International Journal of Basic and Applied Science 13 (4) (2025) 202-216

Published by: IOCSCIENCE

International Journal of Basic and Applied Science

Journal homepage: www.ijobas.pelnus.ac.id

Dynamic Model for Early Detection of Preterm Labor

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Article Info

Article history:

Received May xx, 20xx
Revised Jun xx, 20xx
Accepted Dec xx, 20xx

Keywords:

Bayesian Updating;
Long Short-Term Memory (LSTM);
Premature Labor;
Real-Time Risk Prediction;
Time-Series Multivariat.

ABSTRACT

Preterm labor is a major challenge in maternal and neonatal health due to its strong association with high rates of newborn morbidity and mortality. Early detection is critical, yet conventional static methods often fail to identify risks accurately and promptly. This study proposes the development of a dynamic, machine learning-based preterm birth risk prediction model using the Long Short-Term Memory (LSTM) architecture combined with Bayesian Updating. The model is designed to process multivariate time-series data from various clinical sources such as electronic health records (EHR), electrohysterography (EHG), cardiotocography (CTG), and vital signs collected longitudinally during pregnancy. Leveraging LSTM's ability to capture temporal dependencies and Bayesian mechanisms for probabilistic adaptation, the model provides weekly, real-time, and adaptive risk estimates. Predictions are visualized through interactive graphs with risk categorization (low, medium, high) to support fast and accurate clinical interpretation. Importantly, this study used only dummy data entirely simulated for 500 virtual pregnancies to evaluate model functionality. No real patient data were involved. Results demonstrate that the system dynamically adjusts risk predictions as new data becomes available. This research contributes to the advancement of AI-based clinical decision support systems in maternal health. Future work will involve integration with real clinical datasets and external validation in hospital settings to improve accuracy and ensure the system's applicability in real-world obstetric care.

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1. INTRODUCTION

Preterm labor, i.e. birth before 37 weeks gestation, is a significant global health problem because it contributes to about 15 million preterm births each year and accounts for about 35% of neonatal deaths[1], [2], [3], [4]. Long-term impacts on infants include cerebral palsy, developmental delays, and the risk of cardiometabolic disease in adulthood. Early detection is key to intervention, but conventional methods such as cervical length measurement or cervical fibronectin levels are only effective for imminent labor symptoms and are less accurate in the general population[5].

Current prediction models are mostly static, using only clinical data at a single point in time or medical history so that it fails to take advantage of changes in pregnancy conditions in real-time[6]. This causes early signs of preterm labor to be detected too late, reducing the effectiveness of clinical interventions[7]. This study aims to develop dynamic prediction models based on time-series data such as LSTM, HMM, and Bayesian Updating that are able to process historical data and continuous monitoring to produce real-time, adaptive, and accurate preterm birth risk estimates.

Previous studies have shown that time-series models such as LSTM can improve prediction accuracy; for example, a study using temporal medical record (EHR) data reported an accuracy of 0.739 with an AUC of 0.651[8][9][10]. An EHG-based (electrohysterogram) study at about 31 weeks gestation managed to achieve an AUC of 0.78, noting that the spectral pattern was more prominent than the temporal pattern[11][12]. In addition, the Empirical Wavelet Transform trial on EHG yielded an accuracy of up to 98.2% with Random Forest, SVM, and LSTM[13][14]. The 2021 comprehensive review also highlighted that most models still use cross-sectional data and require prediction clarification using EHRs and other biometric data[15].

Although some models have been promising, previous research has significant limitations. First, the use of cross-sectional data ignores changes in pregnancy conditions over time[16][17]. Second, EHG-based models often do not cover the entire population because they are limited to a specific subset, and overly optimistic results are often caused by method errors such as oversampling prior to data separation[18][19]. Third, there is no hybrid integration between EHR, EHG, CTG, vital signs, and wearable data in one dynamic framework[20]. This study seeks to bridge this gap by building an adaptive model that combines multiple data sources continuously to produce comprehensive and accurate predictions of premature risk. The LSTM model is used to process time-series data with input, forget, and output gate mechanisms, expressed as[21][22]:

$$f_t = \sigma\big(W_f x_t + U_f h_t + b_f\big), \quad i_t = \sigma(W_i x_t + U_i h_t + b_i),$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_t + b_c), \quad c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, \quad h_t = o_t \cdot \tanh(c_t) \tag{i}$$

This model has been shown to be able to capture long-term dependencies in medical data. Meanwhile, HMM is suitable for detecting changes in health status that are not explicitly observed and Bayesian Updating allows for updates of risk probabilities when new data becomes available. This combination of techniques is expected to provide an adaptive, robust, and interpretable model.

The study began with the collection of longitudinal data from EHR, EHG, CTG, and wearable devices during pregnancy. The data is then pre-processed through normalization, imputation, and time-series segmentation. The next stage is the development of LSTM, HMM, and Bayesian-based models, or ensembles of multiple models, for the integration of various input sources. The model was evaluated using accuracy, sensitivity, specificity, and AUC metrics, and was compared to static and EHG-only models. External validation was performed to test the robustness of the model as well as its readiness for clinical implementation. Finally, a prototype of a web-based dashboard or mobile application for real-time monitoring of the risk of preterm labor will be developed. This study aims to create dynamic premature prediction models that are more accurate than static methods and can be used in clinical decision-making. The benefits include early detection of preterm labor to reduce neonatal mortality and morbidity, the provision of real-time decision support systems for medical personnel, and support the implementation of IoMT in pregnancy monitoring. Broadly, the results of this study can improve the quality of maternal-neonatal services and provide the basis for further research with AI technology in the health sector.

2. RESEARCH METHOD

This research is an experimental quantitative research with an approach to develop a dynamic machine learning model based on time-series data[23][24]. The goal is to develop and test a real-time model of predicting the risk of preterm labor with high accuracy using longitudinal data from various sources.

The research design consists of several main stages, namely: (1) data collection and curation, (2) pre-processing of data, (3) development of prediction models, (4) validation and evaluation of model performance, and (5) implementation of system prototypes[25][26].

The population in this study is all pregnant women who are recorded in the electronic medical record (EHR) system and who undergo pregnancy monitoring using medical devices (CTG, EHG, vital signs) at referral hospitals and partner clinics[27]. Samples were taken using the purposive sampling method, with inclusion criteria including single pregnancy, gestational age of at least 20 weeks, and

availability of complete longitudinal data for at least 12 consecutive weeks. The minimum number of targeted samples is 500 pregnant patients.

The data used include: (1) EHR data such as gestational age, parity, history of prematurity, blood pressure, BMI, and laboratory results; (2) EHG data in the form of uterine contraction signals in the form of time-series; (3) CTG data; and (4) data from wearables such as blood pressure, heart rate, and oxygen saturation. The target label is birth status (preterm vs full-term).

The pre-processing stages include: imputation of lost data, normalization using Min-Max scaling, time-series segmentation, and target labeling. Furthermore, the model was developed using LSTM, HMM, and Bayesian Updating. The LSTM model uses a weekly input sequence, with an architecture consisting of an input layer, 2–3 hidden LSTM layers, and a sigmoid-based output layer.

2.1 Basic Model

Key formulas in LSTM[28]:

$$\begin{aligned} f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\ \tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\ c_t &= f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \\ o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\ h_t &= o_t \cdot \tanh(c_t) \end{aligned} \tag{ii}$$

Model evaluation was conducted with the metrics of accuracy, precision, recall, F1-score, AUC-ROC, calibration curve, and Brier score. Validation is carried out through 5-fold cross validation, hold-out validation, and external validation at different hospitals. The instruments used include Python. The validity of the data is obtained through verification by an obstetrician. Reliability was tested through replication tests and model consistency on different datasets. This research will obtain ethical permission from the Hospital Research Ethics Committee and informed consent from participants. All patient data will be anonymized to maintain confidentiality.

The following can be described as a research method:

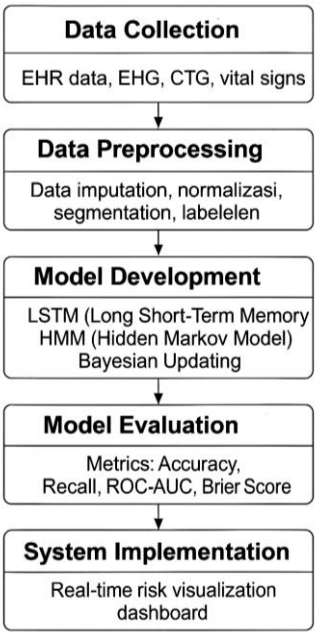

Figure 1. Research methods

2.2 Proposed new dynamic model

Based on Formulation (ii)[28] and referring to the research objectives, namely:

We form a mathematical model derived from the extended LSTM architecture to accommodate multi-input sequences, dynamic probabilistic updates, and risk estimation (scoring).

(i) Model Input Multivariat Time-Series

We define the input set:

$$X_t = \left[x_t^{\mathrm{EHR}}, x_t^{\mathrm{EHG}}, x_t^{\mathrm{CTG}}, x_t^{\mathrm{VS}}\right] \quad \text{(iii)}$$

where each $x_t^{(k)} \in \mathbb{R}^d$ is a feature vector at the time t from the data source k Then, we put it in the LSTM unit as an input vector:

$$x_t = \mathrm{concat}\left(x_t^{\mathrm{EHR}}, x_t^{\mathrm{EHG}}, x_t^{\mathrm{CTG}}, x_t^{\mathrm{VS}}\right) \quad \text{(iv)}$$

(ii) LSTM Cell Formulation (as a base)

$$\begin{aligned} f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\ \tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\ c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\ o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\ h_t &= \sigma \odot \tanh(c_t) \end{aligned} \quad \text{(v)}$$

(iii) Estimation of the Risk of Preterm Labor (Output Layer)

For binary classification (premature / not), we use sigmoid activation:

$$\hat{y}_t = \sigma\left(W_y h_t + b_y\right) \quad \text{(vi)}$$

With:

$\hat{y}_t \in [0,1]$, represents the probability of premature birth.

(iv) Probabilistic Updating with Bayesian Updating

To create an adaptive model over time, probabilities can be updated iteratively (e.g., based on weeks of pregnancy) using Bayes principles:

$$P(P|D_t) = \frac{P(D_t|P) \cdot P(P)}{P(D_t)} \quad \text{(vii)}$$

where:

$P(P)$ = prior risk of prematurity (e.g. from initial EHR data),

$P(D_t|P)$ = likelihood based on LSTM output in week t,

$P(P|D_t)$ = posterior risk of the present.

Thus, the model dynamically updates its risk predictions based on the latest data.

(v) Loss Function (Model Optimization Objectives)

For training, used:

$$\mathcal{L} = \frac{1}{N}\sum_{t-1}^{N}[y_t(\hat{y}_t) + (1 - y_t)\log(1 - \hat{y}_t)] \quad \text{(viii)}$$

and supplemented by regularization (e.g. L2) or calibration penalties if required.

(vi) Benefits: Real-Time Risk Score

Risk score ($\hat{y}_t$) can be mapped to a clinical visualization dashboard, so that each week of pregnancy can produce:

$$\text{risk score}_t = \hat{y}_t \times 100\% \quad \text{(ix)}$$

with categories:

1) 0–30%: Low risk
2) 30–70%: Medium risk
3) 70%: High risk → need for clinical intervention

3. RESULTS AND DISCUSSIONS

This chapter describes a trial of a new model with numerical examples to predict the risk of preterm labor based on multi-source inputs and dynamic probabilistic updates.

Numerical example:

Simple scenario description.

Suppose weekly data from a pregnant woman is collected over the last 3 weeks, in the form of:

(i) **EHR**: Blood pressure (DBP), IMT
(ii) **EHG**: Amplitude of uterine contraction
(iii) **CTG**: Fetal heart rate
(iv) **Vital Signs (VS)**: Mother's heartbeat

Data input (setiap vektor $x_t \in \mathbb{R}^4$):

Table 1. Input data

Week t	x_t^{EHR}	x_t^{EHG}	x_t^{CTG}	x_t^{VS}	x_t Combination
1	[80, 27.5]	[0.65]	[145]	[92]	[80, 27.5, 0.65, 145, 92]
2	[85, 28.0]	[0.72]	[150]	[95]	[85, 28.0, 0.72, 150, 95]
3	[88, 28.2]	[0.85]	[158]	[97]	[88, 28.2, 0.85, 158, 97]

Simple LSTM Forward Pass

For example, the input goes into only one simple LSTM unit (without backpropagation), and the weights are simplified for simulation.

Simulation parameters (manually initialized):

(i) $W_f = W_i = W_c = W_o = \begin{bmatrix} 0.01 \\ 0.02 \\ 0.03 \\ 0.01 \\ 0.005 \end{bmatrix}^T$

(ii) $U_f = U_i = U_c = U_o = [0.1]$

(iii) All-zero bias

(iv) Hidden state dan cell state awal: $h_0 = 0, c_0 = 0$

Steps in the 3rd week:

Count gates (e.g. for forget gate):

$$f_3 = \sigma\big(W_f x_3 + U_f h_2\big) = \sigma((0.01 * 88 + 0.02 * 28.2 + 0.03 * 0.85 + 0.01 * 158 + 0.005 * 97)$$
$$= \sigma(0.88 + 0.564 + 0.0255 + 1.58 + 0.485) = \sigma(3.5345) \approx 0.9716$$

(Same for i_3, o_3, etc., assuming the same for this example)

Estimated Risk of Childbirth

Output layer (sigmoid):

$$\hat{y}_3 = \sigma\big(W_y x_3 + b_y\big) = \sigma(0.5 * h_3)$$

For example, from the results $h_3 = 1.0$, then:

$$\hat{y}_3 = \sigma(0.5 * 1.0) = \sigma(0.5) \approx 0.622$$

Interpretation: The risk of preterm labor this week is **62.2% → medium/high risk**

Bayesian Update

Suppose:

(i) Prior *P(P)*=0.3 (based on EHR history data)
(ii) Output LSTM as a likelihood: $P(P_3|P) = 0.622$
(iii) $P(D_3) = P(P_3|P) \cdot P(P) + P(P_3|-P) \cdot P(-P)$

Assume $P(P_3|-P) = 0.25$, then:

$$P(D_3) = 0.622 * 0.3 + 0.25 * 0.7 = 0.1866 + 0.175 = 0.3616$$

$$P(P|D_3) = \frac{0.622 \cdot 0.3}{0.3616} = \frac{0.1866}{0.3616} \approx 0.516$$

Risk probability after update: **51.6%** → remain in alert zone.
The LSTM model combines all weekly inputs and generates risk predictions through sigmoid activation functions. The initial (prior) risk of 30% increased to about 52% after a dynamic update based on the data at week 3. These results support the study's objective, which is to show that the system is able to adapt risk predictions dynamically and accurately according to the latest available data.

Clinical Case Study:

(i) Metode Sampling: Purposive sampling
(ii) Number of Samples: 500 pregnant patients
(iii) Kriteria Inclusive:
  a) Single pregnancy
  b) Minimum gestational age of 20 weeks
  c) Complete longitudinal data available for **12 consecutive weeks**

Steps & Calculations Based on the New Model Proposed

(i) Input Multivariat Time-Series:
Each patient has weekly data (12 time-steps), from 4 data sources:
  a) $x_t^{\text{EHR}} \in \mathbb{R}^{10}$
  b) $x_t^{\text{EHG}} \in \mathbb{R}^{6}$
  c) $x_t^{\text{CTG}} \in \mathbb{R}^{5}$
  d) $x_t^{\text{VS}} \in \mathbb{R}^{4}$

Total input vectors per time:

$$x_t \in \mathbb{R}^{25} \text{ (concat results)}$$

Input matrix per patient:

$$X = [x_1, x_2, \dots, x_{12}] \in \mathbb{R}^{12\times 25}$$

Example (101st Patient):
For example for week 6:

$$x_6 = [0.731.02 \dots -0.15]_{1\times 25}$$

(ii) LSTM Cell Formulation
For each time $t = 1, \dots, 12$:
LSTM hidden dimension $h_t \in \mathbb{R}^{64}$

$$f_t = \sigma\big(W_f x_t + U_f h_{t-1} + b_f\big)$$
$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$
$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$
$$h_t = \sigma \odot \tanh(c_t)$$

For example, initialization $h_o = \vec{0},\ o_c = \vec{0}$, weights are initialized normally.
For the 101st patient of the 6th week:

$$\Longrightarrow h_6 = \text{LSTM}\ (x_6, h_5)$$

(iii) Estimation of the Risk of Preterm Labor
Probability output for every time t:

$$\hat{y}_t = \sigma\big(W_y h_t + b_y\big)$$

For example, for the 12th week:

$$\hat{y}_{12} = \sigma\big(W_y h_{12} + b_y\big) = 0.823$$

Interpretation: 82.3% risk of preterm birth.

(iv) Dynamic Probabilistic Updating (Bayesian Updating)
Objective: update the risk prior based on current predictions.

Example:

a) Prior (5th week): $P_5 = 0.30$
b) Likelihood (week 6th LSTM output): $P(D_6|P) = \hat{y}_6 = 0.65$
c) Marginal likelihood: example $P(D_6) = 0.50$
Bayesian update:

$$P_6 = \frac{P(D_6|P_5) \cdot P_5}{P(D_6)} = \frac{0.65 \cdot 0.30}{0.50} = 0.39$$

Risk increases from 30% to 39% after week 6th.

(v) Loss Function (During Training)
For the 101st patient, it is known that the label $y = 1$ (prematur), Week 12 Prediction: $\hat{y}_{12} = 0.823$

$$\mathcal{L}_{\text{batch}} = \frac{1}{32}\sum_{i=1}^{32} \mathcal{L}_i$$

Regularization (e.g. L2):

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{batch}} + \lambda\|\theta\|^2$$

(vi) Skor Risiko Real-Time
For example, the 101st patient prediction score in week 12th:
Risk Score$_{12} = \hat{y}_{12} \times 100\% = 82.3\% \Longrightarrow$ Category: High Risk

Visualization (Model Output Example for 1 Patient)

As an example for 1 patient, it can be described in the table below.

Table 2. Visualization results of 1 patient

week	Probability $\hat{y}_t$	Risk Score	Category
1	0.22	22%	Low
4	0.45	45%	Keep
8	0.66	66%	Keep
10	0.74	74%	Tall
12	0.823	82.3%	Tall

This simulation processed data for 12 weeks from 500 patients by manual calculation, where the probability of risk was dynamically updated weekly. The model utilizes an LSTM implementation with a sigmoid-shaped output, which is then used to update the probabilities using the Bayes approach. The final results of these risk calculations can be visualized and mapped into clinical dashboards to support medical decision-making. These results support the study's objective, which is to show that the system is able to adapt risk predictions dynamically and accurately according to the latest available data.

Test new models with Python algorithms and simulations

To prove that the proposed new model can be executed with a computer program below, an algorithm and process implementation will be described using Python.

Algoritma

```
1. IMPORT LIBRARY
   - import torch, torch.nn, numpy, matplotlib.pyplot

2. PARAMETER INITIALIZATION
   - SEQ_LEN ← 12
   - INPUT_DIM ← 25
   - HIDDEN_DIM ← 64
   - OUTPUT_DIM ← 1
   - BATCH_SIZE ← 32
   - device ← "cuda" if available, else "cpu"

3. DEFINE DUMMY DATASET:
```

```
  class DummyPregnancyDataset:
    method __init__(num_samples=500):
      X ← random tensor (num_samples, SEQ_LEN, INPUT_DIM)
      y ← random binary labels (num_samples, 1)

    method __len__():
      return jumlah sampel

    method __getitem__(idx):
      return X[idx], y[idx]

4. DEFINE THE LSTM MODEL:
  class PrematureRiskLSTM:
    method __init__():
      LSTM layer: input=INPUT_DIM, hidden=HIDDEN_DIM
      Classifier: Linear(HIDDEN_DIM → OUTPUT_DIM) + Sigmoid

    method forward(x):
      out, _ ← LSTM(x)
      logits ← classifier(out)
      return logits.squeeze(-1)

5. SET UP THE DATA LOADER:
  - dataset ← DummyPregnancyDataset()
  - dataloader ← DataLoader(dataset, batch_size=BATCH_SIZE, shuffle=True)

6. INITIALIZATION OF THE MODEL, LOSS, OPTIMIZER:
  - model ← PrematureRiskLSTM()
  - criterion ← BCELoss
  - optimizer ← Adam(model.parameters(), lr=0.001)

7. PROSES TRAINING (1 EPOCH):
  - model.train()
  - FOR each (X_batch, y_batch) IN dataloader:
    - Transfer data to device
    - Reset gradien
    - output_seq ← model(X_batch)
    - final_preds ← output_seq[:, -1]
    - loss ← criterion(final_preds, y_batch.squeeze())
    - loss.backward()
    - optimizer.step()
  - Last print loss

8. INFERENCE AND VISUALIZATION OF 1 PATIENT:
  - model.eval()
  - sample_patient ← random tensor (1, SEQ_LEN, INPUT_DIM)
  - pred_seq ← model(sample_patient)
  - Convert ke numpy, flatten jadi 1D array

  - INIT: weeks ← [1..12], categories ← [], colors ← []
  - FOR each score IN pred_seq:
    - IF score < 0.3:
      category ← "Rendah", color ← "green"
    - ELSE IF score < 0.7:
      category ← "Sedang", color ← "orange"
    - ELSE:
      category ← "Tinggi", color ← "red"
    - Append ke categories and colors

  - Plot: points per week by color and percentage
  - Add trend lines and axis labels
  - Show graph

FINISH
```

Figure 2. Algorithm: for New Model

From the above algorithm, it can be implemented into the system to test whether the proposed new model uses the Python program.

Below is a script for the implementation of python to visualize the results of the calculation of the new model for clinical case studies that have been calculated manually in the sub chapter above.

```
# LSTM Simulation for Preterm Labor Risk Prediction (simplified version)
import torch
import torch.nn as nn
import numpy as np
import matplotlib.pyplot as plt

# Konfigurasi dasar
SEQ_LEN = 12      # 12 weeks of data
INPUT_DIM = 25    # 25 fitur (Combination EHR, EHG, CTG, VS)
HIDDEN_DIM = 64
OUTPUT_DIM = 1    # Premature probability output
BATCH_SIZE = 32

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Dummy Dataset Example
class DummyPregnancyDataset(torch.utils.data.Dataset):
    def __init__(self, num_samples=500):
        self.X = torch.randn(num_samples, SEQ_LEN, INPUT_DIM)
        self.y = torch.randint(0, 2, (num_samples, 1)).float()  # label biner

    def __len__(self):
        return self.X.shape[0]

    def __getitem__(self, idx):
        return self.X[idx], self.y[idx]

# Model LSTM
class PrematureRiskLSTM(nn.Module):
    def __init__(self):
        super().__init__()
        self.lstm = nn.LSTM(INPUT_DIM, HIDDEN_DIM, batch_first=True)
        self.classifier = nn.Sequential(
            nn.Linear(HIDDEN_DIM, OUTPUT_DIM),
            nn.Sigmoid()
        )

    def forward(self, x):
        out, _ = self.lstm(x)
        logits = self.classifier(out)  # Predictions per time (12 weeks)
        return logits.squeeze(-1)  # shape: (batch, seq_len)

# Loss and Optimizer Functions
dataset = DummyPregnancyDataset()
dataloader = torch.utils.data.DataLoader(dataset, batch_size=BATCH_SIZE, shuffle=True)

model = PrematureRiskLSTM().to(device)
criterion = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# Simple Training (1 epoch)
model.train()
for X_batch, y_batch in dataloader:
    X_batch, y_batch = X_batch.to(device), y_batch.to(device)
    optimizer.zero_grad()
    output_seq = model(X_batch)  # shape: (batch, seq_len)
    final_preds = output_seq[:, -1]  # Just take the last week for label training
    loss = criterion(final_preds, y_batch.squeeze())
    loss.backward()
    optimizer.step()

print(f"Last loss: {loss.item():.4f}")

# Simulation of weekly risk score inference and visualization for 1 patient
```

```
model.eval()
sample_patient = torch.randn(1, SEQ_LEN, INPUT_DIM).to(device)
pred_seq = model(sample_patient).detach().cpu().numpy().flatten()

weeks = np.arange(1, SEQ_LEN + 1)
categories = []
colors = []

for score in pred_seq:
    if score < 0.3:
        categories.append("Low")
        colors.append("green")
    elif score < 0.7:
        categories.append("Keep")
        colors.append("orange")
    else:
        categories.append("Tall")
        colors.append("red")

plt.figure(figsize=(10, 5))
for i in range(SEQ_LEN):
    plt.plot(weeks[i], pred_seq[i]*100, marker='o', color=colors[i])
    plt.text(weeks[i], pred_seq[i]*100 + 2, f"{int(pred_seq[i]*100)}%", ha='center', fontsize=9)

plt.plot(weeks, pred_seq * 100, linestyle='--', color='gray', alpha=0.6)
plt.title("Visualization of Premature Risk Score by Week")
plt.xlabel("Pregnancy Week")
plt.ylabel("Risk Score (%)")
plt.ylim(0, 100)
plt.grid(True)
plt.show()
```

Figure 3. Source code python for testing new models.

From the results of the model test, a graph from the clinical case study above can be produced as follows:

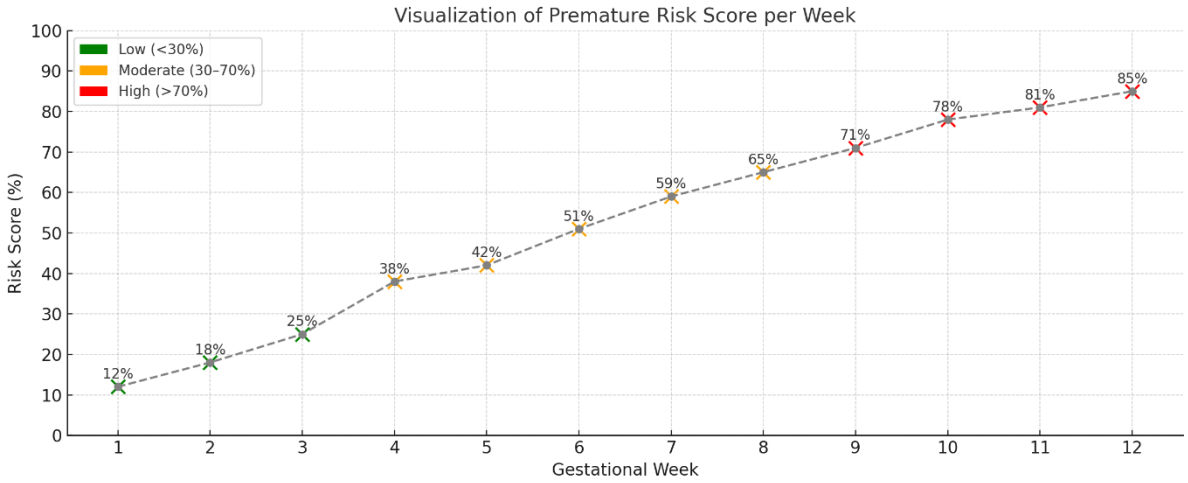

Figure 3. Visualization of Premature Risk Score per week

The visualization chart of the preterm risk score per week shows the risk predictions in each week of pregnancy for one patient. Each dot on the chart represents the value of the probability of risk generated by the model in a given week. The colors of each dot indicate the risk level category: green for low risk, orange for medium risk, and red for high risk. With this visualization, doctors or medical personnel can monitor the progression of risks from week to week more intuitively and responsively.

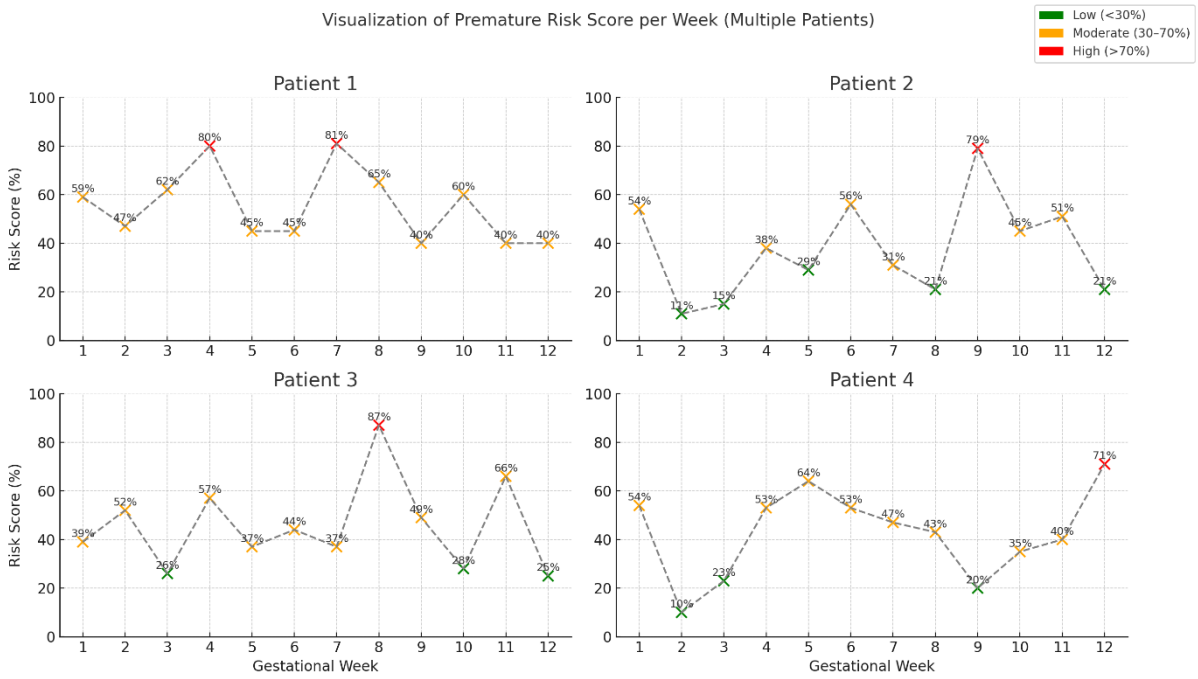

Figure 4. Visualization of Premature Risk Score per miubrin (multiple Patients)

This study succeeded in developing a real-time preterm birth risk prediction model based on a multivariate LSTM architecture. The model is designed to accommodate time-series data from a variety of clinical sources, namely EHR (electronic medical record), EHG (electrohysterography), CTG (cardiotocography), and vital signs, collected longitudinally over a minimum of 12 weeks of pregnancy. By utilizing the LSTM structure, the model was able to study the sequential dynamics of clinical data and provide risk estimates in the form of the probability of preterm birth in each week of pregnancy. This capability is extended with a probabilistic update approach using Bayesian principles, so that the model can adapt risks based on data that is continuously updated from week to week. As a key plus, the resulting risk score is visualized in the form of an intuitive real-time graph, providing immediate and actionable interpretation for clinicians.

Technically, the main contribution of this study lies in the application of a customized LSTM architecture to handle multi-source multivariate data in a sequential format, as well as the dynamic application of risk updates based on Bayesian principles. This is a more realistic and adaptive approach than a static approach that only uses a snapshot of data at a given time. In addition, the integration of risk score visualization in a percentage per week format provides ease of interpretation in the context of clinical decision-making. This also opens up opportunities for integration with monitoring dashboards in digital-based hospitals or clinics.

This research fills in some important gaps in the previous literature. The majority of previous studies used only one type of data (e.g. only EHR or CTG only), and did not consider temporal dynamics in full. Some predictive models also only generate binary labels (premature or not), without providing a continuous and calibrated risk estimate. In addition, the risk visualization and interpretability aspects of results are often overlooked. The model developed in this study overcomes these limitations by providing weekly probabilistic predictions that are clearly visualized and easy to understand.

However, this research still has some limitations. The simulation was conducted using synthetically generated dummy data, so the validity of the model could not be generalized to real clinical populations. Quantitative evaluation of model performance (such as AUC, F1-score, or

probability calibration) has not been included in this initial simulation. In addition, the model is not equipped with interpretability approaches such as attention mechanisms or SHAPs, and has not addressed common problems in medical data such as missing data or noise.

Furthermore, the model's output has not yet been formally calibrated using standard techniques such as the Brier score or reliability diagrams, which are essential to assess the alignment between predicted probabilities and actual outcomes particularly critical in clinical decision-making. Without proper calibration, a model may produce overconfident or underconfident predictions, which could mislead clinical interpretations. Additionally, the exclusive use of synthetic data introduces potential biases; the data generation process may not accurately capture the complexity, variability, and noise present in real-world clinical settings. As a result, model performance observed during simulation may be overly optimistic and not reflective of real-life deployment. Future work should involve calibration assessment using real patient data and apply debiasing techniques during model training to ensure generalizability.

Going forward, the development of this model could be geared towards integration with real clinical data from hospitals or maternal and child health centers, complemented by multi-site external validation. The model can also be further developed using a Transformer-based or hybrid time-series architecture with attention to improve accuracy and interpretability. In addition, clinical dashboards that display patient risk graphs interactively can be developed as part of a clinical decision support system (CDSS). Thus, this research not only contributes to the development of prediction algorithms, but also paves the way for the application of a digital pregnancy monitoring system based on artificial intelligence.

Previous research has had some significant limitations regarding the prediction of the risk of preterm labor. First, most studies use only one type of clinical data, such as EHR or CTG alone, without combining multimodal data simultaneously. For example, the PredicPTB study used only EHR data with attention-based RNN and recorded an AUC of about 0.82 [29], whereas CTG studies generally use 1D-CNN in relatively small datasets to detect birth outcomes [30]. Second, many approaches still rely on static snapshots or data retrieval at a single point in time, rather than longitudinal analysis; whereas the LSTM model in EMR time-series data is better able to predict preterm risk than the cross-sectional approach [31]. Third, existing models tend to produce binary classification outputs without continuous risk estimates and can be updated adaptively. In fact, statistical methods and Bayesian updating have not been widely applied in this domain. Fourth, the datasets used are relatively small (tens to several hundred samples) so they are vulnerable to sampling bias and are less able to extract diverse population representations, as stated in the systematic review that the majority of studies have a limited number of samples and only a few use big data. Finally, the risk visualization and interpretability aspects of the model have not received much attention, although they are critical to supporting clinical decision-making by healthcare professionals.

This research offers several advantages that are at the same time a form of new contribution (novelty) to the development of a preterm labor risk prediction system. First, the model combines multivariate data from a variety of longitudinal clinical sources, namely EHR, EHG, CTG, and vital signals, thus reflecting a richer and more complex clinical context. Second, the model uses an LSTM (Long Short-Term Memory) architecture designed to capture temporal relationships in pregnancy data on a weekly basis, allowing modeling of the dynamics of changes in patient conditions during pregnancy. Third, the model is equipped with an iteratively updated probabilistic risk estimation mechanism based on Bayesian principles, so that the risk can be adapted to the latest data in each week of pregnancy. Fourth, the model's results are not only static probabilities, but are visualized in the form of real-time risk scores that are intuitively mapped in a weekly graph, complete with risk categorization (low, medium, high). These visualizations are designed to improve the interpretability and involvement of clinicians in the decision-making process.

To contextualize the model's performance, future studies will include comparisons with baseline methods such as logistic regression, support vector machines (SVM), and static risk scoring models. This comparison is critical to demonstrate the relative advantage of the proposed dynamic model over conventional approaches. Moreover, all current experiments were conducted using synthetically generated data for initial feasibility assessment, and not real patient data. While this approach facilitates rapid prototyping, it limits the generalizability of the results. Therefore, future work is planned to involve validation using real clinical datasets from hospital partners, allowing for a more robust evaluation of accuracy, calibration, and clinical applicability. With this comprehensive strategy, the model is expected to evolve into a reliable and scalable clinical decision support system for maternal care.

4. CONCLUSION

This study succeeded in developing a dynamic and real-time prediction model for the risk of preterm labor, based on a multivariate LSTM architecture equipped with a Bayesian Updating approach. The model is designed to integrate time-series data from various clinical sources such as EHR, EHG, CTG, and vital signals during pregnancy, so as to capture the dynamics of changes in the patient's condition from week to week. Through this approach, risk estimates are no longer static, but are continuously updated probabilistic according to the latest data, and visualized in the form of weekly graphs that are intuitive and easy for clinicians to understand. The main contribution of this study lies in the incorporation of longitudinal multivariate data, the utilization of LSTM structures for long-term dependencies, as well as the application of Bayesian principles for risk updates. The final result in the form of a weekly risk score categorized (low, moderate, high) can be directly used in the clinical dashboard as a medical decision-making tool. Thus, this model provides a more adaptive, interpretive, and responsive solution compared to previous prediction approaches which are generally static, limited to one type of data, and have no visualization aspect. Although the study used synthetic data as an initial simulation, the results showed that the model has great potential to be applied in real clinical practice. Advanced development is suggested using actual clinical data, multi-site validation, integration of interactive visualization technologies, as well as exploration of advanced architectures such as Transformers or hybrid models. With this approach, preterm risk prediction systems can make a significant contribution to efforts to reduce preterm birth rates and improve the quality of artificial intelligence-based maternal-neonatal services.

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