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EARLY DETECTION OF FOETAL PATHOLOGICAL CONDITIONS WITH NEURAL NETWORK METHOD: IMPLEMENTATION OF BACKPROPAGATION NEURAL NETWORK AND SMOTE ON CARDIOTOCOGRAPHY DATA

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ABSTRACT
This research focuses on the development of an effective classification model for early detection of foetal pathological conditions using Cardiotocography (CTG) data by utilising the Backpropagation Neural Network (BPNN) method. The high maternal mortality rate (MMR) and infant mortality rate (IMR) in Indonesia, including Riau Province, emphasise the importance of accurate prenatal diagnosis. The main challenge of this research is to address the class imbalance issue in the CTG dataset, which is biased towards the Normal class (77.9%) compared to the Suspect (13.9%) and Pathological (8.2%) classes. This problem was addressed by applying the Synthetic Minority Oversampling Technique (SMOTE). The model's performance was evaluated using K-Fold Cross Validation (5-Fold and 10-Fold). The test results showed that the combination of BPNN and SMOTE significantly improved performance, achieving a highest average accuracy of 92.66% and a maximum accuracy of 94.84% in the 10-Fold Cross Validation scheme. The resulting model is stable, has a high generalisation capability, and has great potential to be integrated into an Artificial Intelligence (AI)-based Clinical Decision Support System (CDSS) to support evidence-based health policies in reducing Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR).
Keywords*: Cardiotocography (CTG), Backpropagation Neural Network (BPNN), SMOTE, Classification, Early Foetal Detection, Health AI.*

1. Introduction

Maternal and child health remains a primary pillar of the "Healthy Indonesia 2025" vision. The Indonesian government has set a target to reduce the Maternal Mortality Ratio (MMR) to 183 per 100,000 live births and the Infant Mortality Rate (IMR) to 16 per 1,000 live births by 2024. In Riau Province, while the IMR showed significant improvement (reaching 15.69 per 1,000 live births in 2020), the MMR remains high at 158 per 100,000 live births, directly impacting fetal health outcomes (Kementerian Kesehatan Republik Indonesia. (n.d)).

As a preventive measure, Cardiotocography (CTG) serves as the non-invasive diagnostic gold standard for monitoring fetal well-being, particularly in high-risk pregnancies such as those complicated by preeclampsia or gestational diabetes (Ayres-de-Campos & Bernardes, 2010; Ben M'Barek et al., 2023; Rastogi & Bansal, 2023). The data generated by CTG is vital for medical personnel to identify fetal hypoxia. However, a major challenge is that the interpretation of CTG traces is often subjective and heavily reliant on the clinical expertise of medical staff. This leads to high inter-observer variability and delayed decision-making, demanding more in-depth research to improve the accuracy of CTG interpretation through modern technology (Subasi et al., 2020; Abiyev et al., 2023; Dang et al., 2023)

In recent years, Artificial Intelligence (AI) has emerged as a robust solution to overcome the subjectivity inherent in CTG interpretation (Aeberhard et al., 2023). Various machine learning (ML) studies have explored fetal health classification, such as the utilization of bagging ensemble classifiers to anticipate fetal risks (Subasi et al., 2020). Despite these advancements, significant academic gaps remain in the current literature. Recent scoping reviews indicate that while many

complex deep learning models have been developed, they often suffer from inconsistent performance due to extreme class imbalance in medical datasets—where 'Normal' cases vastly outnumber 'Suspect' or 'Pathological' ones (Sirisha et al., 2024). Most existing ML studies focus predominantly on global accuracy, failing to prioritize recall for minority classes, which are clinically the most critical for life-saving interventions (Mushtaq & Veningston, 2024).

Based on the analysis of state-of-the-art methods, there is a clear research gap regarding the trade-off between computational efficiency and the handling of imbalanced clinical data (77.9% Normal). While newer deep learning approaches like Convolutional Neural Networks (CNN) or Transformers offer high performance, they require massive datasets and high-end computational resources, making them less feasible for real-time, point-of-care devices in resource-limited settings (Francis et al., 2024; Sasikala et al., 2023; Rahmayuni et al., 2026).

Consequently, this study applies the Backpropagation Neural Network (BPNN) due to its proven efficiency in processing non-linear physiological CTG signals with a lower computational footprint(Fan et al., 2024; Rahmayanti et al., 2022). BPNN is a computational model designed to mimic the human brain, operating through a supervised learning mechanism where network weights are iteratively adjusted to minimize classification errors.

The novelty of this work lies in the strategic integration of the BPNN architecture (21-14-3) with the Synthetic Minority Oversampling Technique (SMOTE). Unlike prior studies that utilize standard algorithms on skewed data, this combination is specifically engineered to expand the feature space representation of minority classes through linear interpolation, thereby minimizing model bias toward the majority class (Aeberhard et al., 2023).

The primary objective of this research is to optimize the BPNN-SMOTE architecture for analyzing CTG data to ensure the early detection of fetal pathological conditions, while evaluating how this approach enhances the sensitivity of high-risk detection without compromising overall model stability. Broadly, this research aims to provide a stronger technical foundation for developing AI-based Clinical Decision Support Systems (CDSS) that offer objective and accurate interpretations. This advancement directly aligns with national health digital transformation initiatives to ensure superior human resource development starting from the fetal stage.

2. Literature Review

This research adopts the Knowledge Discovery in Database (KDD) methodology as a framework, where data mining is the core phase for extracting important patterns from data (Dol, 2021; Dang et al., 2023; Jain et al., 2022).Criteria for selection included relevance to AI-based fetal monitoring, class imbalance solutions in medical informatics, and neural network optimization(Dabas & Singh, 2021; Singh, 2021).

2.1 Conceptual Framework: Clinical Decision Support Systems (CDSS)

Modern prenatal care is increasingly transitioning toward data-driven paradigms. A Clinical Decision Support System (CDSS) serves as an intelligent intermediary that translates complex physiological signals into actionable diagnostic insights (Deepa & Jayaraman, 2025). While early CDSS relied on static rule-based engines, recent shifts emphasize Machine Learning (ML) to handle the non-linear nature of Cardiotocography (CTG). The framework adopted in this study integrates the Knowledge Discovery in Databases (KDD) methodology with adaptive neural layers to ensure that the transition from raw fetal heart rate (FHR) signals to clinical categorization (Normal, Suspect, Pathological) is both statistically rigorous and clinically relevant.

2.2 Critical Synthesis of CTG Classification Studies

Recent studies have explored various ML architectures for CTG interpretation. Subasi et al. (2020a) demonstrated the effectiveness of ensemble bagging, but noted limitations in processing raw non-linear signals without extensive feature engineering. Similarly, research by Rahmayanti (Rahmayanti et al., 2022) compared SVM and Random Forest, finding that while these models achieve high accuracy on balanced datasets, their performance degrades significantly when faced with the inherent class imbalance of clinical CTG data.

2.3 The Synergy of SMOTE and Backpropagation Neural Networks (BPNN)

The primary obstacle in fetal health AI is the data skewness, where pathological cases are naturally rare. Standard BPNN training on imbalanced data often leads to a model that excels at identifying healthy fetuses but fails to detect distressed ones (Jan Ben et al., 2023).

The Synthetic Minority Oversampling Technique (SMOTE) addresses this by generating "informed" synthetic samples through linear interpolation between a minority sample and its k-nearest neighbors, rather than simple replication. Analytically, SMOTE expands the decision boundary of the 'Pathological' class in the 21-dimensional feature space, allowing the BPNN's gradient descent to converge on a more equitable weight distribution. This synergy is critical: SMOTE provides the balanced evidentiary base, while BPNN provides the non-linear mapping required to interpret the complex interplay of Baseline FHR, Accelerations, and Decelerations.

2.4 KDD Stages and Algorithmic Optimization

Consistent with (Dol, S. M., & Jawandhiya, 2023), this study utilizes the five-stage KDD framework: Selection, Pre-processing, Transformation, Data Mining, and Evaluation. A critical component of the Transformation stage is Min-Max Normalization, which maps all 21 CTG features to a [0, 1] range, preventing features with larger numerical scales (e.g., Histogram Width) from dominating the weight updates over clinically vital parameters like Prolonged Decelerations. This research adopts the Knowledge Discovery in Database (KDD) methodology as a framework, where data mining is the core phase for extracting important patterns from data (Dol, 2021).

2.5 KDD Stages The KDD stages applied:

1. Data Selection: Selection of relevant CTG data.
2. Pre-processing / Cleaning: Includes removal of data duplication and correction of inconsistencies.
3. Transformation: This stage is crucial for transforming data to fit the algorithm, including Min-Max Scaling Normalisation (Chamidah et al., 2016):

   $$X' = (X - X_{min}) / (X_{max} - X_{min})$$

   This normalisation maps data values to the range [0,1], which has been proven to provide the highest accuracy in several comparative studies (Nasution et al., 2019).
4. Data Mining: The process of pattern recognition using the BPNN algorithm.
5. Interpretation / Evaluation: Assessing the quality of the model using the Confusion Matrix.

2.6 Performance Evaluation Metrics To assess the performance of the BPNN model, metrics Derived from the Confusion Matrix are used (Jalil et al., 2024):

1. Accuracy: Measures how well the model can correctly classify. Accuracy: Measures how well the model can classify correctly.
   $Accuracy = \frac{TN+TP}{TP+TN+FP+FN}$
2. Precision: Measures the proportion of positive predictions that are truly positive.
   Precision = $\frac{TP}{TP+FP}$
3. Recall: Measures the proportion of actual positive data that is correctly predicted as positive.
   Recall = $\frac{TP}{TP+FN}$
4. F1 Score: The harmonic mean of Precision and Recall.
   F1 Score = $\frac{2(Precision\ x\ Recall)}{Precision+Recall}$

2.3 Architecture and Algorithm of Backpropagation Neural Network (BPNN)

BPNN is the most commonly used artificial neural network. Its architecture involves the input layer (x), hidden layer (z), and output layer (y) (Zhuang et al., 2024). The input layer

receives the feature vectors, the hidden layer performs nonlinear transformations, and the output layer generates the final classification or prediction results.

2.3.1 Determination of the Number of Hidden Layer Neurones

The number of neurones in the input and output layers is determined by the number of data features and the number of target classes. The number of hidden neurons was empirically determined using the heuristic rule: $i < m < 2i$, where i denotes the number of input neurons and m denotes the number of neurons in the hidden layer.

2.3.2 BPNN Training Phase

BPNN training phases (Liu et al., 2024) :

1. Initialize the weights and biases randomly.
2. Set the learning rate (η).
3. Repeat the training process until the error reaches the predefined target threshold:
   a. Perform forward propagation:
      i. Compute the outputs of the hidden layer.
      ii. Compute the network output.
   b. Calculate the error between the predicted output and the target output.
   c. Perform backward propagation:
      i. Calculate the output layer deltas.
      ii. Calculate the hidden layer deltas.
   d. Update the weights and biases based on the computed gradients.
4. Store the final optimized weights and biases.
5. Use the trained model to predict new data.

2.4 Handling Data Imbalance with SMOTE

Medical datasets such as CTG often have severe class imbalances. Synthetic Minority Oversampling Technique (SMOTE) is used to address this issue, which can cause the model to be biased towards the majority class. SMOTE generates synthetic data for the minority class through linear interpolation (Chawla et al., 2002):

$$x_{new} = x_i + \lambda(x_{nn} - x_i)$$

where xi is the selected minority sample, xnn is the nearest neighbour, and λ is a random number [0,1]. The advantage of SMOTE is its ability to expand the representation area of the minority class in the feature space, which enhances the model's generalisation.

2.5 Cardiotocography (CTG) and Clinical Parameters

CTG is a non-invasive monitoring technique that records FHR and uterine contractions. The clinical parameters measured and used as classification features are very important :

1. Baseline Activity: Baseline Value, Accelerations, Foetal Movement, Uterine Contractions.
2. Decelerations: Light, Severe, and Prolonged Decelerations (main indicators of foetal distress).
3. FHR Variability: Short Term Variability (STV) and Long Term Variability (LTV) (reflecting the health of the foetal nervous system).
4. Histogram Features: Histogram Width, Min, Max, Number of Peaks, and Tendency (providing a statistical summary of the FHR signal).

The final classification identifies the foetus as: Normal (1), Suspect (2), or Pathological (3).

3. Research Methods

The following is a research methodology for classifying fetal health in pregnant women based on cardiotocogram (CTG) data using the Backpropagation Neural Network (BPNN) method:

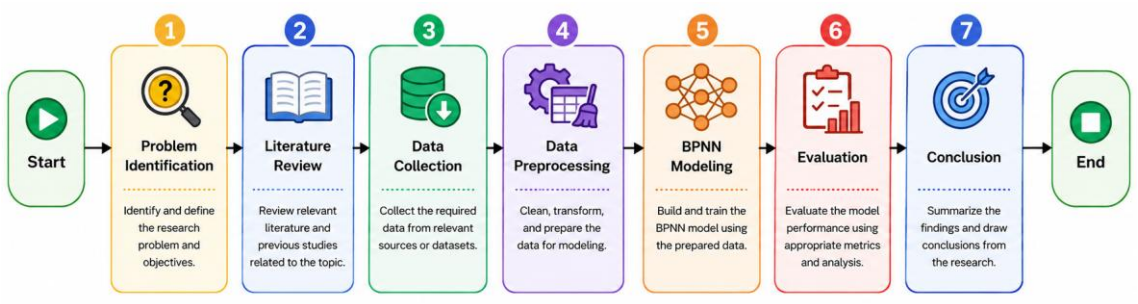

Fig. 1. Research methodology diagram for classifying fetal health in pregnant women based on cardiotocogram (CTG) data

3.1 Data Sources and Characteristics

The dataset used is "Fetal Health" from Kaggle. The initial data consisted of approximately 2,126 samples. The input variables comprise 21 CTG parameters.

3.1.1 Initial Class Distribution

The highly imbalanced data distribution became the focus of preprocessing: a. Normal: 1,655 data (77.9%) b. Suspect: 295 data (13.9%) c. Pathological: 176 data (8.2%) 3.2 Data Preprocessing Steps

1. Data Cleaning: 13 duplicate data rows were identified and removed, leaving 2,113 unique samples used for training and testing.
2. Data Normalisation: All 21 features are normalised to the range [0,1] using Min-Max Scaling to ensure all features have equal weight in the neural network learning process.
3. SMOTE Data Balancing: The SMOTE technique was applied to equalise the number of samples in each class. The amount of data increased to 4938 samples, with a balanced distribution: Normal = 1646, Suspect = 1646, Pathological = 1646. This step is essential to prevent model bias.

3.3 Architecture and Training Parameters of BPNN

The implemented BPNN architecture is 21-14-3 (Input-Hidden-Output).

a. Input Layer: 21 neurones (according to the number of CTG features).
b. Hidden Layer: 14 neurones (using the Sigmoid function).
c. Output Layer: 3 neurones (using the Softmax function) for multi-class classification.

Training Parameters Used:

a. Epoch: 200 (stopped when convergence is reached).
b. Learning Rate: 0.0001.
c. Optimiser: Adam.
d. Loss Function: Categorical Cross-Entropy.
e. Validation: K-Fold Cross Validation (5 and 10).

3.4 K-Fold Cross Validation

The K-Fold Cross Validation (CV) method is used to test the reliability of the model and minimise the risk of overfitting (Wijiyanto et al., 2024). The testing is conducted by dividing the dataset into K=5 and K=10 folds. Each fold is used as test data once, while the remaining folds are used for training.

4. Results and Discussions

This research evaluates model performance across four distinct experimental scenarios:

4.1. Classification Without SMOTE

a) 5-Fold Cross-Validation

The experimental results obtained from the 5-Fold Cross-Validation scheme. Summary of 5-Fold Cross-Validation Without SMOTE are detailed below:

```
==== CROSS-VALIDATION SUMMARY ====
No   fold  test_loss  test_acc   primary_meaning
0     1   0.346002  0.870892     Efficient initial learning, slight
                                 overfitting starts after epoch ~15
1     2   0.302131  0.884706     Most stable model with excellent
                                 generalization capability
2     3   0.305091  0.882353     Model exhibits mild overfitting
3     4   0.333954  0.870588     Overfitting becomes more apparent
4     5   0.283267  0.880000     Mild overfitting observed but with good
                                 convergence
Rata-rata akurasi CV: 0.8777 ± 0.0066

Average CV Accuracy: 0.8777 ± 0.0066
Combined Confusion Matrix:
```

	Normal	Suspect	Pathological
Normal	1558	75	22
Suspect	88	192	15
Pathological	22	38	116

Based on the experimental results, the following conclusions can be drawn:

1. The Backpropagation Neural Network (BPNN) successfully demonstrates effective learning performance across all folds, as evidenced by a significant reduction in loss and a corresponding increase in accuracy.
2. The Training Accuracy across all folds ranges between 88% and 91%, while the Validation Accuracy falls within the 80% to 87% range, indicating a highly stable and strong classification performance.
3. The average accuracy achieved is 87.77%.
4. Although mild overfitting is observed (indicated by a 5–10% variance gap between the training and validation data), the model's overall generalization capability remains highly satisfactory.
5. The consistent convergence patterns across all evaluation folds prove that the model is reliable and robust against test data variations.
6. These findings indicate that the implemented architecture and hyperparameters (including learning rate, neuron count, and epoch limits) are sufficiently optimal for the utilized dataset (e.g., the Fetal Health dataset).

b) 10-Fold Cross-Validation

The next experimental scenario involves increasing the fold value to 10-fold, with the expectation of improving the model's accuracy. The experimental results obtained from the 10-fold cross-validation scheme are detailed below:

```
==== CROSS-VALIDATION SUMMARY ====
   fold  test_loss  test_acc
0     1   0.353811  0.873239
1     2   0.282383  0.906103
2     3   0.260493  0.915493
3     4   0.342913  0.873239
4     5   0.339733  0.887324
5     6   0.338343  0.859155
6     7   0.351082  0.872642
7     8   0.342931  0.853774
8     9   0.318947  0.863208
9    10   0.305433  0.877358

Average CV Accuracy: 0.8782 ± 0.0198
Combined Confusion Matrix:
```

	Normal	Suspect	Pathological
Normal	1560	71	24
Suspect	91	192	12
Pathological	21	40	115

Based on the experimental results, the following conclusions can be drawn:
1. The average accuracy across all folds is 87.82%, which represents an increase from the initial 87.77% achieved during the 5-fold cross-validation scheme. Although the improvement is not highly significant, it yields a net increase of 0.05%.
2. However, the highest peak accuracy was achieved in Fold 3 at 91.54%, whereas the maximum accuracy obtained under the 5-fold scheme was only 88.47% in Fold 2. Consequently, the net improvement for the peak accuracy stands at 3.07%.

4.2. Classification Using SMOTE

a) 5-Fold Cross-Validation

The following is the summary of the experimental results obtained from the 5-Fold Cross-Validation scheme using SMOTE.

```
==== CROSS-VALIDATION SUMMARY ====
   fold  test_loss  test_acc
0     1   0.298837  0.917840
1     2   0.216887  0.917647
2     3   0.266370  0.905882
3     4   0.248826  0.917647
4     5   0.326487  0.936471

Average CV Accuracy: 0.9191 ± 0.0110
Combined Confusion Matrix :
```

	Normal	Suspect	Pathological
Normal	1563	84	8
Suspect	40	244	11
Pathological	10	19	147

From the experimental results, it can be concluded that:
1. The Backpropagation Neural Network (BPNN) model demonstrates excellent, stable, and consistent performance across all folds.
2. The model learns efficiently and stably while maintaining its generalization capability. The balanced data generated by SMOTE effectively bridges the performance between training and validation.
3. The model achieves a high accuracy rate and robust generalization. SMOTE assists the model in recognizing minority classes proportionally, thereby increasing overall accuracy without introducing class bias.
4. SMOTE is proven effective in balancing the dataset, enabling the model to learn fairly across all classes.
5. The parallel and converging loss and accuracy curves prove that the model does not suffer from overfitting and possesses high generalization capability.
6. The average accuracy across all folds is 92%.

b) 10-Fold Cross-Validation

The next experimental scenario involves increasing the fold value to 10-fold, with the expectation of enhancing the model's accuracy. The following are the experimental results obtained from the 10-fold cross-validation scheme.

```
==== CROSS-VALIDATION SUMMARY ====
   fold  test_loss  test_acc
0     1   0.415853  0.934272
1     2   0.177782  0.929577
2     3   0.148160  0.948357
3     4   0.355992  0.906103
4     5   0.350940  0.915493
5     6   0.173725  0.938967
6     7   0.239838  0.938679
7     8   0.291039  0.910377
```

```
    8      9   0.185015  0.919811
    9     10   0.324205  0.924528

Average CV Accuracy: 0.9266 ± 0.0137
Combined Confusion Matrix:
```

	Normal	Suspect	Pathological
Normal	1572	76	7
Suspect	37	247	11
Pathological	7	18	151

From these experimental results, it can be concluded that:

1. The average accuracy across all folds is 92.66%, which represents an increase from the initial 91.91% achieved under the 5-fold scheme. Although the improvement is not highly significant, it yields a net increase of 0.75%.
2. However, the highest peak accuracy was achieved in Fold 3 at 94.84%, whereas under the 5-fold scheme, the maximum accuracy obtained was only 93.64% in Fold 5. Consequently, the net improvement for the peak accuracy stands at 1.2%.

4.3 Evaluation of the BPNN Model Using 5-Fold Cross-Validation

a. Testing Without SMOTE

The model achieved an average accuracy of 87.77% (peaking at 88.47% in Fold 2), but suffered from a strong classification bias toward the majority class (Normal) due to the highly imbalanced data distribution.

b. Testing With SMOTE

The overall average accuracy significantly increased to 91.91% (peaking at 93.64% in Fold 5), showing a net improvement of 3.07% that successfully resolved class imbalance, demonstrated high generalization capability, and showed no signs of overfitting.

4.4. Evaluation of the BPNN Model Using 10-Fold Cross-Validation

a. Testing Without SMOTE

Under the 10-Fold Cross-Validation scheme without SMOTE, the BPNN model demonstrated performance consistency across fold variations by achieving an average accuracy of 87.82% (a marginal 0.05% increase over the 5-fold scheme), a peak accuracy of 91.54% in Fold 3, and a stable loss range between 0.26 and 0.35; however, the combined confusion matrix confirms that class imbalance remains the primary limiting factor, as evidenced by a strong classification bias toward the dominant Normal class (1,560 correct predictions out of 1,655 samples) and higher misclassification rates for the Suspect and Pathological classes.

b. Testing With SMOTE

Implementing SMOTE within the 10-Fold Cross-Validation scheme significantly enhances the BPNN model's performance, achieving an average accuracy of 92.66% (a 0.75% increase over the 5-fold scheme) and a peak accuracy of 94.84% in Fold 3, while effectively balancing the dataset to improve minority class recognition—increasing correct classifications for the *Suspect* class from 192 to 247 and the *Pathological* class from 115 to 151—with a reduced optimal loss range (0.14–0.41) and no signs of overfitting.

4.5 Comparative Analysis between 5-Fold and 10-Fold

The comparison between the 5-Fold and 10-Fold testing results reveals a consistent pattern, both with and without the implementation of SMOTE. In general, increasing the number of folds exerts a positive effect on the stability and reliability of the results, although the overall performance gains remain relatively small.

The following is a summary of the testing results comparison:

Table 1 - Summary of Testing Results

Testing Scheme	Average Accuracy	Highest Accuracy	Average Increase	Maximum Increase
5-Fold Without SMOTE	87.77%	88.47% (Fold 2)	-	-
10-Fold Without SMOTE	87.82%	91.54% (Fold 3)	+0.05%	+3.07%
5-Fold With SMOTE	91.91%	93.64% (Fold 5)	-	-
10-Fold With SMOTE	92.66%	94.84% (Fold 3)	+0.75%	+1.20%

Based on the table above, it can be observed that SMOTE provides a far more significant increase in accuracy compared to merely increasing the number of folds. The average accuracy increased by more than 4% following the application of SMOTE in both the 5-Fold and 10-Fold schemes. The peak accuracy reached 94.84%, demonstrating that the model is capable of performing classification remarkably well.

The improvement in model performance is dominated by the application of SMOTE. Increasing the number of folds from 5 to 10 provides a slight increase in stability, but SMOTE is the determining factor in addressing data bias. The BPNN + SMOTE + 10-Fold Cross Validation configuration was established as the optimal scheme with the highest classification capability and proven generalisation.

These results indicate that the developed model has an adequate level of reliability to be considered as a decision support tool in a clinical environment.

5. Conclusion

The Backpropagation Neural Network (BPNN) model demonstrates excellent and consistent performance in classifying fetal conditions based on cardiotocography (CTG) data. The implementation of the SMOTE technique has proven highly effective in mitigating severe data imbalances, successfully increasing the model's average accuracy from 87.82% to 92.66% under the 10-Fold Cross-Validation scheme, while simultaneously ensuring that the model does not experience overfitting. Consequently, the combination of BPNN + SMOTE + 10-Fold Cross-Validation is established as the optimal configuration in this study, achieving the highest validation accuracy of 94.84%. Ultimately, this research provides a robust technical foundation for the development of an AI-based early detection system, directly supporting evidence-based policymaking in efforts to reduce maternal and infant mortality rates in Indonesia.

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