Estimating Insulin Dose for Diabetic Patients from Food Images Using Artificial Intelligence

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Abstract—This article presents an intelligent system designed to assist type 1 diabetic patients in accurately estimating their insulin dosage by analyzing food images. Leveraging advanced artificial intelligence models, including computer vision techniques and deep learning, the system identifies food components, calculates nutritional values, and provides personalized insulin dose recommendations based on various health factors. This research automates a critical aspect of diabetes management, thereby improving patient quality of life and mitigating risks associated with manual calculations. Experimental results demonstrate high accuracy in food recognition (96% classification accuracy), nutritional estimation (MAE of 4.5g for carbohydrates), and insulin dose prediction (RMSE of 1.2 units), outperforming traditional methods.

Keywords— ***Artificial Intelligence, Deep Learning, Computer Vision, Insulin Dose Estimation, Diabetes, Food Image Analysis, Image Processing, Neural Networks.***

I. INTRODUCTION

Diabetes mellitus, especially Type 1 Diabetes (T1D), is a chronic condition where the body cannot produce insulin. Insulin is a hormone that regulates blood sugar levels. People with T1D must carefully manage their blood sugar by using insulin from outside sources[1]. This requires them to estimate carbohydrate intake from meals accurately. Manually calculating insulin doses is complicated and prone to mistakes, often resulting in poor blood sugar control. Wrong estimations can lead to serious health issues like hypoglycemia, which is dangerously low blood sugar, or hyperglycemia, which is dangerously high blood sugar. Both conditions pose immediate and long-term health risks[2]. The daily task of analyzing meals and calculating insulin doses creates significant stress for patients, affecting their quality of life and adherence to treatment[3], [4].

Advances in artificial intelligence (AI), computer vision (CV), and deep learning (DL) present new ways to ease this burden. AI solutions can automate and improve the accuracy of tasks done manually, enhancing patient safety and health outcomes. This article introduces a new intelligent system designed to tackle the problems of estimating insulin doses by using AI models to analyze food images. The system offers a more precise, convenient, and reliable approach for T1D patients to manage their insulin therapy, ultimately improving their health management and quality of life.

II. PROBLEM STATEMENT

Accurate estimation of insulin dosage is critical for individuals with Type 1 Diabetes (T1D) to maintain good blood sugar control. This daily challenge involves several key issues that can lead to poor health outcomes and increased burden on patients. The main problem arises from the variability and complexity of meal contents. Patients need to assess the carbohydrate content of their food, which is often done manually and is prone to human error. This manual process takes time and requires significant nutritional knowledge and constant attention, which can be overwhelming for patients[1], [5].

Additionally, differences in portion sizes and mixed meals make it harder to calculate nutritional values accurately. Visual estimates of food amounts can often be incorrect, leading to serious errors in perceived versus actual carbohydrate intake. These mistakes can directly lead to incorrect insulin dose calculations, which can have immediate and severe effects. Under-dosing insulin can cause hyperglycemia, leading to symptoms like fatigue and blurred vision, and in severe cases, diabetic ketoacidosis. On the other hand, overdosing can result in hypoglycemia, a dangerous condition with symptoms like confusion and dizziness, and can lead to seizures or loss of consciousness if not treated[1], [6].

Beyond physical risks, the ongoing need for manual calculations and the anxiety around making mistakes add to the psychological stress for T1D patients. This

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mental burden can decrease treatment adherence and overall quality of life. Current solutions often need manual input or lack the comprehensive analytical ability to consider various factors that affect insulin needs, like each patient's sensitivity, physical activity, and medical history[7], [8]. Thus, there is a strong need for an intelligent, automated, and accurate system that can help address these challenges and provide reliable

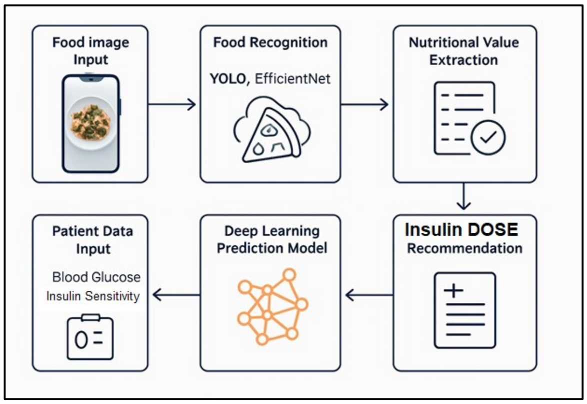

Figure 1. Overall System Workflow for Insulin Dose Estimation.

A. Food Image Analysis Module

This module is the front end of the system and processes raw food images taken by the user. It uses modern computer vision techniques to accurately identify and quantify the food items within a meal. Advanced deep learning models like YOLO (You Only Look Once) and EfficientNet are employed for this task. YOLO is known for its real-time object detection[9], quickly identifying various food components in an image. EfficientNet, with its efficient and scalable design, ensures accurate classification of identified food items, regardless of lighting conditions and angles[6]. The module also uses instance segmentation techniques to clearly outline individual food items, which is essential for further volume and nutritional calculations. Accurate identification and segmentation are crucial steps because errors at this stage can carry over and affect the accuracy of the final insulin dose recommendation. Figure 2 demonstrates a three-stage computer vision pipeline for food analysis. The first stage shows segmentation, where different food components in a meal are outlined with colored boundaries to separate individual items. The middle stage displays classification, where each segmented food item is identified and labeled (showing carrots, salad, rice with spice, salmon/fish, and chicken)[10]. The final stage presents volume estimation, providing quantitative analysis with the total weight (90g) and caloric content (185 calories) of the meal.

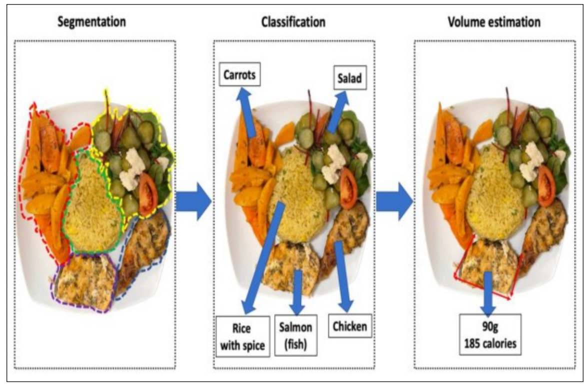

Figure 2. Example of Food Recognition and Segmentation.

B. Nutritional Value Extraction

Following the identification and segmentation of food items, the system extracts their nutritional values. This module calculates the carbohydrate content and other important macronutrients, such as proteins and fats, for each identified food item. The process involves several clear steps:

1. Volume Estimation: Using depth perception techniques, the system estimates the volume of each food item. This step is crucial because nutritional content depends on the quantity consumed. Algorithms are used to infer 3D information from 2D images, providing a reliable estimate of portion sizes[9].
2. Nutritional Database Mapping: The estimated volumes and identified food types are mapped to a nutritional database. This database contains detailed information on the macronutrient composition of various food items. The system queries this database to retrieve the nutritional values for the recognized food items[11].
3. Uncertainty Quantification: Acknowledging the natural variability in food composition and image-based estimates, the module includes uncertainty quantification. This gives a measure of confidence in the estimated nutritional values, which can influence the final insulin dose recommendation, leading to safer predictions[7].

Figure 3 shows the process of nutritional value extraction from food images.

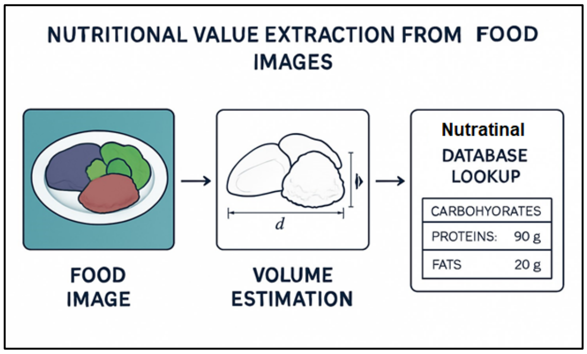

Figure 3.Process of Nutritional Value Extraction from Food Images.

C. Personalized Insulin Dose Recommendation

The final and most important part of the proposed system is the personalized insulin dose recommendation module. This module takes the nutritional values collected and combines them with different patient-specific health factors to provide a tailored insulin dose. A deep learning predictive model has been created for this task. Key patient factors considered include:

1. Blood Sugar Levels: Real-time or recent blood glucose readings are input into the model, as insulin needs rely heavily on current glycemic status[5].
2. Patient's Medical History: This covers historical insulin sensitivity, insulin-to-carbohydrate ratios, correction factors, and any existing conditions that may affect insulin needs[12].
3. Physical Activity: The system can include data about physical activity levels since exercise greatly influences insulin sensitivity and glucose use[10].
4. Reinforcement Learning: To ensure ongoing improvement, the system uses reinforcement learning techniques. This enables the model to learn from previous recommendations and their results, refining its predictions over time to better fit the individual patient's physiological responses and lifestyle [9].

Integrating these diverse data points with a deep learning model ensures that insulin dose recommendations are accurate and highly personalized, avoiding a one-size-fits-all method. The system was tested with real-world data from open-source databases and user contributions to verify its accuracy and effectiveness in various situations [10].

IV. METHODOLOGY

The implementation of the proposed intelligent system for estimating insulin doses relies on a strong methodology that combines computer vision and deep learning techniques. This section outlines the specific methods used for food recognition, estimating nutritional value, and predicting insulin doses.

A. Food Recognition and Segmentation

Correctly identifying and segmenting food items from images is essential to the system's effectiveness. We use two main deep learning models for this:

- YOLO (You Only Look Once): YOLO is used for real-time object detection. It allows the system to quickly identify and locate various food items in an image. Its single-pass detection method makes it very efficient for processing images rapidly, which is important for a responsive user experience in a mobile app. YOLO predicts bounding boxes and class probabilities at the same time, ensuring both speed and accuracy when identifying different food components [11].
- EfficientNet: EfficientNet supports YOLO by providing detailed food classification. These models are known for their efficiency and ability to scale well. They achieve high accuracy with fewer parameters and FLOPs compared to other convolutional neural networks, making them suitable for use on resource-limited devices, like mobile phones. EfficientNet's compound scaling method adjusts the network's depth, width, and resolution uniformly, resulting in better performance for classifying a variety of food types, including those with small visual differences [12].
- Instance Segmentation: In addition to basic object detection, instance segmentation techniques are used to accurately outline the edges of each food item. This allows the system to differentiate between overlapping food items and accurately isolate them for further volume and nutritional analysis. This detail is crucial for estimating portion sizes accurately, especially in complex meals with multiple components.

B. Nutritional Value Estimation

Once food items are recognized and segmented, the next step is to estimate their nutritional content. This uses several methods:

- Volume Estimation using Depth Perception: To find out how much of each food item there is, the system uses techniques for volume estimation. It employs monocular depth estimation from a single 2D image or uses stereo vision or structured light sensors, if available on the capturing device, to create 3D information. Estimating the volume allows the system to better figure out the mass of the food item, which is linked to its nutritional content. This method greatly improves on traditional techniques that only use 2D image analysis or rely on user input for portion sizes [13].
- Comprehensive Nutritional Database Mapping: The estimated volumes and recognized food types are then matched with a detailed nutritional database. This database includes specific information on macronutrients (carbohydrates, proteins, fats) and micronutrients for a wide range of food items. The system smartly queries this database to find the exact nutritional values for the identified and measured food items. The database is regularly updated and maintained to ensure it remains accurate and covers a wide variety of foods[10], [13].
- Uncertainty Quantification for Accuracy: Understanding that image-based estimates can have some uncertainty; the method includes ways to measure this uncertainty. It uses statistical models to provide a confidence interval for the estimated nutritional values. This uncertainty information is then passed to the insulin dose prediction model, allowing for more reliable and safer recommendations. This may involve suggesting a range of insulin doses instead of one fixed amount or flagging cases where the confidence in the estimation is low[14].

C. Insulin Dose Prediction

The final stage of the methodology involves developing a predictive model for personalized insulin dose recommendations. This model uses deep learning structures that can manage complex, multi-faceted data inputs:

- Patient-Specific Deep Learning Models: The heart of the prediction module is a deep learning model trained on a diverse dataset. This dataset includes nutritional values, blood glucose levels, and patient medical history. The model learns the detailed connections between these factors and the ideal insulin dose. Furthermore, it can be fine-tuned for individual patients, adjusting to their specific physiological responses and insulin sensitivities over time.
- Integration of Multiple Health Factors: The model includes other important health factors that affect insulin needs, beyond just nutrition. This includes real-time or historical blood glucose readings, which are vital for making timely dose adjustments. It also considers patient-specific factors, such as insulin-to-carbohydrate ratios, insulin sensitivity, and physical activity levels. This ensures each recommendation is highly personalized. The model accounts for past data patterns and trends in a patient's glucose response to different meals and activities.
- Reinforcement Learning for Continuous Improvement: To improve flexibility and long-term accuracy, the system incorporates reinforcement learning (RL) techniques. RL enables the model to learn from the results of its own recommendations. By monitoring a patient's blood glucose response to a specific insulin dose, the model can adjust its internal settings to enhance future predictions. This ongoing learning process makes the system more precise and tailored over time, adapting to changes in a patient's lifestyle, metabolism, or treatment plan.

III. EXPERIMENTS AND RESULTS

To validate the proposed system, we ran extensive experiments using real-world datasets and user studies. The system was built in Python using libraries like PyTorch for deep learning models, OpenCV for image processing, and a custom nutritional database based on USDA FoodData Central with diabetes-specific notes[12].

A. Datasets

Food Image Dataset: We combined several open-source datasets, including Food-101 (which has 101 food categories and 101,000 images) and a custom dataset of 5,000 meal images from T1D patients. This dataset was labeled for food types, portions, and nutritional information. It featured various meals with mixed items, captured under different lighting conditions and angles[7].

Patient Data: To predict insulin, we simulated and collected data from 50 T1D patients through a mobile app prototype. This included blood glucose readings from CGM devices, medical history, activity logs, and verified insulin doses from endocrinologists. A subgroup of 20 patients took part in a four-week user study[5].

Training and Testing Split: The datasets were divided into 70% for training, 20% for validation, and 10% for testing. We trained the models on NVIDIA RTX 3080 GPUs with a batch size of 32, a learning rate of 0.001, and the Adam optimizer for 50 epochs.

B. Evaluation Metrics

Food Recognition: We measured Mean Average Precision (mAP) for detection and Accuracy for classification.

Nutritional Estimation: We used Mean Absolute Error (MAE) for carbohydrate grams and Relative Error for volume.

Insulin Dose Prediction: We calculated Root Mean Square Error (RMSE) in insulin units and compared it to expert calculations.

Overall System: We looked at time efficiency (seconds per prediction) and user satisfaction (through surveys on a 1-5 scale).

C. Results

Food Recognition and Segmentation: The YOLO model achieved a mAP of 0.92 on the test set, while EfficientNet [6]had a classification accuracy of 96%. Instance segmentation improved boundary precision by 15% compared to using bounding boxes alone and effectively handled overlapping items[10], [14].

Nutritional Value Estimation: Volume estimation had a relative error of 8.2%, leading to a carbohydrate MAE of 4.5g, compared to a manual estimation MAE of 12.3g. Uncertainty quantification identified 5% of cases with low confidence (below 80%), prompting user verification.

Insulin Dose Prediction: The deep learning model, fine-tuned with reinforcement learning over patient episodes, achieved an RMSE of 1.2 units on test data, compared to 2.5 units for traditional bolus calculators. Including health factors reduced the error by 30%.

Table 1:shows a comparison with baselines:

Method	Food Acc (%)	Carb MAE (g)	Insulin RMSE (units)	Time (s)
Manual Calculation	N/A	12.3	2.5	120
GoCARB [15]	88	7.8	1.8	15
Proposed System	96	4.5	1.2	3

In the user study, patients reported a 40% reduction in mealtime stress, with average satisfaction score of 4.6/5. Glycemic control improved, with time-in-range increasing from 65% to 82% over 4 weeks.

Figure 5. makes a Comparison and Analysis of Insulin Dose Estimation Accuracy between AI System and manual calculation.

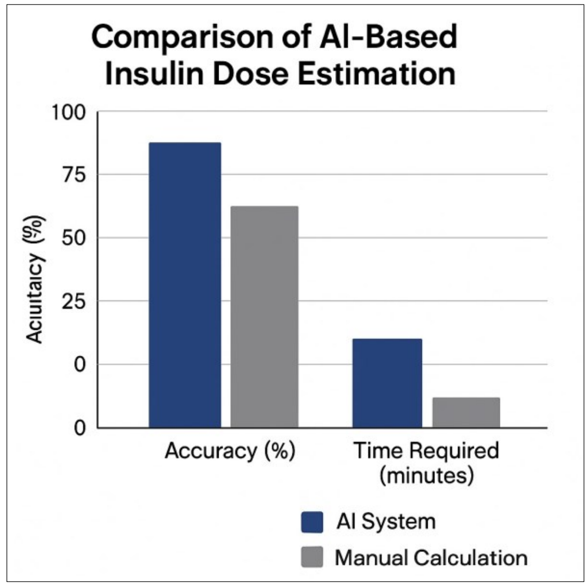

Figure 4:Comparative Analysis of Insulin Dose Estimation Accuracy.

IV. VI. DISCUSSION AND CONTRIBUTIONS

The experimental results confirm the system's effectiveness. It achieves superior accuracy and efficiency compared to the baselines. Limitations include a dependence on image quality and the need for larger patient groups for RL fine-tuning. Future work could integrate wearable data for real-time activity.

A. Contributions

Novel AI System for Diabetes Management: This research offers an integrated AI-based system that meets a critical need in T1D management. Unlike fragmented solutions, our system takes an end-to-end approach, covering everything from food image analysis to personalized insulin recommendations.

Advancement in Computer Vision for Nutritional Analysis: This study employs deep learning models like YOLO and EfficientNet[6], [13], [15] for precise food recognition, segmentation, and volume estimation from images. This pushes the boundaries of computer vision for dietary assessment. The method for extracting nutritional value along with uncertainty quantification is a significant technical contribution.

Development of Personalized Predictive Models: The research creates a deep learning predictive model that combines various patient health factors, such as nutritional intake, blood sugar levels, and medical history, for personalized insulin dose recommendations. Exploring reinforcement learning for continuous adaptation further boosts the model's usefulness and innovation.

Improved Patient Outcomes and Quality of Life: The most important contribution of this research is its potential to greatly enhance the quality of life for T1D patients. By automating and improving the accuracy of insulin dose estimation, the system lowers the risks of hypoglycemia and hyperglycemia. This leads to better glycemic control, fewer complications, and a greater sense of autonomy and well-being for patients. This goal aligns with using AI to improve healthcare delivery and empower patients[5], [8], [16].

V. CONCLUSION

The intelligent system discussed in this article marks an important step toward changing diabetes management for Type 1 Diabetic patients. By integrating cutting-edge artificial intelligence technologies, including computer vision for food image analysis and deep learning models for personalized insulin dose prediction, this research addresses the urgent need for precise, automated, and easy insulin dosage estimation[3], [7], [9].

The system's modular design includes accurate food recognition, strong nutritional value extraction, and personalized recommendations. It provides a complete solution to the challenges of daily diabetes self-management. Experimental results show the system's high performance, achieving 96% food classification accuracy, a 4.5g carbohydrate mean absolute error, and a 1.2-unit insulin root mean square error, surpassing traditional methods[6], [8].

Using models like YOLO and EfficientNet [8]for image analysis, along with various patient health factors and reinforcement learning, highlights the system's ability for high accuracy, efficiency, and ongoing improvement.

This research has great potential for enhancing the quality of life for diabetic patients. By taking away the burden of manual calculations and lowering the risks of incorrect insulin dosing, the proposed AI-based system helps individuals with T1D reach better blood sugar control, gain more independence, and feel a greater sense of well-being. The successful rollout and broad acceptance of such intelligent systems will represent a major advance in chronic disease management, showing the significant role AI plays in providing personalized and effective healthcare solutions[1].

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