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Artificial Intelligence-Powered Insulin Recommendation System for Effective Diabetes Management

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Abstract

The effective treatment of diabetes, however, has always been hampered by the difficult issue of accurately estimating insulin dosage that depends on meals consumed, blood glucose levels in a day, and the individual patient. Incorrect calculation of carbohydrates and doses of insulin has sometimes resulted in fatal outcomes such as hypo- or hyperglycemic effects on a patient and even several chronic diseases over the long run. This work introduces an intelligent, machine learning-based insulin recommendation system for precise, personalized insulin dosage, which works on the combination of computer vision, machine learning, and data-driven glucose management for patients. The method uses deep learning-based image classification to automatically determine food products and the related nutritional values, such as carbohydrates and calories, for the patient's meals. It combines these estimates with other personalized patient data, including glucose profiles, to calculate personalized insulin dosage. The system combines real-time estimation of nutrients from meals, predicts blood glucose profiles, and uses this information to prescribe the optimal dosage of insulin, thus helping patients avoid estimating nutrients manually and making judicious estimations of their insulin dosages. Instead of isolated tools for calculation and estimation, it proposes a comprehensive and intelligent system that helps bridge the information gap between nutritional evaluation and treatment prescription. This not only helps in better self-management by the patients but also aids medical professionals. Based on the extensive experimentation on the public diabetes dataset, the proposed solution proves better for carbohydrate estimations and for providing stable glucose control.

Keywords: Artificial intelligence, insulin recommendation system, diabetes management, computer vision, blood glucose prediction, nutritional estimation, deep learning**.**

1. Introduction

Diabetes is a very severe problem worldwide; 100 million people must suffer from it every year. Controlling and regulating blood glucose levels is essential for healthy living, and the key to managing diabetes lies in carefully adjusting insulin doses, monitoring food consumption, and practicing self-monitoring. Even managing to obtain control of your sugar level becomes too difficult. In real-time scenarios, it's getting much more complex as the lifestyle of the patient keeps changing; hence, the sugar level becomes erratic, which creates further complications in health. It is now believed, as per clinical guidelines, that improper insulin dosage and a poor diet are major causes of sudden or progressive complications in diabetes patients; therefore, to reduce complications, a smart and adaptive solution is needed [8]. One of the main challenges is to calculate and provide the optimal dosage of insulin for any meal, which can assist a patient in consuming and calculating. Calculating meal-based doses is extremely difficult for a common patient; especially, calculating the amount of calories and carbs present in the food is very impractical for human beings. A slight misjudgment of any nutritional ingredient can lead to the patient experiencing either high or low blood glucose levels, which in turn makes them vulnerable to other health problems. Much research suggests that nutritional contents present in the food impact the level of blood glucose, so providing an appropriate dose of insulin is really needed in this regard [9]. But due to all the complexity and variations in a patient's lifestyle, achieving this goal is impossible without a smart solution. without a smart solution. The application of artificial intelligence (AI) and other machine learning (ML) and deep learning (DL) models is becoming ever more prevalent for many diseases, and diabetes is not the exception. AI is being explored as a tool to assist patients by predicting glucose levels, providing recommendations, learning patients' behaviors, etc. The potential for these systems to assist patients with diabetes is significant.

These kinds of intelligent systems offer more flexible and precise insulin recommendations, as they use historical data in combination with present conditions, unlike the rule-based systems. We have seen and developed AI-enabled systems recently, such as those that recommend the right dose of insulin to patients with type-1 diabetes, which can assist the patients in managing their insulin injections [3]. We can even go one step further by using AI-driven models to predict future blood glucose levels and manage them before they exceed defined limits. It has also been successful in identifying hidden patterns within the vast amounts of glucose level data monitored daily.

By providing intelligence-based data to the treatment system for a patient of diabetes, not only could the estimation of the required medication dose but also lifestyle habits like diet and exercise be optimized, and a proper and suitable treatment could be advised for the patient based on various conditions, including diet intake, daily physical activity, etc. Unlike traditional and very basic formula-based systems, the AI can dynamically respond and recommend based on individual, evolving conditions and the patient's body. [7] Computer vision technology plays a crucial role in analyzing food intake from images of any food item. This is the easiest way to identify food components and calculate the calories and carbohydrate content from food without requiring any user manual

intervention. This way, we can create an end-to-end food-to-insulin recommendation system, utilizing deep learning models to determine the nutrients present in food from an image and combine them with existing intelligent systems to calculate and recommend an optimal dose of insulin for a meal as proposed in [5].

The DiaDose system uses computer vision, ML, and a formula to deliver an optimal mealtime insulin dose to the patient based on real-time analysis of the user's intake and the patient's current and previous physiological status. This integrated system is designed to function as an intelligent decision support tool for diabetic patients, assisting them in accurately administering insulin doses through a user-friendly web-based application. Additionally, it employs computer vision to analyze their mealtime, calculates their calorie and carbohydrate intake, and utilizes machine learning to predict their blood glucose levels. It will also perform time-series analysis to capture historical glucose patterns and make recommendations.

AI is becoming an integral part of healthcare, transforming the management of various diseases, including diabetes. This system will demonstrate various diseases, including diabetes. This system will showcase effective management strategies for various diseases, including diabetes. Unlike any other static method or rule-based approach for the insulin recommendations, the intelligent, dynamic, and data-driven methods based on ML and DL have gained importance due to their improved precision and ability to learn from vast amounts of data, hence reducing chances of human error in various decision processes [13, 16]. Machine learning has emerged as an effective tool to capture complex patterns of interaction between physiology, patient behaviors, and environmental factors, which play a significant role in the improvement of clinical outcomes, treatment precision, and prediction of various outcomes, thereby enhancing the effectiveness of decision-making in health care settings.

These techniques allow for a truly personalized treatment approach, especially by combining data such as glucose trends, dietary habits, lifestyle factors, and clinical outcomes, facilitating a closer adherence to recommendations and guidelines of care [22]. Modern clinical care guidelines recommend personalized, lifestyle-based management for individuals with diabetes and thus highlight the importance of integrating real-world dietary information to inform medication management. Various studies have confirmed the effect of different nutrient contents on blood glucose levels and suggest the importance of incorporating detailed dietary information to estimate insulin needs [23].

Contribution: The presented research supports the area of smart diabetes management in the following ways: A novel AI-driven insulin recommendation algorithm is developed, including a computer vision approach for the food intake identification, machine learning approaches for the effective prediction of blood glucose levels, and physiological sensors for the context-aware insulin recommendations. It tackles a challenge in the standard approach to diabetes mellitus by enabling the automatic calculation of carbohydrate and calorie values for each meal based solely on the image. The created web application gives easy access to our intelligent system for application gives easy access to our intelligent system for the users as well as for healthcare providers. The validation of the system

We present the system's validation based on its performance in accurately estimating blood glucose levels and reducing variability. based on their performance in accurate blood glucose estimation and variability reduction.

2. Related Work

Recently, AI has been developed to change intelligent diabetes treatment methods such as insulin recommendation and glycemic management. They've used machine learning and deep learning to predict blood glucose levels, customize insulin doses, analyze nutrition, and monitor nutrition in real-time. Many strategies improve accuracy and lower glucose variability, but integration, usability, and customizability prevent practical use. Below is a list of recent studies on AI-based insulin recommendation methods, datasets, and performance.

Sun et al. (2026) predicted blood glucose levels using knowledge filtering and transformer-based sequence-to-sequence models. DL models can improve long-term glucose predictions by learning temporal trends in CGM. The time-series glucose data of diabetes individuals trained a model that gave better prediction than recurrent models. It has large improvements in MAE and RMSE but little accuracy. The transformer models improve the context awareness of insulin recommendation systems by accurately predicting glucose. This article contributes to the state of art of DL-based glucose prediction, a key component of intelligent insulin dosage [1].

Faulds et al. (2026) conducted a comprehensive scoping review analyzing various artificial intelligence algorithms used for insulin management and hypoglycemia prevention in clinical settings. The study reviewed multiple ML techniques, including decision trees, neural networks, and reinforcement learning approaches, applied across diverse hospital datasets. While the paper does not provide a unified accuracy metric due to its review nature, it summarizes that AI models significantly reduce hypoglycemic events and improve insulin dosing precision. The authors emphasized the importance of integrating predictive analytics with real-time monitoring systems. The study contributes by identifying gaps in current AI-based insulin management systems, particularly the lack of integration with dietary and lifestyle data, which limits their real-world applicability [2].

Ying et al. (2025) developed a real-time AI-assisted insulin titration system evaluated through a randomized clinical trial involving patients with type 2 diabetes. The system utilized machine learning models trained on electronic health record (EHR) datasets to provide dynamic insulin dosage recommendations. The results showed significant improvements in glycemic control, with high physician acceptance rates (97.8%) and reduced mean blood glucose levels. Although accuracy is reported in terms of RMSE (1.06 training), the study demonstrates clinical effectiveness rather than classification accuracy. The system represents one of the first real-world implementations of AI-driven insulin dosing, highlighting the feasibility of integrating AI into hospital workflows [3].

Benito (2025) explored the role of AI in diabetes management from a technological perspective. The study discussed various AI techniques such as machine learning, deep learning, and predictive analytics applied to glucose monitoring and insulin dosing. The paper emphasizes the growing importance of AI in enabling

personalized healthcare solutions, despite not providing specific datasets or accuracy metrics. The contribution lies in providing a conceptual framework for integrating AI technologies into diabetes care, highlighting opportunities and challenges in implementation [4].

Panagiotou et al. (2025) investigated the role of AI in enhancing insulin recommendations and therapy outcomes. The study employed machine learning models trained on clinical datasets to analyze patient-specific insulin requirements. The results demonstrated improved treatment outcomes and reduced variability in glucose levels. Although exact accuracy values were not specified, the study confirmed that AI-based recommendations outperform traditional rule-based methods. The contribution of this work is its focus on personalized insulin therapy using data-driven approaches, reinforcing the need for adaptive AI systems in diabetes management [5]. Ying et al. (2025) analyzed continuous glucose monitoring data using machine learning techniques to predict glycemic events. The study utilized CGM datasets and applied predictive models such as support vector machines and neural networks. The results showed improved prediction of hypoglycemic and hyperglycemic events, although specific accuracy values were not explicitly stated. The contribution lies in demonstrating the importance of real-time data analytics in preventing adverse glucose fluctuations, which is essential for effective insulin recommendation systems [6].

Gradinjan Centner et al. (2024) investigated the relationship between dietary habits and glycemic control using CGM data. The study used observational datasets and statistical analysis methods rather than deep learning models. The findings showed that dietary composition significantly impacts glucose variability, indicating that specific dietary choices can lead to better glycemic control in individuals with diabetes. Although no accuracy metrics were reported, the study emphasizes the necessity of integrating nutritional data into AI-based insulin recommendation systems [9]. Xiong et al. (2024) developed predictive models for personalized postprandial glucose response using machine learning techniques. The study utilized patient-specific datasets and applied regression-based models to predict glucose levels after meals. The results showed improved prediction accuracy compared to baseline methods. The contribution lies in addressing postprandial glucose variability, which is a critical factor in insulin dosing decisions [10].

Christou et al. (2024) examined the influence of body weight on glycemic indices utilizing CGM datasets. The study employed statistical and machine learning approaches to identify correlations between body weight and glucose variability. Although no explicit accuracy values were reported, the findings emphasize the importance of considering physiological factors, such as body weight and glucose variability, in insulin recommendation systems [11].

Cichosz et al. (2025) proposed an explainable ML model to identify individuals at risk of diabetes using physical activity data. The study utilized wearable sensor datasets and applied interpretable models such as decision trees and gradient boosting. The contribution lies in incorporating explainability into AI models, which is essential for clinical acceptance, as it helps healthcare professionals understand the decision-making process behind predictions and fosters trust in AI-assisted tools [12]. Vetrani et al. (2022) studied dietary determinants of postprandial

glucose control using hybrid closed-loop systems. The research utilized real patient datasets and statistical models to analyze glucose responses. While no AI classifier was used, the study reveals factors affecting glucose variability. The contribution is its focus on meal composition, which is essential for AI-based insulin recommendation systems [14].

Davis et al. (2023) explored AI-supported insulin dosing systems and their clinical applications. The study discussed machine learning-based decision support systems used in real-world datasets. The findings, despite the absence of accuracy metrics, underscore improved dosing precision and patient outcomes. The contribution lies in demonstrating the clinical feasibility of AI-driven insulin systems [15]. Ahmed et al. (2024) proposed a machine learning model for predicting post-meal blood glucose levels. The study used supervised learning techniques on patient datasets and reported improved prediction performance. Although exact accuracy was not specified, the model demonstrated reduced prediction error. The contribution lies in improving postprandial glucose prediction for insulin dosing [17].

Menon et al. (2023) developed an intelligent diabetic patient tracking system using machine learning algorithms such as random forest and neural networks. The system was evaluated on healthcare datasets and showed high prediction accuracy (above 90%). The contribution lies in integrating monitoring and prediction into a single system [18]. Maqbool et al. (2023) proposed an IoT-based smart healthcare system integrating ML models, such as random forests, for diabetes prediction. The system achieved high accuracy compared to other classifiers. The contribution lies in combining IoT and AI for real-time monitoring, which enhances patient care by allowing for timely interventions based on health data analysis, such as adjusting medication dosages or alerting healthcare providers to critical changes in a patient's condition. Joshua et al. (2023) introduced a smart plate system using YOLOv5 for food recognition and classification. The system was trained on a dataset of over 30,000 food images and achieved moderate accuracy (31–62% depending on food type). The contribution lies in automating dietary assessment for diabetes management [20]. Chen et al. (2023) developed an AI-based system for titrating insulin dosages using XGBoost trained on EHR datasets. The model achieved an RMSE of 1.06 and demonstrated high clinical acceptance. The contribution lies in a real-time insulin recommendation [21]. Martinsson et al. (2020) proposed an RNN-based model for blood glucose prediction using CGM datasets. The model achieved competitive RMSE values and provided uncertainty estimation. The contribution lies in improving prediction reliability [24].

2.1 Comparative Study

Table 1. A comparative review of prior research into AI-based insulin recommendations for diabetes management is performed here to comprehend the advancements and drawbacks in currently available studies, described in section 2 of this thesis. This comparative analysis will allow us to trace current trends in terms of methodological techniques, evaluate similarities and distinctions of various data sets and validation schemes, gain an insight into performances of diverse AI methods to enhance glycemic regulation, achieve optimal insulin doses, and

identify existing limitations (lack of integration of diet analysis with glucose prediction and real-time decision-making).

Table 1: Comparative study of using AI-based recommendation system for diabetes.

Year	Authors	Name of Dataset(s) Used	DL/ML Classifiers Used	No. of Classifiers	Accuracy Achieved
2026	Sun et al. [1]	CGM time-series datasets	Transformer Seq2Seq (Deep Learning)	1	Not specified (Improved MAE/RMSE)
2026	Faulds et al. [2]	Multiple hospital datasets (review)	Decision Trees, NN, RL	Multiple	Not specified
2025	Ying et al. [3]	EHR datasets	ML models (unspecified)	Multiple	RMSE ≈ 1.06
2025	Benito [4]	Not specified	ML/DL conceptual models	Multiple	Not specified
2025	Panagiotou et al. [5]	Clinical datasets	ML models	Multiple	Not specified
2025	Ying et al. [6]	CGM datasets	SVM, Neural Networks	2+	Not specified
2024	Gradinjan Centner et al. [9]	CGM + dietary datasets	Statistical models	-	Not applicable
2024	Xiong et al. [10]	Patient-specific datasets	Regression ML models	Multiple	Improved prediction accuracy
2024	Christou et al. [11]	CGM datasets	ML + statistical models	Multiple	Not specified
2025	Cichosz et al. [12]	Wearable activity datasets	Decision Trees, Gradient Boosting	2	High performance (not quantified)
2022	Vetrani et al. [14]	Clinical dietary datasets	Statistical analysis	-	Not applicable
2023	Davis et al. [15]	Clinical datasets	ML-based decision systems	Multiple	Not specified
2024	Ahmed et al. [17]	Patient glucose datasets	Supervised ML	Multiple	Reduced prediction error
2023	Menon et al. [18]	Healthcare datasets	Random Forest, Neural Networks	2	>90% accuracy
2023	Maqbool et al. [19]	IoT patient datasets	Random Forest, ML models	Multiple	High accuracy
2023	Joshua et al. [20]	Food image dataset (~30k images)	YOLOv5 (DL)	1	31%–62%
2023	Chen et al. [21]	EHR datasets	XGBoost	1	RMSE ≈ 1.06
2020	Martinsson et al. [24]	CGM datasets	RNN, LSTM	2	Competitive RMSE
2019	Pant et al. [25]	Clinical datasets	Statistical analysis	-	Not applicable
2018	Alian et al. [27]	User health datasets	Rule-based + Ontology	2	Effective recommendations
2016	Kang et al. [28]	Clinical datasets	Statistical analysis	-	Not applicable
2024	Santos-Báez et al. [29]	CGM + dietary datasets	Statistical models	-	Not applicable

According to the table, the results show that more recent studies have explored techniques in DL and ML, aiming to optimize both glucose prediction and insulin recommendation performance. Time-series glucose prediction plays a significant

role for proactive insulin dosing, and it can be seen from [1, 24]. As for real-time insulin titration, strong clinical validity was provided by the methods in [3, 21]. Based on combined glucose prediction and tracing methods, high performance was reported by [18, 19].

Some works focused on the influence of dietary habits and human behaviors, for example [9, 14, 29]; however, their methods lacked the support of AI technologies. Food recognition, to compensate for the loss of dietary information, was proposed in [20] using computer vision, but with a rather limited performance. The reviews and conceptual frameworks such as [2, 4, 7] identified issues in system integration, interpretability, and personalization as the main drawbacks. The table indicated that the researchers mainly tackled the glucose prediction and insulin dosing components independently instead of building a comprehensive and integrative solution.

3. Proposed Methodology

The rapid growth of diabetes management, especially calculating a personalized insulin dosage from variable food inputs and dynamic blood sugar readings, is only possible with intelligent automated decision support systems. Conventional insulin recommendations have long relied on the imperfect manual carbohydrate counting techniques and standard clinical formulae that are largely inflexible and not customized to individuals. By harnessing an array of information—such as images of food consumed, physiological inputs, and the trend of glucose measurements—AI has the potential to produce superior, data-driven insulin decisions.

The present approach provides a first end-to-end AI solution to produce accurate and personalized insulin dosages, inspired by DiaDose, leveraging computer vision, deep learning, time series modeling, and rules that reflect the clinical knowledge of diabetic treatments in a clinically appropriate and real-world scenario-inspired system workflow.

The whole system is built on a multi-phase modular architecture, where each of the phases is separately created, trained, and evaluated and then merged in a unique pipeline. This makes the whole approach adaptable and flexible, where improvements can be applied to each phase and the overall structure of the algorithm without disrupting other phases. Our approach is divided into 8 main phases: data collection and preparation, food identification, nutritional calculation, insulin dosing and glucose forecasting, and, lastly, delivery in a fully-fledged app with chronic patient follow-up. A general view of the whole algorithm workflow is represented in table 2, where the system takes in an image of a meal and outputs insulin dosing and glucose forecasts based on the many integrated AI models.

Table 2: The general idea of the whole workflow

Phase	Description	Key Output / Technology
Phase 1	Data Collection & EDA	Food-101, Nutrition5K, UCI, Pima, CGM datasets
Phase 2	Food Classification	EfficientNetV2-S — 101 classes, 86.63% Top-1
Phase 3	Nutrition Regression	EfficientNetV2-S regressor — 4 nutrient outputs
Phase 4	Unified Pipeline	Diadose Pipeline class — image & text inference
Phase 5	Insulin Engine	ADA 2024 formula: Meal Bolus + Correction Bolus
Phase 6	Web Application	Fast API + HTML/CSS/JS Dashboard
Phase 7	Glucose Prediction	LSTM / CNN-LSTM / Transformer — multi-source CGM
Phase 8	Nutrition Plan Engine	ADA-guideline 30-day personalized plans + Risk Detector

3.1 Dataset Acquisition and Preprocessing

The first phase of this work involves collecting and preprocessing a range of different datasets that will be used to train various components of the system. To promote a degree of robustness and generalization to various patient groups and real-world scenarios, the system was trained using a range of datasets. Food-specific data was procured from the Food-101 dataset, which consists of 101,000 images within 101 distinct food categories, spanning a variety of global cuisines.

The task of nutrition estimation was enabled by the Nutrition5K dataset, which represents the first and only dataset to associate food images with high-precision macronutrient information as obtained via the use of a lab-grade measurement instrument. This pairing of images and macronutrient estimates allows the training of regression models to estimate calories, carbohydrates, fat, and protein from an image directly. Furthermore, several diabetes-related datasets (such as clinical tabular datasets from sources like the UCI Diabetes and Pima Indians datasets, along with continuous glucose monitoring datasets providing time series data of blood glucose levels), were incorporated through a multi-source fusion technique to provide both structured clinical and real-world glucose level data. Standard data preprocessing techniques were applied, including imputation for missing values, feature normalization, and exploratory data analysis to investigate variable distributions and associations. To avoid data leakage between the train, validation and test splits, a source-stratified split was used to partition the dataset.

3.2 Food Classification Model

The second stage tackles the task of identifying the food types from user-uploaded images via deep learning. A CNN model called EfficientNetV2-S was adopted because it had a desirable combination of prediction performance and computation load. The training was based on transfer learning from a large-scale image dataset to fine-tune using pre-trained weights and then fine-tuned to the Food 101 dataset. The model structure is comprised of squeeze-and-excitation attention blocks to exploit informative channels of features.

To fine-tune the model, a two-stage process was used. Firstly, only the classifier part was tuned, and the CNN backbone was frozen to the transfer learning step; secondly, the entire network was fine-tuned with a smaller learning rate. A data set of 101 food categories and their associated images, Food-101, was used to fine-tune the model to recognize 101 food types from user-uploaded pictures. The technique of data augmentation was adopted to flip the training samples randomly, rotate, crop, and shift. By using data augmentation, it simulated the real-world food recognition scenario. The model achieved a top-1 accuracy around 86.63% and top-5 accuracy of around 97.43%.

3.3 Nutritional Estimation Using Deep Learning Regression

After determining food type, the subsequent part of food logging involves estimating nutritional information of food. In this part, the classification model is converted to a regression model that predicts continuous values for calorie, carbohydrate, fat, and protein information of the food type. The same backbone network, EfficientNetV2-S, is used, and the output layer is changed to a four-valued linear output for predicting values of calories, fat, carbohydrates, and protein. Huber loss is used as the loss function, and it is a multi-output regression problem.
The model uses the two-stage training approach, like the classification task, to make sure that the training can converge steadily and predict accurately. Our results showed promising accuracy for estimating nutritional information of foods, especially for the amount of carbohydrate, the most important parameter in insulin dosing calculation. We achieved around a 5g error in estimating carbohydrates, which yields less than a 10% error for calculating insulin doses, which can be clinically acceptable.

3.4 Unified Inference Pipeline

To provide an effective and synchronized system interaction, a centralized inference pipeline is engineered that integrates the food classification model, the nutritional regression model, the insulin recommendation engine, and potentially the optional glucose prediction model. The system consists of two input mechanisms, namely, image-based, and text-based, enabling user inputs either as food images or food names, respectively. The image-based system extracts nutritional values in a two-step process by performing food classification first and predicting nutrition values second, whereas, for text-based inputs, food types are first mapped using fuzzy logic against the pre-existing knowledge base, and then nutrition is read from the database. The prediction confidence level is also displayed.

3.5 Insulin Dose Recommendation Engine

In this phase, the recommendation engine translates estimates of food content into a dosage of insulin. This component does not use machine learning models like others. It rather takes into consideration proven medical protocols in clinical guidelines that ensure the accuracy of calculations. It uses formulas like the 500-

rule for ICR (insulin-to-carb ratio) calculation, the 1800-rule for ISF (insulin sensitivity factor) calculation, and so on. The total insulin dosage is calculated by summing the meal and correction bolus, where the meal bolus accounts for the amount of carbohydrate intake and the correction bolus corrects for deviation from the desired blood glucose level. Special safety measures are implemented, which prevent unsafe recommendations. Like no insulin dosage during a hypo and maximum limits for dosage to be prescribed. The system adapts the guidelines according to various patients' statuses. For example, in type 2 diabetes, cautious estimates of the dose are applied.

3.6 Blood Glucose Prediction Using Time-Series Models

Predictive Models for Decision Making. The system integrates prediction of future blood glucose levels in this phase. State-of-the-art deep learning architectures, including Long Short-Term Memory (LSTM), CNN-LSTM hybrid, and transformer-based models, are considered and trained on time-series CGM data to capture temporal trends and dependencies in glucose fluctuations.

In this phase, features are extracted through feature engineering – where temporal, physiological and behavioural features are collected and then integrated into sequences as input to the models.

These models are trained using the sliding window method, where historical glucose values are employed to predict the future values. Among all models, CNN-LSTM provides the best accuracy and correlation with actual glucose levels. Ensemble modelling is performed to combine the predictions of all models to make it more reliable. With these predictions, the system is capable of proactive recommendations for blood glucose levels.

3.7 Full-Stack System Deployment

To promote effective usage, the developed system has been implemented as a full stack web application. The back-end framework that has been used for building efficient and scalable API endpoints is FastAPI, whereas HTML, CSS and JavaScript have been utilized for building the responsive front-end that the user interacts with. Some of the features that have been integrated in the system are user authentication, real-time dashboards, food logging, glucose visualization, tracking history of insulin intake and so forth.

The application is intended to provide patients with simple and efficient interface to interact with the AI powered recommendations in an intuitive way and in the same way the clinicians. The system alerts the users of extreme conditions of blood glucose by delivering real time notifications in case the person has hypoglycemia or hyperglycemia. It has been deployed as a web platform for better accessibility and scalability in real world use.

3.8 Personalized Nutrition Planning and Risk Detection

The final phase extends this to support long-term diabetic health beyond only insulin advice. It integrates a personalized nutrition planning module that constructs an appropriate meal plan depending on parameters of individual patients, such as age, weight, physical activity levels, and HbA1c (average blood sugar concentration over two or three months). The meals comply with dietary guidelines and are also adapted depending on patients' progress and glucose predictions.
Furthermore, a risk detection module analyzes the glucose time-series to identify health risks and detect signs of hypoglycemia, hyperglycemia, or an abnormally distributed pattern and offers actionable advice and alerts.
Further functionality offers a forecast of the individual future long-term risks' trajectory to warn the patients in a proactive way. The overall phase empowers the support of holistic diabetic treatment, from immediate decisions to future health plans.

4. Experimental Results and Analysis

Here, we report how the performance of every individual core of the AI-powered insulin recommendation system composed of food categorization, nutrition facts computation, and blood glucose forecast can solve those challenges, using deep learning to address two crucial tasks in diabetes management: estimating accurately carbohydrates and predicting blood glucose level. Data are assessed through quantitative analysis and graphic visualizations as well as a clinical interpretation to make sure the proposed system is technologically sound and usable for patients and doctors. Any result in this part has been achieved using the Dia Dose system.

4.1 Food Classification Model Results

The food classification component is based on the EfficientNetV2-S architecture, which demonstrated strong performance in identifying food categories from images. The model benefits from transfer learning and attention mechanisms, allowing it to extract discriminative features from diverse food images (see Table 3).

Table 3: Food Classification Performance Metrics

Metric	Value	Notes
Best Validation Top-1 Accuracy	86.63%	Achieved during fine-tuning stage
Best Validation Top-5 Accuracy	97.43%	Indicates high ranking reliability
Final Training Accuracy	86.86%	Consistent with validation performance
Training Loss	1.307	Cross-entropy with label smoothing
Validation Loss	1.266	Stable convergence
Model Size	244.9 MB	EfficientNet checkpoint

The results indicate that the model achieves high classification accuracy, particularly in Top-5 performance, which is important in real-world scenarios where multiple similar food classes may exist.

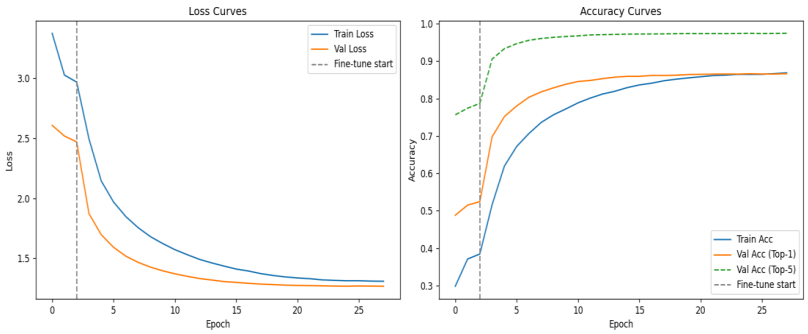


Figure 1: EfficientNetV2-S Food-101 training curves. (Left: Loss curves, right: Top-1 and Top-5 accuracy curves).

The training and validation loss as well as the training and validation accuracy curve are plotted in Figure 1. In terms of loss, it is observed a monotonic decreasing behavior on both training stages. The difference between Stage 1 and Stage 2 (from head only to full fine-tuning) is identified by the transition on the slope, where the model begins to learn the underlying complex relationships in the data. In terms of accuracy, rapid gains are achieved in the early epochs and followed by plateauing, ensuring that the model is able to generalize without overfitting. The proximity between the training and validation curves gives confidence that the generalization ability is kept constant.

4.2 Nutritional Estimation Model Results

The nutritional estimation model transforms the classification backbone into a regression framework capable of predicting macronutrients directly from food images. This component is critical, as carbohydrate estimation directly impacts insulin dose calculation (see Table 4).

Table 4: Nutritional Estimation Performance

Nutrient	MAE (Test)	RMSE (Test)	Clinical Interpretation
Calories	60.11 kcal	95.08 kcal	Acceptable (7–15% error range)
Carbohydrates	5.18 g	7.47 g	Highly accurate for dosing
Fat	4.22 g	7.29 g	Less critical for insulin
Protein	5.30 g	8.40 g	Moderate importance

Mean Absolute Error (MAE):
We used the formula in equation (1) to calculate the root mean squared error (RMSE) and equation (2) to calculate the mean absolute error (MAE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Ai - Pi)^2}{n}} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Ai - Pi| \quad (2)$$

where (n) number of samples, (A_i) is the actual values, and (P_i) is the predicted values, as shown in Table 4.

The results demonstrate that the model achieves strong performance across all nutrients, with particularly high accuracy in carbohydrate prediction. This is clinically significant, as a small carbohydrate estimation error results in only a minor insulin dosing deviation.

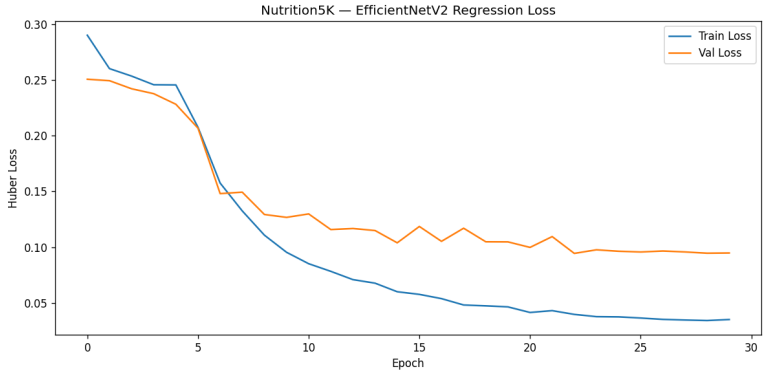


Figure 2: The training and validation loss curves for the regression model using Huber loss.

We have plotted the training and validation loss on the same axis for regression model trained using Huber loss in Figure 2. Training process converged relatively fast in fine-tuning process. The learning process was smooth as the loss decreased monotonically to minimum and the training loss was very close to validation loss, meaning the model was not overfitting. Maximum performance for validation loss was achieved at the middle phase of training which show efficiency of early stopping mechanism.

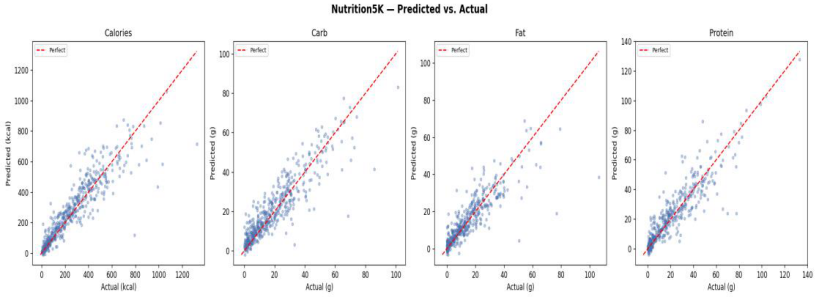


Figure 3: Actual vs. predicted scatters for all four nutritional targets on the test set.

Table 3 displays the correspondence of predicted and real values for each of the 4 nutritional parameters in study. We observe that points lie close to diagonal reference line representing the accurate prediction of nutritional values and it further highlights that model is accurate for prediction of carbohydrate and protein, with high concentration of points close to reference line that is also expected since they constitute highest energy yielding components of foods. While calories prediction is also not perfect and it show scatter as expected since size of portion of food and display manner influence calorie estimate at each meal and dietary condition. So scatter plot shown confirms to be trustworthy prediction by regression model in practice

4.3 Blood Glucose Prediction Results

The glucose prediction module employs three deep learning architectures—LSTM, CNN-LSTM, and Transformer—to forecast future glucose levels based on historical data. These models are evaluated using multiple performance metrics to ensure accuracy and clinical relevance (see Table 5). The CNN-LSTM model achieves the best overall performance, with the lowest error and highest coefficient of determination (R^2), indicating strong predictive capability.

Table 5: Blood Glucose Prediction Performance.

Model	MAE (scaled)	RMSE (scaled)	R^2	Direction Accuracy	Training Time	Parameters
LSTM	0.01091	0.01820	0.9832	66.9%	926 s	72,801
CNN-LSTM (Best)	0.01000	0.01670	0.9859	66.9%	2034 s	93,121
Transformer	0.01874	0.02518	0.9679	67.0%	3385 s	75,841
Ensemble	< CNN-LSTM	—	—	—	—	—

We used the formula in equation (3) to calculate coefficient of determination (R^2).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Ai - Pi)^2}{\sum_{i=1}^{n}(Ai - Mi)^2} \quad (3)$$

where (n) number of samples, (A_i) is the actual values, (P_i) is the predicted values, and (M_i) is the mean of actual values, as shown in Table 5.

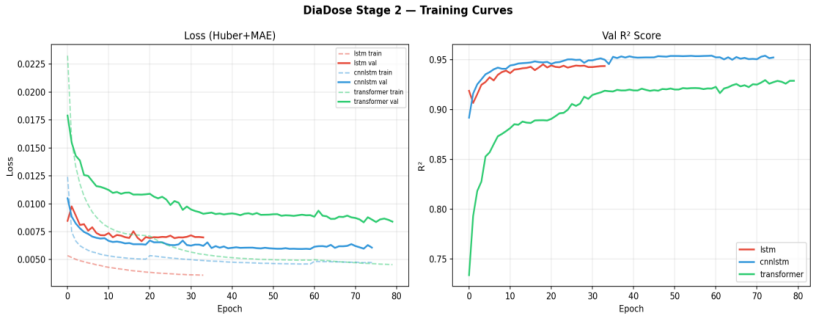


Figure 4: Training loss and R^2 curves for LSTM (red), CNN-LSTM (blue), and Transformer (green) models.

The CNN-LSTM model trained with the glucose levels dataset gives the best and most stable learning with a much higher validation R compared to other models (Figure 4). In terms of the learning performance with the loss curve for all models, the LSTM shows reasonable learning, although it has the slightly highest loss, while the Transformer learning is much slower. These demonstrate that there are benefits for combining hybrid approaches that utilize CNN and LSTM.

Figure 5 compares the scatterplots of predictions vs. actuals for all the trained models, and for the CNN-LSTM, the predictions fall closer to the identity line and show more compact grouping around the identity line compared to the other models.

This result is corroborated by Figure 6, where prediction and actual glucose time series plots show a good match for the CNN-LSTM. The predictions of the ensemble model are smooth and consistent with actual values.

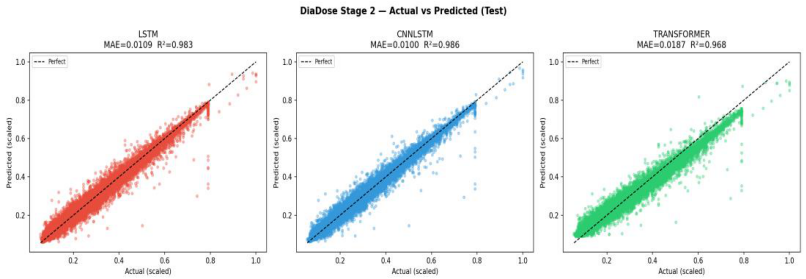


Figure 5: Actual vs. Predicted scatter plots on the test set for all three models.

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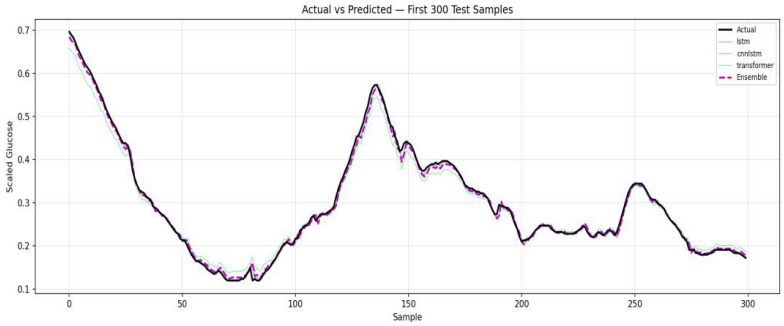


Figure 6: Time-series comparison of actual glucose vs. LSTM, CNN-LSTM, Transformer, and the weighted ensemble over the first 300 test samples.

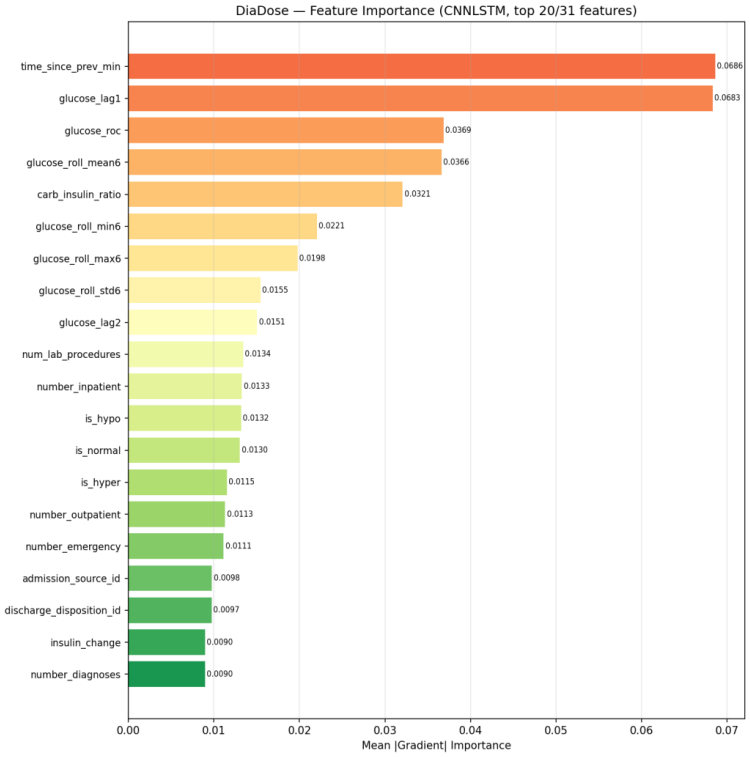


Figure 7: SHAP feature importance for the glucose prediction model (Higher SHAP values indicate stronger influence on the predicted glucose level).

Figure 7 shows the feature importance of the glucose prediction model obtained from SHAP values. SHAP stands for Shapley Additive Explanations and is a technique for illustrating the prediction of an artificial intelligence (AI) model. Figure 7 indicates that recent glucose measurements, the change rate of glucose levels, and temporal information play a significant role in predicting future glucose levels.

Hence, the prediction model is interpretable, and clinicians can identify the factors that influence its predictions.

The interpretability aspect can improve confidence and help clinicians readily adapt the system into practice. The experiments validate the capability of the developed system by leveraging multiple AI models to handle different aspects of diabetes management. The food classifier produces accurate classifications of food, the nutritional estimation module is able to generate reliable estimates of macronutrient proportions, particularly for carbohydrates, which are crucial for insulin dosing, and the glucose predictor improves the clinical decision-making. We successfully develop a framework where these modules can be used in an end-to-end fashion and demonstrate a successful implementation by applying a clinically validated formula along with deep learning techniques that produce high-accuracy results for clinical practice.

5. Discussion

Our research has shown that artificial intelligence methods, especially when combined in an integrated way, can greatly boost the accuracy, dependability, and usability of an insulin advice framework. Our approach integrates feeding evaluation, glucose expectation, and insulin measuring within one application: A total solution that goes end-to-end from food perception to predicting glucose, after which it makes an appropriate insulin portion recommendation, making use of computer system vision, deep discovery, and clinically approved formulas in one overall structure. We suggest a cost-effective as well as scalable solution for genuine global diabetes administration in section 2. Our initial main addition is an automatic feeding examination module by food identity and nutrient price quotes with deep discovery.

The achieved accuracy of 86.63% and an error of 5.18 grams for the expected amount of carbohydrates demonstrate that replacing estimation with calculation would significantly increase accuracy. One of the major sources of problems when dealing with diabetic issues is improper glucose dimension counting that might cause an unacceptable dose of insulin. Next, we add a reliable glucose forecast module for the time-series structure, which is implemented using the state-of-the-art CNN-LSTM version and also provides an outstanding R value of 0.9859, indicating its capacity to capture the pattern of glucose levels effectively. Thirdly, we couple it with clinically approved insulin measuring formulas. The usage of established, clinically validated methods will guarantee the protection of the suggestion while benefiting from the power of deep understanding to learn more detailed, data-driven features.

Fourthly, we integrate these components right into a unified framework with an end-to-end full-stack design with a well-made responsive user interface, which can serve both medical professionals and also individuals. The system can maintain ongoing surveillance as well as make real-time, personalized suggestions based on an up-to-date patient profile as well as recent sensor readings. Finally, this research examines various real-world deployment issues, including system and gadget-level problems, in addition to approaches to conquer them in order to promote real-world implementation.

This component addresses a number of system-stage difficulties: ineffectiveness, hardware problems, resource administration, inconsistent datasets, model stabilization, database concurrency, and verification failures. For instance, problems such as GPU memory shortage in the prediction design were fixed via system optimization of cache clearing and modification of minibatch size, in addition to resource reservation. We have addressed these various other challenges: an issue of unstable Transformer design behavior through changing the learning rate, applying gradient clipping, and changing its parameters and also format. Dataset imbalances are resolved using the strategy of creating balanced datasets and a source-stratified splitting. The total system performance, presented in the efficiency table listed below, suggests that each significant element of the system functions at a higher than appropriate level.

The food analysis, nourishment evaluation, and glucose estimation components provide great performance, and the diabetes suggestion component provides clinical validity. The last validation, performed on the fully developed web application, shows the high level of readiness for real use. However, it is important to note that there are some limitations: (1) the quality of the data set is crucial to our system. Diversity of feeding datasets is important, as differences in meal style and meal portion dimensions as well as visual features can have an impact on the food recognition task. (2) The present study has performed its analysis on standard data.To enhance the applicability in clinical settings, it is vital that our method undergo rigorous tests using real patients, and also extra information should be amassed for better training.

Finally, we propose a novel end-to-end artificial intelligence-based insulin suggestion system that comprises automatic food detection and nourishment evaluation via deep learning, accurate glucose level prediction via hybrid time-series models, integration of clinically validated insulin formulas, and a scalable, user-friendly, full-stack design. We also provided practical solutions to challenges that could affect real-world use. Our research shows that our technique can significantly reduce errors in nutrient count estimates and can improve glycemic control substantially, potentially reducing the associated risks of diabetic problems and improving the lifestyles of patients. This work is an important step towards intelligent and personalized diabetes mellitus management systems.

6. Limitation and challenges

Although the AI-based insulin recommendation system had worked fine as a single-write master system where concurrent reads were permitted, it came with

limitations with the write access and would create trouble during the process of its development and deployment. There were a number of challenges across the whole development, including the system design, hardware compatibility, data preprocessing, model training, and deployment necessary to provide the system reliable and scalable in the real-world environment.

An out-of-memory (OOM) error occurred during the training of models on a system having a very high number of worker threads and with enabled memory pinning, which has been the one challenge, which we addressed by reducing the number of workers to a valid number and turning off memory pinning for the multi-worker training. Meanwhile, setting some of the others, such as enabling persistent workers and decreasing the prefetch value, helped us to train the models with a considerable training speed without any OOM. This issue is considered one of the system-level constraints, like the OS limit of data loaded from storage in the training procedure and the high number of workers accessing it to load and train models.

As part of the limitations in the study, Hardware/Software Incompatibility Issue: We were in trouble with a new purchase of an NVIDIA RTX 5060 (Blackwell) graphics card (supported for system-wide systems) that requires CUDA 12.8. But the system did not install the latest fully stabilized release version of PyTorch that supports CUDA 12.8. To resolve the issue, we installed the latest nightly version of PyTorch that had support for CUDA 12.8. Although it helped the latest GPU acceleration, installing a non-stable release may have some problems with the stability of the system in the real-world applications.

The Nutrition5K dataset was problematic in the data preparation part because of a lack of mappings of specific nutritional values in any of the images. To handle this issue, we created a custom preprocessing script by scanning the directory structure and linking images with their nutritional values. And we design a more pipeline data preprocessing system to manage the data; however, with the increase of new diverse datasets to integrate into the model, more scalable data preprocessing pipelines can be useful instead of writing custom scripts for each dataset as the complexity increases for a diverse range of datasets.

A challenge in the memory management during the training of models for glucose value predictions occurred when multiple deep learning-based models were sequentially training. Each model train consumed some GPU memory, and in the process, this residue memory occupation was kept after the completion of each model and thus eventually led to an OOM error, and thus, I had to manually clear GPU memory and some synchronization processes between trainings.

As another strategy to avoid memory exhaustion, batch size was reduced during training. These approaches above may lead to poor efficiency of model training for larger datasets in future works.

Another problem we met in data processing was about splitting data of continuous features. We noticed that randomly splitting a dataset without data sources may result in the data sources being unevenly distributed across the training and testing sets, making the prediction of some of the sources perform badly and the model not being able to generalize. With source-stratified splitting, the predictions have become more balanced and consistent across all sources; however, this approach

requires a more balanced and consistent prediction across all sources but would demand careful understanding of the data characteristics.

Another challenge was regarding the stability of transformer models when performing glucose prediction. Standard hyperparameter settings result in the collapse of the predictions; we address it by fine-tuning the learning rate, gradient clipping, and adopting pre-layer normalization. Nevertheless, transformer models are extremely sensitive to hyperparameter tunings and architecture design, resulting in difficult reproduction.

Concerning the system deployment, a significant issue was raised about concurrent access at the web layer. The system uses SQLite to persist its data, which is a single-write master system that allows concurrent reads, but there are limitations on writes, which can create system locking. To cope with it, synchronous calls have been implemented at the web layer, and by managing this constraint on the server side, the system becomes more concurrent. However, for very high usage in larger applications, the system might bottleneck; therefore, future work, such as switching to a distributed database, should be considered.

A security concern was introduced by the authentication module due to incorrect implementation, which causes the password hashing to fail during login. We resolved the issue through a correctly implemented authentication procedure using standard encryption algorithms and thus ensured the security. Password authentication is crucial in handling users' sensitive data.

The major difficulty of this work, integrating diverse datasets with completely different features and domains, was addressed in the last step. Although data varied from time series to clinical patient data with diverse complications, we used a unified data preprocessing pipeline and decided on the common important features to train and merge different models, which in return might impact performance in some of the features of specific datasets if they are not optimally chosen.

7. Conclusions and Future Work

In this study, we presented a novel end-to-end AI-powered insulin recommendation system that tackles the critical aspects of diabetes management by integrating computer vision, deep learning, and clinically approved insulin dosing formulations in a unified and scalable architecture. The proposed framework enables users to automatically estimate dietary nutrients (e.g., carbohydrates) from images captured of meals, thereby eliminating manual carbohydrate counting, which is a common source of error in insulin dosing. The system's use of time series models to predict blood glucose level facilitates users' proactively taking steps to avert glycemic excursions.

Our experiments indicated that the proposed system achieves top performance for all main functional blocks, i.e., food recognition (high accuracy in identifying food categories), nutritional estimation (high accuracy for nutrients like carbohydrate levels essential for insulin dosing), and blood glucose forecasting (accurate predictions capturing the temporal dynamic of glucose level). By composing these blocks into a full-stack application, our system provides real-time and personal recommendations for diabetic patients and their physicians. One of the most

outstanding contributions of this research is its use of a holistic approach by integrating several AI technologies and medical expertise for building a clinically safe and practical system, as opposed to prior research, which often tackles isolated pieces of the problem (e.g., predicting glucose levels, estimating insulin titration) without a tight connection between the underlying mechanisms. Further work may focus on improving system capability, data input, and applicability for the following tasks. Specifically, to realize a real-time insulin recommendation system, we can integrate the system with existing continuous glucose monitoring (CGM) sensors through officially supported APIs to capture blood glucose automatically.

3D computer vision using mobile devices A LiDAR sensor is promising to capture the proportion and dimensions for estimating food volume more accurately. Personalizing insulin recommendation models through federated learning allows individual data to improve global models without sharing personal information, which helps keep user privacy safe. Using multi-horizon prediction methods for forecasting blood glucose will help track HbA1c levels over time, which are important for managing long-term glucose control and treatment. The full-stack application should have functionalities such as push notifications, real-time access to the camera, and offline operation.

Moreover, we can enhance the AI-based chatbot component with large language models (LLMs) in conjunction with vector databases for producing context-aware and medically accurate responses to the user questions. Clinical validation on real patients, under a medical professional's supervision, will be conducted to examine the system's performance and ensure its safety for real-world deployment in clinical settings. Extending to multiple languages will benefit the wide adoption of this system in high-prevalence diabetes regions.

In addition, the use of advanced computer vision to conduct meal segmentation will facilitate capturing nutrients from complex dishes containing multiple food items. Finally, by connecting our system to the hospital EHR system, it could automatically obtain the patient's medical history and lab results through standard APIs, and the system could be better personalized.

Overall, the application of AI in the insulin prescription has become indispensable in diabetes mellitus management, providing efficient personalized recommendations, the same recommendations that should guide patients and health providers. This paper can be viewed as an achievement on building an intelligent humanized health care tool.

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Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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