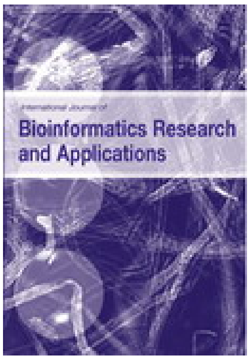

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Foetal weight estimation with descriptive statistics and correlation analysis of significant ultrasonographic parameter and fuzzy artmap classifier

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Foetal weight estimation with descriptive statistics and correlation analysis of significant ultrasonographic parameter and fuzzy artmap classifier

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Abstract: High and low weight of the foetus at birth can be associated with an increased risk of neonatal complications. So far, various techniques have been proposed for estimating birth weight. In the proposed method a powerful fuzzy-neural classifier is used. The method is evaluated on a set of 40 ultrasonographic foetal data, in which foetuses are at 37 and 38 weeks of gestation. The features used for classification training and testing are superior features that have been used by experts in the field for many years, including the length of the femur, the bicuspid diameter, and the circumference of the foetal head. The results of the implementation of the proposed method on the dataset indicate the achievement of 98.96% accuracy, which will be evidence of its good performance on the new data. The new method can be used to provide accurate estimates of foetal birth weight.

Keywords: foetal weight estimation; ultrasonographic parameter; statistics and correlation analysis; fuzzy artmap – ANFIS classifier.

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1 Introduction

To better control the pregnancy and determine how the foetus is growing and make appropriate decisions to terminate the pregnancy, especially in high-risk cases, it is necessary to know the estimated weight of the foetus. Due to the known complications of incorrect estimation, foetal weight estimation is of particular importance. Sonography is the best way to estimate foetal weight. Due to disagreements about different foetal weight estimating methods, the present study was conducted to compare various methods of estimating foetal weight with different methods. The high perinatal mortality rate is related to birth weight (BW) and associated problems. It is well known that prenatal morbidity and mortality increase in foetuses with abnormal BW (Milner and Arezina, 2018).

Pregnant women usually have a foetal weight sonography on the advice of a specialist or midwife. Yet, it is known that sonography weight estimation of the foetus is not accurate and cannot accurately predict foetal weight. Therefore, it cannot be a reliable source for deciding the type of delivery.

Foetal BW can be divided into the following three categories:

- Appropriate for gestational age (AGA): includes infants weighing between 10th and 90th percentiles of gestational age.
- Small for gestational age (SGA): includes infants weighing less than 10th percentile of gestational age.
- Large for gestational age (LGA): includes infants weighing more than 90th percentile at gestational age.
- Low birth weight (LBW): is used to describe very small babies at birth.

It should be noted that limiting the potential complications associated with LBW and overweight foetuses requires accurate estimation of prenatal weight (Ratnasiri et al., 2018).

So far, several studies have been conducted on estimating the BW of the foetus. For example, in Pretscher et al. (2020) study, 756 pregnant women with diabetes between 2002 and 2016 were studied. In this study, ten conventional formulas for estimating foetal weight seven days before delivery were calculated, and the error values of each were determined by measuring foetal weights. The comparison criteria used in this study include median absolute percentage errors (MAPEs), mean percentage errors (MPEs), and the ratio of estimates of the actual weight of the infant at birth.

Mohammadi et al. (2020) were conducted to determine the accuracy of using ultrasound (US) estimation of twin foetuses using an artificial neural network.

Examinations on 186 healthy singleton foetuses within three days of delivery have been performed. Three input variables were used to construct the ANN model: abdominal circumference (AC), abdominal diameter (AD), and biparietal diameter (BPD). Then, a total of 121 twin foetuses was assessed. The comparison criteria used in this study include absolute error and absolute percent error. The absolute and percent error between estimated foetal and actual foetal weight was 261.77 g and 7.81%. Results show that twin estimation of BW by ultrasound correlates reasonably well with the actual weights of twin foetuses.

In Kang et al.'s (2021) study, the Johnson equation was used, one of the well-known methods in estimating foetal weight, the BW, and the estimations of this relationship were investigated, results of which indicated the appropriate accuracy of the method in estimating BW.

Rashid's (2015) study was conducted to determine the accuracy of estimated foetal weight (EFW) by ultrasound, compared with BW, in Bangladesh. A total of 73 foetuses were evaluated. Determination of ultrasonographic foetal weights of Hadlock's method using the head circumference (HC), femur length (FL), and AC was quite accurate in this study. Therefore, the formula can be reliably used to estimate foetal weight in the Bangladeshi population.

In Kadji et al.'s (2020) study, magnetic resonance estimation of foetal weight (MR-EFW) in the third trimester was performed using foetal weight estimation based on sonography estimation of foetal weight (US-EFW) and actual BW by evaluating the factors affecting foetal growth over a long period of time. For this study, two methods, US-EFW and MR-EFW, were employed for 37 foetuses at an average of 33.0 and 37.7 weeks of gestation and plotted on the conventional BW forecast curve at 3 to 39 weeks of gestation. To compare the two methods in this study, the criteria of relative and absolute errors have been used to determine the accuracy of the US-EFW and MR-EFW methods. Finally, regression analysis has been used to investigate the effect of different variables on foetal growth during pregnancy. In Aviram et al.'s (2017) study aiming to investigate the proposed methods in estimating foetal age in pregnancies occurring in the elderly, a comprehensive evaluation of the various relationships proposed in this area was presented, and their results were compared with each other. In this study, 7,996 women and infants were selected from pregnant women with singleton pregnancies, of which 1,618 (about 20.2%) were considered elderly pregnancies. In this study, various comparison criteria such as sensitivity and specificity and known and widely used error criteria such as systematic and random errors have been used. In this research, the proposed methods are divided into six groups, and for each method, the proposed relationship is suggested in a specific group.

Alfirevic et al.'s (2017) study has shown that Doppler sonography is a useful tool during and at the end of pregnancy that can be used to monitor the growth of the foetus during pregnancy to detect growth restriction or macrosomia.

In Heidweiller-Schreurs et al.'s (2018) study, researchers introduced a method for determining the risk of childbirth using the resistance index (RI) component, which was based on foetal weight and Doppler sonography.

In McCowan et al.'s (2018) study, Doppler analysis has been used to determine the foetal weight as a new method with good performance.

Aliyeva and Aydın (2021) suggested that estimating BW with sonography is very important in the decision-making and management of labour complications. Their study investigates the effect of the femur, femur, and clavicular soft tissue thickness on BW using an innovative formula.

Tuten et al. (2021) conducted a study to evaluate the accuracy of foetal weight estimation by the latest prenatal sonography measurement in low BW infants (less than 2,500 g). In this article, a total of 1,082 women were evaluated. Demographic and clinical information of mother and infant and sonography measurements were recorded in the last week before birth. The accuracy of foetal weight estimation and the affecting parameters were examined.

Ricchi et al. (2021) used the Johnson equation, a well-known method for foetal weight estimation, and investigated the BW and the estimated value using this relationship; the results indicated the appropriate accuracy of the method in estimating BW.

In Lee et al. (2009), a total of 211 pregnant participants (gestational weeks 28 to 42) were selected between September 2017 and December 2018 at the Obstetrics and Gynecology Hospital of Beijing Medical University. The three-dimensional limb volume method measured high foetal arm and thigh volume. The foetal size was also measured by two-dimensional sonography. Nine cases were excluded due to incomplete information or the interval between examination and delivery less than seven days. The 202 participants selected by mechanical sampling were divided into a model group (134 cases, 70%) and a test group (68 cases, 30%). The linear relationship between limb volume and foetal weight was examined using Pearson (chi-square) test. The prediction model formula was created using multivariate regression with model group data. Finally, the accuracy of the model formula was confirmed by grouping data and compared with traditional formulas (Stirnemann et al., 2017; Plonka et al., 2020) by t-test and residual analysis. Receptor performance characteristic curves were also calculated for macrosomic prediction.

In the study (Hiwale et al., 2017), the accuracy of foetal weight estimation and the affecting parameters were examined. Data were collected from 300 pregnant women in a tertiary care centre in India. In total, 149 cases were found eligible for the study. The parameters measured in their study included AC, BPD, FL, and HC for foetal weight estimation models for the Indian population. Several formulas for estimating foetal weight were calculated, and the error values were determined by measuring foetal weight. The comparison criteria used in this study include absolute percentage errors and random error of the ratio of estimated BW to the actual weight of the infant at birth. It was observed that the models based on just AC and AC-BPD combinations had statistically significantly lesser MPE than the models based on all other combinations.

Suzuki et al. (2009) found that ultrasonographic foetal weight estimation accuracy is lower for twin gestations than singleton gestations, especially for second twins. They estimated the foetal weight of 103 Japanese twins. Moreover, they compared the clinical usefulness of two Japanese formulas for foetal weight estimation of Japanese twins with and without BPD measurements. To compare the two formulas in this study, the criteria of the absolute error have been used to calculate the accuracy of ultrasonographic foetal weight estimation between first and second twins. Therefore, the formula without BPD may be superior in foetal weight estimation in twin pregnancies, especially for non-vertex second twins.

Sekiguchi et al. (2019) aimed to establish an EFW reference for twin pregnancies in Japan and compare twins' growth with singletons. Three hundred sixty-four pregnant women (190 dichorionic and 174 monochorionic) between 2010 and 2016 were studied.

In this method, the main exclusion criteria were monoamniotic twins, foetal reduction, maternal complications, twin-twin transfusion syndrome, congenital foetal anomalies, and patients with their first visit after 16 weeks gestation. The EFW was measured longitudinally from 16 to 37 weeks gestation. The posterior predictive distribution using hierarchical Bayesian models and determined the EFW corresponding to each Z-score has been calculated. They concluded that the EFW of twins is similar to that of singletons until the mid-second trimester, gradually becoming lower than that of singletons and reaching about 90% of that of singletons in the third trimester.

Finally, Talpur et al. (2017) evaluated and compared the foetal BW estimations of eleven significant relationships, considered one of the most influential studies in this field.

In this study, automatic recognition of the foetal weight is proposed using statistics and correlation analysis of descriptive features of the foetus, which can be extracted from ultrasonic images of the foetus, and a trained fuzzy artmap classifier.

This article starts with an introduction, then explains the basics of the proposed method, details of the proposed method, and implementation of the proposed method in the material and methods part. The third part of this paper contains results and discussion of the proposed method. Finally, in the conclusion section, generalities of the research will be presented.

2 Material and methods

The presence of foetal incompatibility with the mother's pelvis is more associated with an increase in foetal size and is associated with an increase in the rate of instrumental vaginal delivery and caesarean section for macrosomic foetuses compared to normal weight foetuses.

Mean BW can be described as a function of gestational age, defined as standard foetal growth curves for specific populations and races. In general, standard growth curves can be used for a large population of pregnant women who know the exact date of their pregnancy, but their predictive limitations have made them less than an ideal tool for estimating foetal weight in certain patients. In addition, foetal growth curves at both ends of the foetal weight spectrum have the highest error. Also, in foetuses with growth restriction or macrosomia, accurate estimation of foetal weight is essential.

Unfortunately, standard foetal growth charts have little value in assessing obvious abnormalities in foetal weight at birth. Foetal weight increases rapidly after the second trimester of pregnancy. The normal delivery time is 38 to 42 weeks. During this four-week interval, 12.7 grams of foetal weight is added daily.

In this research, a new method based on the use of adaptive network-based fuzzy inference system (ANFIS) is proposed, which this efficient classification method will be examined in the following.

2.1 Sonography

Sonography is usually used during pregnancy to check the condition inside the mother. Sound waves pass through the tissues, so that an image can be seen on the screen of the sonography machine.

2.2 Adaptive network-based fuzzy inference system

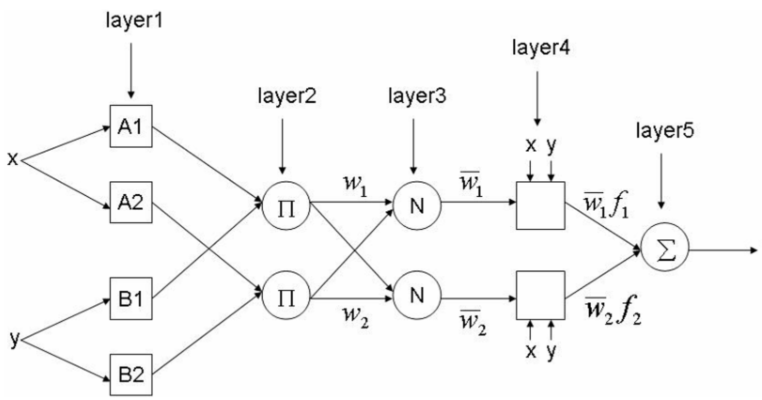
One of the most well-known types of fuzzy artmap networks is the ANFIS. This network is adaptable and teachable and is quite similar in function to the fuzzy inference system. For simplicity, we assume that our fuzzy system has two inputs x and y and its output is z. Now if the rules are as follows:

$$\begin{aligned} &\textit{Rule } 1: \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1 x + q_1 y + r_1 \\ &\textit{Rule } 2: \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2 x + q_2 y + r_2 \end{aligned} \tag{1}$$

And if we use the average centres for the non-fuzzy generator, the output will be as follows:

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \overline{w}_1 f_1 + \overline{w}_2 f_2 \text{ s.t. } \overline{w}_1 = \frac{w_1}{w_1 + w_2}, \overline{w}_2 = \frac{w_2}{w_1 + w_2} \tag{2}$$

Figure 1 ANFIS structure



The equivalent structure of ANFIS will be as follows:

- Layer 1: In this layer, inputs pass through membership functions.

$$\begin{aligned} O_{1,i} &= \mu A_i(x), \quad \text{for } i = 1, 2 \\ O_{1,i} &= \mu B_i(x), \quad \text{for } i = 3, 4 \end{aligned} \tag{3}$$

  The membership functions of any function can be a suitable parameter that in most cases Gaussian functions are selected. Like the general bell-form function:

$$\mu A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{4}$$

  Which are a set of parameters. The parameters of this layer are known as the initial parameters.

- Layer 2: The output of this layer is the multiplication of the input signals, which is actually equivalent to the part of the 'if' of the rules.

$$O_{2,i} = w_i = \mu A_i(x)\mu B_i(y), i = 1, 2 \tag{5}$$

- Layer 3: The output of this normalised layer is the previous layer:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \tag{6}$$

- Layer 4:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i \left(p_i x + q_i y + r_i \right) \tag{7}$$

- Layer 5: The output of this layer is the total output of the system:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

In this paper, to improve the results, we use an adaptive fuzzy neural network, the various parts of which are described, known as the Takagi Sugno ANFIS. In this structure, the neural part is modelled on the human brain system. It provides us with the best possible modelling of data, and its fuzzy part, with its good flexibility, gives us the ability to generalise, in other words, brought good performance on new data in the best way.

Several methods have been proposed for fuzzy neural network training, among which the one-way method and the complete method can be mentioned. In the iterative method, all training patterns are presented to the network as a sequence and only once, but in the complete training method, a sequence consisting of all the learning patterns in the dictionary matrix will be presented to the network and so on. It is repeated so that the network can classify all the training data correctly, or the network weights and the number of nodes are no longer changed. In the training process, along with the evaluation set, the accuracy of the classification is evaluated using a separate dataset after each training repetition, and this process is repeated until no improvement in the percentage of classification accuracy is observed. This method of teaching in scientific circles of machine learning is a well-known method and in related scientific articles, this method has been used more by researchers than the single-repetition method. This method has also been used in this article.

2.3 Mutual evaluation of K parts

Different methods are used to evaluate machine learning methods. In this paper, the method of cross-sectional evaluation of k for $k = 10$ is used. In this method, the whole data are divided into k parts and $k - 1$ part is used for training and the other part is used to test the trained system.

After presenting the basics of the research, the next section is dedicated to describing the proposed method.

2.4 The proposed method

The method proposed in this article consists of several major parts. The first step is the dataset used in this study. The second part is the feature extraction process and finally the third part is the classification process.

2.4.1 Collection of data

The dataset used included 40 foetuses, of which 20 were at 37 weeks and 20 at 38 weeks of gestation. A total of 40 data has been used for this purpose.

Figure 2 Double parietal diameter (see online version for colours)

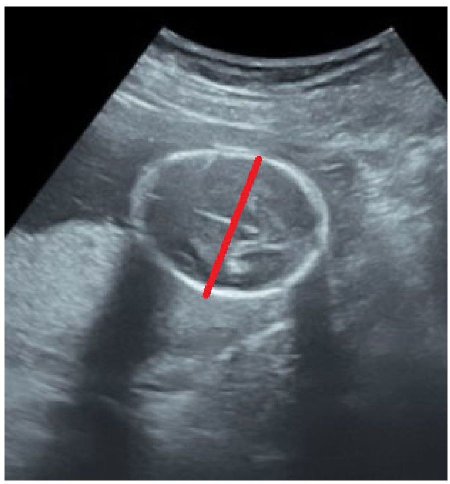


Figure 3 Round foetal head (see online version for colours)

This collection of data has been collected under the supervision of a gynecologist in the hospital and maternity hospital located on the Mashhad hospital in Iran during October

2020 to July 2021. The information in the database is entered under the supervision of a specialist doctor and by the doctor himself according to the questions of mothers whose babies have been born.

Figure 4 The length of the femur of the foetus (see online version for colours)

Foetal weight is usually estimated by calculating three components. First, the diameter of the two parietals or the distance between the two sides of the foetal head is calculated. Of course, because homogeneous babies may be of different sizes, this data alone cannot be relied on and is usually calculated around the foetal head. Figure 2 shows the amount of double parietal diameter for the foetus.

The calculation of the other component, which represents the foetal HC, is shown in Figure 3.

The length of the femur is the tallest bone in the body and can be different in different foetuses with different weights, so this component alone cannot be cited. This component can also be seen in Figure 4.

In the earlier classical methods, the estimate is usually 15% more accurate, meaning that the foetal weight may be 15% or 15% more than the sonography weight. In this article, we try to reduce this amount as much as possible.

According to the research background presented in this article, the recorded components of these embryos include foetal head BPD, foetal HC and foetal femoral bone length (FL), respectively.

The problem is that this estimate of foetal size is much more accurate in the first half of pregnancy, but as the foetus grows, which occurs at varying rates in different foetuses, the accuracy of the sonography depends on the small or medium size of the foetus. Therefore, it can be concluded that the findings of this article will be of great importance due to the fact that foetal weight at birth directly affects the type of delivery (normal or caesarean section).

2.4.2 Feature extraction

Next, the feature extraction process based on the use of regression is designed. One of the powerful descriptive statistical components that can be used to well analyse the correlation between data is the regression model. In statistical models, regression analysis leads to the determination of the relationship between variables. Regression involves many techniques for modelling and analysing specific and unique variables, focusing on the relationship between the dependent variable and one or more independent variables. Regression analysis, especially helps to understand how the value of the dependent variable changes with the change of each of the independent variables and with the stability of the other independent variables.

Regression analysis has been widely used for prediction. Regression analysis has also been used to identify the relationship between independent and dependent variables and the shape of these relationships. In special circumstances, this analysis can be used to infer excellent relationships between independent and dependent variables.

Numerous studies have suggested many techniques for regression analysis. Familiar methods such as linear regression and least squares, which are parametric, in which the regression function are estimated under a limited number of unknown parameters from the data. Non-parametric regression refers to methods that allow regression functions to fit into a specific set of functions with the possibility of unlimited parameters.

In this paper, multiple linear regression using least squares is used. The number of extracted properties at this stage is equal to ten properties.

2.4.3 Feature selection

Finally, the fast correlation-based feature reduction (FCBFR) method was used to select the feature. Eight features have been selected from the mentioned features. In this method of feature selection, the features that provided the most in-class similarity and the least inter-class similarity are selected from among the features for the classification process.

2.4.4 Categorisation

The classification process and the relationships governing the classification used in the research basics section of this article were examined in detail. In this section, we will suffice to provide the classification specifications. It should be noted that to compare the proposed method and further study it, the three classifications of neural network, KNN and finally SVM have also been studied.

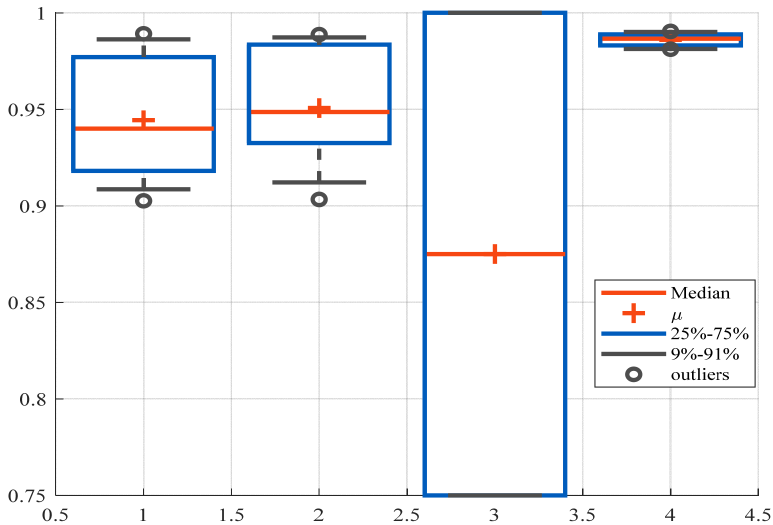
3 Results and discussion

To implement the proposed method, MATLAB software version 2020a has been used and a computer with CPU specifications: I7, RAM: 16 GB, GPU: 4 GB and Windows 10 operating system have been used.

For classification, a neural network classifier with a hidden layer with nine neurons and the number of replications of the algorithm was used three times. The number of classes is 9. The neural network is of the forward type. The KNN classifier is used for K equal to 5 and the SVM classifier with RBF kernel.

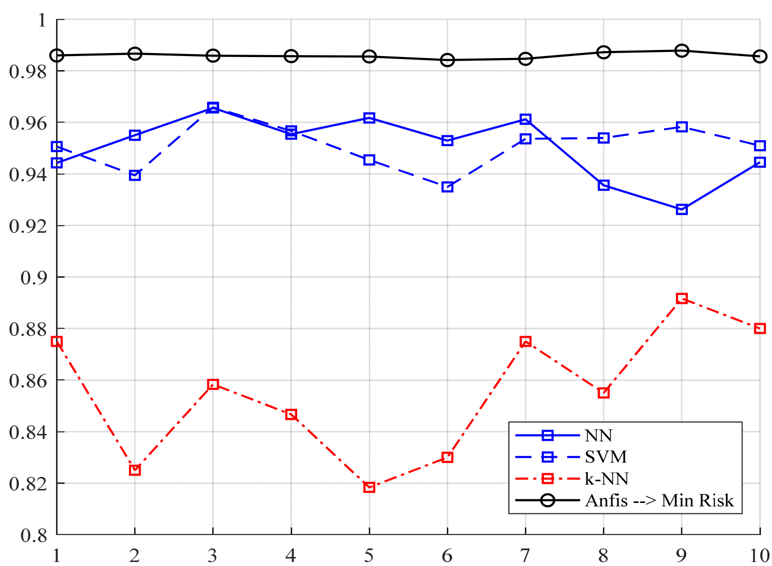
The graph of the accuracy percentage for ten repetitions of the classification process is as follows. It should be noted that one of the implemented iterations is briefly presented in Figure 5.

Figure 5 Results for the implementation of the first part (see online version for colours)



Finally, the final form of summarising all these performances can be seen in Figure 6.

Figure 6 The final results of all performances (see online version for colours)



By evaluating the diagrams shown in Figures 5 and 6, it is possible to obtain the ANFIS classifier in terms of the mean and variance, which has shown the best performance among all classifications. It should be noted that the classification has the best performance with the lowest variance and the highest average value in ten executions. The variance indicates the degree of trust in the proposed method, and the lower it is, the stronger the guarantee as to how much the classification result can be trusted. The average rate also provides the user with the average performance of the proposed method. In Figures 5 and 6, the average is shown with a positive sign.

In Table 1, a comparison of the average accuracy obtained in the proposed method with the other method can be seen.

Table 1 Comparison of the percentage accuracy of the proposed method with other methods

Suggested method	*Backup machine vector*	*KNN*	*Neural network*	*Data*
98.96%	96.83%	87.85%	95.76%	Test data
99.41%	98.1%	91.22%	98.3%	Educational data

4 Conclusions

Diagnosis of foetal weight at birth is one of the most important issues that should be considered in the process of pregnancy to delivery. This determines whether the delivery is natural or by caesarean section. For example, if the baby is over 4 kg, the need for caesarean delivery is examined by a specialist, but less than that does not prevent a normal delivery. On the other hand, the exact weight of the baby indicates its growth and the need to use special health care for it after delivery. So far, researchers have proposed several methods for estimating foetal weight at birth. Each method has its advantages and disadvantages. The main problem in these studies is that the proposed methods have gross errors in the third trimester of pregnancy, so in this article you will find an efficient way to estimate foetal BW using regression and neural fuzzy classification. Let us present the method proposed in this paper was that 40 data, including 20 data at 37 weeks of gestation and 20 data related to 38 weeks of gestation of foetal weight at birth were received and implemented with the help of feature extraction process regression and a total of ten features for each record was provided. In the next step, with the help of a neural fuzzy classifier, the classification process was implemented to estimate the foetal weight, and achieving 98.96% accuracy is a testament to its good performance.

References

Alfirevic, Z., Stampalija, T. and Dowswell, T. (2017) 'Fetal and umbilical doppler ultrasound in high-risk pregnancies', *Cochrane Database Syst. Rev.*, Vol. 13, p.CD007529, DOI: 10.1002/14651858.CD007529.pub4.

Aliyeva, M. and Aydın, S. (2021) 'Use of ultrasound fetal shoulder soft tissue thickness measurement in estimation of fetal weight', *J. Obstet. Gynaecol. Res.*, Vol. 47, pp.1727–1734, DOI: 10.1111/jog.14728.

Aviram, A., Yogev, Y., Ashwal, E. et al. (2017) 'Prediction of large for gestational age by various sonographic fetal weight estimation formulas – which should we use?', *J. Perinatol.*, Vol. 37, pp.513–517, DOI: 10.1038/jp.2017.5.

Heidweiller-Schreurs, C.A.V., De Boer, M.A., Heymans, M. et al. (2018) 'Prognostic accuracy of cerebroplacental ratio and middle cerebral artery Doppler for adverse perinatal outcome: Systematic review and meta-analysis', *Ultrasound Obstet. Gynecol.*, Vol. 51, p.313, DOI: 10.1002/uog.18809.

Hiwale, S.S., Misra, H. and Ulman, S. (2017) 'Ultrasonography-based fetal weight estimation: finding an appropriate model for an Indian population', *J. Med. Ultrasound*, Vol. 25, pp.24–32, DOI: 10.1016/j.jmu.2016.10.006.

Kadji, C., Cannie, M.M., Van, Wettere, M. et al. (2020) 'A longitudinal study on fetal weight estimation at third trimester of pregnancy: comparison of magnetic resonance imaging and 2-D ultrasound predictions', *Fetal Diagn. Ther.*, Vol. 42, pp.181–188, DOI: 10.1159/000453356.

Kang, L., Wu, Q.Q., Sun, L.J. et al. (2021) 'Predicting fetal weight by three-dimensional limb volume ultrasound (AVol/TVol) and abdominal circumference', *Chin. Med. J. (Engl.)*, Vol. 134, pp.1070–1078, DOI: 10.1097/CM9.0000000000001413.

Lee, W., Balasubramaniam, M., Deter, R.L. et al. (2009) 'New fetal weight estimation models using fractional limb volume', *Ultrasound Obstet. Gynecol.*, Vol. 34, pp.556–565, DOI: 10.1002/uog.7327.

McCowan, L.M., Figueras, F. and Anderson, N.H. (2018) 'Evidence-based national guidelines for the management of suspected fetal growth restriction: comparison, consensus, and controversy', *Am. J. Obstet. Gynecol.*, Vol. 218, pp.S855–S868, DOI: 10.1016/j.ajog.2017.12.004.

Milner, J. and Arezina, J. (2018) 'The accuracy of ultrasound estimation of fetal weight in comparison to birth weight: a systematic review', *Ultrasound*, Vol. 26, No. 1, pp.32–41.

Mohammadi, H., Nemati, M., Allahmoradi, Z. et al. (2020) 'Ultrasound estimation of fetal weight in twins by artificial neural network', *J. Biomed. Sci. Eng.*, Vol. 4, pp.46–50, DOI: 10.4236/jbise.2011.41006.

Plonka, M., Bociaga, M., Radon-Pokracka, M. et al. (2020) 'Comparison of eleven commonly used formulae for sonographic estimation of fetal weight in prediction of actual birth weight', *Ginekol Pol.*, Vol. 91, pp.17–23, DOI: 10.5603/GP.2020.0005.

Pretscher, J., Kehl, S., Stumpfe, F.M. et al. (2020) 'Ultrasound fetal weight estimation in diabetic pregnancies', *J. Ultrasound Med.*, Vol. 39, pp.341–350, DOI: 10.1002/jum.15112.

Rashid, S.Q. (2015) 'Accuracy of sonographic fetal weight estimation in Bangladesh', *J. Med. Ultrasound*, Vol. 23, pp.82–85, DOI: 10.1016/j.jmu.

Ratnasiri, A.W., Parry, S.S., Arief, V.N. et al. (2018) 'Recent trends, risk factors, and disparities in low birth weight in California, 2005–2014: a retrospective study', *Matern. Health Neonatol. Perinatol.*, Vol. 4, No. 15.

Ricchi, A., Pignatti, L., Bufalo, E. et al. (2021) 'Estimation of fetal weight near term: comparison between ultrasound and symphysis-fundus evaluation by Johnson's rule', *J. Matern. Fetal Neonatal Med.*, Vol. 3, pp.1070–1074, DOI: 10.1080/14767058.2019.1623874.

Sekiguchi, M., Mikami, M., Nakagawa, C. et al. (2019) 'An ultrasonographic estimated fetal weight reference for Japanese twin pregnancies', *J. Med. Ultrason.*, Vol. 46, pp.209–215, DOI: 10.1007/s10396-018-0921-y.

Stirnemann, J., Villar, J., Salomon, L.J. et al. (2017) 'International estimated fetal weight standards of the INTERGROWTH-21(st) project', *Ultrasound Obstet. Gynecol.*, Vol. 49, pp.478–486, DOI: 10.1002/uog.17347.

Suzuki, S., Shimizu, E., Kinoshita, M. et al. (2009) 'Accuracy of ultrasonographic fetal weight estimation in Japanese twin pregnancies', *J. Med. Ultrasonics*, Vol. 36, pp.157–158, DOI: 10.1007/s10396-009-0225-3.

Talpur, N., Salleh, M.N. and Hussain, K. (2017) 'An investigation of membership functions on performance of ANFIS for solving classification problems', in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, Vol. 226, p.012103.

Tuten, N., Guralp, O., Gok, K. et al. (2021) 'Factors affecting ultrasonographic fetal weight estimation accuracy in low birth weight newborns', *Gynecology Obstetrics & Reproductive Medicine* [online] https://doi.org/10.21613/GORM.2021.1157.