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Using Machine Learning and Administrative Data to Predict Premature Births

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Objective. To assess the potential of using machine learning and administrative birth data for predicting premature births. **Design**. The performance of ordinary least square (OLS) and deep neural network (DNN) classifiers for predicting low birth weight (LBW) and preterm birth (PTB) was compared using randomly selected two million birth records from the US CDC between 2016 and 2018. One million records from 2016 and 2017 were used to train the classifiers, while another million records from 2018 were utilized to test them. For hyperparameter tuning, a grid search with varying numbers of hidden layers, class weights on positive cases, and thresholds, was undertaken. **Setting and Population**: All births in the US **Methods**: ordinary least squares regression, deep neural networks **Main Outcome Measures**. LBW (<2,500g) and PTB(<37 weeks) Results. The classifiers generally showed high accuracy and specificity, however, the DNN classifiers showed much improvement in increasing sensitivity. Based on the results, the highest sensitivity with comparable specificity was 0.71 for LBW and 0.65 for PTB. **Conclusion**. These findings highlight that a ML approach could benefit PCHV programs by helping identify mothers with a high risk of premature birth. In particular, the DNN classifiers with administrative data can provide accessible solutions for public agencies and nonprofit organizations providing PCHV services that are not likely to possess massive clinical data or highly accurate genetic testing equipment.

Title

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Keywords . machine learning, artificial intelligence, prediction, birth outcomes, low birth weight, preterm birth, disadvantaged groups.

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INTRODUCTION

Reducing premature births has been an important public health agenda in the United States at least since the 1980s. Prematurity of infants is one of the critical causes of fetal death and medical complications in infants, *e.g.* , low oxygen level at birth and nervous system problems (1). Russell and colleagues estimated that the costs of hospitalization for infants with low birth weight (LBW) or preterm birth (PTB) would be six times higher than that of other infants without PTB or LBW (2). Moreover, the physical and mental health of newborn babies reproduce socioeconomic disadvantages throughout their lifetime (3).

As the premature birth rate has continuously been high despite advanced medical technologies and prenatal care,(4,5) several Prenatal Care Home Visiting (PCHV) programs have been implemented. A PCHV generally refers to a service in which nurses or trained counselors visit families with a pregnant woman to provide advice for antepartum care treatments or counseling services (6,7). The services mainly provide monitoring to keep mothers receiving appropriate care services and counseling focused on parenting curricula and reducing behavioral risk factors, such as smoking, alcohol/drug use, and mental health problems (7,8). Furthermore, receiving prenatal care on a regular basis is considered as a primary measure of preventing premature births because it becomes a starting point to detect risks at an earlier stage of gestation.(7) PCHV programs specifically target to improve the accessibility to prenatal care for mothers in underserved communities (6,7). Rich evidence finds that infants from mothers in a socially and economically disadvantaged group are exposed to a higher risk of prematurity (9–11).

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With ambitions to reduce disparities in birth outcomes, several PCHV programs have been implemented in the United States, however, the outcomes have been mixed. Two well-known large-scale randomized experiments examined the effectiveness of the home visiting approach to providing prenatal care: Nurse-Family Partnership (NFP) and the Mothers and Infant Home Visiting Program Evaluation-Strong Start (MIHOPE-Strong Start). As an earlier attempt, NFP, as a nonprofit organization, has provided PCHV services for mothers in disadvantaged groups and established evidence-based practices built upon its foundational randomized trials in Elmira, Memphis, and Denver (12). Olds the founder of the program, reported that nurse-visited mothers in the group that received the PCHV service through the program showed fewer rates of preterm births, infections, diseases (e.g., pregnancy-induced hypertension and atrial blood pressures), and higher average birth weight, compared the other group that did not receive the service (8). On the other hand, the MIHOPE-Strong Start is a relatively recent attempt initiated by the Office of Planning, Research, and Evaluation (OPRE) of the Administration for Children and Families (ACF) in 2012 (7). Different from findings of Olds, this program has not produced statistically significant improvements in families' prenatal behaviors and birth outcomes (7).

At its core, the implementation of PCHV stands on the assumption that mothers would seek out the service voluntarily if they need it,*i.e.* , self-efficacy theory (8). However, this may not hold true because individuals' care demands are often not connected to the actual use of care services due to mothers' preferences or lack of knowledge and information. For example, mothers who work full-time might be less likely to have a limited chance to use prenatal care services than mothers who work part-time. Although existing programs often narrow the target based on sociodemographic profiles of mothers, such an approach is still exposed to poor accuracy in screening mothers with high risks. Prematurity at birth is a complex clinical problem that occurs by various sociodemographic and behavioral risk factors (13,14). Therefore, identifying high-risk individuals with only a couple of sociodemographic factors may not be sufficient to account for the causal complexity of birth prematurity.

PCHV interventions may have a higher potential if the agency can selectively encourage mothers for whom a premature birth is highly likely, with higher precision that allows identifying high-risk individuals. To achieve this, this study explores the potential of applying machine learning (ML) techniques in predicting premature births by using the birth data from the National Center for Health Statistics (NCHS) of the Centers for Disease Control and Prevention (CDC). More specifically, this study compares the performances of ordinary linear regression (OLS) and Deep Neural Network (DNN). The application of ML has been increasing in the fields of medicine, including mortality (15), cancer (16), opioids (17), influenzas (18), and mental diseases (19). Different from conventional statistical models that express the outcome as a linear combination of inputs and weights, a DNN classifier improves predictive performance by employing non-linear functions and multiple layers that bridge inputs and outputs (20). By combining this approach with the US birth data that is publicly accessible to most of public agencies, this study shows that attempts to use a home visiting approach for improving birth outcomes among mothers with high risk can benefit from a predictive approach improved by ML.

DATA AND METHODS

Data

This study uses a randomly sampled two million records (one million for training and the rest for testing) of all births in the 50 states, the District of Columbia, and US territories by using the birth data from 2016 to 2018 provided by the NCHS of the CDC. This database includes records of all births in the United States and its territories reported through the birth certificate required by state laws (21). The data includes the information of infants, sociodemographic characteristics of parents, and maternal risk factors. The training data is pulled from the years 2016 and 2017, while using the 2018 data for testing. The study period is limited to after 2016 because this is the first year that all the US states have completed the adoption of the

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2003 revised birth certificate (22).

Outcomes and Predictors

This analysis uses LBW (1 if <2,500g) and PTB (1 if <37 gestational weeks) as the outcome measures of infant prematurity by following the definitions established by the World Health Organization (WHO) (23). Table 1 presents the characteristics of infants in the study sample. Approximately 7% and 9% of infants are coded as LBW and PTB. More than half (51%) of the sample are male, and the percentage of singleton births is 97%. The right-most column indicates that the differences in these characteristics between the training and testing data are not statistically significant.

[Table 1 about here]

Predictors include various factors that can affect birth outcomes (see Appendix 2 for the full list of the predictors). Sociodemographic characteristics of parents are included: maternal age, race, education, marital status, source of payment. Maternal risk factors include live-birth order, mother's body mass index (BMI), weight gain during pregnancy, smoking, infections (e.g., gonorrhea and syphilis), previous preterm birth, hypertension eclampsia, diabetes, hypertension, and the use of infertility treatment.

Approaches for Prediction

This study compares the performance of two approaches: OLS regression and DNN. The OLS classifier expresses the likelihood of premature birth as a linear combination of predictors and weighted. The DNN classifier in this study has a feedforward neural network architecture that constructs non-linear modules with multiple hidden layers between input and output layers (Figure 1). These classifiers are fed by 160 inputs created by 43 variables and produce the probabilities of two classes: one as premature birth and zero as other (no premature birth).

The DNN classifier optimizes weights of inputs by using gradient descent optimization that repeatedly computes outputs and errors based on the given inputs and adjusts weights up to the point where the objective function is minimized (20).

[Figure 1 about here]

In the DNN classifier, each neuron produces outputs as a linear combination of given inputs and weights (24). In the input and hidden layers, the Rectified Linear Unit (ReLU) function adds a non-linear feature to the outputs in the input and hidden layers. The basic form of the ReLU function is:

$f\left(a_j\right) = max(0, a_j)$ [1]

where

$a_j = \sum_{i=1}^{D} w_{j0} + w_{\mathrm{ji}} x_i$ [2]

In the equations, j indexes perceptrons and D denotes the number of inputs to the perceptron. x_i denotes inputs, while $w$denotes weights of the inputs. In each perceptron, this function returnsa_j only if it is larger than 0.

The output layer uses a sigmoidal activation function by considering the binary outcomes. This function returns the output of binary prediction in the range of 0 to 1. The basic form is:

$z(a_j) = \frac{1}{1+exp(a_j)}$ [3]

In training the DNN classifier, the dataset is divided into ten mutually exclusive subsets to iterate training and testing with nine subsets while leaving the last one for performance validation.(25) We set a large batch size of 1,024 and conduct a grid search with different class weights on positive cases, hidden layers, and

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thresholds by considering that LBW and PTB are rare events of which the occurrence rate is less than 10%.(26) The number of units is set as 64, and the dropout rate is set as 0.1.

The model performance is measured by employing three metrics: accuracy, sensitivity, and specificity. Accuracy refers to the proportion of true positives and negatives of the sample, *i.e.* , the proportion of accurate outputs. Sensitivity, measured as the proportion of true positive cases among positive predictions, indicates how the model accurately predicts the outcome. Considering that this study deals with the imbalance with the low rate of LBW and PTB, getting a good sensitivity is more crucial than accuracy and specificity to show that the classifier is sufficiently useful to predict such outcomes that occasionally happen. Lastly, specificity is calculated as the proportion of true negatives among negative predictions. This metric indicates how the classifier predicts births without LBW and PTB accurately.

ANALYSIS AND RESULTS

Model Performance

Table 2 compares the performance of the OLS and DNN classifiers in predicting premature births in 2018. The overall accuracy of all the outputs was high, however, the OLS outputs showed very poor sensitivity. The highest specificity of the OLS classifier is achieved with the cutoff of 0.1 and was 0.22 for LBW and 0.23 for PTB. It steeply decreased as the cutoff increased.

Compared to the OLS approach, the DNN classifiers showed more promising results, particularly in terms of increased sensitivity. The highest sensitivity for predicting LBW using the DNN classifier was 0.64 with one hidden layer and 12:1 of class weighting on positive cases. Similarly, using two hidden layers and a class weight ratio of 11:1, the highest sensitivity for predicting PTB was 0.64. However, the results also show that a higher class weight on positive cases sacrifices accuracy and specificity while increasing sensitivity.

[Table 2 about here]

Figure 2 shows experiments with different levels of the threshold in classifying the output in the output layer. In the plots, the Y-axis indicates the score of performance metrics. Various thresholds from 0.501 to 0.509 are on the X-axis. For example, in Figure 2A, 0.501 means that records are classified as LBW if the predicted outputs are 0.501 or higher. In these experiments, the number of hidden layers and the class weight were respectively set to 1 and 11 that showed the best performance among the settings in Table 2.

By tuning the thresholds, the highest sensitivity for predicting LBW reached 0.69 with a threshold of 0.5012. With this setting, the accuracy and specificity were 0.75 and 0.76, respectively. However, the threshold tuning for predicting PTB showed relatively lower performance than the results based on the default threshold of 0.5 in Table 1. Therefore, the result for predicting PTB with the highest sensitivity in this study was 0.64, with an accuracy of 0.74 and a specificity of 0.75.

[Figure 2 about here]

DISCUSSION

The analysis presented in the preceding pages represents the application of a novel ML-based method for predicting premature births by using administrative birth data. The results demonstrated that the performance of the DNN classifier trained based on various infant and parental characteristics from administrative data can produce a decent level of performance that outweighs the performance of the OLS classifier trained by the same dataset. Although there are some critical missing factors of birth prematurity, such as genetic information, the findings imply that the combination of ML and administrative birth data may have the po-

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tential to identify mothers with high risk and care needs, who need to pay attention to their birth outcomes, which can also improve the effectiveness of public programs providing PCHV services.

From a theoretical point of view, this study is one of the early attempts to confirm the utility of administrative data in predicting premature births. Studies that use administrative birth data for the purpose of predicting birth outcomes have been rare in this area, despite the explosive growth in the amount of data in the public sector and the scientific community. Moreover, as mentioned before, the findings also imply that the combination of ML and administrative data may have the potential to improve the effectiveness of PCHV programs by helping identify mothers with the most need, even though the overall predictive performance of the models should be further improved to allow a more proactive approach in promoting PCHV programs. Therefore, research to develop a model with a higher prediction precision would be necessary. Future research should also make efforts to test with more recent learning algorithms and look for ways to accumulate more data that help improve prediction.

While the findings are encouraging, it is important to also recognize that the predictive approach has the potential risk of systematically excluding some populations that actually demand prenatal care services. The population-based classification and predictive approach compared in this study are all based upon a technique for drawing a boundary dividing potential beneficiaries and other individuals that will not be considered for the program. The only differences between them are whether the model draws on a statistical or ML technique and how many variables are included in the classification. These efforts are expected to allow identifying individuals with the highest need. However, as mentioned before, a downside of these approaches would be that there might be certain individuals or populations left behind because perfect predictive models do not exist and some variables might be missing. An agency that attempts to use a predictive approach for promoting a PCHV program should acknowledge this situation and try to mitigate it with ancillary measures and more traditional strategies with the goal of also including individuals not identified through the predictive models.

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TABLES AND FIGURES

Table 1 . Infant Characteristics of the Study Sample

	2016-2017	2018	t-test
% LBW (<2,500g)	7.25	7.15	*P<0.01*
% PTB (<37 weeks)	9.00	8.98	*P<0.01*

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% Male	51.17	51.17	*P<0.01*
% Singleton birth	96.62	96.80	*P<0.01*

Figure 1 . Conceptual Framework of the Deep Neural Classification.

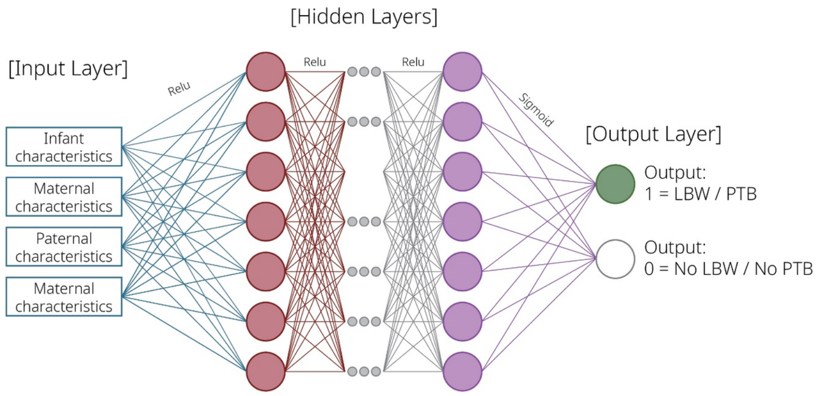

Table 2. Comparison of Model Performance

	LBW Accuracy	**LBW Sensitivity**	**LBW Specificity**	**PTB Accuracy**	**PTB Sensitivity**	**PTB Specificity**
OLS						
Cutoff 0.1	0.7379	0.2190	0.7786	0.7161	0.2340	0.7639
Cutoff 0.2	0.8820	0.0530	0.9470	0.8392	0.0859	0.9138
Cutoff 0.3	0.8983	0.0344	0.9660	0.8757	0.0406	0.9583
Cutoff 0.4	0.8999	0.0325	0.9678	0.8822	0.0330	0.9662
Cutoff 0.5	0.9089	0.0223	0.9783	0.8843	0.0302	0.9688
Cutoff 0.6	0.9224	0.0059	0.9942	0.9012	0.0010	0.9894
Cutoff 0.7	0.9261	0.0016	0.9985	0.9068	0.0037	0.9961
Cutoff 0.8	0.9265	0.0011	0.9991	0.9087	0.0014	0.9985
Cutoff 0.9	0.9268	0.0008	0.9993	0.9092	0.0008	0.9991
DNN: Hidden Layer = 1						
No weight	0.9351	0.1682	0.9937	0.9181	0.1587	0.9927
Weight = 2	0.9343	0.2290	0.9882	0.9166	0.2327	0.9837
Weight = 3	0.9292	0.2956	0.9777	0.9137	0.2686	0.9770
Weight = 4	0.9218	0.3446	0.9659	0.9029	0.3310	0.9590
Weight = 5	0.9114	0.3938	0.9509	0.8900	0.3825	0.9398
Weight = 6	0.8997	0.4372	0.9351	0.8763	0.4239	0.9208
Weight = 7	0.8907	0.4617	0.9235	0.8626	0.4572	0.9024
Weight = 8	0.8685	0.5156	0.8954	0.8449	0.4937	0.8793
Weight = 9	0.8510	0.5496	0.8741	0.8201	0.5367	0.8479
Weight = 10	0.8361	0.5768	0.8559	0.8006	0.5597	0.8243
Weight = 11	0.8191	0.6070	0.8353	0.7559	0.6209	0.7691
Weight = 12	0.8041	0.6252	0.8177	0.7306	0.6516	0.7384
Weight = 13	0.7946	0.6427	0.8062	0.6160	0.7493	0.6029

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Weight = 14	0.7425	0.7016	0.7456	0.6035	0.7628	0.5878
Weight = 15	0.7380	0.7078	0.7403	0.5696	0.7862	0.5484
Weight = 16	0.6809	0.7611	0.6748	0.5504	0.7993	0.5260
Weight = 17	0.6728	0.7670	0.6655	0.5178	0.8230	0.4878
DNN: Hidden Layer = 2						
No weight	0.9318	0.0488	0.9993	0.9150	0.0647	0.9984
Weight = 2	0.9342	0.1134	0.9969	0.9156	0.2462	0.9813
Weight = 3	0.9307	0.2795	0.9804	0.9182	0.1718	0.9914
Weight = 4	0.9328	0.0742	0.9984	0.9179	0.1920	0.9892
Weight = 5	0.9119	0.3904	0.9517	0.9027	0.3333	0.9585
Weight = 6	0.9110	0.3953	0.9505	0.8594	0.4624	0.8984
Weight = 7	0.8918	0.4589	0.9249	0.8569	0.4648	0.8954
Weight = 8	0.7797	0.6583	0.7890	0.8662	0.4492	0.9072
Weight = 9	0.8944	0.4516	0.9283	0.9145	0.2607	0.9787
Weight = 10	0.9033	0.4235	0.9400	0.9137	0.2634	0.9776
Weight = 11	0.9100	0.4004	0.9490	0.8677	0.4392	0.9098
Weight = 12	0.9164	0.3714	0.9581	0.9133	0.2690	0.9766
Weight = 13	0.8900	0.4641	0.9225	0.8876	0.3819	0.9372
Weight = 14	0.8334	0.5805	0.8528	0.7355	0.6378	0.7451
Weight = 15	0.8659	0.5183	0.8924	0.8417	0.4913	0.8760
Weight = 16	0.8317	0.5832	0.8507	0.8182	0.5339	0.8461
Weight = 17	0.9138	0.3835	0.9543	0.7627	0.6048	0.7782

Figure 2. Performance of Deep Neural Network Classifier by Threshold.

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