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A Machine Learning-Based Prediction Model for Preterm Birth in Rural Areas

Dr.S.Jafar Ali Ibrahim[1] , Y. Prathyusha[2], B. Akhila[3], M. Rajini[4], U. Naveen Sai[5]

Associate Professor, Dept. of Information Technology, QIS College of Engineering and Technology, Andhra Pradesh, India

[2,3,4,5]Final Year (B. Tech), Dept. of Information Technology, QIS College of Engineering and Technology, Andhra Pradesh, India

Corresponding author.
Correspondence: Dr.S.Jafar Ali Ibrahim
E-mail jafarali@gmail.com:

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Abstract
Wildfires are a worldwide natural disaster causing important economic damages and loss of lives . Early detection and prediction of fire spread can help reduce affected areas and improve firefighting. Unmanned Aerial Vehicles were employed to tackle this problem due to their HIGH flexibility, their low-cost, and their ability to cover wide areas during the day or night. However , they are still limited by challenging problems such as small fire size, background complexity, and image degradation .To deal with the limitations, we adapted and optimized Deep Learning methods to detect wildfire at an early stage. A novel deep ensemble learning method, which combines EfficientNet-B5 and DenseNet-201 models, is proposed to identify and classify wildfire using aerial images.

1. Introduction

Preterm birth (PTB) is a serious public health problem that adversely affects both families and the society . It is a leading cause of neonatal mortality and morbidity across the world and also the second major cause of child deaths under the age of five years . Over the past two decades, PTB has been a significant research study in healthcare domain. Pregnancy and childbirth unlocked the door for medical experts and researchers to explore various effective strategies to reduce preterm birth in women having pregnancy-related complications. These strategies include healthcare services given to all pregnant women to control PTB and any medical interventions aimed to enhance the knowledge of women on early indications of pregnancy complications. The maternal history of a pregnant woman is a key part of the neonatal studies for providing certain clinical treatments to newborn babies regarding their health, disease, care, and outcomes. Newborn babies are very special. They do not have any previous medical background, and their early neonatal path is directly connected to the maternal history of their mothers . The healthcare services also incorporate the arrangements of essential social and economic support for women before, during, and after pregnancy including educational, medical, and other training programs that facilitate healthy motherhood.

Background

Preterm Birth (PTB): A Comprehensive Overview

Preterm or premature birth is defined as birth, for any reason, occurring before 37 completed weeks (or less than 259 days) of pregnancy. Every year, about fifteen million babies are born prematurely (before 37 completed weeks of gestation), and this is nearly equal to one-tenth of all babies around the world . According to the WHO reports studied in 2005, 12.9 million births or 9.6% of all births across the world occurred prematurely . The rate of preterm birth, however, significantly varies across the world. Preterm birth reflects the most prominent reason for neonatal morbidity and mortality.

Categorization of PTB

PTB can be classified into different categories based on gestational age at birth. The gestational age is defined as the time from the first day of the last menstrual period (LMP) of a woman to birth . The four categories of PTB are as follows:(i)*Extreme PTB (under 28 Weeks).* It is the birth that takes place before 28 weeks of pregnancy(ii)*Very PTB (28 to 32 Weeks).* It is the birth that takes place between 28 and 32 weeks of pregnancy(iii)*Moderate PTB (32 to 34 Weeks).* It is the birth that takes place between 32 and 34 weeks of pregnancy(iv)*Late PTB (34 to 37 Weeks).* It is the birth that takes place between 34 and 37 weeks of pregnancy

Health Impact of PTB

PTB is the main risk factor for newborn mortality and morbidity. It is a leading cause of neonatal mortality and morbidity across the world and also the second major cause of child deaths under the age of five years . It arises between 5 and 10% of all deliveries and involves 70% of neonatal mortality and up to 75% of neonatal morbidity. Premature infants are more likely to suffer than normal birth and are at higher risk of brain paralysis, sensory impairment, respiratory failure, and so on. More than $13 billon of premature cost for maternity service is anticipated only in the USA . Most survivors of PTB face serious problems, often a lifetime of disability, including learning disabilities, visual, and hearing problems. In fact, babies born premature have more health problems compared with babies born at term birth. Term birth refers to babies that are born at 37 to 40 weeks of gestation. Furthermore, babies born at preterm are reported to be at an elevated risk of long-term health problems . Unfortunately, after many years of research in obstetrics, yet the rate of PTB has not decreased . Birth weight is generally associated with PTB and results in its own categorization. Usually, birth weight is simpler to measure precisely and is a first estimation of gestational age. Obviously, the most challenging issue in Gynaecology and Obstetrics is how to control the preterm delivery in pregnant women.

Feature Selection (FS)

The term feature selection in the machine learning, also known as feature subset selection, refers to the process of selecting a subset of excellent features during construction of the predictive model. The presence of redundant and irrelevant features in any datasets (especially in medical datasets) can reduce the accuracy of the model’s prediction and also have the negative impact on the performance of the model. The main goal of any feature selection method is to select the best subset of features by removing redundant and irrelevant features from the datasets in order to reduce the training time and enhance the classifier's predictive performance. In fact, feature selection is typically used as a preprocessing step in data mining. There are three standard approaches of the feature selection algorithm, namely, filter method, wrapper method, and embedded method. For more details about feature selection, one may refer to .(i)*Filter Method*. The filter method measures the relevance of features based on the nature of data. The selection of features is independent of the classifiers used. The filter method is much faster compared with the wrapper method and provides an average accuracy for all the classifiers used. Some of the examples of filter methods are information gain, chi-square test, variance threshold, and so on.(ii)*Wrapper Method*. The wrapper method finds the best subset of features based on a specific machine learning algorithm that we are trying to fit on a given dataset. The evaluation criteria are simply the predictive power of the particular classifier. The wrapper method has higher performance accuracy compared with the filter method but requires more computational time to find best features for a dataset with high-dimensional features. Some of the examples of wrapper methods are forward selection, backward elimination, genetic algorithms, and so on.

Related Works

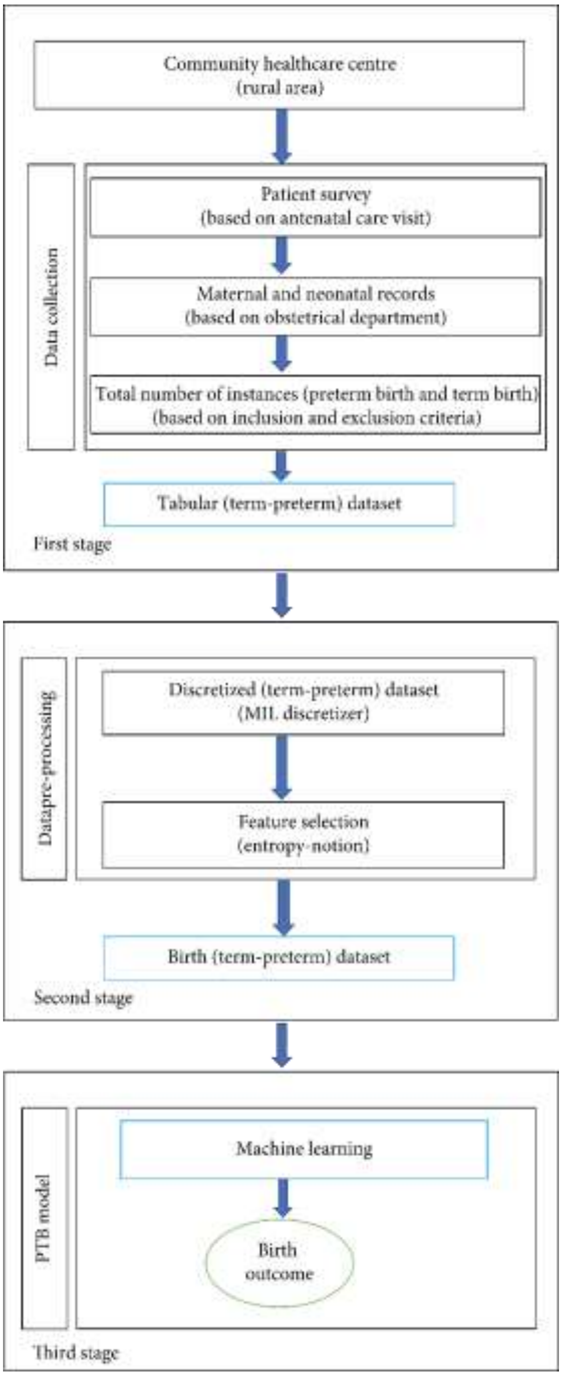
This section focuses mainly on the existing methodologies related to prediction of PTB using machine learning, statistical analysis, and data mining techniques. Some of them are discussed in this section. The study of Mercer et al. was designed to develop a risk-score-based model for predicting PTB. The model can be trained using a multivariate logistic regression technique to explore various risk factors using clinical data available between 23 and 24 weeks' gestation. Goodwin et al. employed the machine learning model to generate 520 predictive rules for PTB with the application of data mining techniques . The study in discussed the deep learning models for predicting preterm delivery using existing electronic medical records (EMRs) of mothers available in healthcare centres.

Weber et al. performed a cohort study to predict spontaneous preterm. The prediction of PTB was performed using numerous classifiers, namely, K-nearest neighbours, lasso regression, and random forests. This study has taken into the consideration of demographic, race-ethnicity, and maternal characteristics. Mailath-Pokorny et al. explored the predictive features for preterm delivery that occurs within 2 days after admission and before 224 days of gestation using the multivariate logistic regression model. The predictive features considered are age of the mother, gestational age during admission, maternal history, vaginal bleeding, cervical length, preterm history, and preterm premature rupture of membranes (PPROM) in their study. Son and Miller presented a prediction model for PTB using cervical length measurement in women with a singleton gestation. To accomplish better predictive performance, they attempted to determine the best cut points of cervical length .

Elaveyini et al. explored the major risk factors of preterm birth using artificial neural networks. PTB prediction was based on the feed-forward backpropagation algorithm. Over the past decades, majority of research studies have been done to enhance the accuracy of prediction of PTB . Researchers are continually making their best efforts to analyse and explore the principal risk factors for preterm delivery . The present article focuses on the machine learning approaches for prediction of birth cases in rural community.

The Proposed Framework: Risk Prediction Conceptual Model (RPCM)

Based on novel feature selection (entropy-notion) approach and several studies in , RPCM is carefully designed to predict the risk of PTB in pregnant women. The workflow of the framework consisting of three stages (Stage-I, Stage-II, and Stage-III) is depicted in Figure 2, and then its each component is detailed.



Conclusion

In this study, the proposed model (RPCM) can be used for prediction of PTB based on excellent features (text-based symptoms) available in obstetrical data. The work focuses on feature selection (entropy-notion) approach by applying machine learning classifiers (DT, LR, and SVM) in order to classify all birth cases into term birth and PTB. Comparing the performances of the classifiers, it is evident that SVM classifier is the most suitable classifier as it achieves an accuracy of 90.9%. According to the findings of this study, the identified risk factors (excellent features) will be helpful in the prediction of PTB, especially in rural community. The developed model supports the decision-making process in maternity care by identifying and alerting the pregnant women at risk of preterm delivery thereby preventing possible complications, reducing the diagnosis cost, and ultimately minimizing the risk of PTB. The present system can be regarded as a successful innovation in Obstetrics to give clinical support to patients during pregnancy consultations. In particular, RPCM claims to assist healthcare professionals to make effective and timely decisions without consulting specialists directly.

The limitation of the present research is that the risk factors for PTB are limited in size and dataset is small, which could be increased to improve the performance of the PTB prediction in the future studies. However, expert knowledge and clinical judgement may still be needed to interpret this risk and take appropriate action in individual cases.

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