CHAPTER: 17

MACHINE LEARNING-BASED CLINICAL DECISION SUPPORT SYSTEM FOR PREDICTING FETAL HYPOXEMIA DURING NON-STRESS TEST

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INTRODUCTION

In the fiscal year 2019-2020, India reported 824,000 under-five deaths. Neonatal deaths, with almost 24 out of 1000 attributed to fetal hypoxia associated with metabolic acidosis (45%), constitute a significant concern. Other leading causes of neonatal mortality include complications from preterm birth (35%), intrapartum events (25%), and infections (10%) [1].

Fetal hypoxia, or intrauterine hypoxemia, is a condition wherein the fetus experiences an inadequate supply of oxygen. This condition can result in irreversible damage to the Central Nervous System and may lead to growth retardation. Readings for fetal hypoxia are categorized as either Reactive or Non-Reactive [2].

To assess fetal conditions, a non-stress test is typically conducted during the 28th to 30th week of pregnancy. This non-invasive screening procedure is employed in pregnancies with a high risk of fetal hypoxia. During the test, key features such as baseline fetal heart rate and fetal movements are analyzed to evaluate fetal well-being [3].

RESEARCH OBJECTIVES

The research aimed to develop a precise and responsive clinical decision support system model capable of identifying pathological fetuses using recorded fetal heart rate data obtained during the non-stress test.

RESEARCH METHODOLOGY

Foetal heart rate recordings, along with 10 other variables, were collected from 1800 pregnant women in their third trimester. The data underwent a feature selection algorithm to identify important variables in the set. The dataset was randomly divided into two independent random samples in the ratio of 70% for training and 30% for testing. After testing various machine learning algorithms based on specificity and sensitivity to accurately classify the fetus into normal, suspected, or pathological categories, the Random Forest algorithm was selected. Using the "shiny" package of R, the model was converted into a webbased platform for use by healthcare providers.

RESULTS & DISCUSSION

The classifier's performance was assessed by comparing the predicted classification values in the test set with the actual values. All 11 independent variables were identified as crucial for predicting the fetal health category. The variables highlighted in green were deemed important in contrast to the shadow variables, encompassing the minimum, maximum, and mean values of the data frame. This outcome suggested that all 11 variables could be effectively utilized in developing the prediction model.

In terms of overall statistics, the model exhibited an accuracy of 94.71%, with a 95% confidence interval between 92.61% and 96.35%. The p-value, less than 2.2e-16, signified the statistical significance of the model in predicting the health category. The Kappa value was calculated as 0.8453, indicating a strong agreement between predicted and actual values. McNamara's test yielded a p-value of 0.004264, further supporting the model's reliability.

Examining error rates in relation to the number of trees, it was observed that the out-of-bag error rate stabilized after 400 trees in the forest model. Subsequent increases in the number of trees did not lead to a significant reduction in the predictability error. This suggested that the model achieved stable performance beyond 400 trees in predicting fetal health categories.

CONCLUSION

The information gathered during antenatal check-ups holds paramount importance for obstetricians and gynecologists in assessing the condition of the developing fetus. Relying solely on visual diagnosis may lack objectivity and accuracy. The likelihood of diagnostic errors is particularly heightened in areas with less-trained healthcare providers, such as remote and rural regions lacking efficient healthcare infrastructure. Therefore, the utilization of clinical decision support tools proves advantageous. In this study, the Random Forest supervised machine learning model, consisting of 1000 trees in the forest, demonstrated an overall accuracy of 94.71%, with a p-value of =< 2.2e-16 indicating statistically significant predictive results for the health category. Beyond 400 trees, the model did not exhibit a significant reduction in the error rate. For predicting category 3, representing the pathological condition of the fetus, the model achieved a sensitivity of 0.88 and specificity of 0.99. Consequently, the model can effectively differentiate between the three categories of fetal health, providing results that can guide actions to safeguard the lives of both the fetus and the mother during childbirth. This has the potential to contribute to the reduction of infant mortality rates and maternal mortality rates.

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