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Unveiling Neural Networks for Personalized Diet Recommendations

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Abstract

The growing prevalence of poor nutrition is a major public health concern, as it fuels the rise of various diseases. Obesity, a silent and rapidly growing threat linked to unhealthy eating, is a prime example. Despite the abundance of information on diets and recipes, finding a personalized approach to healthy eating can be a challenge. Recommendation systems can filter from a food logging dataset the information that best suits the nutrition profile of a given user. A powerful tool to use in food recommendation systems is neural networks. However, the user's available data are often limited, which compromises the performance of neural-based food recommendation models. To enhance user trust in food recommendations, this paper proposes a method using a secondary model to predict the errors of the primary neural network, especially when dealing with limited data.

Keywords: Personalized Nutrition;Error Prediction;Machine Learning

1. Introduction

Obesity is one of the leading risk factors for noncommunicable diseases world-wide [2]. This disease is mainly caused by an energy imbalance between calories consumed and expended. This happens because of the increased intake of food high in fat and sugars and increased physical inactivity [12]. With the increased production of processed foods and the changes in habits, people are consuming more food rich in energy, fats, free sugars, salt/sodium, and less fruit and vegetables [11]. A healthier diet helps prevent obesity, a risk factor for many non-communicable diseases.

Machine Learning (ML) recommendation systems based on neural networks have gained ground over traditional approaches due to their ability to model complex patterns and their lack of assumptions about data [10]. ML methods extract features from data by combining low-level features from denser high-level semantic abstractions. Despite widespread adoption and predictive capabilities, neural networks are popular ML methods that operate as opaque black-box models, obscuring the underlying mechanisms driving their predictions. This lack of transparency in recommendation systems poses significant challenges, particularly when the amount of available data are limited. Such

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is the case of personalized assistants that depend on data provided for a single user. Current limitations in machine learning leave users in the dark about the trustworthiness of individual predictions, particularly when data is scarce. This is a major obstacle, as sparse data is a common challenge across many fields.

Based on the previously described problem, we answer the following research questions:

- RQ1. How can a second model predict the error of a primary neural network, and what insights can be gained from its error predictions?
- RQ2. Which data structure is required to build an error prediction system?
- RQ3. How effective is an error prediction model including features describing the weight of specific inputs on the output obtained using model interpretability techniques?
- RQ4: What insights can be gained into the decision-making process of neural networks by analyzing the error predictions?

This research seeks to improve user confidence in neural network models for nutrition by predicting their errors. This approach aims to make neural networks more transparent, thereby facilitating an understanding of their decision-making process. Improving neural network interpretability, it also expected to improve their reliability and trustworthiness, fostering a deeper comprehension of the rationale behind the predictions.

The paper is organized as follows: Section 2 discusses related research, Section 3 details the methodology, Section 4 presents the experimental results, and Section 5 concludes the findings.

2. Related Work

While the related work on error prediction is very limited, there are several work on the use of machine learning in the nutrition area.

The authors of [3] propose the use of a Multilayer perceptron algorithm for health risk prediction. The experiments were conducted using 3 standard datasets, each of those corresponding to a disease: (1) Wisconsin Breast Cancer (WBC), (2) SaHeart (SHt) and (3) Pima Indians Diabetes (PID). The proposed approach outperformed the other methods in accurately classifying and analyzing medical data. The proposed approach offers a promising solution for finding hidden patterns in real historical medical data and improving risk prediction in the medical domain. In [13] the authors propose a malnutrition predictive model. They collected data from parents in India, respecting children under the age of five. The dataset used consists of 2956 records with 12 parameters and 3 class labels. The purpose approach consists of a Multilayer perceptron classifier with a stochastic gradient descent optimization technique for classifying the data effectively. The method was able to classify 41 out of 44 new kids' data correctly, with an accuracy of 93.6%. The authors of [14] present a food recommendation system based on user preferences and food ingredients. For food content-based recommendations, the authors explore graph clustering, food deep embedding, food similarity calculation, food clustering, and food-based rating prediction. The solution was evaluated using a dataset created by crawling the Allrecipes.com website. The results have outperformed other state-of-the-art approaches. The authors of [7] propose a deep learning system to suggest diets for patients. It analyzes disease, age, and food properties (e.g., calories, protein) using various algorithms (e.g., logistic regression, LSTM). LSTM achieved the best performance (97.74% accuracy) in identifying suitable food for each patient's condition.

The research presented in [8] addresses a method to improve trust in machine learning predictions by calculating confidence scores based on latent space features. The method maps these features to a prior distribution and compares the model's activation patterns with the stored distribution parameters. This approach outperforms traditional confidence scores based on Softmax probabilities on standard datasets, demonstrating the potential of latent space features for trust calibration.

Building on prior work on interpretability limitations, the work presented in [6] explores methods to improve interpretability in biology-inspired deep learning. They acknowledge the potential for these models but highlight the challenges of biased and unreliable interpretations. Their research identifies network properties influencing these biases and proposes methods for more robust and specific interpretations. This emphasizes the importance of developing reliable interpretability techniques for this field. The authors of [1] proposes a new method using causal analysis to understand how pre-trained neural networks work. The method helps identify cause-and-effect relationships within

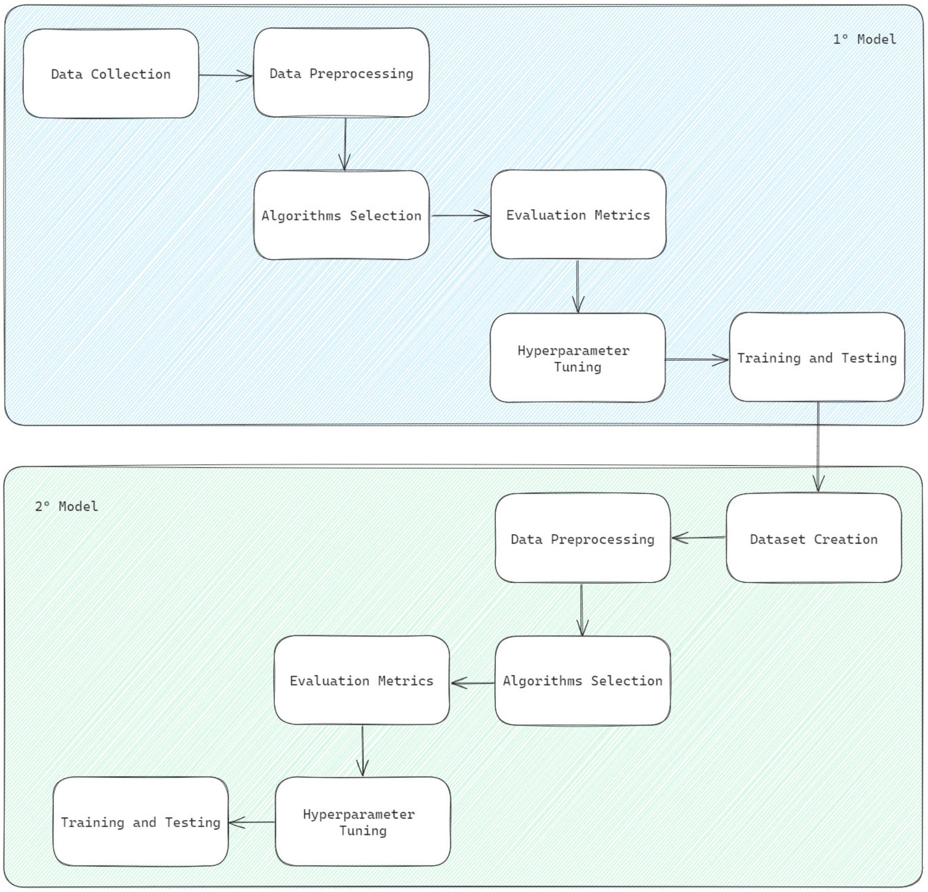

Fig. 1. Methodology adopted to build and evaluate the prediction and error prediction models.

the network, leading to more reliable explanations compared to existing techniques. They tested the method on image classification tasks and found it generates stable and consistent explanations.

Machine learning models are powerful tools, but their predictions are not perfect. A crucial research gap exists in our ability to predict these errors. While models can estimate confidence scores, these often don't reflect real-world performance. This lack of foresight can lead to unreliable decisions and wasted resources. Our work focuses on prediction of these errors in the domain of nutrition.

3. Methodology

This section presents the methodology applied to this research, aimed at describing the process of data gathering, preprocessing, algorithm selection, evaluation metrics, hyperparameter tuning, and training and testing.

Figure 1 presents a diagram with all the different phases, in our methodology approach. It is structured into two parts, each representing one model. They both addresses the prediction model, where we collect and preprocess the data, select the machine learning algorithm, choose the evaluation metrics, tune the model, and train and test it.

The data preprocessing activity involves: (1) manipulating metadata and removing rows containing empty or NULL values; and (2) utilizing the a *minmax* scaller function [5] for data normalization/standardization.

In the algorithm selection phase, we decided on the use of MLP (Multi-Layer Perceptron) [9]. For the error prediction we decided on the RF (Random Forest) algorithm [4].

The performance of the regression models used in the research is evaluated using the metrics MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Square Error) [15].

Features	Features Description
User ID	Anonymized user ID
Date	Diary date
Sodium_Total	Daily aggregate of Sodium intake
Sugar_Total	Daily aggregate of Sugar intake
Fiber_Total	Daily aggregate of Fiber intake
Potass._Total	Daily aggregate of Potassium intake
Iron_Total	Daily aggregate of Iron intake
Calcium_Total	Daily aggregate of Calcium intake
Sat Fat_Total	Daily aggregate of Sat Fat intake
Chol_Total	Daily aggregate of Cholesterol intake
Vit A_Total	Daily aggregate of Vitamin A intake
Trn Fat_Total	Daily aggregate of Trn intake
Mon Fat_Total	Daily aggregate of Mon intake
Ply Fat_Total	Daily aggregate of Ply intake
Calories_Goal	Daily aggregate of Calories goal
Carbs_Goal	Daily aggregate of Carbs goal
Fat_Goal	Daily aggregate of Fat goal
Protein_Goal	Daily aggregate of Protein goal
Sodium_Goal	Daily aggregate of Sodium goal
Sugar_Goal	Daily aggregate of Sugar goal
Fiber_Goal	Daily aggregate of Fiber goal
Potass._Goal	Daily aggregate of Potassium goal
Iron_Goal	Daily aggregate of Iron goal
Calcium_Goal	Daily aggregate of Calcium goal
Sat Fat_Goal	Daily aggregate of Sat Fat goal
Chol_Goal	Daily aggregate of Cholesterol goal
Vit A_Goal	Daily aggregate of Vitamin A goal
Vit C_Goal	Daily aggregate of Vitamin C goal
Trn Fat_Goal	Daily aggregate of Trn goal
Mon Fat_Goal	Daily aggregate of Mon goal
Ply Fat_Goal	Daily aggregate of Ply goal

Table 1. Dataset Features

To optimize the performance of our Multi-Layer Perceptron (MLP) model, we fine-tuned its hyperparameters, including learning rate, number of hidden layers and neurons, batch size, and training epochs. We experimented with various configurations and achieved the best balance between model complexity and performance using an architecture with 256 neurons in the input layer, followed by four hidden layers containing 128, 64, 32, and 16 neurons, respectively. Additionally, a batch size of 64 offered the optimal performance-to-resource ratio, and we employed 100 epochs for training. For the Random Forest (RF) model, we optimized the number of decision trees åthrough multiple runs. The best outcome was achieved with 190 decision trees.

Features	Features Description
Difference Carbs	Carbs Feature Difference
Shap_Values Test Carbs	Carbs Feature Shap_Values Test
Shap_Values Train Carbs	Carbs Feature Shap_Values Train
Difference Fat	Fat Feature Difference
Shap_Values Test Fat	Fat Feature Shap_Values Test
Shap_Values Train Fat	Fat Feature Shap_Values Train
Difference Protein	Protein Feature Difference
Shap_Values Test Protein	Protein Feature Shap_Values Test
Shap_Values Train Protein	Protein Feature Shap_Values Train
Error	MLP Prediction Error

Table 2. Error Derived Dataset Features

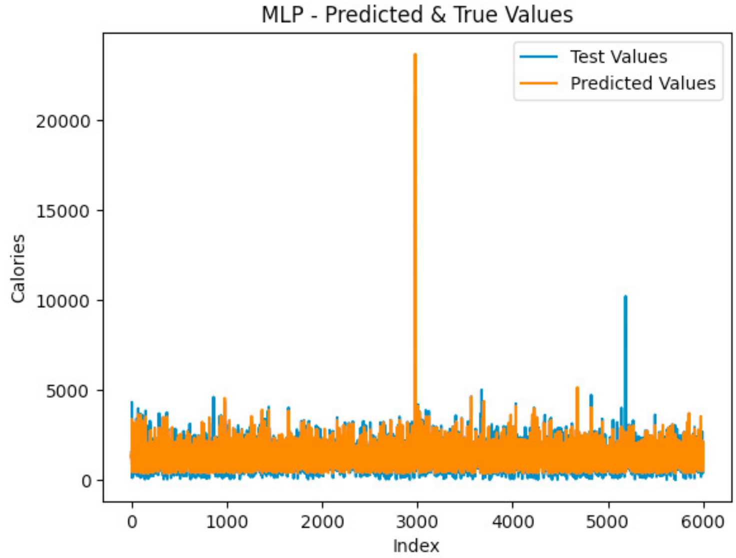

Fig. 2. MLP Predictions 2

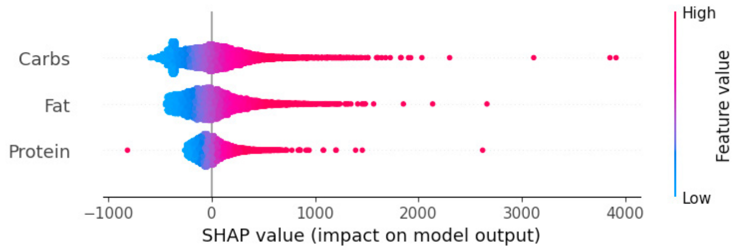

Fig. 3. Shap Values Train Set

4. Experimental Results

This section presents the experimental results and discusses the outcomes of models' hyperparameter tuning, along with sensitive analysis and the model's predictions. The results provided here offer insights into the effectiveness and performance of the models utilized in the developed solution. Figure 2 provides a visual representation of the model's performance. Overall, the predicted and true values overlap, indicating generally accurate predictions.

We used SHAP values to understand how the MLP works and how each feature affects its predictions. Figure 3 illustrates the contribution of each feature (*Carbs, Fat, Protein*) to the train set used for MLP evaluation. To address the main goal of predicting MLP errors, we create a new dataset. This dataset combines the model's prediction errors with the corresponding feature importance scores. We leverage this data to train a Random Forest (RF) algorithm to overcome the MLP's limitations. By analyzing both error patterns and feature importance, the RF can potentially learn to predict future errors more effectively. This concept involves calculating the difference between the *X_test* values and the values from the closest row, for each input feature (*Carbs*, *Fat*, *Protein*) in the first dataset. Subsequently, we retrieve the corresponding feature importance from *X_test* and *X_train*, alongside the MLP prediction errors. The resulting dataset includes the features outlined in Table 2.

Table 3 summarizes the performance of both the original MLP model and the error prediction model (RF). While the MLP achieves reasonable accuracy with an MAE of 133.70, the RF model for error prediction shows slightly higher MAE (139.44) and MSE (110664.20). This suggests that predicting the errors themselves might be a challenging task.

MLP			RF		
MAE	MSE	RMSE	MAE	MSE	RMSE
133,70	83670,07	289,26	139,44	110664,20	332,66

Table 3. Evaluation Metrics - MLP and RF

5. Conclusions

This research investigated the feasibility of predicting errors in neural network models applied to nutrition. We achieved this by constructing a new dataset that combined MLP prediction errors with the corresponding feature importance scores. This data was then used to train a Random Forest model with the aim of surpassing the limitations of the original MLP in error prediction.

The experimental results revealed that while the MLP achieved reasonable accuracy in its primary task, the RF model for error prediction exhibited slightly higher errors. This indicates that predicting the errors themselves might be a complex task for the RF model, despite its ability to analyze both error patterns and feature importance.

Future research could explore alternative techniques for error prediction in MLP models. Additionally, investigating methods to improve the feature importance scores obtained from the MLP could potentially enhance the performance of the error prediction model.

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