The Scientific Temper (2025) Vol. 16 (9): 4791-4799
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2025.16.9.11
https://scientifictemper.com/
RESEARCH ARTICLE

# Hybrid GAN with KNN - SMOTE Approach for Class-Imbalance in Non-Invasive Fetal ECG Monitoring

**Merla Agnes Mary [1], Britto Ramesh Kumar [2]**

## Abstract

Imbalanced fetal electrocardiogram (fECG) datasets often hinder reliable fetal health assessment by biasing predictions toward majority classes. This article presents a two-stage augmentation framework that integrates three generative models: conditional GAN (cGAN), time-series GAN (TGAN), and Wasserstein GAN (WGAN) with a K-nearest neighbor (KNN) - based Adaptive Synthetic Minority Over-Sampling Technique (SMOTE) algorithm to generate physiologically realistic minority-class signals. Preprocessing steps included the removal of missing records and normalization to ensure data consistency. The balanced dataset was used to train a hybrid LSTM–CNN classifier designed to capture both long-term temporal dynamics and localized time–frequency features of fECG signals. The proposed method improved overall classification accuracy by 4–7% and minority-class F1-scores by up to 10% compared to baseline approaches. The framework achieved 97% accuracy and 98% F1-score by combining ensemble GAN-based augmentation with adaptive oversampling for robust and balanced biomedical time-series analysis.

**Keywords**: Fetal Heart Rate, Data Augmentation, TGAN, WGAN, CGAN and KNN-SMOTE (oversampling), LSTM - CNN.
关键词：胎心率，数据增强，TGAN，WGAN，CGAN和KNN-SMOTE（过采样），LSTM - CNN.

## Introduction

Fetal monitoring has advanced significantly over recent decades, driven by technological innovations and evolving clinical practices aimed at enhancing maternal and fetal safety during labour (Kuzu & Santur, 2022). The use of continuous Electronic Fetal Monitoring (EFM), also known as cardiotocography, provides real-time recordings of fetal heart rate and uterine contractions, allowing early detection of fetal distress to prevent hypoxia (Heelan L, 2013). Monitoring fetal health during pregnancy and labor is crucial for avoiding complications such as birth asphyxia, neurological damage, or perinatal death. Cardiotocography (CTG) is a non-invasive system that records Fetal Heart Rate (FHR) and Uterine Contraction (UC) (FIGO 2015). FHR indicates fetal and central nervous system responses to blood pressure, blood inundation, and acid- bridgehead situation. In clinical practice, FHR analysis helps determine fetal tribulation, placental abruption, and chorioamnionitis (Rao, Lin, Jia Lu, Hai-Rong Wu, Shu Zhao, Bang-Chun Lu, and Hong Li, 2024).

Figures 1 and 2 Represent The Real-Time Monitoring Of The Maternal Woman.

CTG interpretation is often subjective and varies with clinician experience, leading to inconsistent diagnoses and delayed interventions. To address this, automated diagnostic systems using ML and DL models have been developed for real-time fetal monitoring (Sundararajan, D. Wang, and R. Min, 2020) (Zhong W, Luo J, Du W, 2023). These methods, along with GANs, help extract fetal signals despite maternal ECG and noise interference. A major challenge remains dataset imbalance, as public databases like CTU-UHB contain more normal than pathological cases, limiting model generalization (Kahankova, Radana Vilimkova, Dominik Vilimek, Seyedali Mirjalili, Vaclav Snasel, Jeng-Shyang Pan, Jitka Horakova, and Radek Martinek, 2024).

FHR traces (Figure 3) show variable decelerations, which are sudden drops in heart rate typically linked to umbilical cord compression during contractions.

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**How to cite this article:** Mary, M.A., Kumar, B.R. (2025). Hybrid GAN with KNN - SMOTE Approach for Class-Imbalance in Non-Invasive Fetal ECG Monitoring. The Scientific Temper, **16**(9):4791-4799.

Doi: 10.58414/SCIENTIFICTEMPER.2025.16.9.11

**Source of support:** Nil

**Conflict of interest:** None.



**Received:** 12/09/2025 **Accepted:** 21/09/2025 **Published:** 23/09/2025

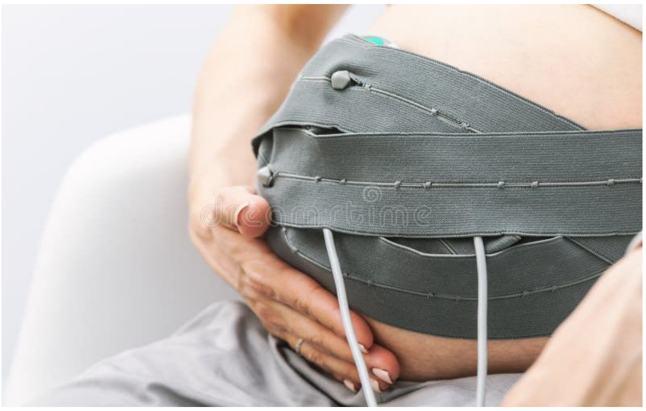

**Figure 1:** Placement of CTG monitoring belts


**Figure 2:** CTG Monitoring for FHR

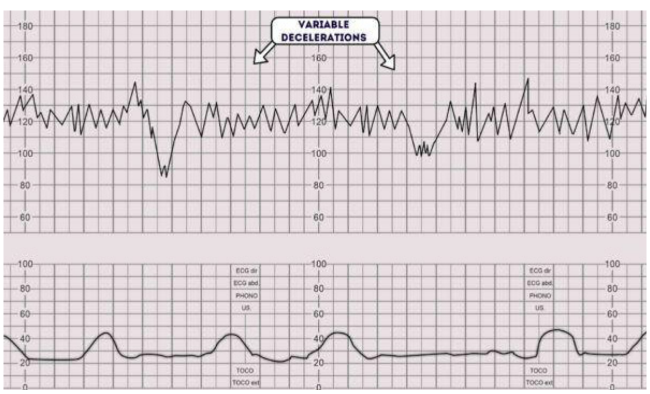


**Figure 3:** Cardiotocography (CTG) showing variable decelerations.

Researchers have increasingly used Generative Adversarial Networks (GANs) to tackle dataset imbalance in fetal ECG studies, where they generate realistic synthetic signals to support model training (M. Mirza and S. Osindero, 2014). Variants such as Conditional GANs (CGANs), Time-series GANs (TGANs), and Wasserstein GANs (WGANs) enable class-specific synthesis, capture temporal patterns, and enhance training stability. Previous works include CT-GANs for CTG feature enhancement and FHRGAN for fetal heart rate signal generation, though they are limited by single-architecture use (R. S. Jayanthi and K. Bhavani, 2023), (A. Venkata Sriram, N. M. Mohamed Aslam, and G. Premkumar, 2024). Traditional methods like SMOTE (Synthetic Minority Oversampling Technique) can augment minority classes but often produce low-variability or redundant samples, reducing their effectiveness for physiological data (N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, 2002). To address these issues, a hybrid framework combining CGAN, TGAN, and WGAN with KNN-based adaptive SMOTE has been proposed, allowing for robust augmentation of minority classes and the generation of physiologically plausible synthetic FECG signals.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive review of recent literature on data imbalance handling techniques. Section 3 details the proposed augmentation framework. Section 4 describes the experimental design and reports the evaluation results. Finally, Section 5 summarizes the key findings and discusses potential directions for future research.

### *Literature Review*

Despite advancements in prenatal care, fetal mortality remains a critical global challenge, underscoring the need for improved methods of early detection and prevention. Recently, more attention has been given to the early identification of fetal issues using decision support tools, such as machine learning. For these tools to work effectively, they need balanced datasets to ensure accurate predictions and proper evaluation of parameters such as fetal heart rate and uterine contractions.

Generative Adversarial Networks (GANs) have emerged as powerful tools in healthcare, helping to overcome challenges related to limited data, privacy concerns, and class imbalance (C. Esteban, S. Hyland, and G. Rätsch, 2017). GAN-based approaches have been employed to augment Cardiotocography (CTG) datasets, enabling the creation of physiologically realistic fetal heart rate and uterine contraction signals, thereby improving the accuracy and generalizability of machine learning models (D. Sujatha and A. Kalpana, 2021).

Akpinar MH, Sengur A, Salvi M, Seoni S, Faust O, Mir H, Molinari F, Acharya UR, (2024) reviewed the application of GANs in healthcare signal processing, specifically targeting fetal ECG and cardiotocography (CTG), which are commonly used in prenatal monitoring. The study highlighted the increasing adoption of conditional GANs (cGANs) and CycleGANs for time-series data generation, emphasizing their effectiveness in producing realistic and balanced datasets.

Jeong JJ, Tariq A, Adejumo T, Trivedi H, Gichoya JW, Banerjee I, (2022) focused on the role of GANs in medical imaging, with particular emphasis on fetal ultrasound analysis. The research demonstrated that GANs effectively augment ultrasound datasets, enhancing the training of deep learning models used for segmentation and

**Table 1:** Comparison Summary of Related Studies

| *Authors* | *Method Used* | *Addresses Class Imbalance* | *Limitations* |
|---|---|---|---|
| Akpinar *et al*. (2024) | CONDITIONAL GANS, CYCLEGAN FOR TIME-SERIES GENERATION | Yes | Lacks experimental results; focuses on review rather than implementation |
| Jeong *et al*. (2022) | GANS FOR IMAGE AUGMENTATION AND SEGMENTATION | Partially | Imaging-focused; doesn't apply to signal data or class balancing directly |
| Amiri *et al*. (2023) | GAN-BASED SIGNAL SYNTHESIS FOR WEARABLE MONITORING | Yes | Mostly conceptual; lacks implementation depth |
| Zhu *et al*. (2025) | ENSEMBLE GANS FOR SYNTHETIC DATA GENERATION | Yes | Not tailored to fetal data; general medical application |
| Yu *et al*. (2024) | CTGGAN (CONDITIONAL GAN FOR FHR SIGNALS) | Yes | Tested on one dataset; lacks real-time/noisy scenario validation |
| Zhang *et al*. (2022) | FHR-GAN (CCWGAN-GP FOR REALISTIC FHR GENERATION) | Yes | No hybrid approach; evaluated on a single dataset |
| Mohan *et al*. (2023) | HYBRID (GAN + SMOTE + ENSEMBLE LEARNING WITH 1D-RESNET, XGBOOST) | Yes | High complexity; heavy computation; feature engineering needed |
| Dewi *et al*. (2022) | TIME-SERIES GAN (TSGAN) | Yes | Lacks detailed analysis of GAN limitations like mode collapse |
| Özseven *et al*. (2024) | COMPARISON OF GAN, SMOTE, AND VAE | Yes | Inconsistent baselines across techniques; limited to MIT-BIH ECG |
| Alba *et al*. (2022) | FEATURE SELECTION + UNDERSAMPLING + SMOTE (NO GAN) | Yes | Warns against oversampling before split; no GAN used |

classification of the GANs in improving fetal imaging and prenatal diagnostics.

Amiri, Z., Heidari, A., Navimipour, N.J. (2024) reviewed deep learning in biomedical informatics, noting the use of GANs for synthesizing fetal signals from wearable and remote monitoring devices. Their findings emphasized GANs' potential to enhance data availability, diagnostic accuracy, and real-time monitoring and decision-making in fetal health care.

Tronchin, Lorenzo, Tommy Löfstedt, Paolo Soda, and Valerio Guarrasi (2025) investigated the use of ensemble GANs across a range of medical datasets, including both signal and image modalities. The combination of multiple GAN models was found to produce richer and more diverse synthetic data, contributing to greater robustness in diagnostic training. Ensemble GANs were shown to enhance the generalizability and reliability of working with limited or highly variable datasets.

Chen, Lin, Shuicai Wu, and Zhuhuang Zhou (2025) proposed Attention R2W-Net, a deep learning framework designed to extract fetal ECG (FECG) from maternal abdominal ECG signals. The model incorporated recurrent residual modules and attention gates to accurately isolate fetal signals, even in the presence of noise. Performance across various datasets surpassed that of earlier models, indicating strong potential for non-invasive fetal cardiac monitoring.

Yu, Zichang, Yating Hu, Yu Lu, Leya Li, Huilin Ge, and Xianghua Fu (2024) introduced CTGGAN, a conditional GAN developed to generate realistic fetal heart rate (FHR) signals using the CTU-UHB dataset. By conditioning on class labels such as "normal" and "pathological," CTGGAN effectively produced minority-class samples. However, the model was primarily tested on a single dataset and under non-real-time conditions, limiting its applicability in more complex scenarios.

Zhang, Yefei, Zhidong Zhao, Yanjun Deng, and Xiaohong Zhang (2022) developed FHR-GAN, a specialized model based on the Wasserstein GAN with gradient penalty (CCWGAN-GP), to generate realistic FHR signals. The aim was to address issues of data scarcity and class imbalance. The model preserved essential signal morphology, aiding in improved generalization for downstream tasks.

Mohan *et al*. (2023) presented a hybrid framework that combined GAN-generated samples with ensemble learning for the detection of fetal hypoxia. SMOTE was also used to improve the representation of the minority class. The pipeline integrated linear features, Discrete Wavelet Transform (DWT), and 1D-ResNet for feature extraction, with XGBoost serving as the ensemble classifier. Nevertheless, the system introduced increased complexity and required significant computational power along with careful feature engineering.

Puspitasari, Riskyana Dewi Intan, M. Anwar Ma'sum, Machmud R. Alhamidi, and Wisnu Jatmiko (2022) implemented a Time-Series GAN (TSGAN) to synthesize fetal heart rate (FHR) signals, aiming to mitigate class imbalance.

**Table 2 :** Parameter in the dataset

| Types of data | Parameters |
|---|---|
| Maternal data | 1. Age<br>2. Parity<br>3. Gravidity |
| Delivery data | 1. type of delivery (vaginal; operative vaginal; CS)<br>2. duration of delivery; meconium-stained fluid; type of measurement |
| Fetal data | 1. Sex<br>2. Birth weight |
| Fetal outcome data | 1. Analysis of umbilical artery blood sample (i.e. pH; pCO2; pO2; base excess and computed BDecf)<br>2. Apgar score; neonatology evaluation (i.e. need for O2; seizures; admission to NICU) |

While promising for fetal abnormality detection, the study did not thoroughly investigate challenges like mode collapse or the model's ability to generalize to unseen data.

Özseven, Turgut (2024), evaluated GANs, SMOTE, and Variational Autoencoders (VAE) for data augmentation in ECG signal classification. GAN-based augmentation resulted in an approximate increase in classification accuracy, while SMOTE achieved the best balance performance at 86.4%. VAE outperformed other methods when trained solely on synthetic data. However, comparisons across methods were hindered by inconsistent baseline metrics.

Nieto-del-Amor, Félix, Gema Prats-Boluda, Javier Garcia-Casado, Alba Diaz-Martinez, Vicente Jose Diago-Almela, Rogelio Monfort-Ortiz, Dongmei Hao, and Yiyao Ye-Lin, (2022) addressed class imbalance in preterm birth prediction using electrohysterography (EHG) signals. Optimal results were achieved by combining feature selection with undersampling of the validation set. The study emphasized the effectiveness of resampling strategies like SMOTE. The authors cautioned against applying oversampling before data splitting to avoid overfitting

The literature review highlights the importance of resampling methods like SMOTE combined with Generative Adversarial Networks (GANs) in addressing class imbalance in datasets for prenatal health monitoring. Techniques such as conditional GANs, CycleGANs, CTGGAN, and FHR-GAN can generate realistic fetal heart rate (FHR) and fetal ECG data. This improves the accuracy, recall, and precision of diagnostic models. Additionally, studies that combine GANs with feature integration and ensemble learning have achieved further improvements, especially in identifying abnormal cases within minority classes.

## Methodology

This section describes the dataset, methods, flow diagram, and evaluation metrics used for the proposed techniques (Ensemble of GANs and KNN-based adaptive SMOTE).

### *Dataset*

The proposed method employs a validated dataset from the Czech Technical University (CTU) in Prague and the University Hospital in Brno (UHB), comprising 552 cardiotocography (CTG) recordings. These recordings were carefully selected from a larger set of 9,164 collected between 2010 and 2012 at UHB. Each CTG recording begins no more than 90 minutes before delivery and lasts up to 90 minutes, capturing the critical final stages of labor (Goldberger, A., L. Amaral, L. Glass, J. Hausdorff, P. C. Ivanov, R. Mark, J. E. Mietus, G. B. Moody, C. K. Peng, and H. E. Stanley, 2000)

The dataset comprises two physiological signals: Fetal Heart Rate (FHR) and Uterine Contraction (UC), both sampled at a rate of 4 Hz. Figure 4 presents the FHR and Uterine Contraction signals for normal data. Table 2 presents the parameters involved in the dataset that enhance the signal quality. This high-resolution sampling enables detailed analysis of fetal responses to labour activity.

**Table 3:** summarizes the accuracy and loss values at selected epochs

| *S. No.* | *Epochs* | *Balanced Accuracy (%)* | *Cross-entropy Loss* |
|---|---|---|---|
| 1 | 10 | 85.2 | 0.34 |
| 2 | 20 | 88.4 | 0.25 |
| 3 | 30 | 90.3 | 0.221 |
| 4 | 40 | 92.1 | 0.186 |
| 5 | 50 | 93.2 | 0.159 |
| 6 | 60 | 94.3 | 0.128 |
| 7 | 70 | 94.6 | 0.115 |
| 8 | 80 | 95.0 | 0.107 |
| 9 | 90 | 95.6 | 0.096 |
| 10 | 100 | 97.3 | 0.084 |

### *Proposed Methodology*

The proposed approach addresses the data imbalance of the minority class to enhance fetal health prediction by combining three GAN models—Wasserstein GAN (WGAN), Conditional GAN (CGAN), and Time-series GAN (TGAN) within an ensemble framework, producing synthetic FHR/UC signals for underrepresented classes (Normal cases where pH>=7.05, in suspicious the pH>=7.05 and pH<7.05 then in Pathological cases pH<7.05). The generated data is further improved using KNN-based Adaptive SMOTE, which helps ensure that interpolated samples preserve physiologically plausible continuity across high-dimensional features. Figure 5 illustrates the flow of contributions to the data imbalance for minority classes (pathological and suspicious).

### *Data Quality Assessment*

A preliminary step is taken to identify and address missing values, which helps prevent incomplete data from causing bias or reducing the effectiveness of later learning models. In the dataset, where  represents the number of samples and  for the number of features, we perform a systematic check for invalid or missing entries. The locations of these missing values are identified as follows:

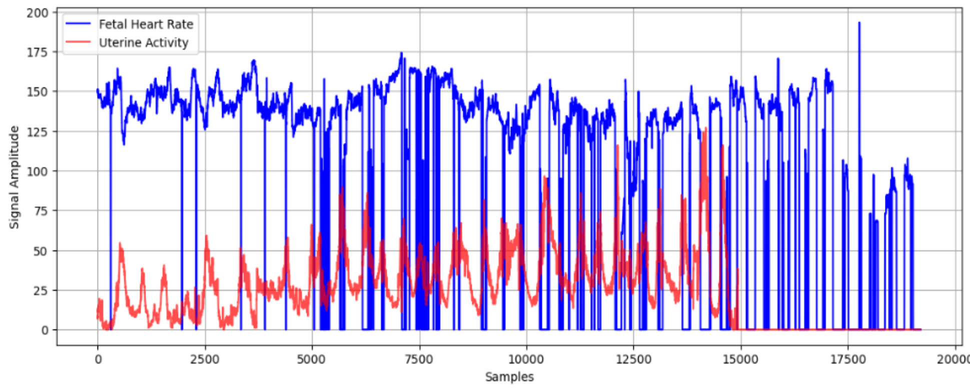


**Figure 4:** FHR and Uterine Activity Signals

***Detection Criteria***

A value $D_{i,j}$ is flagged as missing if it satisfies:

$$D_{i,j} \in \{NaN, None\} \vee D_{i,j} = \{(X_i, y_i)\}_{i=1}^{N} \tag{1}$$

where $X_i$ *is* the multivariate time-series containing FHR and UG signals, and $y_i$.

***Missing Value Handling***

- If $y_i$ (pH label) is missing, remove the instance:

$$D \leftarrow D \setminus \{(X_i, y_i) \mid y_i \text{ is missing}\} \tag{2}$$

- For missing signal points in $X_i$:
  - If gap length $g \leq g_{max}\, g$ fill via spline interpolation:

$$x(t) = \sum_{j=0}^{m} a_j B_j(t) \tag{3}$$

where $B_j(t)$ are cubic B-spline basis functions.

  - If $g > g_{max}\, g$ remove the record. (4)

***Classification of the dataset***

- The CTU-UHB Fetal CTG Dataset is partitioned into three disjoint subsets (Normal, Suspicious and Pathological) based on the target label $y_i$ (the pH value associated with each CTG record).

$$\begin{aligned} D_{Normal} &= \{X_i \,/\, y_i \geq 7.15\} \\ D_{Suspicious} &= \{X_i \,/\, 7.05 \leq y_i < 7.15\} \\ D_{Pathological} &= \{X_i \,/\, y_i < 7.05\} \end{aligned} \tag{5}$$

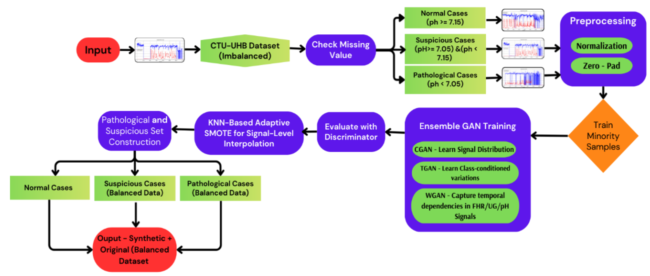


**Figure 5:** The block diagram of the Proposed Work

***Preprocessing***

Normalization scales data to a standard range or distribution, improving learning and convergence. Zero padding adds zeros to data to align shapes or preserve dimensions. Each sequence is normalized:

$$\tilde{X}_i = \frac{X_i - \mu_{X_i}}{\sigma_{X_i}} \tag{6}$$

where and are the mean and standard deviation of the sequence.Sequences are zero-padded or truncated to length :

$$X_i^{pad} = \begin{cases} [X_i, 0, \ldots, 0] & if\ |X_i| < L \\ X_i\,[1:L] & Otherwise \end{cases} \tag{7}$$

***Ensemble GAN Training***

This phase uses a hybrid ensemble that incorporates TimeGAN, WGAN-GP, and CGAN to capture temporal

**Table 4:** Comparison with existing work

| *Author* | *Method used* | *Dataset* | *Performance* |
|---|---|---|---|
| Zhang et. al (2021) | CCWGAN-GP (FHRGAN) | CTU-UHB | Accuracy = 93.6%<br>F1-Score = 92.8% |
| Mohan et. al (2023) | GAN + SMOTE + Ensemble (Xgboost, Resnet) | CTU - UHB | Accuracy = 96.2%<br>F1- Score = 96 % |
| Lingping et. al (2025) | Borderline-SMOTE | CTU-UHB | Accuracy = 91.6%<br>F1score = 90% |
| Qazi et. al (2025) | GAN | CTU – UHB | Accuracy = 94.2 %<br>F1 Score = 81.1 % |
| Proposed Methodology | Ensemble GAN + KNN-Based Adaptive SMOTE | CTU – UHB | Accuracy = 97 %<br>F1 Score = 98 % |

dynamics and class-conditioned variation in pathological and suspicious signals.

### *Conditional GAN (CGAN)*

Class-conditional data distributions $pdata\,(x\,|\,y)$ are learned by CGAN by conditioning the discriminator and generator on auxiliary data, including class labels or attributes.

$$\overset{minmax}{G\ \ D}\, E_{x\sim p_{data}}\left[logD\left(x \mid y\right)\right] + E_{z\sim p_z}\left[log\left(1 - D\left(G\left(z \mid y\right) \mid y\right)\right)\right] \quad (8)$$

### *TGAN*

TimeGAN variants retain both the statistical and temporal features of the original signals. G uses a recurrent chain to model sequence dynamics, and outputs ˆ = G ( ).

$$h_t = f_{RNN} h_{t-1,z_t}$$
$$\hat{X} = G\left(h_T\right) \quad (9)$$

### *WGAN*

WGAN minimizes the Wasserstein (Earth Mover's) distance between the generated and real distributions and produces a real-valued score.

$$L_{WGAN} = E_{x\sim p_{data}}[D(x)]E\hat{x} \sim pg[D(\hat{x})] \quad (10)$$

The union of $S_{CGAN} \cup S_{TGAN} \cup S_{WGAN}$ typically, train separate generators and discriminators critics for each branch and combine their outputs.

$$S_{GAN} = S_{CGAN} \cup S_{TGAN} \cup S_{WGAN} \quad (11)$$

### *Evaluate with Discriminator*

Synthetic samples are scored using the discriminator A higher threshold τ means stricter quality control and fewer synthetic samples will pass. A sample ˆ is retained if:

$$D\phi\left(\hat{x}\right) \geq \tau \quad (12)$$

### *KNN–Adaptive SMOTE*

SMOTE (Synthetic Minority Oversampling Technique) creates artificial minority class samples by interpolating between a minority instance and one of its closest minority neighbors. Let be a minority sample, and $N_k(X_m)$ it's K-Nearest Neighbors in the minority set. Find k-nearest neighbors:

$$\left[\ NN_k\left(x_i\right) = \left\{\ x_{i1},\ x_{i2},\ x_{i3}, \ldots x_{ik}\right\}\right]$$

Synthetic interpolation is:

$$X_{new} = X_m + \lambda\left(X_{nn} - X_m\right) \quad (13)$$

where $X_{nn} \in N_k(X_m)$ and $\lambda \sim \mathcal{M}(0,1)$. The adaptive version modifies based on local density:

$$\tilde{\lambda} = \lambda.\frac{\rho_{max} - \rho\left(X_m\right)}{\rho_{max} - \rho_{min}} \quad (14)$$

where $\rho(X_m)$ is the density around .

### *Final Balanced Dataset*

The final dataset is:

$$D_{balanced} = D_{Normal} \cup (D_{Suspicious} \cup D_{Suspicious}) \cup (D_{Pathological} \cup D_{Pathological}) \quad (15)$$

where represents synthetic samples from GAN + SMOTE.

### *Classifier Input*

After GAN + KNN-Adaptive SMOTE augmentation, the balanced dataset is used to train a hybrid LSTM–CNN classifier:

- LSTM captures temporal dependencies:

$$h_t = \sigma\left(W_h h_{t-1} + W_x x_t + b\right) \quad (16)$$

After feature extraction from LSTM + CNN, the final hidden representation (or a pooled CNN feature map) is fed into a dense layer:

$$\hat{y} = Relu\left(W_o h_T + b_o\right) \quad (17)$$

Loss Function — Categorical Cross-Entropy c. The objective is to minimize the classification loss:

$$L_{cls} = -\sum_{c=1}^{C} y_c log\left(\hat{y}_c\right) \quad (18)$$

Where:

- $y_c \in \{0,1\}$ is the true one-hot label
- ˆ is the predicted probability for class
- 

A balanced dataset is evaluated using a hybrid LSTM–CNN classifier, where CNN layers extract local features and LSTM modules capture temporal dependencies, yielding robust classification of prenatal health conditions.

### *Algorithm 1: Pseudocode for Data Augmentation Using Ensemble GANs with Adaptive KNN-SMOTE*

**Input:** D: Original dataset

### Handle Missing Value:

- If pH label ( is missing, remove the instance: $D \leftarrow D \setminus \{(X_i, y_i) \mid y_i \text{�} is\ missing\}$

### *Classify the dataset*

Assign fetal condition classes based on pH thresholds:

$$D_{label} = \begin{cases} Normal\ , & if\ pH \geq 7.1 \\ Suspicious, & if\ pH < 7.15\,and\ pH \geq\ 7.05 \\ Patholocial, & if\ pH < 7.05 \end{cases}$$

### *Preprocess*

- Normalize each sequence $X_i = \left(\frac{x - mean_x}{std_x}\right)$
- Zero-padded to the length L $X_i^{pad} = X_i, 0, \ldots 0$

### *Ensemble GAN-Based Augmentation*

- Train three GAN models on minority classes.
- cGAN: $L_G = -E\left[D\left(G(z)\right)\right]$

- TGAN: $z \sim p(z \mid x), x = G(z)$
- $S_{GAN} = S_{CGAN} \cup S_{TGAN} \cup S_{WGAN}$ WGAN $: G(z \mid y) -> x\_y$
- Combine Synthetic Data:

### KNN-Based Adaptive SMOTE

- Merge original and generated samples:

$$D_m \leftarrow D_{orig} \cup D_{GAN}$$

- Find minority sample

$$xi : \left[\, NN_k\left(x_i\right) = \left\{\, x_{i1},\, x_{i2},\, x_{i3}, \ldots x_{ik} \right\} \right]$$

- Collect all SMOTE-generated samples:

$$\left[\, D\_\{smote\} = x\_\{new\}\hat{}\{(j)\} \,\right]$$

- Repeat until all classes are balanced:

$$\mid Dnorm \mid \approx \mid Dsusp \mid \;\approx\; \mid Dpath \mid$$

### Final Dataset Construction

Combine all data: $D_{aug} = \mid Dnorm \mid \cup \mid Dsusp \mid \;\cup\; \mid Dpath \mid$

### Train Classifier

- Use $D_{aug}$ to train the classifier with LSTM + CNN $h_t = \sigma\left(W_h h_{t-1} + W_x x_t + b\right)$
- Also fed into the dense layer by the Relu activation function: $\hat{y} = Relu\left(W_o h_T + b_o\right)$

**Output**: Balanced Dataset.

The proposed augmentation workflow is outlined in Algorithm 1.

The approach systematically preprocesses the data, generates physiologically realistic synthetic signals, and ensures balanced class distributions before classifier training.

### Experimental Results

The effectiveness of the proposed ensemble GAN with Adaptive KNN-SMOTE was evaluated on the CTU–UHB dataset. Experiments assessed the impact of the augmentation strategy on class balance, signal diversity, and classification accuracy. As illustrated in Figure 6, the dataset exhibited a pronounced imbalance, with 81% Normal, 12% Suspicious, and 7% Pathological cases, which can bias model training toward the majority class.

After applying the proposed Ensemble GAN with Adaptive KNN-SMOTE, the dataset achieved near-uniform distribution, with 447 Normal, 430 Suspicious, and 410 Pathological samples (Figure 7). This balance reduced bias, improved generalization, and enhanced the classifier's ability to detect minority cases accurately.

Figure 8 illustrates representative synthetic fECG signals generated by WGAN, cGAN, and TGAN, normalized for visualization.

### Classification Metrics

A hybrid LSTM–CNN classifier was trained on the augmented dataset to evaluate the effectiveness of the proposed

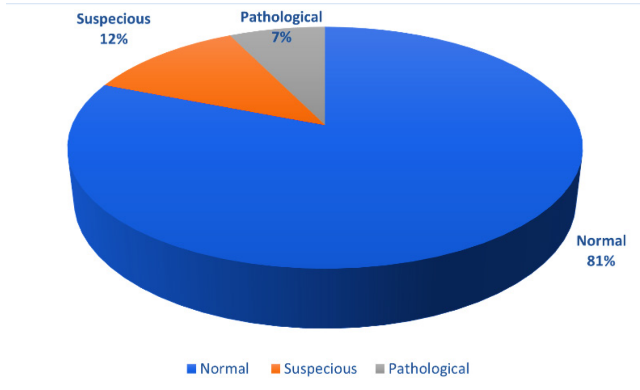


**Figure 6:** Distribution of Dataset CTU-UHB before Augmentation

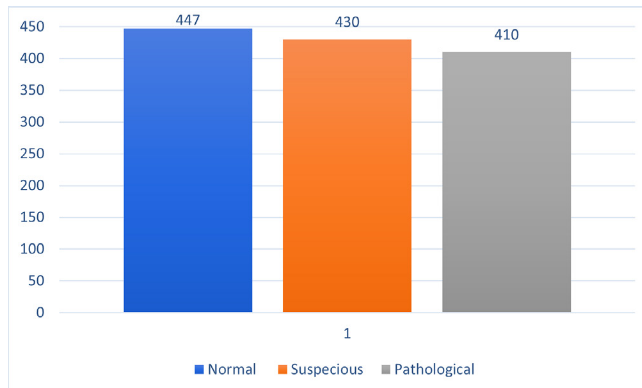


**Figure 7:** Distribution of dataset after the Data Augmentation

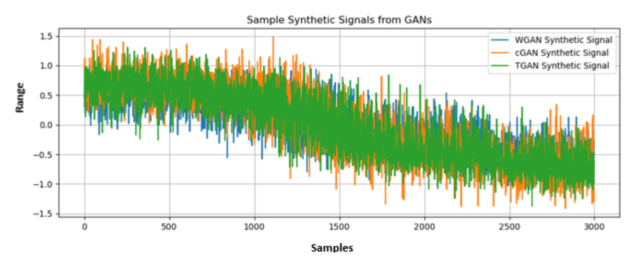


**Figure 8:** Synthetic signals generated by Ensemble GAN

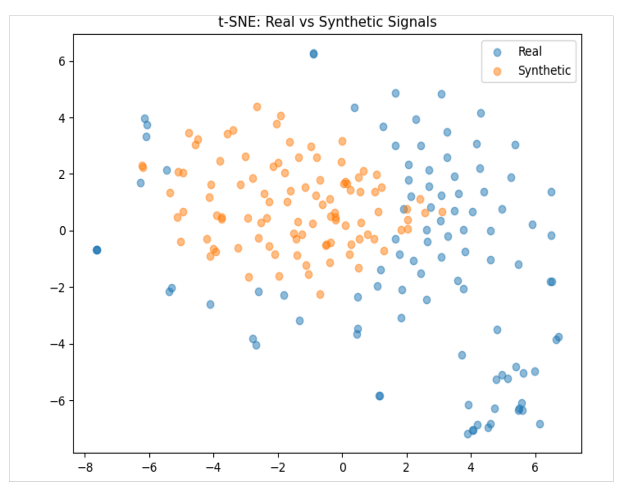


**Figure 9:** Scatter plot of real and synthetic comparison data

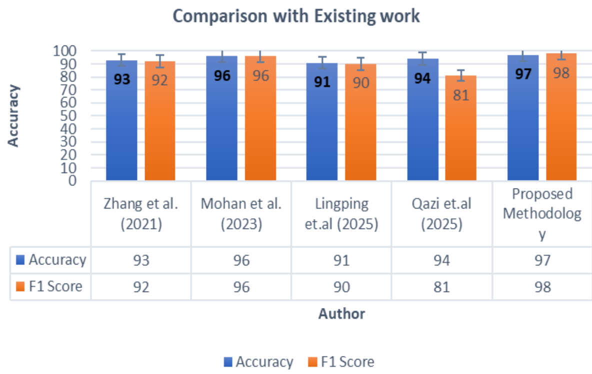


**Figure 10:** Comparison with existing work

Ensemble GAN with Adaptive KNN-SMOTE framework. Across 100 epochs, the model achieved 97% balanced accuracy with a cross-entropy loss of 0.084, improving from 85% accuracy and 0.34 loss at 10 epochs. This steady convergence without signs of overfitting (Table 3) confirms that the augmentation strategy successfully reduces class imbalance and strengthens the classifier's ability to recognize minority cases.

The t-SNE projection in Figure 9 shows that synthetic and real fECG samples occupy closely overlapping feature spaces, confirming the physiological realism and diversity of the generated signals.

Table 4 compares studies addressing class imbalance in the CTU–UHB fetal ECG dataset. The proposed Ensemble GAN with Adaptive KNN-SMOTE achieved the best results, with 97% accuracy and 98% F1-score, highlighting its effectiveness in improving minority-class detection in fetal health assessment.

Figure 10 compares Accuracy and F1-score between existing methods and the Ensemble GAN with the Adaptive KNN-SMOTE approach on the CTU–UHB dataset. The method effectively improves the classification of minority classes (suspicious and pathological) by generating physiologically plausible synthetic samples and refining them with Adaptive SMOTE.

### *Limitations and Future Work*

Since this study relied solely on the CTU–UHB dataset, the results may not capture the full variability of fetal ECG in real-world settings. While GAN-based augmentation aims for physiological realism, it can still introduce subtle inaccuracies that risk biasing the classifier. The combined use of multiple GANs with adaptive SMOTE also increases computational cost, potentially limiting real-time use. Moreover, excessive augmentation of minority classes may cause overfitting if synthetic signals lack sufficient diversity.

Future work should validate this framework on larger, multi-center datasets to confirm generalizability. Incorporating explainable AI methods can further enhance interpretability, strengthen clinical trust, and support practical adoption.

## Conclusion

This study presents a two-stage augmentation framework that effectively mitigates class imbalance in fetal ECG-based health assessment. By integrating ensemble GANs (cGAN, TGAN, WGAN) with Adaptive KNN-SMOTE, the method generates clinically valid synthetic signals and enhances classifier performance. Coupled with a hybrid LSTM–CNN, it achieved 97% accuracy and 98% F1-score, outperforming existing approaches and significantly improving minority-class detection. These results demonstrate the framework's potential to strengthen fetal monitoring systems and provide a robust foundation for reliable automated diagnosis in imbalanced biomedical time-series applications.

## Acknowledgement

I would like to acknowledge and express my sincere gratitude to the Head of the Department for guidance, resources, and timely feedback, and to the Principal of the Institution for providing the facilities and institutional support necessary to write and complete the paper.

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Figure 1: https://www.istockphoto.com/photo/pregnant-woman-performing-cardiotocography-or-ctg-monitoring-fetal-heartbeat-and-gm1162543462-318915500?searchscope=image%2Cfilm

Figure 2: https://respbuy.com/product-category/hospital-equipments/foetal-monitors/

Figure 3: https://www.vistexhospital.org/

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