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Multi-Task Deep Learning with SHAP Explainability for Personalized Nutrition Prediction

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Abstract: *The purpose of this article is to address key gaps in the current personalized nutrition recommendation models. These gaps include limited personalization, limited explainability, and single-nutrient assessment/prediction. This study develops a multi-task deep neural network machine learning model to predict multiple dietary components simultaneously by taking into account individual genetic, phenotypic, and lifestyle factors. The study uses publicly available datasets that are sourced, pre-processed, and partitioned into training and test sets. Data pre-processing steps ensure data quality. Model performance is assessed using RMSE, MAE, and the coefficient of determination (R^2). Model interpretability is enhanced through SHAP-based explanation techniques, which transparently elucidate feature contributions to model predictions. The proposed model offers comprehensive, personalized, and interpretable nutrition recommendations, with the goal to improve user trust, adoption, and dietary decision-making. This study contributes scalable, evidence-based methodologies advancing personalized nutrition through multi-nutrient prediction and explainable AI.*

Key Words: *machine learning; personalized nutrition; multi-task learning; explainable AI; SHAP; dietary recommendations; deep neural networks; personalization.*

I.INTRODUCTION

Current deep-learning models for personalized nutrition are still built and designed around one-task-at-a-time architectures. These networks function with single-nutrient processing at a time[1] and there's an urgent need to create new analytical tools which reveal the complex relationships between genes, diet, lifestyle, and microbiome[2]. Research shows that current models handle nutrients as separate entities yet they have not adopted multi-objective frameworks which would integrate these interactions for developing complete dietary recommendations. The majority of current models operate with standard dietary recommendations which fail to address individual differences that arise from unique genetic makeup, personal characteristics, and daily habits[3].

Users receive less relevant and accurate dietary recommendations because these systems do not provide detailed personal customization. AI models that use black-box systems generate outputs which remain unexplained to users and healthcare professionals who struggle to accept AI recommendations because the decision-making process remains hidden[4]. Therefore, there is a critical need for transparent, interpretable models capable of simultaneously predicting multiple nutritional components, to deliver precise, personalized, and actionable dietary advice.

This research uses Multi-Task Learning (MTL) to solve these problems through a machine learning strategy which trains models on multiple connected prediction tasks at the same time. The model predicts multiple dietary nutrients at once through MTL, which achieves better results by understanding how different nutrients relate to each other.[1] the model structure depends on Deep Neural Networks (DNNs) which have the ability to analyze complex nonlinear patterns in high-dimensional multi-modal data that includes genetic information, phenotypic, lifestyle and, environmental features[5]. The model provides understandable explanations about feature effects which produce nutrient predictions through Explainable Artificial Intelligence (XAI) methods that use Shapley Additive Explanations (SHAP) to generate explanations after model training[6], [4].

Key terms used in this study include:

Personalized nutrition: The practice of creating nutrition plans that adapt to individual biological and lifestyle characteristics for delivering exact dietary needs[3].

Multi-Task Learning (MTL): A form of inductive transfer that boosts generalization by jointly learning several related tasks with a common representation, exploiting the domain knowledge present in each task's training signal[7].

Deep Neural Networks (DNN): artificial neural networks with multiple hidden layers that enable hierarchical learning of data representations. These networks process data through several nonlinear transformations, allowing them to recognize complex patterns from large datasets[8].

Explainable Artificial Intelligence (XAI): The creation of models that solve problems while showing their decision-making process to human understanding[3].

Shapley Additive Explanations (SHAP): The XAI method that shows how each feature contributes to the final prediction value[6]. The following sections of this paper follow this order: The material and methods section provides details about data sources, preprocessing steps, feature selection methods, model design, training methods, and explain ability integration. The following sections show the experimental results, which include both the predictive performance of the model and its explain ability assessment. The discussion section examines the results by explaining them and showing their limitations and potential research directions for future studies that aim to enhance personalized nutrition through explainable multi-nutrient machine learning models.

II.MATERIAL AND METHODS

The research used a quantitative computational approach to build a multi-task deep learning model with explainable features for personalized nutrition recommendations. The method allowed the analysis of numerical information through a predefined structure, which also produced predictions for these multiple nutritional components: calories, fats, proteins, and carbohydrates.

The multitask deep neural network model for personalized nutrition was trained using the Personalized Medical Diet Recommendations dataset from Kaggle, a platform focusing on data science and machine learning that hosts a repository of publicly-accessible datasets, with contributions coming in from users and organizations. The dataset contains 5000 individual records, with data about demographic details (age, sex, height, weight, and BMI), lifestyle factors (exercise frequency, sleep quality, tobacco and alcohol use), clinical indicators (chronic disease status and genetic predisposition), dietary intake data (macronutrients and calorie counts) and wearable device metrics (heart rate and activity levels). The study used secondary data in which the implementation of a census sampling method was used to retain all complete and consistent records while removing those with major missing values and data inconsistencies.

Data preprocessing involved: cleaning and imputing minor missing values, normalizing continuous features and, encoding of categorical variables. The process of feature engineering together with dimensionality reduction methods helped improve learning speed and eliminate duplication. The dataset underwent division into training and test subsets, with cross-validation to improve model stability.

The model consisted of a multi-task deep neural network trained through supervised learning. The model used shared hidden layers to extract common features while each nutrient prediction had its own separate output layer. Model performance was evaluated on three regression metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and, the coefficient of determination (R^2). Shapley Additive Explanations (SHAP) was applied as a post-training tool to elucidate feature importance and produce understandable model predictions. This methodological framework was adopted to ensure research reproducibility, clinical relevance, and data reliability.

III.RESULT

This study evaluated the predictive performance as well as explainability of a multi-task learning (MTL) deep neural network model compared to individual single task learning (STL) models for predicting four nutritional outcomes namely: calories, protein, carbohydrates, and fats.

A. Predictive Performance

The multi-task learning (MTL) model showed stable and major performance gains as compared to single-task Learning STL models for every nutrient as per the data in Table 1. The protein prediction results showed the biggest improvement, with the R^2 value increasing from 0.65 in STL to 0.96 in MTL. The RMSE and MAE values also dropped by more than 60%. The MTL model produced better results than the Single task learning (STL) baseline models for fats and carbohydrates although the improvement was less than what was seen in protein prediction. The MTL framework delivered better results than the baseline model for calorie prediction, although the improvement was less pronounced.
Table 1 presents a detailed comparison of RMSE, MAE, and R^2 metrics between the MTL and STL models.

Table 1: Comparison of predictive performance between multi-task and single-task learning models

Nutrient	Metric	Multi-task Model	Single-task Model
Calories	RMSE	128.1	137.69
	MAE	107.37	115.53
	R^2	0.96	0.9581
Protein	RMSE	9.34	26.23
	MAE	7.79	22.1
	R^2	0.96	0.6522
Carbohydrates	RMSE	30.71	37.3

	MAE	26.34	30.67
	R^2	0.89	0.8324
Fats	RMSE	9.25	15.07
	MAE	7.85	12.22
	R^2	0.94	0.8477

Figure 1 and Figure 2 graphically illustrate the RMSE and R^2 disparities, respectively, underscoring the performance advantage of MTL across all target nutrients

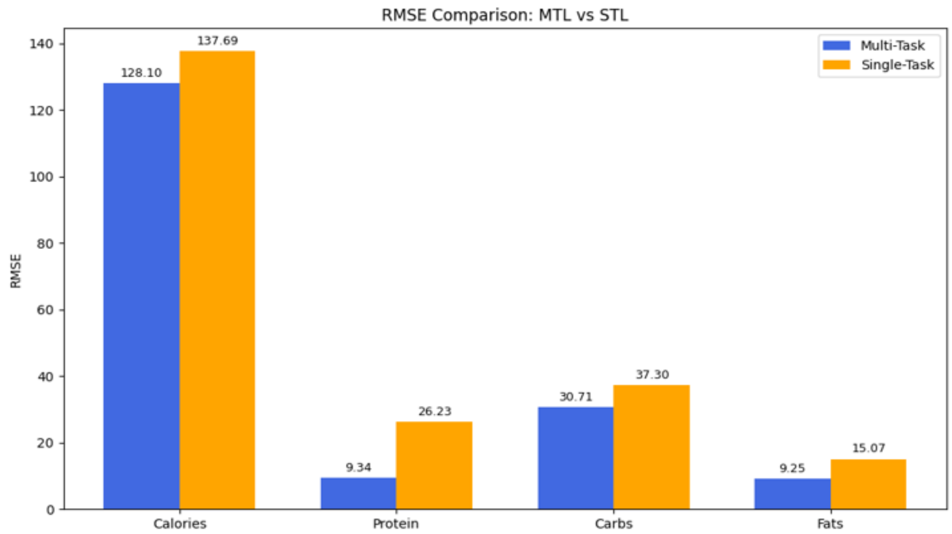

Figure 1. Comparison of RMSE values for STL and MTL models across nutrients.

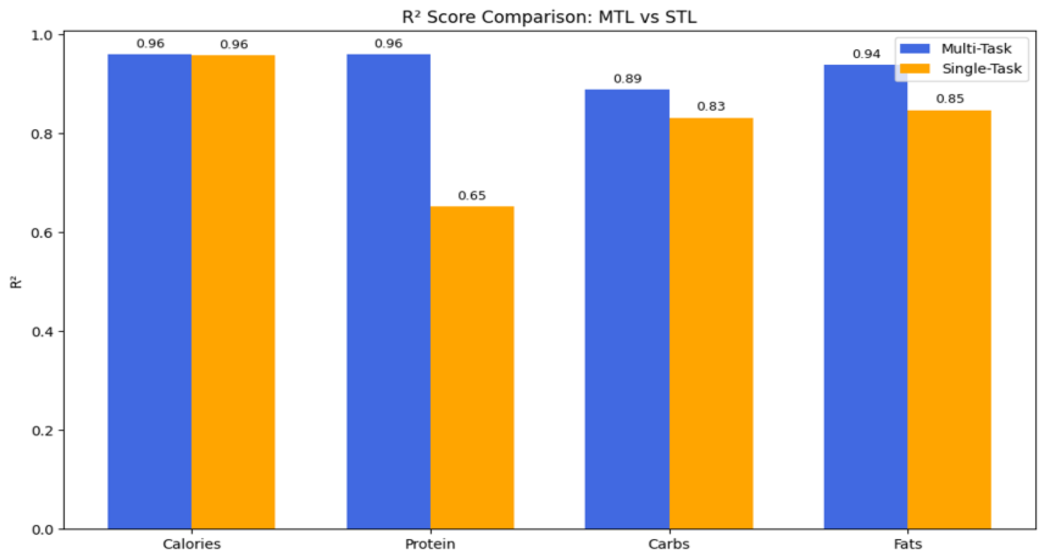

Figure 2. Comparison of R^2 values for STL and MTL models across nutrients.

B. Model Explain ability

Shapley Additive Explanations (SHAP) was applied with the goal of improving model interpretability. Physical activity and chronic disease status were consistently the most influential predictors. BMI and calorie intake mostly took precedence in calorie prediction, whereas the protein intake prediction was dominated by the dietary intake variables and physical activity levels.

Figures 3 and 4 are the SHAP summary plots for calorie and protein predictions. This confirms that the model relied on physiologically and clinically meaningful features, enhancing transparency and validating the model's internal logic.

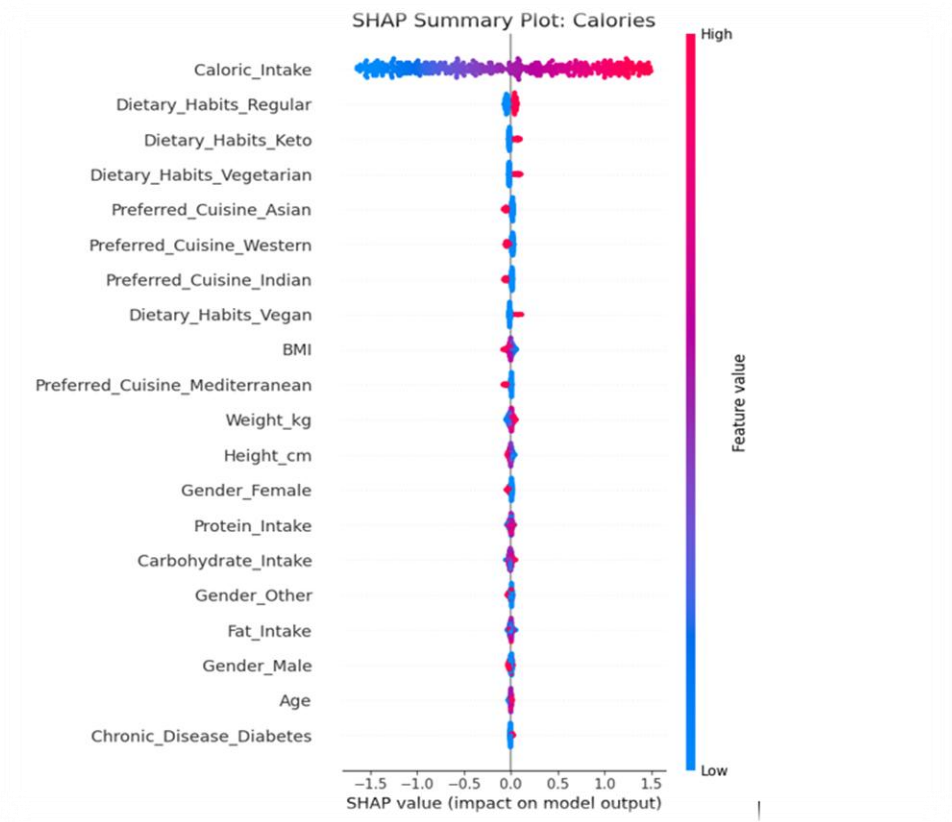

Figure 3. SHAP feature importance for prediction of calories.

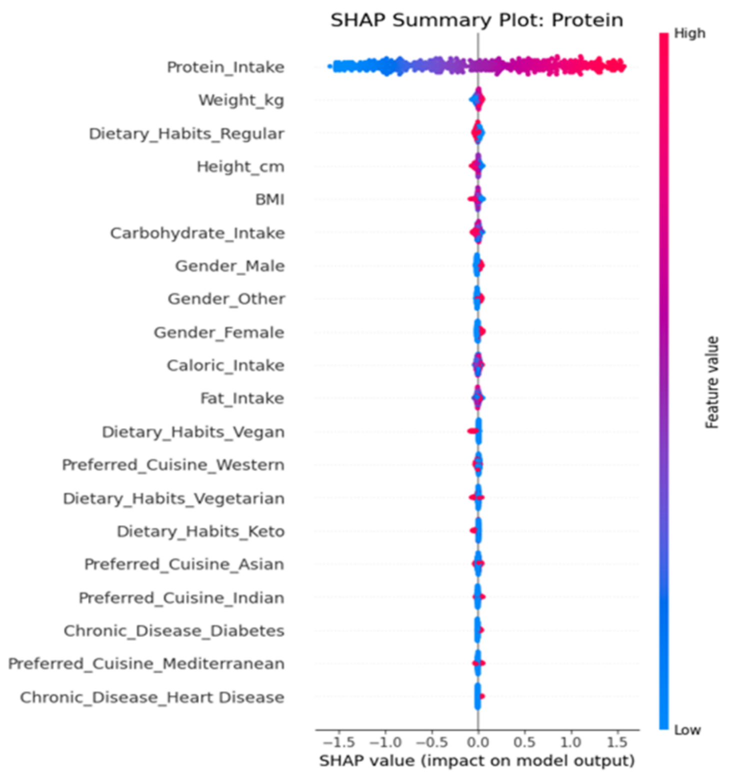

Figure 4. SHAP feature importance for prediction of protein.

These results showed that the model's predictions lined up with physiologically and clinically meaningful factors, thereby enhancing the transparency of the model and supporting its potential use in personalized nutrition applications.

C. Key Findings

The Multi-Task-Learning model delivered better prediction results than the individual Single-Task-Learning models for all the nutritional components and showed its strongest performance in protein prediction, with an R^2 of 0.96 versus 0.65.

The SHAP analysis demonstrated that the model predictions resulted from core clinical and lifestyle variables which enhanced the model's interpretability.

The MTL framework used explain ability to create better model transparency, which resulted in improved accuracy for personalized nutrition system deployment.

IV.DISCUSSION

This showed a sound empirical validation of the merits of multi-task learning (MTL) in personalized nutrition modeling. Relative to single-task learning (STL), the MTL model consistently delivered improved predictive performance across multiple nutrient outcomes, particularly highlighted by the substantial gain in protein prediction accuracy ($R^2 = 0.96$ vs. 0.65), aligning with the foundational theory of MTL, which posits that shared representations facilitate better inductive transfer and generalization among related tasks[7].

Further, the capability of the MTL model to capture synergies between nutrients—reflected in improved fats and carbohydrates predictions—indicates that shared hidden layers effectively embed correlations across dietary components, acting as regularizes to reduce overfitting[9]. This insight is especially pertinent in nutrition science due to intricate nutrient interactions[10].

A noteworthy advancement is the integration of explain ability through SHapley Additive Explanations (SHAP). Neural networks face criticism as 'black boxes' in clinical settings[11] but SHAP provided clear global and local explanations, consistently identifying BMI, activity levels, and dietary preferences as top contributors. The system delivers precise results that could build trust among stakeholders and promote transparency, thereby supporting the implementation of translational AI systems in healthcare nutrition[4].

Additionally, the importance of multi-modal feature integration - including demographic, physiological, and lifestyle data—was underscored, producing a richer and more accurate predictive framework consistent with precision nutrition guidelines[1]. Nevertheless, challenges linked to rigorous data preprocessing persist as key considerations for practical model deployment.

Taken together, these findings indicate that MTL, augmented with explainable AI techniques, delivers not only enhanced accuracy but also interpretability. This positions it as a compelling, ethically sound approach for next-generation personalized nutrition systems.

Limitations

Despite these strengths, several limitations remain. The research findings fail to represent various populations because the participants lack demographic variety. The model focuses on a limited number of 4 macronutrient targets, excluding micronutrients and biomarkers important for any thorough assessment of the type of diet being followed. Self-reported data collection methods give rise to multiple measurement errors as methods require respondents to disclose some private information about themselves. While SHAP method provides more explainability, it operates post hoc, and therefore cannot achieve the same level of transparency levels as inherently interpretable models.

V.CONCLUSION

This study proved that the multi-task learning model combined with Shapley Additive Explanations (SHAP) generated promising predictive personalized nutrition models. The MTL model gave better performance than STL baselines because it simultaneously aimed at predicting multiple nutritional components (calories, proteins, carbohydrates, and fats) based on demographic, lifestyle, and clinical features. From the evaluation, the protein prediction saw the biggest improvement among all nutrients between the two models as shared representations actually helped the model learn actual nutrient interrelationships better ($R^2 = 0.96$ vs. 0.6522), thus highlighting the importance of shared representations in capturing nutrient interdependencies.

Important interpretability was achieved through the integration of SHAP, which allowed predictions to be clearly attributed to variables like BMI, physical activity, and dietary preferences. The explain ability framework established healthcare AI adoption through its ability to improve accountability and trust which revealed complete model reasoning transparency. The results also emphasized the ongoing significance of thorough data preprocessing and validated that incorporating multi-modal features is necessary for successful personalization in nutrition systems.

These developments will potentially boost health results by delivering specific dietary plans which match individual variations. The strong predictive benefits and increased transparency strongly support MTL as a foundational framework for future AI-driven dietary decision-support tools, even though issues with data quality and practical implementation still exist.

The research study demonstrates that multi-task neural networks combined with explain ability methods create an effective method for building interpretable and scalable data-driven nutrition recommendation systems. The system faces ongoing challenges with data quality and real-world implementation yet its predictive accuracy and transparent design prove MTL stands as a promising base for upcoming AI dietary support systems.

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