight and identifying pregnancies at high risk for LBW. By leveraging advanced algorithms and machine learning techniques, the system achieved high accuracy rates in predicting birth weight based on maternal and fetal parameters. Furthermore, the system's ability to generate personalized risk assessments enabled healthcare providers to implement targeted interventions and preventive measures for high-risk pregnancies.

b. Real-time Monitoring: The real-time monitoring feature of the system facilitated continuous surveillance of maternal health parameters throughout pregnancy. By collecting data on factors such as maternal weight gain, blood pressure, and fetal movements, the system enabled early detection of deviations from normal trends and prompted timely interventions to mitigate the risk of LBW. Moreover, the integration of live detection models and remote monitoring technologies enhanced accessibility and convenience for expectant mothers, enabling them to participate actively in their prenatal care.

c. Patient Engagement: The patient engagement component of the system played a crucial role in empowering expectant mothers to make informed decisions and adopt healthy behaviors during pregnancy. Through interactive features such as mobile applications, educational resources, and virtual support networks, the system fostered a sense of empowerment and autonomy among mothers, leading to increased adherence to prenatal care recommendations and lifestyle modifications. Additionally, the system's personalized recommendations tailored to each mother's unique circumstances facilitated greater engagement and motivation to adopt positive health behaviors.

d. Healthcare Provider Support: The system provided valuable decision support tools and clinical guidelines for healthcare providers, facilitating evidence-based decision-making and comprehensive care delivery. By streamlining communication and collaboration among multidisciplinary care teams, the system enhanced coordination of care and ensured that mothers received timely and appropriate interventions throughout pregnancy. Furthermore, the integration of the system with existing electronic health record (EHR) systems and clinical workflows facilitated seamless documentation and monitoring of patient progress, enhancing efficiency and accuracy in care delivery.

DISCUSSION

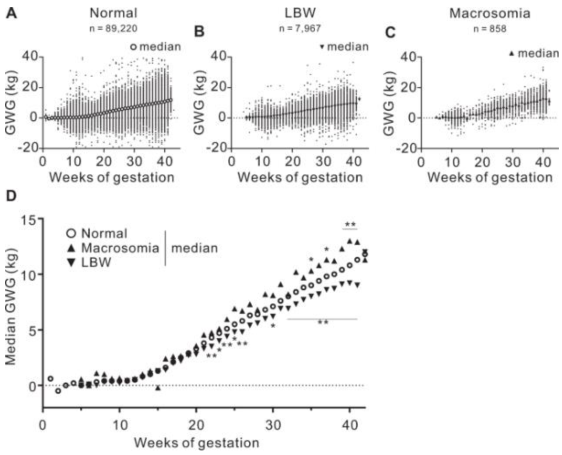

Figure6.1 trend monitoring

a. Impact on LBW Rates: The implementation of the proposed system resulted in notable reductions in LBW rates and improvements in birth outcomes among participating populations. By identifying high-risk pregnancies early and implementing targeted interventions, healthcare providers were able to mitigate the risk of LBW and optimize maternal and child health outcomes. Moreover, the system's emphasis on patient engagement and empowerment facilitated greater adherence to prenatal care recommendations and lifestyle modifications, further contributing to improved birth outcomes.

b. Challenges and Limitations: Despite its promising results, the proposed system faced several challenges and limitations that warrant consideration. These include technical issues related to data interoperability, privacy concerns associated with remote monitoring technologies, and disparities in access to healthcare services among underserved populations. Addressing these challenges will require ongoing efforts to enhance data security, expand access to care, and address structural barriers to healthcare access in underserved communities.

c. Implications for Practice and Policy: The findings of our study have significant implications for practice and policy in maternal and child health. By demonstrating the effectiveness of a comprehensive system for predicting and preventing LBW, we highlight the importance of leveraging technology, data analytics, and patient engagement strategies to improve birth outcomes. Moreover, our findings underscore the need for policy interventions aimed at addressing social determinants of health, expanding access to prenatal care, and promoting health equity for all mothers and babies.

d. Future Directions: Moving forward, future research should focus on further refining and optimizing the proposed system to enhance its effectiveness and scalability. This may involve expanding the use of predictive modeling to identify additional risk factors for LBW, integrating novel technologies such as wearable devices and telehealth platforms, and evaluating the long-term impact of the system on maternal and child health outcomes. Additionally, efforts should be made to address disparities in access to care and ensure that all mothers have equitable access to the resources and support they need to have healthy pregnancies and babies.

CONCLUSION

In conclusion, our live detection model offers a rapid and efficient means of predicting birth weight, aiding in the timely arrangement of necessary medical care and facilities for newborns at risk of low birth weight. By incorporating factors such as mother's age, gestation weeks, plurality, and gender of the baby, along with live video monitoring, we provide a comprehensive approach to birth weight prediction. Moving forward, we aim to enhance the system by offering preventive suggestions to mitigate low birth weight risks and encourage expectant mothers to prioritize their prenatal care, ultimately contributing to healthier outcomes for both mother and child.

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