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An Intelligent Framework for Early Low Birth Weight Prediction Using Machine Learning

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***Abstract* – Low birth weight (LBW), defined as a birth weight of less than 2500 grams, is one of the leading indicators of neonatal morbidity, infant death, and long-term developmental difficulties. Healthcare professionals should be able to detect pregnancies at risk of delivering infants with low birth weights early on, which might improve maternal and newborn outcomes. Traditional risk assessment methods rely heavily on maternal history and clinical findings, but they may not always provide reliable predictions. An artificial intelligence (AI) framework for the early diagnosis and classification of Low Birth Weight is presented in this research, which makes use of demographic, clinical, and prenatal healthcare data for mothers. The proposed system uses a variety of supervised machine learning algorithms for data collection, preprocessing, feature selection, model training, and performance comparison evaluation. These algorithms include Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Extreme Gradient Boosting (XGBoost). The dataset is prepared for training prediction models by performing operations such handling missing values, eliminating outliers, decreasing noise, and optimising features. To determine the most effective prediction model, experimental evaluations are conducted on Accuracy, Precision, Recall, and F1-Score. The Random Forest Classifier has the highest prediction accuracy among the evaluated classifiers, at around 84.81%. A web app developed on Django allows medical professionals to enter maternal health data. The program employs an internal prediction engine to generate real-time risk estimates for low birth weight. The user interface is easy and engaging. A more effective decision-support tool within the proposed framework may lead to better prenatal healthcare planning, earlier diagnosis, and fewer issues with low birth weight in newborns.**

***Keywords* – Low Birth Weight, Machine Learning, Maternal Healthcare, Random Forest, XGBoost, Support Vector Classifier, Decision Tree, Predictive Analytics, Django Web Application, Neonatal Health.**

I. INTRODUCTION

The World Health Organization (WHO) defines low birth weight (LBW) as a weight at delivery of less than 2,500 grams, and it is one of the most critical public health crises worldwide. A higher chance of neonatal mortality, infant morbidity, delayed development, and long-term health issues are all closely related. Many factors, such as maternal malnutrition, inadequate prenatal care, low socioeconomic level, and complications during pregnancy, contribute to the underweight birth of millions of newborns annually, mostly in developing countries. Pregnancies at risk of Low Birth Weight must be identified early on to optimise neonatal and maternal healthcare outcomes. Conventional approaches to LBW risk detection have relied on clinical examinations, prenatal observations, maternal demographic data, and medical professionals' knowledge and knowledge [1, 2]. Although these approaches provide valuable clinical insights, they may not always be able to identify high-risk pregnancies in their early stages.

The complex relationship between maternal health, behavioral factors, medical history, and physiological indicators makes it difficult for conventional risk assessment approaches to detect anomalies in foetal development. Consequently, there is a rising need for intelligent prediction systems that can promptly and precisely detect potential dangers. the three Machine learning (ML) algorithms have advanced to the point that they can sift through mountains of healthcare data, find connections between clinical factors that were previously unknown, and make accurate predictions. Supervised learning algorithms have substantially enhanced medical diagnosis, disease prediction, patient risk assessment, and clinical decision support. Using maternal healthcare data from the past, machine learning models can correctly classify pregnancies as either Low Birth Weight (LBW) or Not Low Birth Weight (Not-LBW). Healthcare professionals are able to make intervention choices faster using this. various sources

Several machine learning approaches, including Decision Tree Classifier (DTC), Support Vector Classifier (SVC), Random Forest Classifier (RFC), and Extreme Gradient Boosting (XGBoost), have successfully tackled prediction difficulties in maternal healthcare. Which approach is the best depends on the dataset's attributes, feature relationships, computational complexity, and prediction accuracy. Healthcare prediction applications using diverse clinical datasets are well-suited to ensemble learning algorithms like XGBoost and Random Forest due to their improved performance in decreasing overfitting and enhancing model generalization. The period from [15] to [18]:

In addition to selecting appropriate machine learning algorithms, feature engineering and data preparation play a crucial role in developing a prediction model. The accuracy of predictions and the consistency of models are greatly enhanced when missing value handling, outlier elimination, noise reduction, feature selection, and dataset balancing are undertaken. Metrics like F1-Score, Accuracy, Precision, and Recall make it possible to compare different prediction models objectively and assess categorisation performance thoroughly. (6, 7, 18)

This project aims to develop a smart framework for low birth weight prediction. It will utilise machine learning to analyze mother demographics, clinical data, and prenatal healthcare records in order to reliably identify high-risk pregnancies. The suggested framework uses XGBoost, Decision Tree Classifier (DTC), Support Vector Classifier (SVC), and Random Forest Classifier (RFC) to systematically gather data, preprocess it, pick features, train models, evaluate their performance compared to others, and finally make predictions. To find the best prediction model using conventional classification metrics, experimental assessment is carried out.

Deploying the created machine learning model as a Django-based web application enhances the practical usefulness of the suggested prediction system. Medical providers may use the app's user-friendly interface to safely input a mother's healthcare data and get real-time projections of her baby's low birth weight. With its implementation, the prediction model becomes a useful clinical decision-support tool that may help obstetricians, gynecologists, and other healthcare professionals with prenatal care, newborn issues related to low birth weight, and early intervention.

II. BACKGROUND STUDY

There has been a lot of interest in using Machine Learning (ML) in maternal and neonatal healthcare because of its ability to assess complicated clinical data and generate accurate predictions for pregnancy-related issues. One of these effects that remains a major healthcare issue is low birth weight (LBW), which is associated with newborn mortality, impaired physical development, and long-term developmental problems. The use of predictive modelling to the early detection of high-risk pregnancies has been the subject of much research. This would allow for the prompt initiation of medical therapies.

Various statistical and machine learning studies have looked at the possibility of predicting low birth weight using information about the mother's demographics and prenatal treatment. Traditional methods for predicting low birth weight mostly relied on multiple regression analysis to include into account the mother's age, nutritional condition, pregnancy history, and clinical observations. Although these methods were effective in identifying critical maternal risk variables, their predictive power was severely limited when used to huge and diverse healthcare datasets. Research into complex nonlinear relationships between many clinical factors prompted the use of advanced machine learning methods.

A lot of recent research has been devoted to building prediction models using supervised machine learning techniques as XGBoost, Decision Trees, Random Forests, Artificial Neural Networks, and Support Vector Machines (SVMs). Automated learning of complex decision boundaries from historical maternal healthcare information is one way these technologies have improved prediction accuracy. When it comes to clinical data that is noisy, ensemble learning algorithms like XGBoost and Random Forest have shown to be more resilient, less prone to overfitting, and better at generalising models.

Prediction models for neonatal mortality among babies with Very Low Birth Weight (VLBW) and Extremely Low Birth Weight (ELBW) have also been investigated by a number of studies. These research used statistical and machine learning tools to analyse large healthcare datasets in order to assess the risk of death and identify critical clinical parameters impacting newborn survival. Despite the promising results, the effectiveness of these prediction models hinged on the quality, quantity, and diversity of the clinical information used to construct them.

Improvements in healthcare prediction systems via feature engineering, data preparation, and model optimisation constitute another significant field of study. Prediction accuracy and model dependability may be greatly enhanced by taking care of missing values, eliminating outliers, choosing useful clinical characteristics, balancing datasets, and doing cross-validation. Modern healthcare prediction frameworks also rely on hyperparameter optimisation techniques such as GridSearchCV, ensemble learning approaches, and feature correlation analysis. Using these methods, predictive models may improve their accuracy and generalisability to a wider range of patient groups.

Table I. Summary of Existing Low Birth Weight Prediction Techniques

Study	Methodology	Major Contribution
Multiple Regression Models	Statistical Regression Analysis	Early prediction of LBW using maternal clinical characteristics.
Neonatal Mortality Prediction	Statistical & Machine Learning Models	Risk estimation for VLBW and ELBW infants.
Machine Learning-Based LBW Prediction	SVM, Decision Tree, Random Forest, XGBoost	Improved prediction accuracy through supervised learning.
Healthcare Data Analytics	Feature Engineering & Cross-Validation	Enhanced model reliability and performance optimization.
Proposed Work	**SVC, DTC, RFC, XGBoost with Comparative Analysis**	Early prediction of Low Birth Weight using optimized machine learning models and a

There has been a lot of success in using machine learning to forecast maternal healthcare, but there are still certain problems that need fixing. It is challenging to generalise the models used by many current prediction systems to varied populations since these systems are often built using relatively limited datasets. Furthermore, the accuracy of predictions may be affected by differences in healthcare infrastructure, clinical practices, socioeconomic status, and maternal health. In response to these shortcomings, the current study builds an all-encompassing Low Birth Weight Prediction Framework using Machine Learning. The framework incorporates data preprocessing, feature selection, supervised learning algorithms, comparative model evaluation, and web-based deployment to offer maternal healthcare providers accessible and dependable decision support.

III. PROPOSED CHAT ANALYSIS FRAMEWORK

Early classification and prediction of low birth weight (LBW) in newborns may be achieved using the proposed framework and maternal demographic, clinical, and prenatal healthcare data. The whole prediction process consists of gathering data, cleaning it, choosing features, creating a machine learning model, testing it, and eventually producing a forecast. Accurately identifying pregnancies that are at risk of producing infants with low birth weight may lead to early clinical intervention and improved healthcare outcomes for both the mother and the baby. To do this, the framework integrates many supervised learning methods.

Using a comprehensive maternal healthcare dataset with 1,799 items, models are built throughout the data collection phase of the prediction approach. Birth weight (LBW) and non-LBW (not LBW) cases are both included in the dataset, which is compiled from public healthcare and research sources. Some of the characteristics that are documented include the mother's demographic information, the outcomes of clinical examinations, pregnancy notes, physiological measurements, and other specifics. These criteria provide the necessary clinical information to build reliable prediction models that can distinguish between low-risk and high-risk pregnancies.

Prior to training a model, data preparation improves the quality of the dataset gathered. Data completeness is ensured by efficiently processing missing values and deleting outliers and noisy observations, which improves data consistency. Making the cleaned dataset usable by supervised learning algorithms is the next stage. To further ensure that the prediction process is guided by the most valuable attributes, correlation-based feature analysis is used to choose relevant clinical characteristics. When preprocessing and feature selection are done effectively, the model performs better and computation complexity is reduced.

The processed information is fed into four supervised machine learning algorithms: Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Extreme Gradient Boosting (XGBoost). Since each algorithm is created independently using the same training data, you may compare their performance with full impartiality. With the use of maternal health indicators, the Decision Tree algorithm generates interpretable decision rules, and the Support Vector Classifier constructs optimal decision boundaries, both of which are used to classify pregnancies. Both XGBoost and Random Forest enhance prediction robustness via the use of ensemble learning to combine several decision trees, while XGBoost does so by continuously minimising classification mistakes using gradient boosting approaches.

To ensure accurate model development, the dataset is divided into training, validation, and testing subsets using a 60%-20%-20% split. The use of k-fold cross-validation during training helps ensure that the model is stable and avoids overfitting. Our goal in testing all of the machine learning algorithms in the same setting is to provide an unbiased comparison of their prediction capabilities. This evaluation method ensures dependable performance across unknown maternal healthcare data and enhances model generalisability.

Common classification metrics used to assess the constructed prediction models include Accuracy, Precision, Recall, and F1-Score. We may evaluate the accuracy of the predictions made by the different machine learning algorithms by comparing them using these criteria. Based on the results of the trials, the recommended healthcare decision-support system uses the most accurate prediction model.

Table II. Proposed Low Birth Weight Prediction Framework

Phase	Description
Data Collection	Acquisition of maternal healthcare dataset containing 1,799 LBW and Not-LBW records.
Data Preprocessing	Missing value handling, outlier removal, noise reduction, and data transformation.
Feature Selection	Correlation-based selection of significant maternal and clinical attributes.
Model Development	Training SVC, Decision Tree, Random Forest, and XGBoost classifiers.
Model Validation	60–20–20 train-validation-test split with k-fold Cross-Validation.
Performance Evaluation	Comparison using Accuracy, Precision, Recall, and F1-Score.
Final Prediction	Identification of pregnancies with Low Birth Weight risk using the best-performing classifier.

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IV. MACHINE LEARNING MODEL DEVELOPMENT

In order to classify pregnancies as Low Birth Weight (LBW) or Not Low Birth Weight (Not-LBW), the proposed framework for predicting LBW uses many supervised machine learning techniques. By comparing the prediction capabilities of different classification algorithms, the primary objective of model creation is to find the most reliable model to assist moms in making early healthcare decisions. Every model is trained using the same preprocessed dataset to ensure that the performance evaluation is fair and consistent.

Prior to training the model, the maternal healthcare dataset is optimised for features. Clinical observations, physiological data, prenatal exam results, mother demographics, and pregnancy-related parameters are selected using correlation-based feature analysis. This feature selection strategy enhances the accuracy of Low Birth Weight prediction by eliminating unnecessary variables and retaining just the most important ones. With the revised feature set, computational complexity during model training is lowered while classification accuracy is enhanced.

To begin making predictions, the Support Vector Classifier (SVC) is used. This method locates the hyperplane in a high-dimensional feature space that maximises the distance between the LBW and Not-LBW categories. Applying kernel functions, SVC effectively accounts for nonlinear interactions between maternal healthcare parameters and provides excellent classification results for small clinical datasets. However, as dataset sizes increase, it becomes more difficult to optimise its hyperparameters for optimal prediction performance.

Afterwards, the Decision Tree Classifier (DTC) is used to construct an understandable classification model. By recursively partitioning the dataset, the approach selects the most valuable maternal healthcare features based on metrics such as information gain and Gini impurity. Clearly defined decision rules are provided by the created decision tree to aid healthcare professionals in understanding the prediction process. Despite their excellent interpretability, Decision Trees are more likely to overfit when trained on complex healthcare datasets.

The recommended design gets around the problems with individual decision trees by using the Random Forest Classifier (RFC), an ensemble learning technique that constructs several decision trees using randomly selected data and feature subsets. By aggregating the individual projections from these trees by majority voting, we may improve prediction accuracy, decrease overfitting, and increase model robustness. Random Forest, which excels at handling heterogeneous healthcare data, is one of the key prediction models proposed by the framework.

Ultimately, the prediction model relies on the XGBoost algorithm. By constructing a succession of decision trees, XGBoost is able to decrease the prediction errors produced by previous models. The XGBoost algorithm is able to simulate complicated nonlinear interactions with less overfitting by integrating regularisation and gradient boosting. Consequently, healthcare datasets with a large number of related clinical characteristics have excellent prediction power when using the method.

The dataset is structured with a training subset comprising 60% of it, a validation subset 20%, and a testing subset 20%, all of which ensure precise model evaluation. Using k-fold cross-validation, we also assess how well each classifier performs when applied to different data divisions. We use Accuracy, Precision, Recall, and F1-Score for assessment in order to conduct a thorough comparison of the prediction performance of the constructed models. Experimentation establishes the best effective classifier as part of the intended system for low birth weight prediction.

Table III. Machine Learning Models Used for LBW Prediction

Algorithm	Purpose	Major Characteristics
Support Vector Classifier (SVC)	Binary classification	Maximum-margin classifier suitable for nonlinear decision boundaries.
Decision Tree Classifier (DTC)	Rule-based prediction	Easily interpretable hierarchical decision-making model.
Random Forest Classifier (RFC)	Ensemble classification	Combines multiple decision trees to improve accuracy and reduce overfitting.
Extreme Gradient Boosting (XGBoost)	Boosting-based prediction	Sequential learning with regularization for enhanced predictive performance.

V. PERFORMANCE EVALUATION

To test how well the proposed Low Birth Weight (LBW) prediction method works, we used it to a maternal healthcare dataset that had 1,799 records that included both LBW and Not-LBW cases. Before training the model, the dataset is thoroughly prepared by handling missing values, eliminating outliers, decreasing noise, and optimising features, among other tasks. The produced machine learning models gain from these preprocessing methods since they improve data quality and provide consistent and reliable prediction input.

In all, the dataset consists of a training subset that accounts for 60% of the total, a validation subset that accounts for 20%, and a testing subset that accounts for 20%. Because of this, we can compare the algorithms' prediction abilities in an unbiased manner. Using k-fold cross-validation, we may evaluate the model's resilience even more thoroughly while decreasing the chances of overfitting. This assessment method ensures a fair comparison of classifier prediction performance by training and evaluating all machine learning algorithms in the same experimental circumstances.

The proposed system evaluates four separate supervised machine learning methods: Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Extreme Gradient Boosting (XGBoost). When evaluating each model, standard classification measures include F1-Score, Accuracy, Precision, and Recall. By adjusting these parameters, we can compare the classifiers' ability to detect low birth weight pregnancies with a minimum of false positives.

Experimental analysis also includes the use of visual tools for model evaluation, such as confusion matrices and feature correlation heatmaps. Possible clinical variables impacting the prediction of low birth weight may be better understood with the use of a correlation heatmap, which displays the interrelationships between various elements of maternal healthcare. Confusion matrices are generated for every classifier and provide detailed information on the LBW and Not-LBW cases that were correctly classified. The accuracy and reliability of the classifier's predictions may be tested in this way.

The results of the comparison testing show that all of the constructed classifiers can reliably predict low birth weight, although to varying degrees. Due to the intricacy of the clinical information, the Support Vector Classifier generates comparatively lower prediction accuracy, while the Decision Tree Classifier gives higher interpretability and intermediate classification performance. The Extreme Gradient Boosting (XGBoost) model has strong prediction capabilities when it comes to modelling nonlinear interactions among maternal healthcare parameters. However, the Random Forest Classifier achieves the highest overall prediction performance by bolstering robustness and reducing overfitting via the use of ensemble learning, which combines many decision trees.

From what we can see from the trials, the Random Forest Classifier achieves higher accuracy (84.63 to 84.81% vs. 75.00% vs. 50.19% for Decision Tree and Support Vector, respectively). The Random Forest model fares better than its rivals because of ensemble learning, GridSearchCV, decision tree optimisation, and the combination of predictions from many independently trained models. The recommended Low Birth Weight prediction framework is most effective when used with Random Forest as a classifier because to the combined generalisability and accuracy gains from both methods.

VI. DJANGO-BASED WEB APPLICATION

Incorporating the trained ML model into a Django-based web app makes the proposed LBW prediction method more workable. By securely entering maternal clinical data into the app's intuitive interface, healthcare professionals may get real-time predictions about the likelihood of low birth weight. Combining machine learning with a web-based deployment platform, the recommended technique helps identify high-risk pregnancies early. It is a beneficial clinical decision-support tool.

The Django framework manages databases, validates data, does preprocessing, creates predictions, infers from machine learning, authenticates users, and registers patients. Prenatal healthcare, demographic, and clinical data may be entered by logged-in medical workers using secure online forms. Prior to prediction, the data is validated and preprocessed to ensure it conforms to the format used to train the model.

Using the preprocessed and optimised maternal healthcare data, we ask the trained Random Forest Classifier to decide whether a pregnancy is associated with Low Birth Weight (LBW) or Not Low Birth Weight (Not-LBW). Quick clinical decisions may be made with the aid of the web interface, which promptly shows the prediction and classification findings. The Random Forest model has been selected to be the primary prediction engine in the deployed application due to its exceptional performance in experimental evaluation.

As an added feature, the developed web app may manage a centralised database. User profiles, consultation details, prediction outcomes, patient records, and information on maternal healthcare factors are all stored in this database. A unified administrative dashboard allows for the monitoring of registered healthcare providers, the management of patient information, the examination of prediction history, and for general system maintenance. With this centralised architecture, data management is made easier, and future healthcare reporting and clinical analysis will be facilitated.

The Django application's modular design allows for the operation of its frontend, backend, machine learning prediction engine, and relational database with ease. Extending the current system is possible via integration with HIS, EHRs, automated report generation, mobile healthcare applications, real-time clinical monitoring, and cloud-based deployment. These enhancements will make maternal healthcare services that use machine learning even more successful in preventing babies and moms from being born with low birth weight.

VII. CONCLUSION

This paper presents a Machine Learning-based Low Birth Weight (LBW) Prediction Framework to identify pregnancies that are likely to deliver kids with low birth weights early on. The proposed approach integrates supervised machine learning techniques with maternal demographic data, clinical observations, and prenatal healthcare parameters to improve prediction accuracy and enable rapid clinical decision-making. The whole prediction process consists of collecting data, cleaning it, choosing features, creating a machine learning model, testing it against rivals, and eventually releasing it publicly. The developed framework provides a robust decision-support system that utilises structured data from maternal healthcare to improve neonatal and maternal healthcare outcomes.

Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Extreme Gradient Boosting (XGBoost) are the four supervised learning methods that the proposed system evaluates using industry-standard metrics including Accuracy, Precision, Recall, and F1-Score. Experimental comparisons show that although all classifiers successfully predict low birth weight, the Random Forest Classifier has the highest prediction accuracy of 84.81%. The recommended framework is best suited to Random Forest's usage of ensemble learning, optimisation of GridSearchCV, and use of numerous decision trees, all of which enhance prediction reliability and mitigate the risk of model overfitting.

The trained prediction model becomes more realistic when implemented as a web application using Django. Through its user-friendly interface, this software provides healthcare providers with a secure means of inputting maternal healthcare data and receiving real-time forecasts of low birth weight. By using an online clinical decision-support platform that integrates machine learning, physicians may enhance prenatal care for high-risk pregnancies. This platform will boost accessibility, allow early intervention, and simplify the process.

More comprehensive hospital datasets could be linked in the future, along with deep learning models, electronic health records (EHR) prediction automation, cloud-based healthcare service launches, mobile health app enablement, and explainable AI techniques to improve model transparency and clinical interpretability. Possible results of these advancements include more precise forecasts and improved administration of healthcare to mothers and newborns.

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