COMBINATION OF SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE (SMOTE) AND BACKPROPAGATION NEURAL NETWORK TO CONTRACEPTIVE IUD PREDICTION

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Abstract: Data imbalance occurs when the amount of data in a class is more than other data. The majority class is more data, while the minority class is fewer. Imbalance class will decrease the performance of the classification algorithm. Data on IUD contraceptive use is imbalanced data. National IUD failure in 2018 was 959 or 3.5% from 27,400 users. Synthetic minority oversampling technique (SMOTE) is used to balance data on IUD failure. Balanced data is then predicted with neural networks. The system is for predicting someone when using IUD whether they have a pregnancy or not. This study uses 250 data with 235 major data (not pregnant) and 15 minor data (pregnant). From 250 data divided into two parts, 225 training and 25 testing data. Minority class on training data will be duplicated to 1524%, so that the amount of minority data become balanced with the majority data. The results of predictive with an accuracy rate of 99.9% at 1000 epoch.

1. INTRODUCTION

Various researches on imbalance classes, for example (Zhou and Liu, 2011) said that overcoming multi-class problems is more difficult than two classes. Solutions for unbalanced class data are divided into data level and algorithm level categories. Methods at the data level change the distribution of datasets to be balanced and then evaluated to improve detection of minority classes. While the algorithm level method will modifies the data mining algorithm to solve unbalanced data class problems.

Data imbalance occurs when one class has higher number of object than the other class, which is called as majority and minority class. We proposed the Synthetic Minority Oversampling Technique (SMOTE) method as a solution for handling unbalanced class data (Chawla et al., 2002). Processing algorithms that ignore data imbalances will tend to favor the major classes, while minor classes will be ignored (Chawla et al., 2004).
Classification algorithms will experience a decrease in performance when facing an imbalanced class (Garcia, 2012).

The development of computer technology is able to imitate the work of the human brain in weighing and making decisions, this is called neural networks. The advantages of making these decisions will be used to predict the successful use of contraceptives IUD. Several implementations of backpropagation neural network in the health sector are TB detection (Purnamasari, 2013), dengue fever (Widodo, et al., 2014), cervical cancer (Susanto, 2012), each with 100%, 74%, and 95.14% accuracy.

Contraceptive failure is the occurrence of pregnancy while using contraception properly. The annual failure of contraceptive IUD tends to be below 5% of the success rate, for example in 2018 the failure rate is 959 or 3.5% of the total successful contraceptive IUD users or 27,400 people (BKKBN, 2018). The ratio of contraceptive IUD failure rate is very small when compared with the success rate, thus the synthetic minority oversampling technique is suitable to be used for balancing the data.

Based on above problem analysis, this study uses a combination of synthetic minority oversampling technique (SMOTE) and backpropagation neural network to handle imbalance classes for predicting the successful use of contraceptive IUD.

2. LITERATUR REVIEW

2.1. Imbalance Class

Class imbalance in small datasets is very detrimental to research in data mining because machine learning fakes difficulties in classifying minority classes correctly. Small dataset will bring up a phenomenon called class imbalance. According to Li and Sun (2012) if the proportion of minority class samples constitutes less than 35% of the dataset, the dataset is considered imbalanced. While according to He and Ma (2013) class it can be said to be imbalance class if the difference in mayor data is twice plus one of the minor classes (2n + 1). This phenomenon occurs when the incidence ratio between one case and another is imbalanced (imbalance ratio). Data imbalance is when the number of objects in a data class is more than the other classes. Data classes whose objects are outgrowing in number called major classes while others are called minor classes. Most of the algorithms assume that the class distribution tested is balanced and causing wrong to classify values in each classes. When the classification algorithm tests imbalanced datasets, they tend to focus on the majority class and ignore the minority class, causing errors in the minority class classification.

2.2. Synthetic Minority oversampling Technique (SMOTE)

Processing algorithms that ignore imbalances data will tend to be covered by major classes and ignoring minor classes. Chawla et al. (2002) proposed the SMOTE method as one of the solutions to handling unbalanced data that is different from the previous oversampling method, which is duplicating data randomly. The SMOTE method adds the number of minor class data to be equivalent to the major class by generating artificial data. Artificial data is made based on k-nearest neighbor. Artificial data generation with numerical scale is different from categorical. Numerical data measured the distance of proximity to Euclidean distance while categorical data was simpler, called the mode value. Minor data duplication process flowchart with the SMOTE method is shown in Figure 1.
2.3. Backpropagation

Backpropagation is one of the neural network models. Backpropagation trains networks to get a balance between the ability to recognize patterns used during training and to give correct responses to inputs that are similar though not the same as the patterns used during training (Siang, 2005). Backpropagation architecture consists of one or more input units plus one unit of bias, one hidden screen consisting of one or more units plus one unit of bias, and one or more units of output, as shown in Figure 2.

The backpropagation training algorithm is described as follows:

a. Step 0 : Initialize all weights with small random numbers, epoch = 1, determine the learning rate ($\alpha$), specify the number of units on the hidden layer ($Z$) and specify the termination conditions. The termination is a max epoch maximum and an accuracy value.

b. Step 1 : If epoch $\neq$ max epoch and the accuracy value, do steps 2-9.

c. Step 2 : For each pair of training data (1 to $a$ where $a$ is the amount of training data), do steps 3 – 8.

d. Phase I : Feed-Forward
   Step 3 : Each input unit receives a signal and passes it to the hidden unit above it.

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*Figure 1 Flowchart of Data Duplication Process with SMOTE*
Step 4 : Calculate all output in hidden units $z_p$ ($p = 1, 2, ..., n$).

\[ z_{\text{net}}_p = v_{p0} + \sum_{i=1}^{n} x_i v_{pi} \]  
\[ z_p = f (z_{\text{net}}_p) = \frac{1}{1 + e^{-z_{\text{net}}_p}} \]  

Step 5 : Calculate all output network in unit $y_m$

\[ y_{\text{net}}_m = w_{m0} + \sum_{p=1}^{n} z_p w_{mp} \quad m = 1, 2, ..., n \]  
\[ y_m = f (y_{\text{net}}_m) = \frac{1}{1 + e^{-y_{\text{net}}_m}} \]

e. Phase II : Backpropagation

Step 6 : Calculate factor $\delta$ the output unit based on unit output errors $\delta_m$ ($m = 1, 2, ..., n$)

\[ \delta_m = (t_m - y_m) f'(y_{\text{net}}_m) = (t_m - y_m)y_m(1 - y_m) \]  
Calculate the weight change rate $\Delta w_{mp}$ with the acceleration rate $\alpha$

\[ \Delta w_{mp} = \alpha \delta_m z_p \quad m = 1, 2, ..., n \quad \text{and} \quad p = 0, 1, ..., n. \]  

Step 7 : Calculate factor $\delta$ hidden units based on errors in each hidden unit $\delta_p$

\[ \delta_{\text{net}}_p = \sum_{m=1}^{n} \delta_m w_{mp} \quad (p = 1, 2, ..., n) \]  
\[ \delta_p = \delta_{\text{net}}_p f'(z_{\text{net}}_p) = \delta_{\text{net}}_p z_p (1 - z_p) \]  
Calculate weight change rate $\Delta v_{pi}$ with the acceleration rate $\alpha$

\[ \Delta v_{pi} = \alpha \delta_p x_i \quad p = 1, 2, ..., n; \quad i = 0, 1, ..., n \]

f. Phase III : Weight change

Step 8 : Calculate all the weight change
Change in line weight leading to the output unit

\[ w_{mp}(baru) = w_{mp}(sekarang) + \Delta w_{mp} \quad m = 1, 2, ..., n; \quad p = 0, 1, ..., n \]  

Weight change that led to the hidden unit

\[ v_{mp}(baru) = v_{mp}(sekarang) + \Delta v_{pi} \quad p = 1, 2, ..., n; \quad i = 0, 1, ..., n \]

g. Step 9 : Change the epoch value

\[ epoch = epoch + 1 \]

Calculate the acuuracy value

\[ accuracy = \frac{\text{total of recognized training data}}{\text{total of all training data}} \times 100\% \]
2.4. Contraceptive IUD Prediction

There are seven types of contraceptives and drugs in general. Pills and injections are contraceptive drugs. While IUDs, Intra-Uterin Device (IUD), Medical Female Surgery (MOW), Male medical surgery (MOP) and condoms are contraceptive devices. Using contraceptive devices and drugs correctly sometimes there is still an unwanted pregnancy or failure. In this study, failure due to the use of contraceptives IUD will be predicted.

2.5. Prediction System Evaluation

This study uses confusion matrix for evaluation of predictive systems. Confusion matrix is a method used in evaluating the classification performance by comparing the results of predictions made by the system with the predicted results that should be, as shown in Figure 3. TP (True Positive) is positive data detected correctly, TN (True Negative) is the number of negative data detected correctly, FP (False Positive) is negative data that is detected as positive data and FN (False Negative) is the opposite number of data from FP.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \times 100\%$$ (13)
Precision = \frac{TP}{TP + FP} \times 100 \%

Recall = \frac{TP}{TP + FN} \times 100 \%

3. METHODOLOGY
3.1. Prediction System Framework

Research predictions of contraceptive IUD using a combination of synthetic minority oversampling technique (SMOTE) and backpropagation neural network methods starting from input: data from IUD x_1 to x_{13} variables are pre-processed by converting data into numbers to simplify computational processes in the system. The data that has been converted is then divided into 2 parts, testing and training data. In the training data, a minor class data duplication process is carried out to balance the data in the major class with the synthetic minority oversampling technique (SMOTE) method while the data testing is not duplicated. Balanced training data is then carried out by training and testing process with a backpropagation neural network to find the best value for accuracy. The resulting output is a contraceptive IUD prediction and predictive system evaluation with confusion matrix. Confusion matrix works by comparing the results of predictions made by the system with the prediction results should be. The concept of a system framework is shown in Figure 4.

3.2. Data and Variable Research

The research data was taken from the K4/KB Family Planning participant status card form derived from the results of a family planning Field Officer (PLKB) survey. From the K4 KB/form, 13 determinant variables were taken which involved a team of medical experts who were competent in the field of Family Planning and at the same time determined the input values to be used as predictions. The data used for contraceptive IUD prediction were 250 data, 235 data were successful (not pregnant) with targets (T = 0) and 15 data were failed (pregnant) with targets (T = 1). Variables x_1 to x_{13} with input values and prediction targets are shown in Table 1.
| Variable           | Category   | Input Values |
|-------------------|------------|--------------|
| Age ($x_1$)       | 19 – 30 years | 0            |
|                   | 31 – 40 years | 0            |
|                   | 40 – 49 years | 0.5          |
| Last Type ($x_2$) | Pills      | 0            |
|                   | Injection   | 0.3          |
|                   | IUD        | 0.3          |
| Breast Feeding ($x_3$) | Yes  | 0            |
|                   | No         | 0.3          |
| Vaginal Bleeding ($x_4$) | Yes | 1            |
|                   | No         | 0            |
| Old leucorrhoea ($x_5$) | Yes | 1            |
|                   | No         | 0            |
| Tumor (breast, uterus) ($x_6$) | Yes | 1            |
|                   | No         | 0            |
| Weight ($x_7$)    | < 40 Kg    | 0            |
|                   | 44 – 64 Kg | 0            |
|                   | 65 – 70 Kg | 0.5          |
|                   | > 70 Kg    | 1            |
| Blood Pressure ($x_8$) | < 90/60 mmHg | 0           |
|                   | 90-120/60-79 mmHg | 0          |
|                   | 121-139/80-89 mmHg | 0         |
|                   | 140-159/90-99 mmHg | 0.5        |
|                   | 160-179/100-119 mmHg | 1          |
|                   | >180/120 mmHg | 1          |
| Position of Uterus ($x_9$) | Retroflection | 1          |
|                   | Anteflection | 0          |
| Signs of inflammation ($x_{10}$) | Yes | 0.5         |
|                   | No         | 0            |
| Tumor (Gynecological) ($x_{11}$) | Yes | 1           |
|                   | No         | 0            |
| Signs of diabetes ($x_{12}$) | Yes | 1           |
|                   | No         | 0            |
| Blood clotting disorders ($x_{13}$) | Yes | 1           |
|                   | No         | 0            |
| Target (T)        | Failed (pregnant) | 1           |
|                   | Success (not pregnant) | 0          |

The data used for contraceptive IUDs prediction are then converted by reference to Table 1. Conversions are carried out to change the qualitative data contained in variables into numbers to simplify the computational systems. After all the values of the variable are converted into numbers, then it changed to the *.csv file extension, thus divided into 2 parts, testing and training data. In the training data, a minor data duplication process is carried out to balance the data in the major class.

From 250 data, 235 are major data / success (T = 0) and 15 are minor data / failed (T = 1). Then the system randomly divides the data into 2 parts: training and testing data with 26 IUD testing data, 24 major / successful data (T = 0), 2 minor data / fail (T = 1) and 224 IUD training data, 211 major data (T = 0), 13 minor data / fail (T = 1). 13 training data on minor classes were duplicated to 1524% using SMOTE and it becomes 198 minor artificial data. In that case, minor class data became 211 data or equivalent to major class

**Mustaqim (Combination Of Synthetic Minority Oversampling Technique)**
data, with 13 original minor data and 198 artificial minor data. Testing data and training data that already balanced then predicted using backpropagation neural network.

4. RESULT AND DISCUSSION
4.1. Results of Prediction System Training
     This study uses 424 data, 212 original data and 212 artificial data, using the best architecture of backpropagation neural network based on the results of training: 3 layer hidden, learning rate \((\alpha) = 0.1\); momentum = 0.9 and sigmoid activation function. The training experiment was conducted 5 times at 10, 50, 100, 500, as well as 1000 epochs and the best accuracy value was 100% at 100, 500 and 1000 epochs. Some training trial scenarios to get the best accuracy are shown in Table 2.

4.2. Prediction System Test Results
     Results with 26 data testing and using the best backpropagation neural network architecture are 3 layer hidden, learning rate \((\alpha) = 0.1\); momentum = 0.9 and sigmoid activation function. The testing experiment was conducted 5 times at 10, 50, 100, 500, as well as 1000 epochs and the best accuracy value was 99.9% at 1000 epochs. Some testing trial scenarios to get the best accuracy are shown in Table 3.

4.3. Prediction System Performance Evaluation
     Prediction system performance evaluation is done by the confusion matrix method. Evaluation was carried out 5 times at 10, 50, 100, 500 and 1000 epoch. The results obtained have the best accuracy value of 99.6% at epoch 500 and 1000. Results of IUD prediction system performance evaluation are shown in Figure 5.

| Epoch | Lr(\(\alpha\)) | Training Data | Hidden Layer | Momentum | Accuracy |
|-------|---------------|---------------|--------------|----------|----------|
| 10    | 0.1           | 424           | 1            | 0.9      | 98.0%    |
| 50    | 0.1           | 424           | 1            | 0.9      | 98.7%    |
| 100   | 0.1           | 424           | 1            | 0.9      | 99.0%    |
| 500   | 0.1           | 424           | 1            | 0.9      | 99.0%    |
| 1000  | 0.1           | 424           | 1            | 0.9      | 99.0%    |
| 10    | 0.1           | 424           | 2            | 0.9      | 98.0%    |
| 50    | 0.1           | 424           | 2            | 0.9      | 98.0%    |
| 100   | 0.1           | 424           | 2            | 0.9      | 98.5%    |
| 500   | 0.1           | 424           | 2            | 0.9      | 99.0%    |
| 1000  | 0.1           | 424           | 2            | 0.9      | 99.0%    |
| 10    | 0.1           | 424           | 3            | 0.9      | 98.0%    |
| 50    | 0.1           | 424           | 3            | 0.9      | 99.0%    |
| 100   | 0.1           | 424           | 3            | 0.9      | 100.0%   |
| 500   | 0.1           | 424           | 3            | 0.9      | 100.0%   |
| 1000  | 0.1           | 424           | 3            | 0.9      | 100.0%   |
| 10    | 0.1           | 424           | 4            | 0.9      | 98.0%    |
| 50    | 0.1           | 424           | 4            | 0.9      | 98.3%    |
| 100   | 0.1           | 424           | 4            | 0.9      | 98.0%    |
| 500   | 0.1           | 424           | 4            | 0.9      | 99.0%    |
| 1000  | 0.1           | 424           | 4            | 0.9      | 99.0%    |

Table 3 IUD Prediction System test Results
### Table

| Epoch | Lr(\(\alpha\)) | Testing Data | Hidden Layer | Momentum | Accuracy  |
|-------|----------------|--------------|-------------|----------|-----------|
| 10    | 0.1            | 26           | 1           | 0.9      | 93.0%     |
| 50    | 0.1            | 26           | 1           | 0.9      | 94.7%     |
| 100   | 0.1            | 26           | 1           | 0.9      | 97.0%     |
| 500   | 0.1            | 26           | 1           | 0.9      | 98.0%     |
| 1000  | 0.1            | 26           | 1           | 0.9      | 98.0%     |
| 10    | 0.1            | 26           | 2           | 0.9      | 93.9%     |
| 50    | 0.1            | 26           | 2           | 0.9      | 96.0%     |
| 100   | 0.1            | 26           | 2           | 0.9      | 98.5%     |
| 500   | 0.1            | 26           | 2           | 0.9      | 98.0%     |
| 1000  | 0.1            | 26           | 2           | 0.9      | 98.0%     |
| 10    | 0.1            | 26           | 3           | 0.9      | 93.7%     |
| 50    | 0.1            | 26           | 3           | 0.9      | 97.9%     |
| 100   | 0.1            | 26           | 3           | 0.9      | 98.3%     |
| 500   | 0.1            | 26           | 3           | 0.9      | 99.2%     |
| 1000  | 0.1            | 26           | 3           | 0.9      | 99.9%     |
| 10    | 0.1            | 26           | 4           | 0.9      | 93.2%     |
| 50    | 0.1            | 26           | 4           | 0.9      | 95.3%     |
| 100   | 0.1            | 26           | 4           | 0.9      | 97.0%     |
| 500   | 0.1            | 26           | 4           | 0.9      | 98.0%     |
| 1000  | 0.1            | 26           | 4           | 0.9      | 98.0%     |

### Figure 5

Measurement of Predictive System Performance With Confusion Matrix

By using equations (14), (15) and (16), the accuracy values, precision and recall at 500 epoch are as follows:

\[
Accuracy = \frac{234 + 15}{234 + 1 + 0 + 15} \times 100\% = 99.6\%
\]

\[
Precision = \frac{234}{(234 + 1)} \times 100\% = 99.5\%
\]

\[
Recall = \frac{234}{(234 + 0)} \times 100\% = 100\%
\]

### 4.4. Comparison of Data Accuracy Values using the SMOTE Technique and without SMOTE in Imbalance Class

The contraceptive IUD prediction system using the combination of synthetic minority oversampling (SMOTE) and neural network methods for handling imbalanced class has a very good prediction accuracy value of 99%. The SMOTE method works well in handling imbalance classes, as evidenced by the increase in the accuracy value that is quite significant, while the imbalance class data without SMOTE process tends to be high (100%) in the major class but low in the minor class (0%). The comparison of the accuracy values using the confusion matrix, shown in Figure 6.
Figure 6 Confusion Matrix Predictions Accuracy Without SMOTE Method

Figure 6 is the result of prediction accuracy without SMOTE, the system predicts that the accuracy value tends to be high in the major class 100% (target class = 0), but unable to predict the minor class (0%) (target class = 1). The system is unable to predict minor classes (target class = 1) at all epochs 10, 50, 100, 500 and 1000, while the average accuracy value of the overall data tends to be fixed at 94% at epoch 10, 50, 100, 500 and 1000.

5. CONCLUSIONS

Based on the results of the research, several conclusions can be drawn. Prediction accuracy value from a combination of synthetic minority oversampling technique (SMOTE) and backpropagation neural network is 99%. The combination of both methods is proven to be able to predict unbalanced classes with good predictive results while data predictions without SMOTE process tend to be high in the major class (100%) and not successfully predict in the minor class (0%). Therefore this research can be used as a reference in future research to handle unbalanced data. Based on the conclusion above, the system can be used as a reference to predict the success of a contraceptive IUD.

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