International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

Predicting the Childbirth Mode using ExhaustiveFeature Selection and Machine Learning Techniques

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***Abstract*—There are various modes of childbirth like caesarean section, vaginal delivery, assisted delivery and so on. The task of predicting the mode of child birth earlier is a crucial task for the medical professionals. A model is developed to forecast the mode of childbirth using data analytics and machine learning techniques. The developed prototype will assist the healthcare professionals to make informed decisions and avoid birth risks. The task entails gathering a dataset that contains several characteristics that influence the mode of birth like the age of the mother, their medical history, prenatal care and many more. Exhaustive feature selection approach is applied to identify the most significant features linked to the type of birth. The developed model is tested using different machine learning algorithms like Linear Regression (LR), Decision Tree Classifier (DT), Random Forest (RF), and Support Vector Machine (SVM). The performance metric of the model is evaluated using metrics like metrics like Accuracy, Precision, and Recall. The outcomes state that Random Forest outperforms all other with an accuracy of 92%. The developed model will assist the healthcare practitioners to make more informed judgments on predicting the mode of child birth.**

Keywords*— *Linear Regression; Decision Tree; Random Forests; Optimization; prediction; Machine Learning; SVM

I. Introduction

A. Motivation

The motivation behind the project of predicting modes of childbirth using ML algorithms stems from the need to improve the decision-making process in obstetrics and enhance overall birth outcomes. Childbirth is a critical event that involves complex factors and considerations. Determining the most appropriate mode of delivery, whether it be vaginal, cesarean section, or assisted, is crucial for the well-being of both the mother and the baby. By developing a reliable predictive model using ML algorithms, healthcare professionals can benefit from data-driven insights and evidence-based decision-making. The model takes into account various factors that influence the mode of childbirth, such as the mother's age, medical history, prenatal care, and other relevant features. This comprehensive analysis helps in identifying high-risk cases and predicting the need for interventions, allowing healthcare providers to allocate resources efficiently and plan appropriate interventions tailored to the individual's circumstances.

B. Problem statement

Machine learning algorithms can be used to assess data from a variety of characteristics that influence childbirth mode, such as maternal health, gestational age, and fetal weight. However, in order to construct an accurate model, it is necessary to determine the most essential features that contribute to the forecast. This project's problem statement is to investigate various machine learning algorithms and feature selection strategies in order to determine the most essential features for predicting the mode of childbirth and to develop a model that accurately predicts the mode of childbirth based on these features.

C. Objective

The objective of the project is to develop an accurate predictive model using ML algorithms that can assist healthcare professionals in making informed decisions about the mode of childbirth. The project aims to improve birth outcomes by accurately predicting whether a vaginal delivery, Cesarean section, or assisted delivery is likely for each individual case. By considering relevant input features and personalized factors, the model will help optimize resource allocation, enhance decision-making, and contribute to the advancement of knowledge in obstetrics and maternal health.

D. Scope

Collecting and preprocessing a dataset containing relevant features related to childbirth, such as maternal age, medical history, and prenatal care. Focus is made on selecting appropriate ML algorithm like Support Vector Machine and Neural Network for mode of childbirth prediction. We train and optimize the selected ML models using the preprocessed dataset. We estimate the performance of the model's using metrics like precision, accuracy, recall, and F1 score. We develop a user-friendly interface and integrating the predictive model into existing healthcare systems for practical application. The ethical considerations including patient privacy and data security is considered throughout the project. Finally we document the project methodology, findings, and insights, and effectively communicating the results to healthcare professionals and stakeholders.

II. LITERATURE SURVEY

Pereira and colleagues [1] conducted a study to predict types of delivery (normal, cesarean, forceps, and vacuum) by identifying obstetric risk factors through data mining. In their study, different data mining techniques were applied, such as DT, generalized linear models (GLMs), support vector machines (SVMs), and naive Bayes (NB). Among these models, the most satisfactory results for statistical metrics, with the best accuracy and specificity, were achieved using DT. Some studies focused on the values of ultrasound measurements relative to the outcomes of deliveries; for example, in [2] Bishop's scores and translabial ultrasound measurements were compared to determine the suitability of induction of labor. Cervical length and fetal head–pubis symphysis distance were measured using translabial ultrasound. The predictive value of the Bishop's score, cervical length, and fetal head–pubis symphysis distance were determined using multivariate analysis. The results showed that translabial measurements were a more suitable method for monitoring labor progress than the Bishop's score. In [3] the authors examined the likely outcomes of labor, including the risk of prolonged pregnancy and the need for cesarean section due to failed induction. The study concluded that measurement of cervical length at 37 weeks could determine the risk of an emergency cesarean section. Some studies have been carried out to predict risks during pregnancy, such as the probability of premature birth, vaginal delivery after cesarean section, and the suchlike. In paper [4] researchers conducted a study to develop a personalized tool for predicting vaginal births after cesarean deliveries using different machine learning methods: gradient boosting, RF, balanced RF, and AdaBoost ensembles. Similarly, in [5] a model is developed to predict vaginal births after cesarean sections using multivariate analysis. The multivariate model using the features evaluated through stepwise regression had an area under the curve of 72.3%, while the multivariate model developed using features reported by [6] prediction model, had an area under the curve of 75.7%. In another study [7] aimed to evaluate the voluntary termination of pregnancy and identify the consequent risks for patients, using DT, SVMs, and GLMs to perform classification. The study [8] proposed a prediction model based on a C4.5 classification tree to determine the importance of different pregnancy attributes or features for predicting risk levels and complications during pregnancy. In another study, [9] developed a decision support system to accurately identify mothers who were at risk of preterm birth and the attributes responsible for it. Research work [10] depicts the child delivery, maternal mortality and severe morbidity associated with low-risk planned cesarean delivery versus planned vaginal delivery. In summary, the literature review identified certain issues. First, some studies predicted modes of delivery and the risks associated with childbirth using several machine learning techniques. Second, different sets of features were used in different studies, and different algorithms were used for the same purpose. Third, in some cases, the accuracy differed despite the number of features being the same. Fourth, most of the research focused on predicting modes of delivery, rather than focusing on the features, although it was clear that the number of features played an important role. Fifth, despite the studies carried out in this field, the researchers did not reach decisive conclusions about the best features for predicting delivery outcomes. More studies therefore need to be conducted to enable modes of delivery to be predicted in real time, with acceptable accuracy, using only necessary and minimum features. Such studies would allow mothers to give birth to their children using the safest possible childbirth procedures; thus, this work focused on predicting modes of delivery, using an optimum number of features, to assist medical professionals and pregnant mothers by reducing severe risks and complications during childbirth.

III. PROPOSED METHODOLOGY

The model is proposed to predict the mode of childbirth using machine learning techniques.It is comprised of the following stages as discussed below.

A. Data Collection

Gather a diverse dataset containing relevant features related to childbirth, including maternal age, medical history, prenatal care, and other factors known to impact the mode of delivery. Ensure the dataset includes labeled instances indicating the actual mode of childbirth.

B. Data Preprocessing

Deal with missing values, outliers, and inconsistencies to tidy up the dataset. Perform necessary transformations, such as encoding categorical variables and scaling numerical features, to prepare the data for analysis.

C. Exploratory Data Analysis (EDA)

Analyze the dataset to learn about the feature distribution and relationships. Determine any patterns, correlations, or outliers that may have an impact on the mode of birthing.

D. Feature Extraction

Select the most informative features using exhaustive feature selection approach. The method evaluates each of the features as brute force and returns the best combination of feature. We choose features that have a significant impact on predicting the mode of childbirth while considering interpretability and computational efficiency.

E. Model Selection

Select appropriate categorization Machine Learning methods, such as support vector machines, decision trees, logistic regression, random forests, or neural networks. Consider factors such as computing requirements, interpretability, and algorithm performance.

F. Model training and evaluation

Using the dataset, create training and testing sets. Train the chosen models on training data and assess their performance using appropriate metrics such as accuracy, precision, recall, and F1 score. To ensure a robust evaluation, use cross-validation.

G. Hyper parameter Tuning

Make the models' hyperparameters more efficient. Use approaches such as grid search or random search to determine the optimal hyper parameter values that maximize the model's performance.

H. Model Validation

Validate the trained models on a separate validation dataset or through additional testing on unseen data. Verify that the models generalize well and make accurate predictions for new instances.

I. Model Deployment and Application

Deploy the validated models in a practical setting by integrating them into healthcare systems or developing a user-friendly application. Provide healthcare professionals with an interface to input patient information and obtain predictions on the mode of childbirth.

J. Monitoring and Maintenance of the Specifications

Continuously monitor the performance of the deployed models and gather feedback from healthcare professionals. Update the models periodically to incorporate new data and evolving medical practices, ensuring the accuracy and relevance of the predictions.

IV. EXPERIMENTAL ILLUSTRATION

The working and demonstration of the developed model is illustrated using the below figures and experimental results are discussed further.

Fig. 1. Snapshot of the Sample Registration Page

Figure 1. represents the sample of the registration page where the new patient need to submit the details and register themselves. Once the user is registered , the registered patients can login for further processing using their credentials as represented in Figure 2.

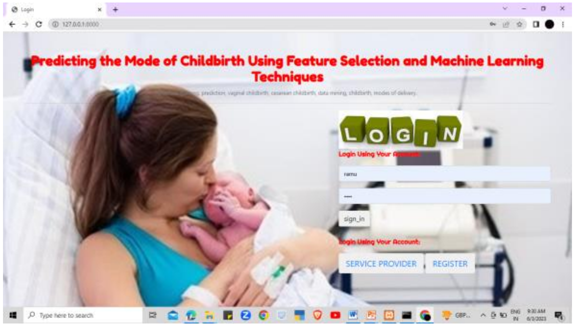

Fig. 2. Snapshot of the Sample Login Page

The user interface page is depicted in Figure 3. This page acts as an interface between the patient and the model.

Fig. 3. User Interface Page

Once the patient communicates with the model the administrator is provided with access control as shown in Figure 4.

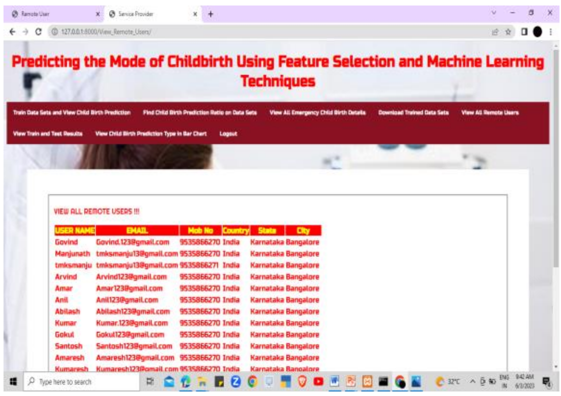

Fig. 4. Service provider Interface Page

Once the patient has succesfully registered then the details from the case sheet and other relevant informations are filled to the system. The model analyses the input and predicts the mode of the child birth. The best fit of the model is foung usinmachine learning techniques. The results of predicted outcomes are shown in Figure 5 and Figure 6.

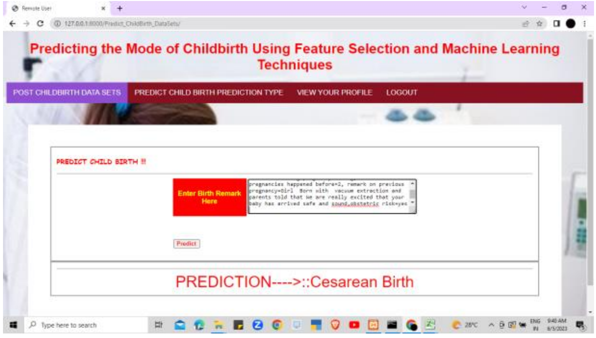

Fig. 5. Output Predicting the type of birth

Fig. 6. Prediction output

V. RESULTS AND DISCUSSION

The results of the developed model are evaluated using different metrics like accuracy, precision, and recall as shown in Figure 7.

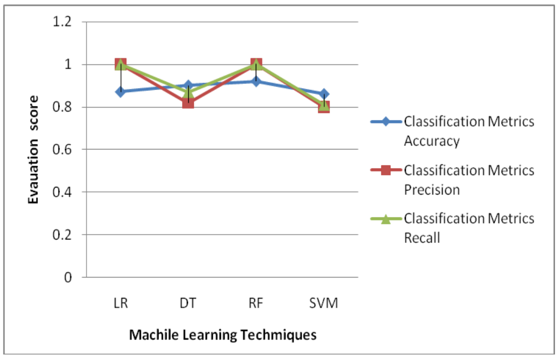

Fig. 7. Performance chart of evaluation metrics

Table I depicts the evaluation outcomes of the above algorithms and Random Forest outcomes the other algorithms with an accuracy of 0.92.

TABLE I. PERFORMANCE RESULTS

ML	*Classification Metrics*		
	Accuracy	*Precision*	*Recall*
LR	0.87	1.00	1.00
DT	0.90	0.82	0.87
RF	0.92	1.00	1.00
SVM	0.86	0.80	0.81

VI. CONCLUSION

Choosing the finest modes of birthing is necessary for the safety of both mothers and babies, but the ideal elements to consider while making such decisions have yet to be discovered. By completing a thorough empirical study, this study investigated all available features and divided them into distinct categories before employing a machine learning feature selection approach. The outcomes of applying machine learning algorithms to combinations of these categories (classes) were afterwards utilized to establish the optimal algorithm for predicting the best childbirth model with the fewest features. The approach's efficiency was demonstrated by the performance for features.

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