Fetal weight estimation for prediction of fetal macrosomia: does additional clinical and demographic data using pattern recognition algorithm improve detection?

Shimon Degani[1], MD
Dori Peleg[2]
Karina Bahous[1], MD
Zvi Leibovitz[1], MD
Israel Shapiro[1], MD
Gonen Ohel[1], MD

Ultrasound Unit, Department of Obstetrics and Gynecology, Bnai-Zion Medical Center, Ruth and Baruch Rappaport Faculty of Medicine[1], Faculty of Electrical Engineering[2], Technion-Institute of Technology, Haifa, Israel

Reprint requests to: Prof. Shimon Degani, MD
Department of Obstetrics and Gynecology
Bnai-Zion Medical Center, PO Box 4940,
Haifa 31048, Israel.
E-mail: sdegani@tx.technion.ac.il
Tel/Fax 972-4-8740245

Summary

Objective. **The aim of this study was to test whether pattern recognition classifiers with multiple clinical and sonographic variables could improve ultrasound prediction of fetal macrosomia over prediction which relies on the commonly used formulas for the sonographic estimation of fetal weight.**
Study design. **The SVM algorithm was used for binary classification between two categories of weight estimation: >4000gr and <4000gr. Clinical and sononographic input variables of 100 pregnancies suspected of having LGA fetuses were tested.**
Results. **Thirteen out of 38 features were selected as contributing variables that distinguish birth weights of below 4000gr and of 4000gr and above. Considering 4000gr. as a cutoff weight the pattern recognition algorithm predicted macrosomia with a sensitivity of 81%, specificity of 73%, positive predictive value of 81% and negative predictive value of 73%. The comparative figures according to the combined criteria based on two commonly used formulas generated from regression analysis were 88.1%, 34%, 65.8%, 66.7%.**
Conclusions. **The SVM algorithm provides a comparable prediction of LGA fetuses as other commonly used formulas generated from regression analysis. The better specificity and better positive predictive value suggest potential value for this method and further accumulation of data may improve the reliability of this approach.**

KEY WORDS: ulltrasound, fetal weight estimation, macrosomia, pattern recognition algorithm.

Introduction

Excessive fetal weight is associated with a significant increase in perinatal morbidity and mortality. It has also been associated with maternal complications that include postpartum hemorrhage and operative delivery. At delivery the macrosomic fetus is more likely to suffer shoulder dystocia, traumatic injury and birth asphyxia.
Estimated fetal weight is the most frequent approach to the sonographic diagnosis of macrosomia (1, 2). A number of other sonographic parameters have also been proposed for prediction: measurements of a number of fetal body parts, including the fetal abdomen and head, as well as ratios of body parts, such as the FL/AC and AC/BPD (2-4).
Sonographic prediction of fetal weight in large-for-gestational-age fetuses based on weight estimation equations is associated with overestimation and the reliability of these methods has been questioned by some authors (3, 5).
Improvement in the accuracy of identifying the macrosomic fetus compared to reliance on traditional measurements of abdominal circumference, femur length and head circumference was reported by Sokol et al (5): by adding clinical variables of maternal diabetes mellitus, height and weight. They found this approach using multivariate analysis to yield better prediction than the current "one function fits all" approach.
Training of a pattern recognition algorithm to predict macrosomia may offer a new approach to the medical problem. Pattern recognition algorithms are computer programs that can be used to discover complex relations within data sets. They permit the recognition of patterns in complex biological data sets that cannot be detected with conventional linear statistical analysis (6). Previously, two studies have utilized an artificial neural network computer programs for the estimation of fetal weight (7, 8). Mean percent error of estimated fetal weight as compared to actual birth weights were 4.7% and 6.0%. These preliminary studies were found to provide better ultrasound estimation of fetal weight than estimations by means of commonly used formulas generated from regression analysis.
Maternal and environmental factors have been associated with macrosomia, such as previous history of macrosomia, multiparity, maternal obesity, maternal age and height (9, 10).
The aim of the present study was to test if the computerized pattern recognition algorithm with multiple clinical and sonographic variables could improve ultrasound prediction of fetal macrosomia over prediction using weight estimation with the other commonly used formulas generated from regression analysis.

Study design

One hundred gravidas seen as outpatients or admitted in early labor to our department and suspected of having fetuses weighing 4000 gr. and over were referred for ultrasound evaluation. Input variables included clinical data (maternal and paternal age, ethnic origin, weight and height, weight gain during pregnancy, previous deliveries and birth weights, clinical weight estimation and fundal height), and sonographic data (Tables I, II). Large for gestational age (LGA) was defined as estimated fetal weight of 4000 gr and above.

The medical problem presented in this study was translated into a binary classification problem (two categories: weight ≥4000 gr termed '1', weight <4000 gr termed '-1'). The primary goal of a classifier is to produce a predictor of the class of an unlabeled example with the lowest probability of error. In this classification problem an additional objective was to decide which feature was relevant for successful prediction. Classification algorithms with such a dual goal are termed feature selection algorithms.

In the field of pattern recognition there is a multitude of feature selection algorithms (14-16). The classifier used in this paper is the SVM algorithm (16). The final classifier is linear, i.e.

$$f(x_1,...,x_d) = \text{sgn}\left(\sum_{i=1}^{n} w_i x_i + b\right),$$

where $x_1,\ldots,x_d$ are the features, $w_i,\ldots,w_d$ and b are the weights and bias respectively calculated by the algorithm and the sign function is

$$\text{sgn}(t) = \begin{cases} 1, t \geq 0 \\ -1, t < 0 \end{cases}$$

A feature x_i is termed as "selected" if the absolute value of the corresponding weight w_i is larger than a predetermined threshold.

Sensitivity, specificity positive and negative predictive values were calculated for each method.

Table I - Input variables.

1. Gravidity
2. Parity
3. Number of normal deliveries
4. Number of spontaneous abortions
5. Number of therapeutic abortions
6. Birthweights in previous deliveries
7. Number of previous CS
8. Weight of mother at her birth
9. Weight of mother before pregnancy
10. Weight of mother at delivery
11. Height of mother
12. Husband's weight (actually)
13. Husband's height
14. Husband's birth weight
15. GCT
16. OGTT
17. Diabetes mellitus (yes or no)
18. Fundal height
19. Mother's AC
20. Sex of baby
21. BPD
22. OFD
23. HC
24. AC
25. FL
26. Cheek-to-cheek
27. Subcutaneous thickness at abdomen
28. Humerus circumference
29. Subcutaneous thickness at humerus
30. Foot length
31. Chest circumference
32. Chest/BPD ratio
33. AC/BPD ratio
34. HC/chest ratio
35. FL/AC ratio
36. AC/FL ratio
37. EFW clinical
38. Week of pregnancy at delivery

Results

Thirteen of 38 features analyzed by the pattern recognition algorithm were selected as relevant for the prediction of macrosomia: number of pregnancy; route of delivery; maternal weight at term; maternal height at term; paternal weight; paternal height; fundal height; fetal abdominal circumference; fetal gender; fetal head circumference; humeral circumference; chest circumference; gestational age.

The dataset was randomly divided into 5 contiguous training and test sets. Each training set contains 80 patterns and the corresponding test set consists of 20 patterns. The error, which is defined as the average on the

Table II - Sonographic biometric data to evaluate macrosomic fetuses.

Commonly used measurements	Specific Measurement	Biometric ratios
BPD	Cheek to cheek diameter [22]	H/Chest
OFD	Abdominal subcutaneous tissue thickness [21]	AC/BPD
HC	Humeral soft tissue thickness [11]	AC/FL FL/AC
FL	Chest circumference [12]	H/A
AC	Foot length [13]	Chest/BPD

Table III - Sonographic criteria for macrosomia in the general population (adapted from Doubilet et al. [17]).

Criteria	Sensitivity (%)	Specificity (%)	Predictive Values (%) Positive	Negative
Elevated FL [18]	24	96	52	88
Elevated AC [18]	53	94	63	89
High EFW [18,27-29]	11-65	89-96	38-67	83-91
Elevated BPD [18]	29	98	71	92
Present study				
Shepard [28]	78.6	37.2	63.5	55.2
Hadlock [29]	86.2	43.9	68.6	69.2
Combined	88.1	34	65.8	66.7
PRA81.4	73.2	81.4	73.2	

PRA= Pattern Recognition Algorithm.

5 problems, was 0.22. The final classifier was calculated using all the examples.
Taking weight of more than 4 kg as positive 48 patients were correctly diagnosed as true positive, 11 were false positive, 30 were true negative and 11 false negative, (the bias: b=0.84508).
Sensitivity, specificity, positive and negative predictive values of commonly used formulas generated from regression analysis to detect macrosomia and the method used in the present study are shown in Table III.
Combined criteria based on the two weight estimation formulas (considering prediction of a LGA fetus by any of these formulas) resulted in a better sensitivity as compared to the SVM algorithm (88.1% vs 81%). However the specificity and positive and negative predictive values were far better using the pattern recognition algorithm (73.2% vs 34% and 81.4% vs 65.8% respectively). The ROC curve (Figure 1) was significantly above the 450 diagonal line of unity.

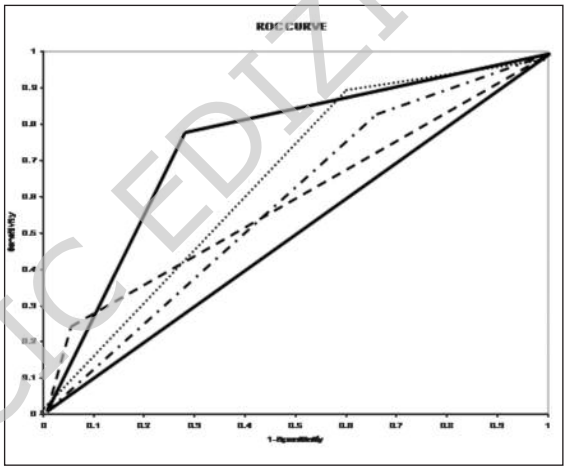

Figure 1 - Receiver-operating characteristics curve for PRA (Pattern Recognition Algorithm) as compared to other formulas in the prediction of fetal macrosomia. (——) Area under curve (AUC) (0.813; 95% CI:0.743-0.892) differs significantly from the area (0.500) under the 450 line of unity (p<0,001). There is significant difference from the AUC of the other methods accordingly: Hadlock 1982 (·····); Shepard 1982 (— — —); Miller 1988 (– – –). 0.723 (p<0.002); 0.692 (p<0,001); 0.673 (p<0.001).

Discussion

In the present study the specificity and predictive values of the pattern recognition algorithm proved to be better than other methods of fetal weight estimation based on commonly used formulas derived from regression analysis.
Although the sensitivity of the algorithm was not found to be superior to the sensitivity of other methods, the specificity and positive predictive value of this model is better than these values for other sonographic criteria for macrosomia in the general population (17, 18). Some of the widely used formulas for weight estimation in fetuses that are appropriate for gestational age, are based on small study groups, even smaller than our group (28, 29).
Fetal macrosomia has been traditionally related to maternal diabetes mellitus, but only 2% of infants with macrosomia are born to diabetic mothers. The accurate and timely prediction of fetal macrosomia is an important goal because it may impact on delivery management. When this condition is recognized an elective cesarean section can be scheduled to reduce the risk of shoulder dystocia and brachial palsy. Another option although controversial would be induction of labor before the state of macrosomia is reached. A routine policy of elective cesarean section is also controversial in
case of suspected macrosomia (30). Our suggested approach to macrosomia prediction may enable better research on the issue of induction/cesarean.
The equations used for weight estimation are designed for fetuses with normal body composition whereas macrosomic fetuses and more often fetuses in diabetic pregnancies have a high percentage of fat tissue which has a lower density than of muscle tissue. This may result in weight overestimation or greater percentage error in these fetuses (19). To overcome this limitation various methods were recommended: Measurement of subcutaneous tissue thickness (20, 21) at the level of upper arm and thigh, or indirectly by cheek to cheek diameter (22), ponderal index (23) and volume measurements of arm and thigh using 3D ultrasound (24, 25). Computer assisted analysis provides applications to evaluate multiple sonographic variables (26), but the sensitivity remains insufficient.

The management of a multifactorial condition deserves a non-uniform attitude. The low predictive value for macrosomia of single ultrasound parameters and ponderal indices suggests that these are not indicative of birth weight in large-for-gestational-age infants (27). Moreover, even combined use of four indices (growth profile) did not improve the effectiveness of ultrasound in detecting fetal macrosomia. To enhance the predictive value of the sonographic estimated fetal weight in macrosomic fetuses other factors can be used in a complimentary fashion. Previous history of macrosomia, multiparity, maternal obesity, maternal age and maternal height, excessive weight gain during pregnancy, prolonged gestation and slow delivery are some of the factors that have empirically been associated with macrosomia (9, 10).

Farmer et al. (7) used a biologically simulated intelligence model that included gestational age, fundal height, age, gravidity, and height, compared with results obtained from previously published formulas relying on the abdominal circumference and femur length. The biologically simulated intelligence yielded an average error of 4.7% from actual birth weight, statistically better than the results obtained from regression models. Chuang et al. (8) used six input variables to construct an artificial neural network model: biparietal diameter, occipito-frontal diameter, abdominal circumference, femur length, gestational age and fetal presentation. In a training group, the artificial neural network model was better than the other compared formulas in fetal weight estimation and a validation group further proved the results. Comparable models are obtainable from different ANN programs provided that both the network architecture and training algorithm are optimized (31).

The accuracy of our suggested test is now under study on large population in various gestational ages. It is not clear yet if in those fetuses who have been evaluated around 40 weeks the test is less accurate as compared to those evaluated earlier in pregnancy. However, the crucial time of weight estimation is close to term.

The aforementioned pattern recognition algorithm was demonstrated to be a promising approach for the prediction of fetal macrosomia. Since the nature of the algorithm involves optimization by training, the performance of the method may be further improved by accumulation of additional data.

References

1. Ocer F, Kaleli S, Budak E, Oral E. Fetal weight estimation and prediction of fetal macrosomia in non-diabetic pregnant women. Eur J Obstet Gynecol Reprod Biol 1999;83: 47-52.
2. Combs CA, Rosenn B, Miodovnik M, Siddiqi TA. Sonographic EFW and macrosomia: is there an optimum formula to predict diabetic fetal macrosomia? J Matern Fetal Med 2000;9:55-61.
3. Hirata GI, Medearis AL, Horenstein J, Bear MB, Platt LD. Ultrasonographic estimation of fetal weight in the clinically macrosomic fetus. Am J Obstet Gynecol 1990;162:238-42.
4. Jazayeri A, Heffron JA, Phillips R, Spellacy WN. Macrosomia prediction using ultrasound fetal abdominal circumference of 35 centimeters or more. Obstet Gynecol. 1999;93: 523-6.
5. Sokol RJ, Chik L, Dombrowski MP, Zador IE. Correctly identifying the macrosomic fetus: improving ultrasonography-based prediction. Am J Obstet Gynecol 2000;182: 1489-95.
6. Baxt WG. Application of artificial neural networks to clinical medicine. Lancet 1995 Oct 28;346:1135-8.
7. Farmer RM, Medearis AL, Hirata GI, Platt LD. The use of a neural network for the ultrasonographic estimation of fetal weight in the macrosomic fetus. Am J Obstet Gynecol 1992;166:1467-72.
8. Chuang L, Hwang JY, Chang CH, Yu CH, Chang FM. Ultrasound estimation of fetal weight with the use of computerized artificial neural network model. Ultrasound Med Biol 2002;28:991-6.
9. Hansen JP. Older maternal age and pregnancy outcome: a review of the literature. Obstet Gynecol Surv 1986;11: 726.
10. O'Leary JA. Preconceptional risk factors. In O'Leary JA ed. Shoulder dystocia and birth injury. New York; McGraw-Hill, 1992.
11. Sood AK, Yancey M, Richards D. Prediction of fetal macrosomia using humeral soft tissue thickness. Obstet Gynecol 1995;85:937-40.
12. Winn HN, Rauk PN, Petrie RH. Use of the fetal chest in estimating fetal weight. Am J Obstet Gynecol 1992;167:448-50.
13. Meirowitz NB, Ananth CV, Smulian JC, McLean DA, Guzman ER, Vintzileos AM. Foot length in fetuses with abnormal growth. J Ultrasound Med 2000;19:201-5.
14. Guyon I, Elisseeff A. An introduction to variable and feature selection. Journal of Machine learning research 2003 pp 1157-1182.
15. Peleg D, Meir R. A feature selected algorithm based on the global minimization of a generalization error bound. Proceeding of the 18th Conference on Neural Information Processing Systems 2004 (on-line article http://www.ee.technion.ac.il/~rmeir/rmeir_publications.html).
16. Glenn Fung, Olvi L. Mangasarian. Data Selection for Support Vector machines Classifiers. Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining 2000;64-70.
17. Doubilet PM, Benson CB, Callen PW. Ultrasound evaluation of fetal growth In Ultrasonography in Obstetrics and Gynecology Callen PW ed. 4th edition , WB Saunders Co. p. 216, 2000.
18. Miller JM Jr, Brown HL, Khawli OF, Pastorek JG 2nd, Gabert HA. Ultrasonographic identification of the macrosomic fetus. Am J Obstet Gynecol 1988;159:1110-4.
19. Alsulyman OM, Ouzounian JG, Kjos SL the accuracy of intrapartum ultrasonography fetal weight estimation in diabetic pregnancies. Am J Obstet Gynecol 1997;177:503-506.
20. Chauhan SP, West DJ, Scardo JA, Boyd JM, Joiner J, Hendrix NW. Antepartum detection of macrosomic fetus: clinical versus sonographic, including soft-tissue measurements. Obstet Gynecol 2000;95:639-42.
21. Petrikovsky BM, Oleschuk C, Lesser M, Gelertner N, Gross B. Prediction of fetal macrosomia using sonographically measured abdominal subcutaneous tissue thickness. J Clin Ultrasound 1997;25:378-82.
22. Abramowicz JS, Robischon K, Cox C. Incorporating sonographic cheek-to-cheek diameter, biparietal diameter and abdominal circumference improves weight estimation in the macrosomic fetus. Ultrasound Obstet Gynecol 1997;9: 409-13.
23. Miller JM Jr, Korndorffer FA Jr, Kissling GE, Brown HL, Gabert HA. Recognition of the overgrown fetus: in utero ponderal indices. Am J Perinatol 1987;4:86-9.

24. Chang FM, Liang RI, Ko HC, Yao BL, Chang CH, Yu CH. Three-dimensional ultrasound-assessed fetal thigh volumetry in predicting birth weight. Obstet Gynecol 1997;90: 331-9.
25. Liang RI, Chang FM, Yao BL, Chang CH, Yu CH, Ko HC. Predicting birth weight by fetal upper-arm volume with use of three-dimensional ultrasonography. Am J Obstet Gynecol 1997;177:632-8.
26. Hsieh FJ, Chang FM, Huang HC, Lu CC, Ko TM, Chen HY. Computer-assisted analysis for prediction of fetal weight by ultrasound-comparison of biparietal diameter (BPD), abdominal circumference (AC) and femur length (FL). J Formo sMed Assoc 1987;86:957-64.
27. Rosati P, Exacoustós C, Caruso A, Mancuso S. Ultrasound diagnosis of fetal macrosomia. Ultrasound in Obstetrics and Gynecology 1992;2:23-29.
28. Shepard MJ, Richards VA, Berkowitz RL, Warsof SL, Hobbins JC. An evaluation of two equations for predicting fetal weight by ultrasound. Am J Obstet Gynecol 1982;142:47-54.
29. Hadlock FP, Harrist RB, Sharman RS, Deter RL, Park SK. Estimation of fetal weight with the use of head, body, and femur measurements--a prospective study. Am J Obstet Gynecol 1985;151:333-7.
30. Spellacy WN, Miller S, Winegar A, Peterson PQ. Macrosomia--maternal characteristics and infant complications. Obstet Gynecol 1985;66:158-61.
31. Plumb AP, Rowe RC, York P, Brown M. Optimisation of the predictive ability of artificial neural network (ANN) models: a comparison of three ANN programs and four classes of training algorithm. Eur J Pharm Sci 2005;25: 395-405.