Application of Computational Technique in
Design of Classifier for Early Detection of
Gestational Diabetes Mellitus

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Abstract

Gestational Diabetes Mellitus (GDM) is defined as any degree of glucose intolerance with onset or first recognition during pregnancy. In view of maternal morbidity and mortality as well as fetal complications, early diagnosis is an utmost necessity in the present scenario. In developing country like India, early detection and prevention will be more cost effective. Oral Glucose Tolerance Test (OGTT) is the crucial method for diagnosing GDM done usually between 24th and 28th week of pregnancy. The proposed work focuses on early detection of GDM without a visit to the hospital for women who are pregnant for the second time onwards (multigravida patients). A decision support system using Multilayer Neural Network which learns to classify GDM and non GDM patients using Back
Propagation learning algorithm is developed. The classifier proves to be an efficient model for diagnosis of GDM without the conventional method of blood test by providing newly designed parameters as inputs to the network.

**Keywords:** Gestational Diabetes Mellitus, Diagnosis, Artificial Neural Network, Back Propagation, Classification

### 1 Introduction

Diabetes is sweeping the globe as a silent epidemic largely contributing to the growing burden of non-communicable diseases and mainly encouraged by decreasing levels of activity and increasing prevalence of obesity. Gestational diabetes mellitus is one of the most common medical complications during pregnancy and is associated with several maternal and neonatal complications. Gestational diabetes is caused by the hormones of pregnancy which is produced when the placenta supports the growing fetus. These hormones may interfere with the mother’s ability to produce and use her own insulin. Usually this form of diabetes goes away after the delivery but women who have had gestational diabetes have a 20 to 50 percent chance of developing Type 2 diabetes. The factors associated with an increased risk of GDM include older age, increased weight, family history of diabetes, personal history of GDM and particular ethnic origins. Worldwide, reported prevalence rates of GDM have ranged from 3% to 21% and it has been increasing rapidly in recent years. As a result, strategies to identify and treat GDM are being implemented in many countries. It has found to be more prevalent in urban than rural areas. In a random survey 16.2% of pregnant women were found to have GDM in the Chennai urban population.

GDM can affect the developing fetus throughout the pregnancy. A mother’s diabetes can result in birth defects and an increased rate of miscarriage in early pregnancy. The birth defects that occur most often affect major organs such as the brain and heart. During the second and third trimester, it can lead to over-nutrition and excess growth of the baby. In addition, when high blood sugar from the mother causes hyperinsulinemia (high insulin levels) in the baby, after birth the baby's blood sugar can drop very low. Babies born to mothers with untreated gestational diabetes are typically at increased risk of problems such as being large for gestational age, jaundice and low blood sugar. If left untreated, it can also cause seizures or stillbirth. Women with unmanaged gestational diabetes have a higher incidence of pre-eclampsia and Caesarean section; their offspring are prone to develop childhood obesity and also type 2 diabetes later in life.

Gestational diabetes is detected by using an oral glucose tolerance test usually at 24-28 weeks. If the patient has had gestational diabetes in a previous pregnancy, the OGTT will be carried out at 16-18 weeks. This will be followed by a repeat OGTT at 28 weeks if the first test is normal. As the disease has severe health implications for both mother and child, early diagnosis of GDM is an important public health issue.
2 Literature Survey

Surabhi Nanda et al. [9] developed a model for the prediction of GDM from maternal characteristics and biochemical markers at 11 to 13 weeks’ gestation. A prospective screening study on early prediction of pregnancy complications was used to create the predictive model of GDM based on maternal characteristics. Thach S. Tran et al. [10] compared the discriminative power of prognostic models for early prediction of women at risk for the development of GDM using four currently recommended diagnostic criteria based on the 75-g OGTT. It was concluded that a simple prognostic model using age and BMI at booking could be used for selective screening of GDM in Vietnam and in other low- and middle-income settings. The purpose of study of Ozcimen EE et al. [6] was to predict GDM in the first trimester. Fasting glucose and insulin were measured in the first trimester and the homeostasis model assessment-insulin resistance index (HOMA-IR) was calculated for each patient. These values were compared with the results of the second-trimester glucose tolerance test. Okeh U.M et al. [5] proposed to develop a semi-parametric generalized linear mixed model (GLMM) method. This method was applied in evaluating the impact of covariates on the accuracy of diagnostic test results by way of obtaining a common cut off value for screening 50g glucose challenge test(GCT) for the three trimesters of pregnancy. The proposed method was illustrated using data on GDM. Caipo Zhang et al. [2] in their paper used fuzzy integral to structure the diagnostic model of gestational diabetes mellitus. The Sugeno measure was obtained by training of BP neural network. As the BP neural network is easy to get into local optimum, the algorithm of simulated annealing was used to optimize the BP neural network to obtain an approximate global optimal solution. Lohse N et al. [4] through their study examined the cost-effectiveness of GDM screening and postpartum lifestyle management using a mathematical model (GD Model). The long-term impact of screening was estimated using the published CORE diabetes model. The authors concluded that a universal screening programme to identify gestational diabetes mellitus was highly cost-effective in both India and Israel. J.K. Olarinoye et al. [3] compared the diagnostic performances of 75g and 100g Oral Glucose Tolerance Tests in detecting GDM in Nigerian pregnant women and concluded that 100g OGTT criteria was more stringent than that of 75g OGTT in identifying GDM. Sreedevi E et al. [8] presented a paper that deals with study and development of algorithm to develop an initial stage expert system to provide diagnosis to the pregnant women who are suffering from GDM by means of OGTT.

The above survey clearly shows that when considering the inputs to all these systems, there is at least one input value for which the patient should get the help of a doctor or a hospital staff. The proposed system aims to help pregnant women in the early stage in diagnosing GDM without even taking a blood test and hence is cost effective. Moreover, this will help the patient to be aware in advance and take precautionary measures like make changes in dietary behavior and participate actively in physical exercise so that GDM can be averted.
3 Methodology

The proposed work implements an Artificial Neural Network (ANN), a supervised multilayer feed forward network with Back propagation learning algorithm. ANN is particularly useful when the primary goal is classification and it is known that this technique for diagnosis of diabetes gives much better results than other existing techniques.

Artificial Neural Network: An Artificial Neural Network (ANN) is a computational structure that is inspired by observed process in natural networks of biological neurons in the brain. It contains highly interconnected simple computational units called neurons. They have an adaptive nature and learn by example in solving problems. This is a non-parametric pattern recognition method which can recognize hidden patterns between independent and dependent variables. ANN are widely used for classification and diagnosis in various thirst areas like effective decision making in medical field, signal processing and so on. In biochemical analysis, artificial neural networks have been used to track glucose levels in diabetes, analyze blood and urine samples.

The main principle of neural network computing is the decomposition of the input-output relationship into a series of linearly separable steps using hidden layers. The classification system contains three different modules. First module is input module. It will receive a new patient’s input and hand it over to the second module. Second module is a trained neural network system which will classify the given input patient’s case record into high risk or low risk for GDM. Third module is an output module which will display the classification system output. Computation takes place in the hidden layer and output layer. There is no computation in input layer which has nodes simply to receive the input from the user.

With a single forward pass through the network, the output of a Feed Forward Neural Network for any given input pattern \( z_p \) is calculated. For each output unit \( o_k \),

\[
O_{k,p} = f_{o_k} \left( \sum_{j=1}^{J+1} w_{kj} f_{y_j} \left( \sum_{i=1}^{I+1} v_{ji} z_{i,p} \right) \right)
\]

where \( f_{o_k} \) and \( f_{y_j} \) are respectively the activation function for output unit \( o_k \) and hidden unit \( y_j \); \( w_{kj} \) is the weight between output unit \( o_k \) and hidden unit \( y_j \); \( z_{i,p} \) is the value of input unit \( z_i \) of input pattern \( z_p \); the \((I + 1)\)-th input unit and the \((J + 1)\)-th hidden unit are bias units representing the threshold values of neurons in the next layer.

Back propagation Training Algorithm: The Back propagation algorithm has had a major impact and is readily applied to a large number of diverse problems such as function approximation, classification and forecasting. In particular, it is widely recognized as a powerful tool to train ANN.
The Back propagation algorithm trains a given feed forward multiplayer neural network for a predefined set of input-output example pairs. When an input pattern has been applied to the first layer of network units, the network examines its output response to the sample input compared to the known output and the error value is calculated for each output unit. Based on the error, the connection weights are updated. The weight adjustment is done through mean square error of the output response to the sample input. Until the error value is minimized, the set of these training patterns are presented repeatedly to the network.

**Stochastic Gradient Descent Learning Algorithm:**
Initialize weights, \( \eta, \alpha \) and the number of epochs \( t = 0 \);
While stopping condition(s) not true do
Let \( \varepsilon_T = 0 \);
For each training pattern \( p \) do
Do the feed forward phase to calculate \( y_{i,p} (\forall j = 1, \ldots, J) \)
and \( o_{k,p} (\forall k = 1, \ldots, K) \);
Compute output error signals \( \delta_{0,k,p} \) and hidden layer error signals \( \delta_{y_{i,p}} \);
Adjust weights \( w_{kj} \) and \( v_{ji} \) (back propagation of errors);
\( \varepsilon_T = \sum_{k=1}^{K} (o_{k,p} - a_{k,p})^2 \);
end
\( t = t + 1 \);
end

The gradient of these back propagated error measures can then be used to determine the desired weight modifications for connections that lead into these hidden nodes [1].

### 4 Implementation

**Data Collection:** The real time data was collected from past patient records from a multi-speciality hospital in Chennai, Tamil Nadu, India. The patient data sets of 110 records each consisting of ten parameters was extracted from the outgoing patient’s records from January 2013 to March 2013. On consultation with gynaecologists and taking into account the several factors that are clinically relevant for a pregnant woman to develop GDM, the study variables used are as shown in Table 1.

The first three parameters involve general information like age, family history of diabetes in first degree relatives and Body Mass Index. Fourth to eighth parameters deal with previous pregnancy information such as presence of GDM, birth of a baby who weighed more than 3.8Kg, death of a baby before 20 weeks, birth of a baby with defects in spinal cord, heart or brain, death of a baby after 20 weeks.
weeks respectively. The last two parameters reveal information on history of urinary, skin or vaginal infections and polycystic ovary syndrome [7].

**Table 1: The parameters chosen for the study along with sample table**

<table>
<thead>
<tr>
<th>S No</th>
<th>Study Variable</th>
<th>Classification Network Variable type</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Age</td>
<td>Integer [continuous]</td>
<td>23</td>
<td>30</td>
<td>27</td>
<td>35</td>
<td>26</td>
<td>32</td>
</tr>
<tr>
<td>2</td>
<td>Family history of diabetes</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>Pre pregnancy body mass index</td>
<td>Integer [continuous]</td>
<td>20.1</td>
<td>25.5</td>
<td>32.2</td>
<td>27.1</td>
<td>22.6</td>
<td>25.8</td>
</tr>
<tr>
<td>4</td>
<td>History of GDM</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>Delivery of a large infant (&gt;3.8Kg)</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>History of miscarriage</td>
<td>Y or N [character]</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>Abnormal baby in previous pregnancy</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>History of stillbirth</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>Infections (Urinary, Skin, Vaginal)</td>
<td>Y or N [character]</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>History of Polycystic ovary syndrome</td>
<td>Y or N [character]</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Architecture Design:** A supervised three layered feed forward neural network was constructed to classify the GDM patient dataset. In the model for diagnosing GDM, one input layer, one hidden layer and an output layer are used as seen in Fig. 1. Input layer contains 10 nodes to receive the patient input data. Hidden layer contains 15 hidden nodes which have the link with the input layer and the output layer. The problem of diagnosing diabetes has been treated as a binary classification i.e., the outputs in the model are either 0 or 1. Value 1 is interpreted as "diagnosed to be a GDM patient" and value 0 is interpreted as “diagnosed to be a non GDM patient".
5 Experimentation and Result

The GDM diagnosis neural network was modeled using a classification network and the results are presented. Neural Network toolbox of MATLAB R2010a was used to develop a classification model for GDM data. The data sets were divided into 70% of training, 15% of validation and remaining 15% of testing. Experiments were conducted on three different architectures by varying the number of hidden neurons as 15, 20 and 25. Better classification results were obtained for the architecture containing 15 neurons in the hidden layer.

Fig. 2 shows the results of regression testing conducted on the ANN architecture for training, validation, testing and combination of all the three while
Fig. 3 depicts the performance of the ANN based on mean square error is generated for training, testing and validation. The best validation performance was at the third generation where the mean square value was 0.12506. It was found that Gradient Descent learning algorithm minimizes the error as generation proceeds. As shown in Fig. 4, the global minima of mean square error was found to be 0.075309 at the 9th generation. After the 9th generation, there was an increase in the gradient value. The validation dataset on the ANN revealed the minimum gradient at the 9th generation. The linearly separability of the classification data into two groups has patients diagnosed with GDM and normal patients with outputs 1 and 0 respectively is shown in Fig. 5.

The classification results for the data set show that 90.91% of the data was correctly classified while 9.09% were incorrectly classified. The result indicates that the network has been well trained and could be used for identifying pregnant women with risk of GDM.

6 Conclusion

Even though shortly after delivery glucose tolerance usually returns to normal, there is strong evidence that women with GDM have a high risk for developing diabetes in the course of their lives. As GDM is widely prevalent, many pregnant women have the fear of acquiring it. The risk during pregnancy is less if GDM is diagnosed earlier. Therefore early identification of women at risk of GDM is recommended to prevent complications.

To conclude, the Artificial Neural Network classifier helps to detect GDM in advance by using newly designed input parameters based on risk factors for multigravida pregnant women without even going to the hospital thereby reducing the cost for different medical tests and hence would be highly beneficial for pregnant women.
References


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