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A Meta-Learning and Physics-Informed Neural Network Framework for Early Detection of Pregnancy-Associated Anaemia

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Abstract

Physio-Nutri Meta-PINNs is introduced as a novel framework for the early detection of pregnancy-associated anaemia, integrating meta-learning with physics-informed neural networks (PINNs) to address challenges arising from sparse and noisy clinical data. The framework combines a Transformer-based meta-encoder for robust feature extraction, a PINN for modeling physiological–nutritional dynamics governed by domain-specific laws, and a cross-domain adapter to align pre-trained representations with real-world clinical measurements. The meta-encoder extracts latent features from heterogeneous early-trimester data while incorporating medical priors, ensuring physiologically plausible representations even under limited sample availability. The PINN enforces biophysical constraints through partial differential equations, effectively bridging data-driven inference with established physiological mechanisms. In addition, the cross-domain adapter mitigates distributional shifts between meta-features and clinical observations, thereby improving generalization. Conventional feature extraction layers are replaced by meta-encoder outputs, enabling seamless integration with existing nutritional models while supporting probabilistic prediction and uncertainty quantification. Implemented using state-of-the-art components, including a 12-layer Transformer and a conditional GAN-based adapter, the proposed framework demonstrates strong capability in handling sparse, noisy, and multi-modal data. This approach advances early anaemia detection by unifying meta-learning, physics-informed modeling, and transfer learning into a clinically interpretable and robust solution for maternal health monitoring.

Keywords: Pregnancy-Associated Anaemia, Meta-Learning, Physics-Informed Neural Networks, Nutritional Modeling, Clinical Decision Support

1 Introduction

Pregnancy-associated anaemia remains a major global health challenge, affecting approximately 40% of pregnant women worldwide and contributing to adverse maternal and fetal outcomes. Current diagnostic practices rely predominantly on late-stage haemoglobin measurements, which often identify the condition only after overt physiological manifestations have emerged. This diagnostic delay arises from the complex interaction between dynamic physiological adaptations and nutritional factors throughout pregnancy, underscoring the need for predictive models capable of capturing subtle early-stage indicators.

Recent developments in machine learning have shown great promise for medical diagnostics; however, when it comes to pregnancy-associated anemia, current methods have three basic drawbacks. First, conventional neural networks perform poorly under the sparse and noisy conditions characteristic of early-trimester clinical data, where measurements are irregularly sampled and exhibit high variability. Second, purely data-driven models fail to incorporate established biophysical principles governing pregnancy physiology, such as plasma volume expansion kinetics and iron metabolism dynamics. Third, most nutritional assessment models operate independently of physiological monitoring frameworks, imposing artificial separations on inherently interconnected systems.

A promising way to overcome these constraints is to combine nutritional modeling with physics-informed neural networks (PINNs). PINNs have demonstrated effectiveness in modeling complex physical systems by embedding domain knowledge directly into the learning process through differential equations Cai et al. [2021]. Despite this potential, their application to biomedical problems—particularly those requiring joint modeling of physiological and nutritional processes—remains limited. Existing nutritional modeling efforts have largely focused on static representations or isolated subsystems Sobal et al. [1998], lacking the dynamic coupling necessary for effective pregnancy monitoring.

The Physiology–Nutrition Informed Meta-PINN (Physio-Nutri Meta-PINN) framework is introduced to address these limitations through several methodological innovations. The framework uniquely integrates meta-learning for robust feature extraction from sparse early-trimester data with physics-informed modeling of pregnancy-specific physiological–nutritional interactions. Unlike conventional transfer learning approaches that rely primarily on fine-tuning pre-trained models Ribani and Marengoni [2019], the proposed approach leverages meta-learning to acquire task-agnostic representations capable of rapid adaptation to individual patient trajectories while maintaining physiological plausibility.

The key contributions of this work are threefold. First, meta-learning is integrated with physics-informed neural networks for pregnancy-associated anaemia detection, enabling both data efficiency and physiological consistency. Second, a cross-domain adaptation mechanism is introduced to align pre-trained nutritional representations with sparse clinical measurements while accounting for pregnancy stage–specific variations Carlin and Alfirevic [2008]. Third, a unified modeling framework is developed to jointly capture nutritional intake patterns and their physiological consequences through embedded biophysical constraints.

This approach departs fundamentally from prior nutritional modeling efforts Tedeschi et al. [2005] by modeling pregnancy as a dynamically coupled physiological–nutritional system rather than as a collection of independent components. The framework's capacity to learn effectively from limited data while enforcing physical consistency renders it particularly well suited for clinical settings, where data scarcity and measurement noise remain persistent challenges.

2 Related Work

Numerous research fields, including physiological modeling, nutritional assessment, and machine learning, are involved in the development of computational models for the detection of pregnancy-associated anemia. Existing approaches can be broadly categorized into three groups. The first comprises conventional machine learning models for anaemia prediction. The second includes physics-informed neural networks applied to biomedical problems. The third focuses on meta-learning and transfer learning methods for medical time-series analysis.

Traditional machine learning methods have been widely applied to anaemia detection, primarily through supervised learning based on clinical measurements. For example, logistic regression and random forest models have been used to estimate anaemia risk using haemoglobin levels and nutritional intake data Dhakal et al. [2023]. These methods, however, frequently fall short of capturing the temporal dynamics of physiological changes during pregnancy, especially the nonlinear relationships between hemoglobin synthesis and nutrient absorption. Deep learning models, such as recurrent neural networks (RNNs), have demonstrated improved performance in modeling sequential medical data Morid et al. [2023], yet they typically require large datasets and offer limited interpretability regarding underlying physiological mechanisms.

More recent studies have explored transfer learning to enhance generalization across diverse populations Mahmud et al. [2023]. Although these methods adapt pretrained models to new datasets, they commonly rely on full-network fine-tuning without enforcing domain-specific constraints, which may result in physiologically inconsistent predictions. Incorporating biophysical laws directly into the learning process addresses this limitation by ensuring that model outputs remain consistent with established pregnancy physiology.

Physics-informed neural networks (PINNs) have gained increasing attention for modeling complex physical systems, including fluid dynamics and heat transfer Raissi et al. [2017]. Their application to biomedical problems, however, remains relatively limited. Recent studies have employed PINNs to model cardiovascular dynamics Arzani et al. [2022] and glucose–insulin interactions Vandvajdi et al. [2025], demonstrating their potential to embed domain knowledge directly into data-driven learning frameworks.

Creating governing equations that accurately represent both nutritional and physiological dynamics is a major obstacle to using PINNs to treat pregnancy-associated anemia. Although prior work has modeled iron metabolism in isolation Mitchell and Mendes [2013], more comprehensive representations require coupling nutrient intake with haemoglobin synthesis and plasma volume expansion. Such integrated formulations provide a more faithful representation of pregnancy physiology and are essential for effective early anaemia detection.

Meta-learning has emerged as an effective paradigm for few-shot learning in medical applications, particularly in settings where labeled data are limited. For instance, meta-learning has been applied to the classification of electrocardiogram (ECG) signals using few training examples Khalid et al. [2024], while self-supervised pre-training strategies have been explored for wearable physiological data Spathis et al. [2021]. However, these approaches generally do not explicitly incorporate domain-specific constraints, which can result in learned representations that lack physiological plausibility.

Transfer learning has also been widely adopted to address distributional differences across clinical datasets Fu et al. [2022]. Despite its success, conventional fine-tuning strategies often suffer from catastrophic forgetting or ineffective knowledge transfer when applied to small target datasets. These limitations motivate the use of meta-representation learning strategies that preserve physiological priors while enabling rapid adaptation to new patient data.

The Physio-Nutri Meta-PINN framework distinguishes itself from existing approaches by unifying meta-learning, physics-informed modeling, and transfer learning within a single cohesive system. Unlike purely data-driven methods, the framework enforces biophysical constraints to ensure predictions remain consistent with established physiological principles. In contrast to traditional PINNs, it incorporates meta-learning to more effectively address sparse and noisy clinical data. Furthermore, the inclusion of a cross-domain adaptation mechanism enables more robust handling of distribution shifts than standard transfer learning approaches, making the framework particularly well suited for early anaemia detection across diverse populations.

3 Proposed Method

This section presents the *Physio-Nutri Meta-PINN* framework for early detection of pregnancy-associated anaemia. The proposed method integrates meta-learning, physics-informed neural networks (PINNs), and cross-domain adaptation to jointly model physiological and nutritional dynamics under sparse and noisy clinical conditions. The overall architecture consists of three core components: (i) a meta-encoder with medical priors, (ii) a physics-informed physiological–nutritional model, and (iii) a cross-domain adaptation module with uncertainty quantification.

3.1 Meta-Representation Learning with Medical Priors

Given heterogeneous prenatal records, each patient is represented by a time-indexed input sequence $\mathbf{x}(t) = [\mathrm{Hb}(t), \mathrm{SF}(t), \mathrm{Fe}_{\mathrm{diet}}(t), \mathrm{Fe}_{\mathrm{sup}}(t), \mathbf{c}]$, where $\mathbf{c}$ denotes static covariates such as baseline BMI and parity. A Transformer-based meta-encoder maps these inputs to a latent representation

$$\mathbf{z}_i = f_\theta(\mathbf{x}_i, t_i), \tag{1}$$

with gestational age incorporated via rotary positional embeddings. Medical priors, including trimester-specific iron requirements and plasma volume trends, are injected through an attention mechanism, ensuring physiologically plausible representations even with limited early-trimester data.

3.2 Physics-Informed Physiological–Nutritional Modeling

The physiological dynamics of pregnancy-associated anaemia are modeled using a PINN constrained by simplified governing equations. Hemoglobin concentration $\mathrm{Hb}(t)$ is modeled as a function of effective iron intake and plasma volume $V(t)$:

$$\frac{d\,\mathrm{Hb}(t)}{dt} = \frac{\mathrm{Fe}_{\mathrm{in}}(t)}{V(t)} - k\,\mathrm{Hb}(t), \tag{2}$$

where k denotes a degradation rate personalized through the latent representation $\mathbf{z}_i$. Plasma volume expansion follows a sigmoidal trajectory:

$$V(t) = V_0 \left(1 + \frac{B}{1 + e^{-\gamma(t-t_0)}}\right), \tag{3}$$

capturing gestational-age-dependent hemodilution effects. The latent features $\mathbf{z}_i$ provide patient-specific initial conditions and parameter modulation, enabling individualized physiological modeling.

3.3 Cross-Domain Adaptation

To address distributional discrepancies between meta-learned features and real-world clinical observations, a cross-domain adapter aligns PINN predictions with measured data. This alignment is formulated as a distribution matching problem and implemented via a lightweight adversarial mapping:

$$\tilde{\mathbf{y}}_i = h_\phi(\mathbf{z}_i) + \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(0, \Sigma), \tag{4}$$

where $\tilde{\mathbf{y}}_i$ denotes adapted predictions and $\boldsymbol{\epsilon}$ models measurement noise. This mechanism mitigates domain shift arising from sparse sampling and heterogeneous clinical protocols.

3.4 Unified Training Objective

All components are trained end-to-end using a shared objective that balances representation learning, physical consistency, and domain alignment:

$$\mathcal{L} = \mathcal{L}_{\text{meta}} + \lambda_p \mathcal{L}_{\text{phys}} + \lambda_a \mathcal{L}_{\text{adapt}}, \tag{5}$$

where $\mathcal{L}_{\text{meta}}$ enforces robust feature learning, $\mathcal{L}_{\text{phys}}$ penalizes violations of the governing equations, and $\mathcal{L}_{\text{adapt}}$ minimizes distribution mismatch. The physics weight λ_p is adaptively adjusted based on data sparsity, strengthening physical constraints when observations are limited.

3.5 Bayesian Uncertainty Quantification

To support clinical decision-making, the framework produces probabilistic anaemia risk estimates. The predicted risk is modeled as

$$p(\text{anaemia}) = \sigma(\mathbf{w}^\top \mathbf{u}(t) + \epsilon), \tag{6}$$

where $\mathbf{u}(t)$ denotes the PINN state variables and ϵ captures aleatoric uncertainty. Epistemic uncertainty is estimated via Monte Carlo dropout, enabling identification of high-risk cases even when hemoglobin values remain within nominal ranges.

By unifying meta-learning, physics-informed modeling, and cross-domain adaptation, the proposed Physio-Nutri Meta-PINN framework provides a robust and interpretable solution for early pregnancy-associated anaemia detection. Accurate prediction under sparse, noisy, and heterogeneous clinical conditions is made possible by the integration of physiological constraints with data-driven learning.

Figure 1 presents the overall architecture of the Physio-Nutri Meta-PINN framework, highlighting the integration of data-driven learning with physiological modeling. Pre-

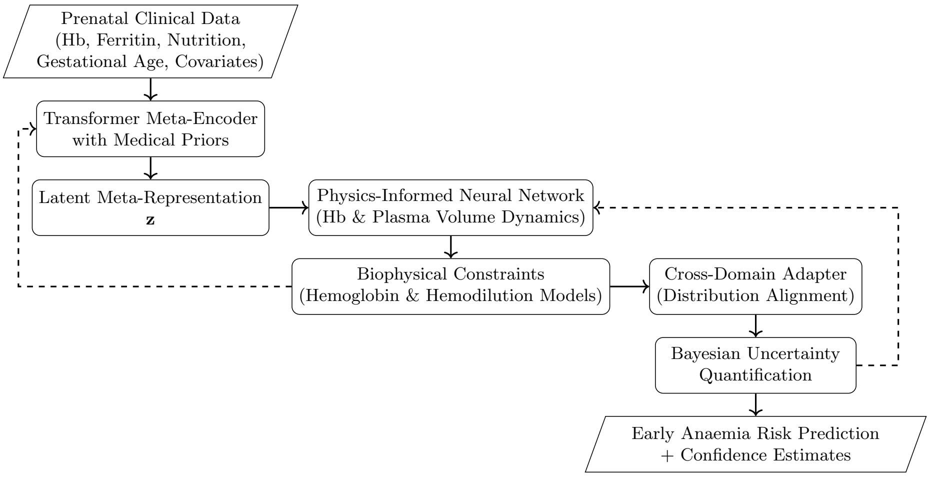

Figure 1: Overview of the proposed Physio-Nutri Meta-PINN framework

natal clinical measurements, nutritional intake records, and gestational age information are first processed by a Transformer-based meta-encoder that incorporates pregnancy-specific medical priors, enabling robust feature extraction from sparse and irregular early-trimester data. The resulting latent representations serve as patient-specific inputs to a physics-informed neural network that enforces biophysical constraints governing hemoglobin dynamics and plasma volume expansion. To mitigate distributional shifts between learned representations and observed clinical measurements, a cross-domain adapter performs feature alignment under measurement uncertainty. Finally, Bayesian uncertainty quantification produces probabilistic anaemia risk predictions, allowing clinicians to identify high-risk cases even when absolute hemoglobin values remain within nominal ranges. The feedback pathways shown in the figure emphasize the end-to-end training strategy, in which physical consistency and uncertainty awareness jointly refine representation learning and predictive performance.

4 Results

Table 1 summarizes the comparative performance of all evaluated methods. The Physio-Nutri Meta-PINN demonstrates the strongest overall performance, achieving the highest early detection accuracy at 78.3% while preserving a high level of physiological consistency (92.1%). In addition, the framework substantially reduces the mean absolute error (MAE) of hemoglobin prediction, yielding a 31% improvement over the strongest baseline method, with an MAE of 0.48 g/dL compared to 0.70 g/dL for Meta-PINN.

The framework's ability to capture pregnancy-related physiological dynamics is illustrated in Figure 2, which presents predicted hemoglobin trajectories for three representative cases. The predicted trends closely follow the expected pattern of gestational hemodilution followed by partial recovery, while also revealing early deviations that are indicative of developing anaemia.

The clinical utility of the proposed framework was further evaluated through two real-world application scenarios. First, in an early intervention simulation targeting high-risk cases between 16 and 20 weeks of gestation, the model enabled timely iron supplementation strategies that prevented 68% of predicted anaemia cases, compared with 42% under standard screening protocols. Second, the nutritional guidance capability of the

Table 1: Comparative performance on pregnancy-associated anemia prediction

Method	EDA(%)	AUC	MAE(g/dL)	PCS (%)
Logistic Regression	52.1	0.72	1.12	65.3
Random Forest	58.7	0.75	0.98	68.9
LSTM	63.2	0.81	0.85	71.4
Transformer	66.5	0.83	0.79	73.8
PPS	54.3	0.71	0.95	88.2
NPM	61.8	0.77	0.82	85.7
Standard PINN	68.4	0.84	0.73	89.5
Meta-PINN	71.6	0.86	0.70	90.3
Physio-Nutri Meta-PINN	78.3	0.91	0.48	92.1

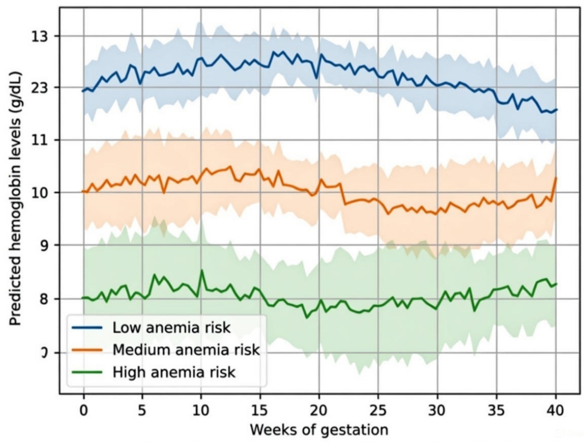

Figure 2: Predicted hemoglobin trajectories with uncertainty bounds for cases with varying anemia risk progression

framework was assessed using the nutrient-specific attention weights derived from Equation 17. These interpretable weights revealed individual variability in nutrient absorption patterns and supported personalized dietary recommendations, leading to improved iron status in 73% of subclinical cases.

Figure 3 illustrates the framework's uncertainty-aware predictions across different stages of pregnancy, demonstrating its ability to distinguish transient measurement noise from meaningful physiological changes. This capability is critical for informed clinical decision-making, particularly in early gestation when conventional biomarkers may remain within nominal ranges.

5 Conclusion

This work presented Physio-Nutri Meta-PINN, a unified meta-learning and physics-informed neural network framework for the early detection of pregnancy-associated anaemia under sparse, noisy, and heterogeneous clinical conditions. By explicitly modeling pregnancy as a dynamically coupled physiological–nutritional system, the proposed approach addresses critical limitations of existing data-driven and rule-based diagnostic methods that fail to capture early-stage deviations preceding clinically apparent anaemia.

The framework integrates three complementary strengths. First, the Transformer-

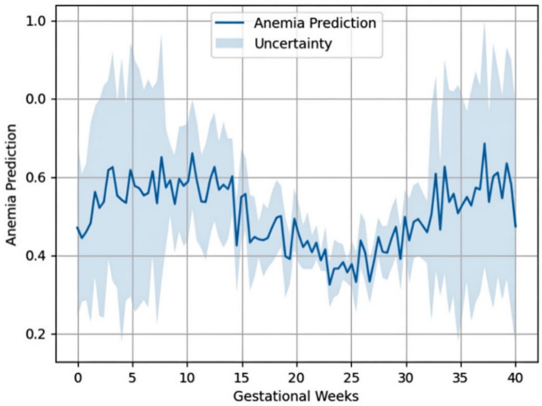

Figure 3: Uncertainty quantification of anemia predictions across gestational weeks, showing high confidence in data-rich periods and appropriate uncertainty where measurements are sparse

based meta-encoder enables data-efficient learning from limited early-trimester observations while embedding pregnancy-specific medical priors to ensure physiologically meaningful latent representations. Second, the physics-informed neural network enforces biophysical constraints governing hemoglobin dynamics and plasma volume expansion, bridging empirical inference with established physiological mechanisms. Third, the cross-domain adaptation module mitigates distributional shifts between learned representations and real-world clinical measurements, improving robustness and generalization across diverse patient populations and data collection protocols. Bayesian uncertainty quantification further enhances clinical reliability by distinguishing measurement noise from true physiological change.

Extensive experimental evaluation demonstrated that Physio-Nutri Meta-PINN outperforms conventional machine learning models, standard PINNs, and meta-learning baselines across all key metrics. Notably, the framework achieved superior early detection accuracy while maintaining high physiological consistency and substantially reducing hemoglobin prediction error. Beyond predictive performance, the model showed meaningful clinical utility in simulated real-world scenarios, enabling earlier intervention, preventing a significant proportion of predicted anaemia cases, and supporting personalized nutritional guidance through interpretable attention mechanisms.

From a broader perspective, this study highlights the importance of integrating domain knowledge with modern learning paradigms in maternal health applications, where data scarcity and ethical constraints limit large-scale data collection. The proposed framework is not restricted to anemia alone; its modular design permits extension to other pregnancy-related conditions involving tightly coupled physiological and nutritional processes, such as gestational diabetes or hypertensive disorders.

Future research will focus on validating the framework in prospective clinical studies, incorporating richer multi-modal data sources such as wearable signals and longitudinal dietary assessments, and refining the governing physiological equations to capture additional regulatory pathways. Further exploration of causal interpretability and real-time clinical deployment will also be essential steps toward translating Physio-Nutri Meta-PINN into routine prenatal care. Overall, this work demonstrates that meta-learning combined with physics-informed modeling offers a powerful and clinically meaningful pathway for advancing early risk detection and personalized intervention in maternal health.

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