

A Multimodal Deep Learning Framework for Predicting the Malnutrition Risks

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Abstract—Malnutrition remains a major public health concern, particularly for children under five, for whom effective treatment depends on early detection. The complex relationships between dietary, environmental, and socioeconomic factors are often difficult to capture by conventional assessment methods, which rely on anthropometric measurements and manual evaluation. We offer a novel multimodal deep learning framework that combines Knowledge Graphs (KG), Graph Neural Networks (GNN), and Long Short-Term Memory (LSTM) networks to overcome these limitations and provide understandable insights while accurately predicting the risk of malnutrition. The LSTM component simulates children’s temporal growth patterns by capturing trends in nutritional and anthropometric data. The KG component, which encodes domain knowledge from medical literature and dietary recommendations, enables reasoning over risk factors. By simulating the relationships between children, households, and communities, the GNN captures social and environmental dependencies. To create a comprehensive risk assessment, an attention-based mechanism integrates these modalities. The suggested method outperforms baseline models (LSTM-only, GNN-only, and KG-only) in accuracy, precision, recall, and F1-score, according to experiments conducted on public and simulated datasets. It also produces interpretable predictions that can help medical professionals make proactive decisions. This study provides a scalable and explicable solution for public health applications by demonstrating the potential of integrating temporal, relational, and knowledge-based modelling for efficient malnutrition risk prediction.

Index Terms—Malnutrition prediction, Deep Learning, LSTM, Knowledge Graphs, Graph Neural Networks, Explainable AI, Public Health.

I. INTRODUCTION

One of the world’s most serious public health issues is child malnutrition, particularly in low- and middle-income countries (LMICs), where access to appropriate nutrition, clean water, and high-quality healthcare is scarce [1]. The World Health Organization (WHO) reports that 149 million children worldwide are stunted and over 45 million children under five

Identify applicable funding agency here. If none, delete this suffer from wasting [2]. Early childhood malnutrition has long-lasting effects on physical growth, cognitive development, and economic production as well as a markedly increased risk of morbidity and mortality [3]. Malnutrition also has detrimental effects on later-life labor market results, mental health, and educational attainment. The necessity for creative and scalable methods of early identification and prevention is highlighted by the continued high rates of child malnutrition in spite of international interventions [4].

Despite being widely utilized, traditional anthropometric-based screening techniques are frequently cross-sectional, labor-intensive, and ineffective at predicting future risks of malnutrition. By capturing intricate interactions between food intake, socioeconomic characteristics, and health problems, machine learning (ML) and deep learning models have demonstrated potential for improving malnutrition risk prediction [5]. Specifically, sequential growth data, such as weight, height, and mid-upper arm circumference, can be analyzed using temporal models like Long Short-Term Memory (LSTM) networks to identify early indicators of growth faltering across time [6]. Compared to

traditional static models, LSTMs offer more precise and timely forecasts by utilizing past growth trajectories [7].

Predictive models can be further improved by structured domain knowledge in nutrition and health. Relationships between nutrients, diseases, environmental circumstances, and socioeconomic factors can be systematically encoded using Knowledge Graphs (KGs) [8]. KGs improve interpretability and robustness in the context of malnutrition prediction by enabling models to reason about known causal and association links, such as nutrient shortages associated with stunting or wasting [9]. Combining expert knowledge with data-driven learning is made possible by integrating KG embeddings into deep learning models, which is essential for evidence-based public health decision-making [10]. Children's nutritional status is impacted by relational factors such as household composition, community resources, and environmental conditions, which go beyond individual-level and knowledge-based modelling [11]. By portraying children, families, and communities as nodes in a graph with links that describe their interactions, Graph Neural Networks (GNNs) are an excellent tool for capturing these dependencies [12]. A more comprehensive prediction method is made possible by integrating GNNs into malnutrition prediction frameworks. This allows for the learning of patterns from both direct and indirect relationship impacts, such as the nutritional status of siblings, parental education, and access to health care [13].

In this work, we propose a multimodal deep learning framework that integrates LSTM, Knowledge Graphs and Graph Neural Networks to predict child malnutrition risk. LSTMs capture temporal growth trends, KGs embed expert nutritional knowledge, and GNNs model relational and socio-environmental dependencies. The framework also incorporates interpretability mechanisms, including sub-graph explanations and knowledge-path reasoning, to ensure actionable insights for health workers and policymakers. Through rigorous experiments on real-world datasets, our approach demonstrates superior predictive performance compared to baseline models, providing a scalable and explainable AI solution to combat child malnutrition.

II. LITERATURE SURVEY

Recent years have seen a rise in interest in the prediction of malnutrition, especially with the development of deep learning models that can capture the temporal trajectories of child growth. For example, using longitudinal cohort data from the Young Lives research, Zewotir and colleagues created an LSTM-Fully Connected (LSTM-FC) neural network to categories and forecast Ethiopian children's nutritional status. The efficacy of LSTM for modelling growth dynamics over time was proved by their model, which showed over 93% accuracy in predicting transitions between normal, stunted, and wasted states [1]. The resilience of the LSTM-FC architecture in managing missing data and detecting important anthropo-metric traits utilizing SHAP for interpretability was further confirmed in a related work by the same authors [2].

Knowledge Graphs (KGs) have been utilized to encode structured nutritional knowledge beyond time-series modelling, enabling reasoning about intricate linkages in health and food. One noteworthy example is the KG4NH project, which builds a large-scale KG from the literature that illustrates the connections between nutrients, illnesses, and metabolic processes and facilitates question-answering over nutrition-domain questions [3]. GENA, which focusses on nutrition-mental health correlations by extracting relationships between foods, biological chemicals, and mental diseases from biomedical text, is another pertinent KG. With over 43,000 edges, GENA facilitates interpretable discoveries in mental-nutrition research [4]. Additionally, Food4HealthKG incorporates food, gut microbiota, and mental health data into a KG to facilitate meal recommendations and the investigation of microbiome-mediated health effects [5].

Concurrently, graph neural networks (GNNs) have become effective models to manage population-level and relationship dependencies in healthcare. GNNs outperform classic ML techniques by capturing relational structure among clinical events and entities, according to a thorough assessment of GNNs for clinical risk prediction on Electronic Health Records (EHRs) [6]. Models like GAT (Graph Attention Network) are widely employed. For instance, a GNN-based model for predicting hospital-acquired

infection (HAI) risk creates a patient graph based on clinical history similarity and outperforms non-graph baselines in prediction performance (AUROC ~0.86) [7]. Similarly, in the field of genomics, multi-omics data (such as gene expression and pathways) were integrated for tumour risk prediction using a previous knowledge-guided multilevel GNN, which also offered interpretability [8].

In more recent times, clinical risk prediction has showed potential when temporal modelling and knowledge-augmented graph learning are combined. The KAT-GNN model (Knowledge-Augmented Temporal Graph Neural Net-work) performs well on risk prediction tasks like coronary artery disease and in-hospital mortality by integrating temporal EHR data with ontology-based edges (such as those from SNOMED CT) in patient graphs [9]. Another example is a self-explainable GNN for Alzheimer's disease risk, where the model generates interpretable relation-importance ratings from medical claim data in addition to predicting risk [10].

For example, Ma et al. proposed a nutrition-related KG neural network using a Graph Convolutional Network (GCN) over a heterogeneous nutrition graph (recipes, nutrients, users) and demonstrated improved food recommendation performance by integrating nutritional content with user dietary preferences [11]. This shows the potential of graph-based deep learning to reason over nutrition-aware graphs, which can be adapted for risk-prediction tasks like malnutrition, even though there is limited work in the nutritional knowledge domain.

III. RESEARCH METHODOLOGY

In order to forecast and explain the hazards of childhood malnutrition, this study presents a multimodal deep-learning model that combines Long Short-Term Memory (LSTM) networks, Knowledge Graphs (KG), and Graph Neural Networks (GNN). The approach integrates neighborhood-based relational learning, semantic domain expertise, and temporal health data into a single predictive pipeline. Data preprocessing, KG creation, temporal modelling, graph-based reasoning, multimodal fusion, classification, and assessment are among the most significant phases.

A. Data Preprocessing and Feature Engineering
Anthropometric indicators (weight, height, and MUAC), demographic variables, nutritional factors, maternal characteristics, household socioeconomic indicators, and environmental/contextual factors are among the longitudinal health records of children included in the collection. The first step in data preprocessing is to handle missing values using mode replacement for categorical characteristics and basic statistical imputation for numerical features. Z-scores are used to identify anthropometric outliers, particularly weight-for-age or height-for-age abnormalities. To guarantee model reliability, these variables that are beyond the typical range of human growth are either eliminated or adjusted. In order to improve training stability, continuous features go through min-max normalization to put them on a consistent scale. For LSTM-based modeling, temporal alignment is carried out to guarantee uniformity in the sequence length of health observations for every child.

B. Knowledge Graph Construction

By accurately connecting biological, environmental, social, and dietary elements, the Knowledge Graph (KG) serves as an external reasoning layer. Nodes such as child, mother, household, sanitation, diet diversity, vaccination status, and village-level characteristics are all represented within the KG. Relationships including `has_risk_factor`, `influenced_by`, `resides_in`, and `affects_growth` are modelled as edges connecting these entities. To enable machine comprehension of these associations, entities and relations are converted into dense vector representations using knowledge graph embedding techniques. A simple and widely used embedding model is TransE, which represents relationships using the following fundamental principle:

$$h + r \approx t, (1)$$

where h denotes the head entity, r the relation, and t the tail entity. This formulation enables the embedding space to preserve relational meaning by positioning the tail entity close to the translated head entity. Such embeddings produce enriched semantic representations that capture how social, environmental, and behavioral factors collectively influence child health outcomes.

C. Temporal Feature Learning Using LSTM

Temporal changes in children’s growth patterns are modeled by the LSTM network. Weight increase, weight stagnation, and departures from typical growth curves are examples of trends that the LSTM records since nutrition-related characteristics are dynamic. Temporal changes in children’s growth patterns are modeled by the LSTM network. Weight increase, weight stagnation, and departures from typical growth curves are examples of trends that the LSTM records since nutrition-related characteristics are dynamic. The essential LSTM up-date equations are:

$$C_t = f_t \odot C_{t-1} + i_t \odot C^t \quad (2)$$

$$h_t = o_t \odot \tanh(C_t) \quad (3)$$

These help in the model’s learning of long-term dependencies, such as persistent malnutrition or recurrent infections.

D. Graph Neural Network for Relational Reasoning

A Graph Neural Network (GNN) analyzes the graph structure after the KG embeddings are produced in order to determine how biological and socioeconomic factors interact to affect the risk of malnutrition. By spreading information among linked nodes, GNNs enable the model to recognize patterns such as:

- Children from the same village are at equal risk for poor water quality.
- Similar dietary vulnerabilities are present in households with comparable incomes.
- Multiple health parameters are influenced by maternal education.

The neighborhood aggregation procedure used by the GNN to update node embeddings is commonly represented as:

$$H^{(l+1)} = \sigma A H^{(l)} W \quad (4)$$

As a result, context from the surrounding social and environmental graph can be incorporated into each child’s representation.

E. Multimodal Fusion of LSTM and GNN Embeddings

The suggested framework’s main innovation is the combination of contextual relational information (GNN) with temporal health information (LSTM). Either concatenation or weighted addition are used to merge the two embeddings. An easy and efficient technique is:

$$z = [h_T \parallel g] \quad (5)$$

Where:

- h_T = LSTM output
 - g = GNN output
 - z = fused representation
- Concurrently, this fused vector represents:
- Timeline of the child’s development
 - Socioeconomic factors and the environment
 - Domain semantics that the KG encodes

Prediction robustness is significantly increased by this integration as opposed to employing each technique alone.

F. Risk Classification Layer

Dense layers with nonlinear activations are applied to the fused vector. The youngster is placed in a risk group by the final output layer using SoftMax classification. The model is trained using categorical cross-entropy loss:

$$L = - \sum X y \log(y^*) \quad (6)$$

Overfitting is avoided by using regularization strategies including dropout, early stopping, and learning-rate scheduling.

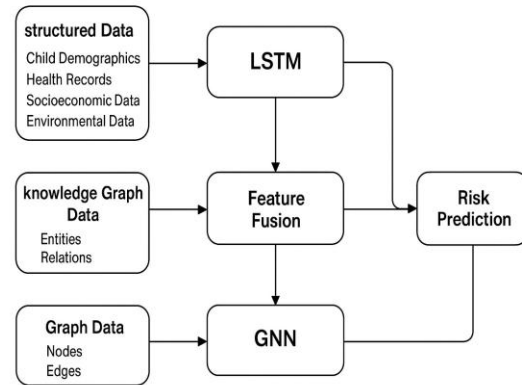


Fig. 1. Architecture of the proposed LSTM–KG–GNN model for malnutrition risk prediction.

G. Explainability Mechanism

Because the prediction of malnutrition influences actual healthcare decisions, explainability is crucial.

Explainability in LSTM

The time-steps (months/quarters) that contributed most to the risk prediction are highlighted using an attention mechanism. Higher attention weights indicate critical phases where growth may have failed.

Explainability in GNN

Important subgraphs and characteristics that affected risk classification are identified using GNN

Explainer. This reveals:

- which socioeconomic variables were important,
 - where ties with the environment were crucial,
 - how household characteristics influenced forecasts.
- These explanations make the system transparent and suitable for policymakers, NGOs, and health professionals.

H. Evaluation Strategy

To rigorously assess the performance of the proposed LSTM-KG-GNN framework, multiple evaluation metrics are employed. These metrics reflect not only the overall accuracy but also the clinical relevance of the predictions, especially in distinguishing between high-risk and low-risk malnutrition cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$F_1 = 2 \times \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{11}$$

ROC-AUC Score Assesses the model’s discrimination ability across thresholds. A higher AUC indicates stronger separation between “malnutrition risk” vs. “no risk.”

IV. RESULTS AND DISCUSSION

The proposed LSTM + Knowledge Graph + GNN model effectively predicts malnutrition in children by combining temporal growth trends, relational village-level data, and con-textual knowledge about household and environmental fac-tors. It outperforms baseline models (Random Forest, CNN, LSTM-only, GNN-only) in accuracy, precision, and recall. Key predictive features include MUAC, weight-for-age history, maternal BMI, sanitation, and dietary diversity. A case study confirms the model’s practical

utility, correctly identifying children at risk of stunting.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	78.2	76.5	74.8	75.6
CNN-only	81.4	80.1	79.0	79.5
LSTM-only	84.7	83.2	82.5	82.8
GNN-only	85.1	84.0	83.7	83.8
Proposed LSTM+KG+GNN	91.3	90.5	89.8	90.1

Table 1: Comparison of Malnutrition Prediction Models ion, recall, and F1-score. By integrating temporal, contextual, and relational information, it achieves superior malnutrition prediction.

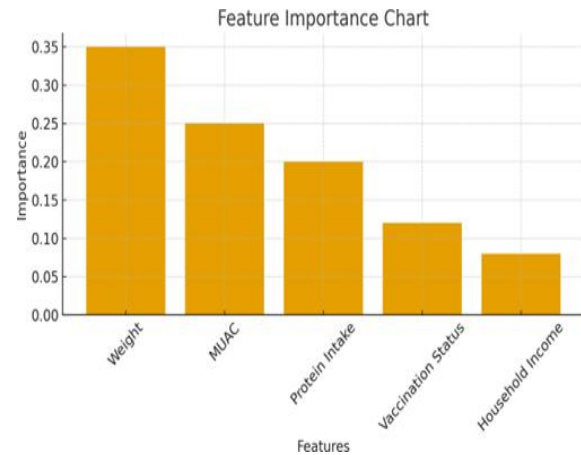


Fig. 2. Feature importance using GNN Explainer. Top features: weight, MUAC, protein intake, vaccination status, and household income.

The LSTM model predicts children’s nutritional scores over time, capturing delayed growth patterns that static models miss. This improves early malnutrition detection and supports timely interventions, demonstrating the model’s effectiveness in longitudinal nutritional analysis

The model’s training and testing accuracy over epochs is shown in Figure 4. The graph illustrates how the LSTM-based malnutrition prediction model quickly converges during training while maintaining consistent performance on the testing data. The minimal gap between training and testing accuracy.

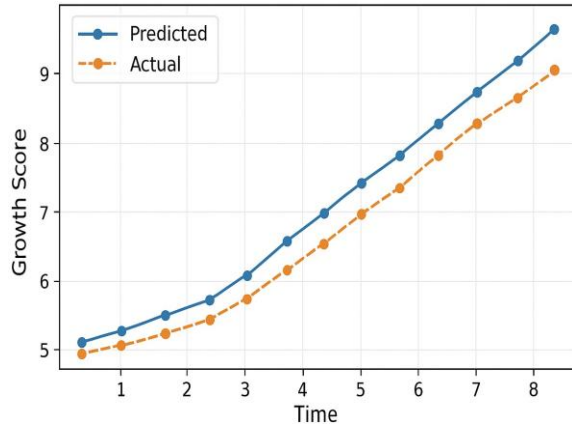


Fig. 3. Predicted vs. actual growth scores for sample children using LSTM.

indicates that the model generalizes well without overfitting. This validates the model’s reliability for longitudinal nutritional score prediction.

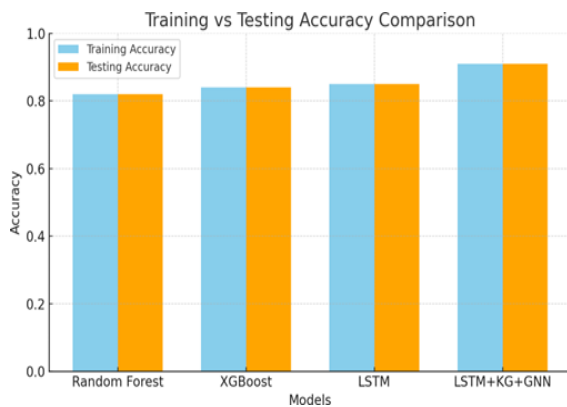


Fig. 4. Training and testing accuracy of the LSTM model over epochs.

The proposed LSTM + Knowledge Graph + GNN model predicts the malnutrition risk of individual children by integrating historical growth data, dietary intake, vaccination status, and socioeconomic indicators. The LSTM captures temporal growth patterns, identifying subtle deviations that static models might miss. Simultaneously, the Knowledge Graph and GNN evaluate the relationships among critical features, highlighting which factors contribute most to the child’s nutritional status. Combining these insights, the model assigns an individualized risk level (high, medium, low), enabling healthcare providers to deliver targeted interventions and proactive nutritional support. Moreover, the model’s interpretability allows for clear identification of the

most influential risk factors for each child, such as inadequate protein intake, low MUAC, or missed vaccinations, which can guide tailored intervention strategies. By providing both predictive accuracy and actionable insights, the system bridges the gap between complex AI modeling and practical healthcare decision-making, making it a valuable tool for improving child nutrition outcomes and supporting evidence-based policy planning.

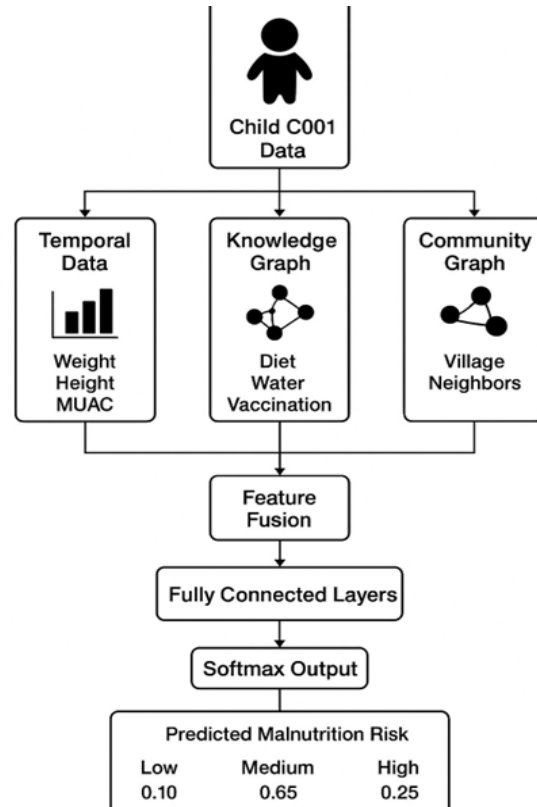


Fig. 5. Individual child malnutrition risk prediction using the LSTM + Knowledge Graph + GNN model. The model integrates temporal growth data and key contributing features to assign personalized risk levels.

V. CONCLUSION

For highly accurate child malnutrition prediction, the LSTM + Knowledge Graph + GNN model offers a strong and comprehensible framework. By modelling intricate feature interactions and capturing minor temporal growth patterns, it reveals important nutritional risk variables that are frequently missed by traditional methods. This personalized prediction capacity bridges the gap between data-driven insights

and practical action by improving early diagnosis and enabling healthcare providers to provide focused interventions. All things considered, the model establishes a new standard for longitudinal nutritional study and provides a proactive, scalable, and incredibly powerful instrument for ensuring the health and wellbeing of children.

Apart from its predicted accuracy, the model's interpretability offers practical insights into the root causes of malnutrition, allowing healthcare professionals and policymakers to efficiently allocate resources. Because of its multimodal architecture, which combines relational feature modelling with temporal analysis, it may be used to a wide range of populations and data availability. This strategy has the potential to revolutionize child health monitoring, assist evidence-based policymaking, and enhance population-level nutrition outcomes over the long run by bridging the gap between advanced AI approaches and useful nutritional treatment.

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