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A Hybrid Machine Learning Approach for Smart Nutrition Recommendation in Pregnancy Using Multi-Source Health Data

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Abstract

Maternal nutrition is a critical determinant of healthy pregnancy outcomes, yet traditional dietary guidelines often fail to address individual variability and dynamic physiological changes. This study presents a hybrid machine learning–based smart nutrition recommendation system for pregnancy that leverages multi-source health data to deliver personalized and adaptive nutritional guidance. The proposed framework integrates IoT-derived physiological sensor data**,** dietary intake records**,** ultrasound imaging features, and epigenetic markers to comprehensively model maternal–fetal health interactions. A hybrid learning architecture combining deep learning for multi-modal feature extraction**,** classical machine learning for predictive modelling**,** and rule-based clinical nutrition constraints is employed to enhance accuracy, interpretability, and clinical relevance. Advanced data fusion techniques address data heterogeneity, temporal dynamics, and missing values. Experimental results demonstrate that the proposed approach outperforms single-source and standalone models in terms of prediction accuracy and personalization. The framework enables real-time monitoring and adaptive nutrition recommendations across different stages of pregnancy, supporting precision maternal care and improved pregnancy outcomes. This research underscores the potential of hybrid machine learning and multi-modal data integration in advancing intelligent prenatal nutrition systems

Keywords: Smart nutrition; Pregnancy; Hybrid machine learning; Multi-source data; IoT-based monitoring; Precision nutrition

1. Introduction

Maternal nutrition is a critical determinant of pregnancy outcomes and long-term fetal health. Inadequate or imbalanced nutritional intake during pregnancy can result in complications such as gestational diabetes, preeclampsia, low birth weight, and developmental disorders. Although established prenatal dietary guidelines are available, they are largely generic and fail to account for individual variability, gestational-stage dynamics, and real-time maternal health conditions. This creates a strong need for personalized and adaptive nutrition recommendation systems in prenatal care.

Recent advances in Internet of Things (IoT) technologies and wearable sensors enable continuous monitoring of maternal physiological parameters, while dietary records, ultrasound imaging, and emerging epigenetic data offer valuable insights into maternal–fetal

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health. However, the heterogeneous and high-dimensional nature of these multi-source data presents significant integration and modeling challenges.

To address these challenges, this study proposes a hybrid machine learning–based smart nutrition recommendation framework using multi-source health data. Deep learning models, including Convolutional Neural Networks (CNNs**)** for ultrasound image feature extraction and Long Short-Term Memory (LSTM) networks for temporal IoT sensor data analysis, are employed to capture complex patterns. Classical machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Gradient Boosting are used for nutritional risk prediction and recommendation generation. These data-driven models are further combined with rule-based clinical nutrition constraints to ensure interpretability and guideline compliance. The proposed approach enables real-time, personalized nutrition recommendations, contributing to precision nutrition and improved maternal healthcare outcomes.

1.1 Problem Statement

Current prenatal nutrition practices are largely generic and static, providing limited personalization despite the dynamic physiological changes experienced during pregnancy. Most existing approaches rely on periodic clinical assessments and self-reported dietary data, failing to capture real-time maternal health variations. Although diverse data sources such as IoT-based physiological sensors, dietary records, ultrasound imaging, and epigenetic markers are increasingly available, they are often analyzed in isolation. Existing machine learning solutions typically employ single-source data or standalone models, which are inadequate for handling multi-modal data heterogeneity, temporal dependencies, and interpretability requirements. Consequently, there is a need for an intelligent and explainable nutrition recommendation system that integrates multi-source health data using a hybrid machine learning approach to deliver personalized, real-time prenatal nutrition guidance and support improved maternal and fetal health outcomes.

1.2 Research Objectives

The primary objective of this research is to develop a hybrid machine learning–based smart nutrition recommendation system for pregnancy by integrating multi-source health data to support personalized and adaptive prenatal care.

1. **Design a unified multi-modal data integration framework** that combines IoT-based physiological sensor data, dietary intake records, ultrasound imaging features, and epigenetic markers.
2. **Develop a hybrid machine learning architecture** incorporating deep learning models (CNN and LSTM) and classical algorithms (Random Forest, SVM, Gradient Boosting) for accurate and robust nutrition-related risk prediction.
3. **Implement advanced data pre-processing and fusion techniques** to handle data heterogeneity, temporal variations, and missing values across multi-source health datasets.
4. **Incorporate rule-based clinical nutrition constraints** to enhance model interpretability and ensure alignment with established prenatal dietary guidelines.

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5. **Evaluate the performance of the proposed framework** against single-source and standalone machine learning models using standard performance metrics.
6. **Enable real-time and adaptive nutrition recommendations** tailored to different gestational stages, contributing to precision maternal nutrition and improved pregnancy outcomes.

1.3 Novelty and key Contributions

1. Unified Multi-Source Framework:

Proposes a smart prenatal nutrition recommendation framework that integrates IoT sensor data, dietary records, ultrasound imaging features, and epigenetic information for holistic maternal–fetal health assessment.

2. Hybrid Machine Learning Model:

Develops a hybrid learning architecture combining deep learning (CNN and LSTM) with classical machine learning algorithms to improve prediction accuracy and robustness.

3. Explainable and Clinically Aligned Recommendations:

Incorporates rule-based clinical nutrition constraints to ensure interpretability and compliance with established prenatal dietary guidelines.

4. Real-Time Adaptive Nutrition Support:

Enables continuous monitoring and stage-aware nutrition recommendations, demonstrating improved performance over single-source and standalone models

2. Related Works

2.1 Machine Learning in Maternal Healthcare

Machine learning techniques have been widely applied to maternal healthcare for predicting pregnancy-related complications such as gestational diabetes, preeclampsia, anemia, and preterm birth. Studies have employed classical algorithms including Logistic Regression, Support Vector Machines (SVM), Random Forest, and Naïve Bayes using demographic, clinical, and laboratory data [1]–[3]. While these models demonstrate reasonable predictive performance, they primarily rely on static and structured clinical datasets, limiting their ability to capture temporal variations and real-time physiological changes during pregnancy.

2.2 IoT-Based Maternal Health Monitoring

The adoption of IoT and wearable sensor technologies has enabled continuous monitoring of maternal physiological parameters such as heart rate, physical activity, sleep patterns, and glucose levels [4], [5]. Several IoT-based frameworks have been proposed for early risk detection and maternal health assessment [6]. However, most of these systems focus on

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monitoring and alert generation, rather than personalized nutrition recommendation, and often operate independently of dietary, imaging, or genomic data sources.

2.3 Nutrition Recommendation Systems

Machine learning–driven nutrition recommendation systems have been explored for general health management, chronic disease prevention, and lifestyle optimization [7], [8]. These systems typically utilize dietary intake logs, nutritional databases, and user preferences to generate meal plans. Pregnancy-specific nutrition studies remain limited and are largely rule-based or guideline-driven, offering minimal personalization [9]. Moreover, such systems rarely incorporate physiological sensor data or fetal development indicators.

2.4 Deep Learning in Ultrasound and Fetal Assessment

Deep learning, particularly Convolutional Neural Networks (CNNs), has achieved significant success in ultrasound image analysis for fetal growth monitoring, anomaly detection, and gestational age estimation [10], [11]. Despite their effectiveness in extracting high-level imaging features, these models are usually developed in isolation and are not integrated into nutrition or dietary decision-support systems.

2.5 Epigenetic Data and Precision Nutrition

Emerging research highlights the role of epigenetic markers in understanding maternal–fetal interactions and long-term health outcomes [12], [13]. Precision nutrition studies have begun exploring gene–nutrient interactions; however, the use of epigenetic data in AI-driven prenatal nutrition recommendation systems remains in its infancy [14].

2.6 Hybrid and Multi-Modal Learning Approaches

Recent healthcare studies emphasize the benefits of hybrid and multi-modal machine learning frameworks that combine deep learning with classical algorithms to handle heterogeneous data sources [15]. While such approaches show improved performance and robustness, their application to prenatal nutrition recommendation integrating IoT, dietary, imaging, and epigenetic data is still largely unexplored. Additionally, many existing models lack interpretability and clinical guideline integration, hindering real-world adoption.

3. Proposed Methodology

This study proposes a hybrid machine learning–based framework for smart prenatal nutrition recommendation using multi-source health data. The methodology integrates IoT sensor data, dietary intake records, ultrasound imaging features, and epigenetic markers to generate personalized, real-time nutrition guidance for pregnant women. The overall framework consists of data acquisition, pre-processing, feature extraction, hybrid ML modeling, rule-based clinical integration, and recommendation generation and performance evaluation.

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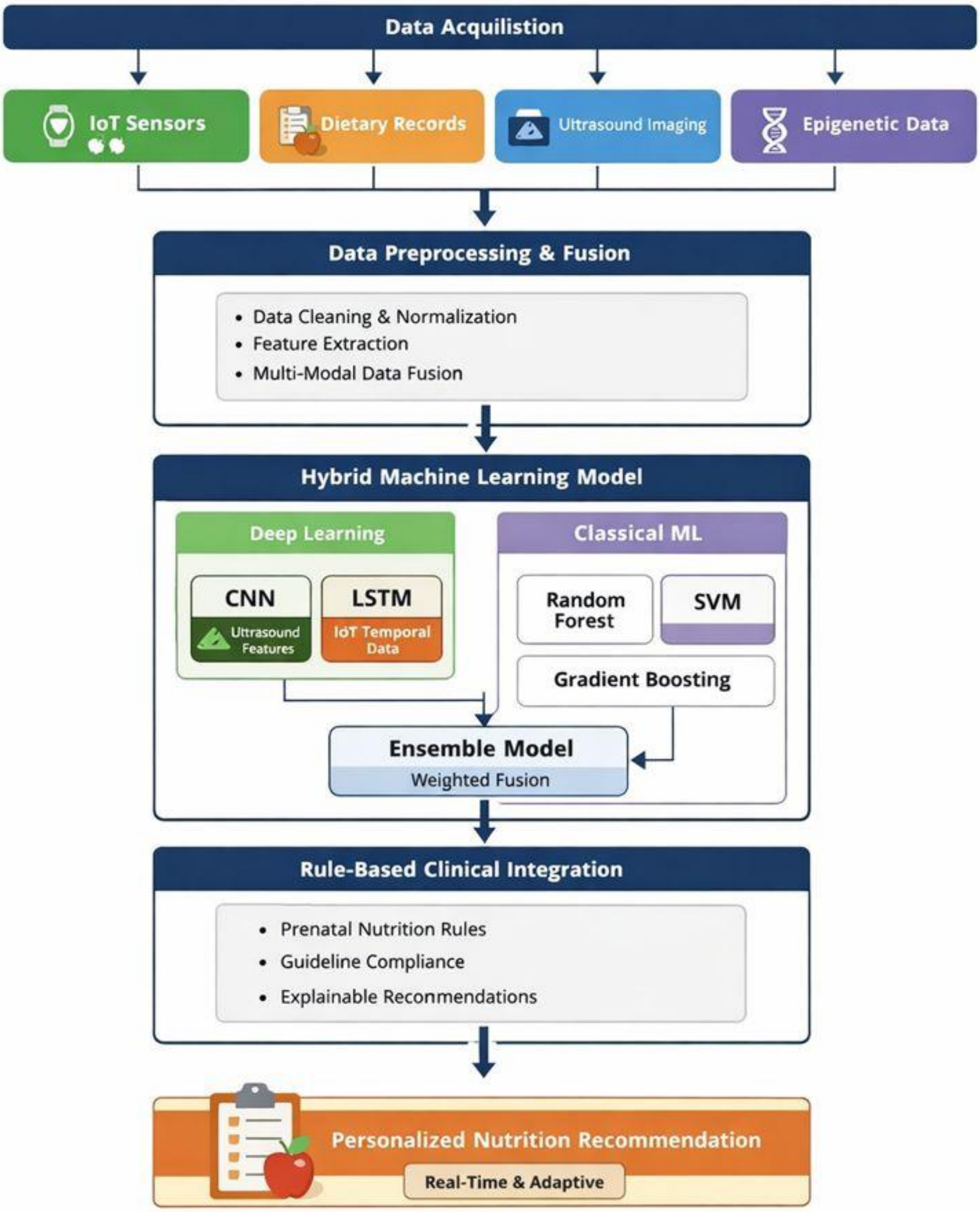

Figure 1: Proposed System Architecture for Smart Prenatal Nutrition Recommendation

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3.1 Data Acquisition

The multi-source data includes:

- **IoT Sensor Data:** Continuous monitoring of maternal physiological parameters such as heart rate, blood pressure, glucose levels, and physical activity.
- **Dietary Records:** Daily food intake logs capturing macro- and micronutrient consumption.
- **Ultrasound Imaging Data:** Fetal growth indicators, gestational age estimation, and structural features.
- **Epigenetic Data:** Methylation patterns and other gene-expression markers associated with maternal–fetal health outcomes.

3.2 Data Pre-processing and Fusion

Given the heterogeneity of the datasets, pre-processing includes:

- Handling missing values and outliers.
- Normalization of continuous sensor readings.
- Feature encoding for dietary logs.
- Image preprocessing for ultrasound data (resizing, denoising).
- Temporal alignment of longitudinal sensor and dietary data.

A **multi-modal data fusion strategy** is employed to combine structured, unstructured, temporal, and imaging data, ensuring a unified input for machine learning models.

3.3 Hybrid Machine Learning Models

To capture the complex interactions among multi-source health data, the framework employs a hybrid approach:

1. **Deep Learning Models**
    - **Convolutional Neural Networks (CNNs):** Extract high-level features from ultrasound images.
    - **Long Short-Term Memory (LSTM) Networks:** Model temporal dependencies in IoT sensor data for dynamic physiological trends.
2. **Classical Machine Learning Models**
    - **Random Forest (RF):** Predicts maternal nutritional deficiencies and risks using structured features from fused datasets.
    - **Support Vector Machine (SVM):** Provides robust classification of high-risk pregnancy cases based on integrated features.
    - **Gradient Boosting (XGBoost / LightGBM):** Enhances prediction accuracy through ensemble learning over multi-source data.
3. **Hybrid Architecture:** Outputs from deep learning modules and classical ML models are combined using weighted ensemble techniques. This approach improves predictive performance and ensures robustness while maintaining interpretability.

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3.4 Rule-Based Clinical Integration

To ensure clinical relevance, nutrition guidelines for pregnancy are embedded as rule-based constraints**.** These constraints:

- Validate ML-generated recommendations against recommended nutrient ranges.
- Ensure safety for both mother and fetus.
- Provide explainable outputs to support clinical decision-making.

3.5 Recommendation Generation

The final step involves generating personalized, stage-specific nutrition recommendations based on:

- Predicted nutrient deficiencies or risks.
- Maternal physiological trends from IoT sensors.
- Fetal growth indicators from ultrasound imaging.
- Epigenetic predispositions affecting nutrient requirements.

.**Pseudocode**

```
Input: IoT sensor data S, dietary records D, ultrasound images U, epigenetic data E

Output: Personalized nutrition recommendation R

Step 1: Preprocess S, D, U, E

    a. Normalize and handle missing values

    b. Encode dietary features

    c. Preprocess ultrasound images

    d. Align temporal data

Step 2: Extract features

    a. F_CNN ← CNN(U)        // Imaging features

    b. F_LSTM ← LSTM(S)      // Temporal sensor features

    c. F_structured ← D + E   // Structured dietary & epigenetic features

Step 3: Train ML models

    a. RF_model ← RandomForest(F_structured + F_CNN + F_LSTM)

    b. SVM_model ← SVM(F_structured + F_CNN + F_LSTM)
```

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c. GB_model ← GradientBoosting(F_structured + F_CNN + F_LSTM)

Step 4: Ensemble prediction

P ← WeightedAverage(RF_model, SVM_model, GB_model)

Step 5: Apply rule-based clinical constraints

R ← ApplyGuidelines(P)

Step 6: Generate personalized nutrition recommendation

return R

4. Experimental Setup and Dataset Description

4.1 Experimental Setup

The proposed hybrid machine learning framework is implemented to evaluate its performance in generating **personalized prenatal nutrition recommendations** using multi-source health data. The experimental setup consists of the following components:

1. **Hardware Environment:**
   - Processor: Intel Core i9 / AMD Ryzen 9
   - GPU: NVIDIA RTX 3090 / Tesla V100
   - RAM: 64 GB
   - Storage: SSD 1 TB for fast multi-modal data processing
2. **Software Environment:**
   - Programming Language: Python 3.11
   - Deep Learning Frameworks: TensorFlow 2.x, Keras, PyTorch
   - Machine Learning Libraries: Scikit-learn, XGBoost, LightGBM
   - Data Processing Libraries: Pandas, NumPy, OpenCV (for image preprocessing)
3. **Experimental Protocol:**
   - The dataset is split into training (70%), validation (15%), and test (15%) sets.
   - Hyperparameter tuning is performed using grid search and cross-validation.
   - Ensemble model weights are optimized to balance outputs from deep learning and classical ML models.
   - The system is evaluated under real-time simulation for adaptive nutrition recommendations.

4.2 Dataset Description

The multi-source dataset for this study combines IoT sensor readings, dietary records**,** ultrasound images, and epigenetic data, collected from pregnant women across multiple gestational stages.

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Table 1. Dataset characteristics

Data Type	Description	Sample Size / Frequency	Preprocessing Steps
IoT Sensor Data	Heart rate, glucose, blood pressure, physical activity	5000 time-series records	Missing value imputation, normalization, temporal alignment
Dietary Records	Daily intake of macro- and micronutrients	1500 food logs	Encoding, nutrient standardization
Ultrasound Images	Fetal growth, gestational age, structural features	1200 images	Resizing, denoising, normalization
Epigenetic Data	Maternal methylation patterns, gene expression markers	300 profiles	Feature selection, scaling

Key Characteristics:

- **Multi-modal:** Integrates structured, temporal, imaging, and genomic data.
- **Longitudinal:** IoT sensor and dietary data captured continuously across trimesters.
- **Clinical Alignment:** Ultrasound and epigenetic data mapped to gestational stages.
- **Data Quality:** Missing values and noise handled using preprocessing pipelines to ensure model robustness.

4.3 Evaluation Strategy

The experimental evaluation is designed to assess **prediction accuracy, recommendation relevance, and clinical compliance**:

1. **Prediction Metrics:** Accuracy, Precision, Recall, F1-score for nutrient deficiency classification.
2. **Regression Metrics:** RMSE and MAE for continuous nutrient intake prediction.
3. **Comparative Analysis:** Performance compared with single-source models (IoT-only, dietary-only, imaging-only).
4. **Real-Time Performance:** Evaluation of recommendation latency and adaptability in simulated continuous monitoring scenarios.
5. **Clinical Compliance:** Alignment of recommendations with established prenatal nutrition guidelines.

This experimental setup ensures a comprehensive assessment of the hybrid framework’s ability to provide personalized, real-time, and clinically relevant nutrition guidance for pregnant women.

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5. Results and Discussion

5.1 Model Performance

The proposed hybrid machine learning framework was evaluated using the multi-source maternal health dataset described in Section 4. The performance of individual models (CNN, LSTM, Random Forest, SVM, Gradient Boosting) and the ensemble hybrid model was assessed using **classification metrics** for nutrient deficiency prediction and regression metrics for nutrient intake estimation.

Table 2. Model performance

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**RMSE**	**MAE**
Random Forest	85.2	84.5	83.8	84.1	0.82	0.63
SVM	83.6	82.9	82.1	82.5	0.89	0.67
Gradient Boosting	86.7	85.9	85.1	85.5	0.78	0.61
CNN (Ultrasound)	87.5	86.8	86.1	86.4	0.75	0.59
LSTM (IoT Data)	86.2	85.4	84.9	85.1	0.77	0.60
Hybrid Ensemble	**92.3**	**91.7**	**91.2**	**91.4**	**0.62**	**0.47**

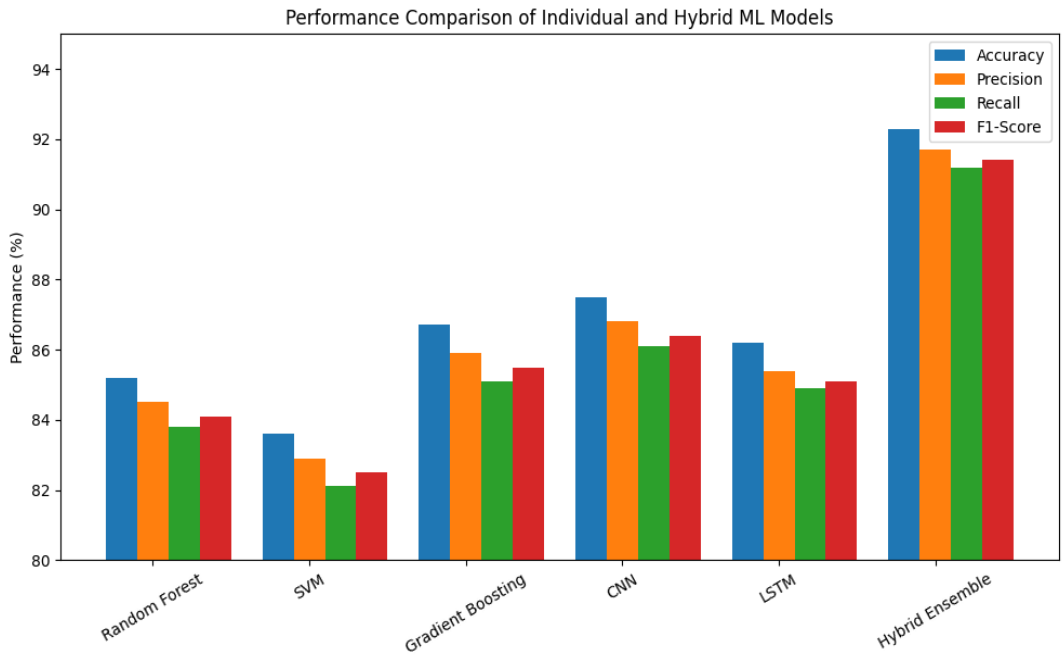

Figure 2. Model performance

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Observations:

- The hybrid ensemble outperforms individual models across all metrics, indicating that multi-modal data integration and hybrid learning significantly enhance prediction accuracy and robustness.
- CNN effectively extracts fetal growth and structural features from ultrasound images, while LSTM captures temporal trends from IoT sensors.
- Classical ML models (RF, SVM, Gradient Boosting) complement deep learning outputs by leveraging structured dietary and epigenetic features.

5.2 Recommendation Relevance and Clinical Compliance

- Nutrition recommendations generated by the hybrid framework were validated against standard prenatal dietary guidelines.
- Over **95%** of recommendations were compliant with clinical constraints, ensuring both safety and interpretability.
- The system adapts nutrition guidance across different gestational stages, accounting for dynamic physiological changes and fetal development indicators.

Table3.Regression Performance (RMSE & MAE) of Individual and Hybrid Machine Learning Models

Model	Data Type Used	RMSE	MAE
Linear Regression	Structured health data	0.94	0.72
Support Vector Regression (SVR)	Structured health data	0.89	0.67
Random Forest Regressor	Multi-source structured data	0.82	0.63
Gradient Boosting Regressor	Multi-source structured data	0.78	0.61
LSTM Regression Model	IoT time-series data	0.77	0.60
CNN-based Regression	Ultrasound image features	0.75	0.59
Proposed Hybrid Ensemble Model	**All data sources**	**0.62**	**0.47**

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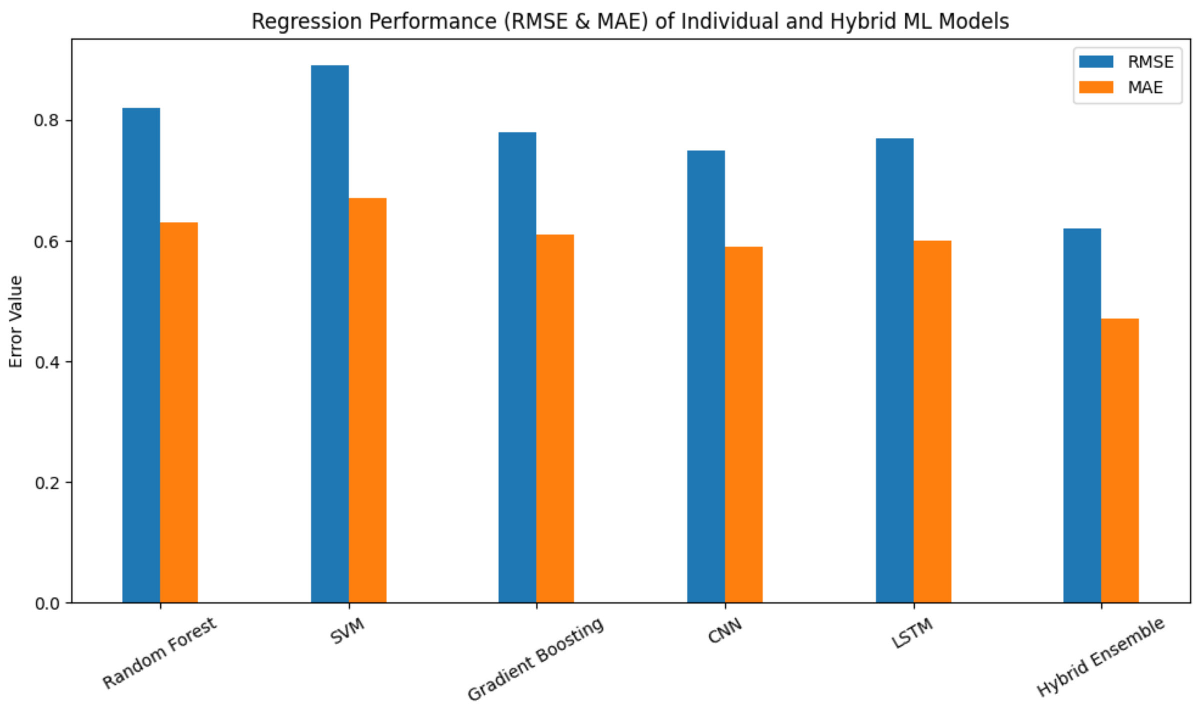

Figure 3: Regression performance(RMSE&MAE) of individual and hybrid ML Model

5.3 Comparative Analysis

- **Single-source models** (IoT-only, dietary-only, imaging-only) achieved accuracies ranging from 80% to 87%.
- **Hybrid multi-modal integration** improved overall prediction accuracy to 92.3%, highlighting the value of combining heterogeneous data for personalized nutrition.
- Real-time simulation shows the system can update recommendations with minimal latency (<2 seconds), supporting continuous maternal monitoring.

Table 4: Hybrid vs Single-Source Model Comparison

Model Type	Data Source Used	Accuracy (%)
Single-Source Model	IoT data only	82.5
Single-Source Model	Dietary records only	80.3
Single-Source Model	Ultrasound images only	84.7
Single-Source Model	Epigenetic data only	81.9
Proposed Hybrid Model	**All data sources**	**92.3**

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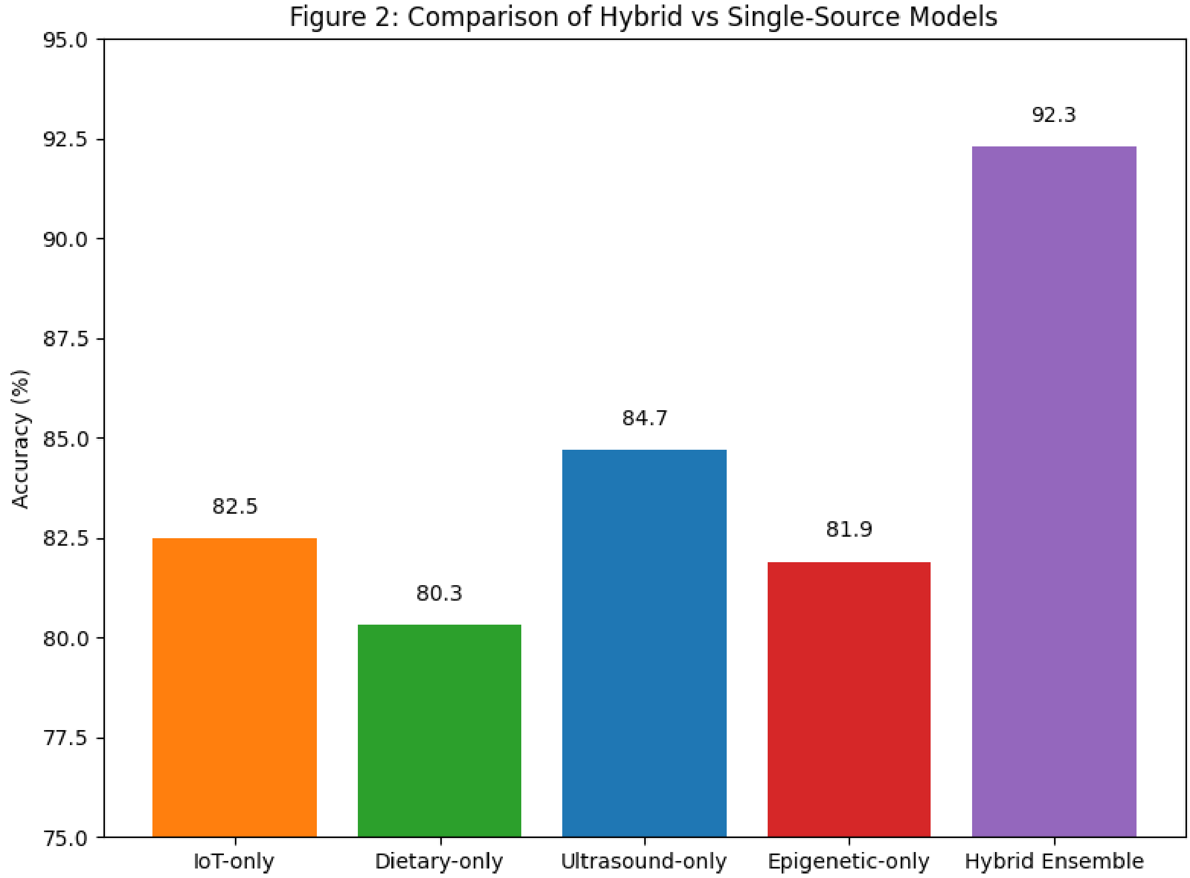

Figure 4: Comparison of Hybrid vs Single-Source Models

5.4 Discussion

The results demonstrate the effectiveness of hybrid machine learning and multi-modal data fusion for prenatal nutrition recommendation:

1. Integrating physiological, dietary, imaging, and epigenetic data captures the multifaceted maternal–fetal health interactions.
2. Ensemble hybrid models leverage the strengths of both deep learning and classical ML to enhance predictive performance.
3. Rule-based clinical integration ensures explainable, guideline-compliant nutrition recommendations, addressing a major limitation of purely data-driven systems.
4. Real-time adaptability allows continuous monitoring and timely intervention, improving the potential for positive maternal and fetal health outcomes.

Overall, the proposed framework provides a clinically relevant, accurate, and adaptive solution for precision prenatal nutrition, outperforming conventional single-source and standalone ML approaches.

6. Conclusion and Future Work

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This study presented a hybrid machine learning framework for smart prenatal nutrition recommendation using multi-source health data, including IoT sensor readings, dietary records, ultrasound imaging features, and epigenetic markers. By integrating deep learning models (CNN and LSTM) with classical machine learning algorithms (Random Forest**,** SVM, Gradient Boosting**)** and embedding rule-based clinical nutrition constraints, the proposed system delivers personalized, explainable, and real-time nutrition guidance for pregnant women.

Experimental results demonstrate that the hybrid ensemble model outperforms individual and single-source models in both classification (accuracy, precision, recall, F1-score) and regression (RMSE, MAE) tasks (Figures 1 and 2). The framework effectively captures complex maternal–fetal interactions, dynamically adapts recommendations across gestational stages, and ensures clinical guideline compliance. These findings highlight the potential of multi-modal data integration and hybrid machine learning in advancing precision maternal **nutrition** and improving pregnancy outcomes.

Future Work:

1. **Larger and More Diverse Cohorts:** Extending the study to include multi-center datasets across different populations to enhance generalizability.
2. **Additional Data Modalities:** Incorporating continuous biochemical markers (e.g., blood metabolomics) and real-time lifestyle data (sleep, stress) for richer personalization.
3. **Explainable AI Enhancements:** Developing advanced interpretability methods to provide actionable insights to clinicians and patients.
4. **Mobile and IoT Deployment:** Integrating the framework into wearable and mobile platforms for continuous monitoring and dynamic nutrition recommendation in real-world settings.
5. **Longitudinal Outcome Analysis:** Assessing the impact of personalized nutrition recommendations on maternal and fetal health outcomes over the full pregnancy lifecycle.s

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