DEEP LEARNING BASED REGRESSION WITH SWISH HYPERBOLIC TANGENT FOR PREGNANCY HEALTH RISK CLASSIFICATION

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Abstract

Maternal health is the foremost characteristic of women's health during pregnancy. Particularly, during pregnancy, several health aspects like age, heart rate, blood disorders, etc. can give rise to pregnancy complexities. This designing a Deep Neural Network based York Regression with Swish Hyperbolic Tangent (DNN-YRSHT) method for Pregnancy Health Risk classification. The proposed method for pregnancy patient risk classification comprises of five layers as, input are passed to input layer that is then transmitted to first hidden layer. In first hidden layer Hybrid Class Balanced Standardization-based Pre-processing is applied to class balancing and normalization process separately. In the second hidden layer, York Regression-based Feature Selection model is using relevant further processing. Third hidden layer, Swish Hyperbolic Tangent Activation Function is applied to classify health risk level into two classes, namely low risk or high risk and is transmitted to output layer. In this manner, maternal risk level classification is performed with higher accuracy and computationally efficient manner. The DNN-YRSHT method can assist medical personnel in making quick decisions, improving level of care provided to expectant mothers and their unborn children in a timely manner.

Keywords: Deep Neural Network, Hybrid Class Balanced Standardization, York Regression, Swish Hyperbolic, Tangent Activation Function

1. Introduction

Maternal health risk prediction employs Deep Learning (DL) algorithms to investigate several factors and predict likelihood of complications during pregnancy. A weighted random forest (WRF) algorithm was proposed [1] to predict early-onset preeclampsia (PE). However, prediction was not assessed. Echo Dense Inception Blending and Dense Reservoir Inception Modular Network in [2] establish features for miscarriage prediction. Nevertheless, training time was not focused. Extreme Gradient Boosting and Principal Component Analysis was introduced in [3] for efficient detection and treatment of fetal diseases. But, real-time fetal health system was not used. Optimized single-dimensional Convolutional Neural Network (1DOCNN) was introduced in [4]. Safe, simple, home-comfortable, low-cost, and reliable monitoring framework was designed in [5] to monitor uterine electro hysterography (EHG). However, it failed to recruit pregnant women with high risk of premature labor. Deep learning-based automatic semantic segmentation was designed in [6] for predicting preterm labor and promoted transferability of EHG technique. But, the time complexity was not reduced. An untargeted metabolomic profiling was designed in [7] with serum, tongue coating and saliva of pregnant women. A active learning technique to ascertain most influential data samples was proposed in [8] resulting in improved accuracy. An enhanced predictive method was presented in [9] to boost maternal risk classification with improved accuracy. Machine learning (ML) techniques were employed in [10]. Yet another method to improve risk classification by combining artificial neural network with random forest algorithms was presented in [11]. A comprehensive method for high risk pregnancies employing functional and non functional requirements were designed in [12].A method using artificial intelligence (AI) to relate high, low risk and mid risk during pregnancy was presented in [13] for advancing maternal health care. Yet another method to focus on high risk pregnancy with features were identified in [14] to offer accurate diagnostic performance. Influence of pelvic girdle pain and its association with pregnancy issues were addressed in [15] by using logistic regression and extreme gradient boosting with improved precision.

1.1 Contributions of the work

- To design Hybrid Class Balanced Standardization-based Pre-processing classification time is said to be improved by means of application over-sampling and under-sampling.
- To present York Regression-based Feature Selection model, Principal Latent Feature Analysis, Regression Modeling with Selected Target Factors and fine-tuned parameter estimation selects the most influential features with improved precision and recall.
- To develop Swish Hyperbolic Tangent Activation Function and applying Swish 'T_B' as classifier where weights are fine-tuned and does not stops learning even in case of neuron outputs zero, therefore ensuring accurate pregnancy health risk classification.
- Extensive simulation results demonstrate better pregnancy health risk classification in terms of classification time, precision, recall and accuracy compared with other methods.

2. Related works

A portrayal of literature review involving both qualitative and quantitative analysis performed in the period between May and June 2025 was investigated in [16].An artificial neural network-based method [17] used for maternal health risk prediction. A detailed investigation for predicting maternal health care was presented in [18]. A holistic review on risk prediction for pregnancy outcomes was investigated in [19]. ML technique was applied in [20] to ascertain risk patients early and impart personalized predictions throughout pregnancy. In [21] ML and DL techniques were applied for automation pregnancy health risk prediction with major focus on accuracy aspect. Yet another method to ease pregnancy prediction using large language model was proposed in [22]. An adverse pregnancy outcome employing ML technique was presented in [23] to ascertain the wide- spread and risk elements for adverse pregnancy outcomes. Research work in [24] investigated the prospective application of Logistic Regression, Adaboost, and Random Forest, 1-D CNN and ANN for predicting and investigating challenges in women, inspired utilization of ML techniques in research dimensions of medical diagnosis. A descriptive systematic review on pregnancy health risk prediction in recurrent pregnancy loss was investigated in [25].In [26] the outcomes of premature birth and risk associated with pregnant sample data was avoided. The proposed method was also tested for reliability and accuracy. An in depth survey of application of ML and DL techniques for detailed healthcare predictive data analytics was presented in [27]. Nevertheless, the efficiency of ML classifiers is obstructed by intrinsic class imbalance. A Generative Adversarial Network was presented in [28] with intent of generating high-quality results while maintaining the statistical properties in an accurate fashion. A method for recurrent pregnancy loss along with retrospective study in China was conducted in [29] to efficiently identify high risk groups.

3. Materials and methodology

This study proposes DNN-YRSHT method to boost maternal risk classification accuracy using minimal and straight forwardly collectible clinical features. Figure 1 shows the framework of proposed DNN-YRSHT method.

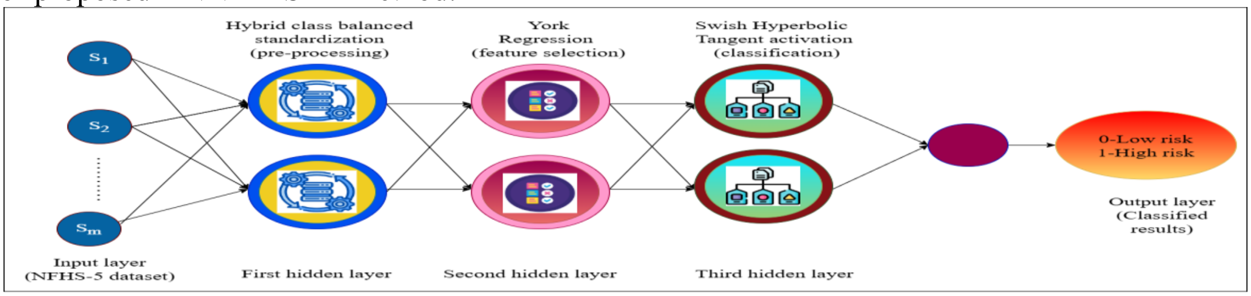

Figure 1 Framework of DNN-YRSHT method

As figure illustrated the proposed method is split into five layers. They are input layer, three hidden layers and one output layer for pregnancy health risk

3.2 Dataset Acquisition

The proposed method uses National Family Health Survey-5 (NFHS-5) dataset and can be accessed via https://www.kaggle.com/datasets/ravisinghiitbhu/nfhs5 [30]. The NFHS-5 includes 136,136 maternal data samples and 95 features. This tabular view pinpoints multiplicity and affluence of data for pregnancy complication classification.

Preg_Complication column summary:
1 : 75284 records
0 : 24716 records

	Res_Age	State	Edu_level	Water_Source_Time	Toilet_Facility	House_electricity	House_radio	House_tv	House_bicycle	House_motorcycle	House_car
0	38	Jammu & Kashmir	2	0	1	1	1	1	0	0	0
1	39	Jammu & Kashmir	1	0	1	1	1	0	1	0	0
2	30	Jammu & Kashmir	2	0	1	1	0	1	1	0	0
3	32	Jammu & Kashmir	2	0	1	1	1	1	1	0	0
4	29	Jammu & Kashmir	2	0	1	1	1	1	1	0	1

[100000 rows x 94 columns]

Figure 2 Sample view of the NFHS-5 dataset

3.3 Input layer

In the proposed method, number of maternal data samples 'S' from National Family and Health Survey-5 dataset 'DS' extracted as input and passed to input layer. The input layer 'IV' is formulated in the form of vector as given below.

$$IV = \begin{bmatrix} S_1F_1 & S_1F_2 & \dots & S_1F_n \\ S_2F_1 & S_2F_2 & \dots & S_2F_n \\ \dots & \dots & \dots & \dots \\ S_mF_1 & S_mF_2 & \dots & S_mF_n \end{bmatrix} \quad (1)$$

From equation (1)'m' samples 'S_m' and 'n' features 'F_n'. The input layer transmits maternal data, 'IV' to first hidden layer.

3.4 Hybrid Class Balanced Standardization-based Pre-processing

In first hidden layer, Hybrid Class Balanced Standardization-based Pre-processing is applied to raw samples that perform class balance and normalization process. Figure 3 shows the block diagram of Hybrid Class Balanced Standardization-based Pre-processing.

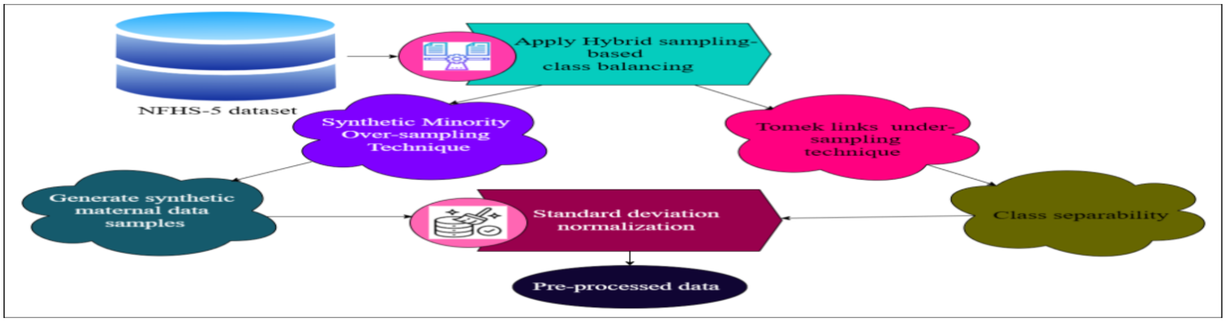

Figure 3 Block diagram of Pre-processing

As shown figure, data point samples obtained from NFHS-5 dataset as input. First, Hybrid Sampling-based Class Balancing is applied for combining heterogeneity of over-sampling minority class and under-sampling majority class. Next, class balanced maternal data point samples are subjected to Standard Deviation Normalization Process that ensures better feature comparison significantly.

3.4.1 Hybrid Sampling-based Class Balancing

Synthetic Minority Over-sampling Technique is utilized for generating synthetic maternal data samples. The Tomek links to under-sample maternal data points by discarding pairs of nearest neighbors from opposite classes. Then, distance between random maternal data points and its 'k' nearest neighbors are calculated to select arbitrary maternal data point.

$$Ratio_{OS}[IV] = \frac{No_{rm}[IV]}{No_m[IV]} \qquad (2)$$

From (2) Hybrid Sampling-based Class Balancing ratio '$Ratio_{OS}[IV]$' is formulated based on minority and majority class '$No_{rm}[IV]$' and '$No_m[IV]$'. A hybrid model combining Tomek links under-sampling and Synthetic Minority over-sampling to address class imbalance.

3.4.2 Standard Deviation Normalization Process

Standard Deviation Normalization process is carried out to prevent features of maternal data point samples. By sticking down all features on a proportionate magnitude, each one comes up with equally to the method's results. Standard Deviation Normalization Process the normalized value of input vector 'IV' is calculated as given below.

$$PS = Normalized(S_i) = \frac{S_i}{STD(IV)} \qquad (3)$$

$$STD(IV) = \frac{1}{(n-1)} \sum_{i=1}^{n} (S_i - IV')^2 \qquad (4)$$

$$IV' = \frac{1}{n} \sum_{i=1}^{n} S_i \qquad (5)$$

From (3), (4) and (5) normalized maternal data point sample results '$Normalized(S_i)$' are arrived based on standard deviation values of input vector.

3.5 York Regression-based Feature Selection model

In the second hidden layer, York Regression-based Feature Selection model is applied to select the relevant features for efficient classification.

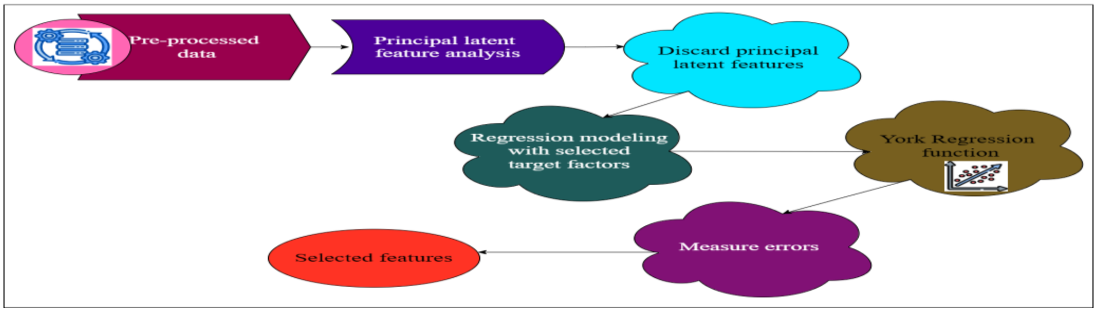

Figure 4 Block diagram of York Regression-based Feature Selection model

As shown in figure, pre-processed samples provided as input to York Regression-based Feature Selection model. Here, principal latent feature analysis, regression modeling with selected target factors and fine-tuned parameter estimation by applying York regression function. To start with factor analysis is applied to large set of initial features '$\{F_i\}_{i=n\ or\ 95}$' from dataset 'DS'. This factor analysis step identifies principal latent features and selecting influential features. These principal latent features are then discarded from further processing.

$$q_m = Xp_m + z + e_m \quad (6)$$

The features other than principal latent features are used as independent variables to select target features. The target features reduces issues that exist in original features.

$$q_m = Yr_m + z + e_m \quad (7)$$

From equations (6) and (7) factor regression model, integrating Principal Latent Feature Analysis and Regression Modeling with Selected Target Factors is modeled as given below.

$$Uq_m = Xp_m + Yr_m + z + e_m \quad (8)$$

From equation (8), '$m-th$' observation 'Uq_m' results combined with Principal Latent Feature Analysis and Regression Modeling, 'r_m' design factors, regression coefficient 'Y' of design factors, intercept 'z' and Gaussian noise 'e_m'. Finally, target features in subsequent regression steps are subject to measurement errors. The slope, '$Slope$'and 'v' intercept, 'FS' of best-fit line is represented in terms of summations of computations. The William-York regression fit a best-fit straight line to a set of maternal data point samples when both '$\boldsymbol{u}$' and '$\boldsymbol{v}$' features are subject to measurement error**s** and these errors may be correlated.

$$FS = v' - Slope u' \quad (9)$$

$$Slope = \frac{\sum W_i \alpha_i V_i}{\sum W_i \beta_i U_i}, v' = \frac{\sum W_i v_i}{\sum W_i}, u' = \frac{\sum W_i u_i}{\sum W_i}, V_i = v_i - v', U_i = u_i - u' \quad (10)$$

$$W_i = \frac{Wu_i Wv_i}{Wu_i + m^2 Wv_i - 2 m r_i \alpha_i}, \alpha_i = \sqrt{Wu_i Wv_i}, \beta_i = \left[\frac{U_i}{Wv_i} + \frac{mV_i}{Wu_i} - (mU_i + V_i)\frac{r_i}{\alpha_i}\right] \quad (11)$$

From (9), (10) and (11)', 'U' and 'V' intermediated calculated values with weight 'W', associated to each maternal data point. Also, lower correlated measurement errors selects higher probability of feature and higher correlated measurement errors selects lower probability of feature. Then, data points with selected influential features are transmitted to third hidden layer.

3.6 Swish Hyperbolic Tangent Activation-based classification

Finally in third hidden layer, classification between low risk and high risk is arrived using Swish Hyperbolic Tangent Activation Function. It is expressed as given below.

$$f(PS;\beta,\alpha) = PS\sigma(\beta PS) + \alpha \tanh(PS)\,|FS \quad (12)$$

$$= PS\sigma(\beta PS) + \alpha(2\sigma(2PS) - 1)|FS \quad (13)$$

$$= PS\sigma(\beta PS) + 2\alpha\sigma(2PS) - \alpha|FS \quad (14)$$

From (12), (13) and (14), '$\sigma(PS)$' represents sigmoid function for pre-processed samples for influential features 'FS' activated via a trainable parameter 'β', and a hyper-parameter 'σ' employed in scaling '$tanh$' function from '$(-1,+1)$' to '$(-|\alpha|,|\alpha|)$'. By applying Swish 'T_B' as classifier even if neuron outputs zero gradient flows back through it during back propagation so its weights are fine-tuned and does not stops learning. The Swish Hyperbolic with Tanh Bias (Swish-TB) is mathematically formulated as given below.

$$f_B(PS;\beta,\alpha) = \sigma(\beta PS)(PS + 2\alpha) - \alpha \quad (15)$$

$$= PS\sigma(\beta PS) + \alpha \tanh(\beta/2PS) \quad (16)$$

From equations (15) and (16) continuous differentiable function assists in smooth gradient flow, therefore ensuring precise and accurate classification results. Finally the classified results of complication or no complication are provided as output in output layer. The pseudo code representation of DNN-YRSHT for pregnancy health risk classification is given below.

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \ldots . S_m\}$', Features '$F = \{F_1, F_2, \ldots \ldots, F_n\}$'
Output: robust classification
Step 1: **Initialize** '$m = 100000$', '$n = 95$', '$\alpha = 0.1$', '$\beta = 1.0$' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Samples 'S' and Features 'F' **//Input layer** Step 4:Generate input vector results according to (1) **//First hidden layer** **//Hybrid Sampling-based Class Balancing** Step 5: Generate Hybrid Sampling ratio according to (2) **//Standard Deviation Normalization Process** Step 6: Generate Standard Deviation Normalization results according to (3), (4) and (5) Step 7: **Return** pre-processed sample results 'PS' **//Second hidden layer** Step 8: **For** each Dataset 'DS' with Features 'F' and pre-processed sample results 'PS' Step 9: Obtain the principal latent features according to (6) Step 10: Perform Regression Modeling with Selected Target Factors according to (7) Step 11: Combine Principal Latent Feature and Regression Modeling with Selected Target Factor according to (8) Step 12: Evaluate York Regression function to generate feature selected results according to (9), (10) and (11) Step 13: **Return** features selected 'FS' Step 14: **End for** **//Third hidden layer** Step 15: **For** each Dataset 'DS' with pre-processed sample results 'PS' and features selected 'FS' Step 16: Generate Swish-T activation function for the pre-processed sample results with corresponding features selected according to (12), (13) and (14) Step 17: Generate Swish-TB results according to (15) and (16) Step 18: **Return** classified results Step 19: **End for** **//Output layer** Step 20: **For** each Dataset 'DS' with pre-processed sample results 'PS', features selected 'FS' and classified results Step 21: **Return** classified results of complication (i.e. low risk) or no complication (i.e. high risk) Step 22: **End for** Step 23: **End for** Step 24: **End**

Algorithm Deep Neural Network based York Regression with Swish Hyperbolic Tangen

4. Experimental setup and discussion

The simulation results of DNN-YRSHT and existing Weighted Random Forest (WRF) [1] and EDI-Blend and DRIM-Net [2] is implemented in Python high-level general-purpose programming language. Simulations are performed with five performance metrics.

4.1 Analysis of classification time

. A significant amount of time is said to be consumed from starting pre-processing till classification and this is said to be classification time 'CT '. It is measured as given below.

$$CT = \sum_{i=1}^{m} S_i * Time\ (Classification) \quad (17)$$

From equation (17) the sample maternal data points 'S_i' and actual time involved in classification '$Time\ (Classification)$' process. It is measured in terms of seconds (sec).

4.2 Analysis of precision

Precision 'Pre ' refers to accuracy of positive predictions or to be more specific denotes out of all positive predictions how many sample maternal data points were correct.

$$Pre = \frac{TP}{TP+FP} \tag{18}$$

From the above equation (18) true positive rate 'TP' and false positive rate 'FP'

4.3 **Analysis of recall**

Recall ' Rec'refers to identify all relevant sample maternal data points or to be more specific to find out of all actual positive samples how many did corresponding method identified.

$$Rec = \frac{TP}{TP+FN} \tag{19}$$

From the above equation (19) the false negative rate 'FN'

4.4 Analysis of classification accuracy

Classification accuracy 'Acc' is a performance metric that evaluates ratio of correct classification made by a method out of total number of classifications.

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \tag{20}$$

From the above equation (20) true negative rate 'TN'

Table 1 Classification time / **Table 2 Precision**

Samples	Classification time (sec)			Precision		
	DNN-YRSHT	WRF [1]	EDI-Blend and DRIM-Net [2]	DNN-YRSHT	WRF [1]	EDI-Blend and DRIM-Net [2]
10000	2500	3100	3300	0.97	0.96	0.95
20000	2585	3085	3135	0.95	0.85	0.8
30000	2625	3125	3175	0.91	0.81	0.76
40000	2685	3185	3235	0.9	0.8	0.75
50000	2715	3245	3285	0.85	0.75	0.7
60000	2755	3285	3315	0.82	0.72	0.67
70000	2835	3355	3385	0.8	0.7	0.65
80000	2885	3395	3425	0.84	0.74	0.69
90000	2915	3475	3505	0.86	0.76	0.71
100000	2955	3495	3585	0.88	0.78	0.73

Table 3 Recall / **Table 4 Classification accuracy**

Samples	Recall			Classification accuracy		
	DNN-YRSHT	WRF [1]	EDI-Blend and DRIM-Net [2]	DNN-YRSHT	WRF [1]	EDI-Blend and DRIM-Net [2]
10000	0.99	0.98	0.98	0.97	0.96	0.94
20000	0.96	0.81	0.71	0.95	0.88	0.78
30000	0.93	0.78	0.68	0.93	0.86	0.76
40000	0.91	0.76	0.66	0.91	0.84	0.74
50000	0.85	0.7	0.6	0.89	0.82	0.72
60000	0.82	0.67	0.57	0.88	0.8	0.7
70000	0.86	0.71	0.61	0.85	0.78	0.68
80000	0.89	0.74	0.64	0.89	0.81	0.71
90000	0.92	0.77	0.67	0.92	0.84	0.74
100000	0.94	0.79	0.69	0.94	0.87	0.77

The table shows better DNN-YRSHT technique result with reduced classification time by 29% and 45%, with improved precision by 13% and 23% , Recall by 5%and 18%, classification accuracy by 5%and 18% when compared with [1], [2],

5 Conclusion

The proposed DNN-YRSHT method achieves pregnancy health risk classification with objective of providing timely remedies in case of complication. The simulation consequences validated that DNN-YRSHT method provides better results in performance metrics.

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