Analyzing and Predicting Blood Glucose Responses to Dietary Intake

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***Abstract*—Maintaining stable blood glucose levels is essential for overall health, yet the dietary factors influencing these fluctuations remain complex and highly individualized. In this study, we analyze continuous glucose monitoring data in conjunction with a detailed food diary to identify specific foods and food combinations ("red foods") that consistently lead to marked glucose spikes. By correlating the timing of meals with subsequent glucose elevations above clinically relevant thresholds (e.g., 140 mg/dL), we assess both the magnitude and duration of these glucose excursions and link them to preceding dietary intake. Using this approach, we highlight foods that frequently exacerbate glycemic responses and compare them against more stabilizing ("green") foods—those that may help moderate glucose increases when consumed together. To further quantify these relationships, we employ text-based feature extraction and regression models to predict glucose responses from meal descriptions. Our results demonstrate that certain refined carbohydrates, sweetened beverages, and sugary snacks often precipitate higher glucose excursions, while the presence of fibrous vegetables and lean proteins may mitigate such effects. This framework offers a data-driven method for pinpointing problematic foods and guiding more balanced dietary choices, ultimately aiming to inform personalized nutrition strategies for improved glycemic control.**

I. Introduction

Managing blood glucose levels is not just a clinical concern; it touches the everyday lives and experiences of individuals living with diabetes and other metabolic conditions. For many, this management process can be challenging, involving continuous glucose monitoring, careful dietary planning, and a constant awareness of how their food choices influence their overall health. When imbalances occur, they can lead to serious complications, including cardiovascular diseases, nerve damage, and vision problems. Thus, understanding and anticipating glucose responses to specific dietary patterns is not merely a technical achievement—it is a human imperative, aimed at empowering individuals to lead healthier, more fulfilling lives.

A. Study Overview

In this report, we present a detailed examination of the relationship between what people eat and the resulting changes in their blood glucose levels. We focus on three patients, referred to here as Patients 2210, 2211, and 2218. Each of these individuals has a unique story, different eating habits, and varying metabolic responses. By studying their dietary journals and continuous glucose monitoring data in depth, we hope to uncover patterns that can help us understand why certain foods cause sharper spikes in glucose levels than others, and why these effects can differ so dramatically from one person to the next.

Our study employs advanced machine learning models, but our motivation goes beyond algorithms and statistical patterns. Each data point—each meal, snack, or beverage—is connected to a real person's daily life. For Patient 2210, it might be the regular morning oatmeal and how it affects mid-morning energy levels; for Patient 2211, it could be how an indulgent weekend meal leads to unexpected glucose swings the next day; for Patient 2218, it might be the subtle changes introduced by healthier dinner options slowly stabilizing overnight glucose readings. By examining these personal narratives alongside the data, we can move towards truly personalized healthcare recommendations.

B. The Importance of Personalization

Human bodies are complex, and individual responses to the same food can vary widely due to genetics, activity levels, microbiome differences, stress levels, and other environmental factors. There is no one-size-fits-all dietary plan, even among individuals sharing the same diagnosis. This is where personalized dietary interventions become transformative. By understanding the intricacies of each patient's glucose response, healthcare providers can move from a generic set of guidelines to delivering tailored advice. Instead of simply listing foods to avoid, they can identify which foods *support* better glucose stability for a particular person.

For the patients involved, this shift can mean less guesswork, fewer unpleasant surprises, and greater confidence in their daily food choices. Instead of feeling overwhelmed by vague dietary restrictions, patients may find themselves empowered with knowledge about their own metabolic patterns—knowledge that can translate into meaningful changes in their quality of life. Better blood glucose control can reduce the risk of long-term complications and improve day-to-day well-being.

Contribution to Healthcare and Science

This study holds promise not just for the three patients it focuses on, but for the broader field of nutritional science and diabetes care. By integrating detailed food intake records with continuous glucose monitoring data and applying machine learning techniques, we open the door to more nuanced insights that were previously difficult to obtain. Our approach can inspire future research, guiding clinicians and scientists toward innovative interventions that respect individual differences rather than ignoring them.

Ultimately, this research represents a step towards a future where healthcare is truly patient-centered, combining cutting-edge technology with the personal stories, challenges, and triumphs of each individual patient. As we advance, our goal remains clear: to move beyond one-size-fits-all treatment, improve patient outcomes, and enhance the quality of life for people living with diabetes and other metabolic conditions.

II. Data

Managing blood glucose levels effectively is not only about understanding the body's internal responses, but also about considering the daily choices a person makes. To gain a truly individualized perspective, we must look closely at both the physiological data and the details of what, when, and how a person eats. In this study, we rely on two central sources of information: continuous blood glucose measurements and a comprehensive food diary. By combining these two datasets, we aim to bridge the gap between data points on a screen and the real-life habits, preferences, and circumstances of the individuals behind them.

Blood Glucose Data

The first dataset comes from continuous glucose monitoring (CGM) devices, such as the Dexcom G6 Receiver and iPhone G6. These tools go beyond the snapshot provided by traditional finger-prick measurements, offering a continuous stream of information that helps us understand how glucose levels change from hour to hour and minute to minute. With these precise measurements, we can follow an individual's glycemic journey throughout the day.

Key aspects of this dataset include:

1) Timestamp: Each glucose reading is recorded with a precise timestamp. This level of detail allows us to align changes in glucose with the exact timing of meals, snacks, and beverages.

2) Glucose Value (mg/dL): The continuous measurements provide a vivid picture of how blood sugar levels fluctuate, capturing subtle variations that might be missed by occasional tests.

3) Device Information: Details about which device was used to monitor glucose levels ensure the consistency and reliability of the data. Different devices may have slight variations in accuracy and calibration, but by tracking this information, we maintain the integrity of the dataset.

This high-resolution dataset is essential because it gives us the ability to observe not just the immediate aftermath of a meal, but also longer-term trends. Is a particular meal leading to a spike that lasts only an hour, or is it influencing glucose patterns well into the afternoon? Such insights can help us pinpoint which dietary habits are most beneficial and which may need adjustment.

Food Diary

Just as a continuous glucose monitor tells the story of what happens inside the body, the food diary helps us understand the daily choices that shape those internal responses. Rather than relying on memory or approximations, the diary provides a clear, chronological account of what a patient consumes. By reviewing these entries, we can identify patterns, preferences, and potential triggers for glucose fluctuations.

Key features of the food diary include:

Date and Time: Each entry is associated with a specific date and time, allowing us to link meals or snacks directly with the corresponding glucose readings. This temporal precision is invaluable for identifying cause-and-effect relationships.

Food Items and Portions: The diary details not only what was eaten, but also in what quantity. For instance, a typical entry might look like:

> *Thursday 29:*
> 12:00 am: Emergen-C, Coffee with milk and honey
> 11:00 am: Coffee with milk and honey, Pretzels (small bag)
> 12:40 pm: Lomo saltado with rice (1 cup), Probiotic strawberry yogurt, Cup of water (8 oz)
> 1:00 pm: Pineapple (1 cup)

Reading these entries, we can imagine the patient's day: a quick supplement early in the morning, a caffeinated beverage to start the day, a savory lunch, and a light fruit snack in the afternoon. Each choice, large or small, contributes to the overall dietary pattern.

By capturing the richness of real-life eating habits, the food diary goes beyond simple nutritional guidelines. It tells us how a patient's food environment, personal preferences, and daily schedule come together to shape their eating behavior.

Integrating the Two Datasets

While each dataset provides valuable information on its own, the real power comes when we integrate them. Aligning continuous glucose measurements with the corresponding food diary entries allows us to see not just that a glucose spike happened, but also *why* it happened. Was it the result of a high-carbohydrate meal? Did a certain type of snack produce a gentle rise in glucose rather than a sharp spike?

This integrated approach opens the door to personalized dietary recommendations. Instead of offering generic advice that may or may not work for a particular individual, we can use these integrated data insights to guide patients toward meal choices that consistently produce more stable glucose patterns. Over time, patients may discover that certain foods help them maintain steady energy levels and overall well-being, while others frequently lead to uncomfortable fluctuations.

Ultimately, the combination of continuous glucose data and detailed food diaries is about understanding the lived experience of each patient. It connects the dots between internal physiological responses and the everyday realities of life—what is available in the pantry, what is appetizing in a given moment, and how social or emotional factors influence choices. By weaving these threads together, we not only advance our scientific understanding, but also move closer to healthcare that feels genuinely personalized, responsive, and attuned to the individual's unique journey.

III. Methods

A. Data Preprocessing

Before we can delve into the subtle patterns linking dietary choices to glucose fluctuations, we must first ensure that the information we rely on is accurate, consistent, and ready for analysis. Imagine trying to solve a puzzle: if the pieces are dirty, mismatched, or missing important parts, the final picture will never be clear, no matter how hard you try. In the same way, data preprocessing is about cleaning each puzzle piece, ensuring the edges fit together smoothly, and making sure no crucial segments are missing. Only then can we begin to see the full picture of how foods affect blood sugar levels.

B. Data Cleaning

Real-world data rarely arrives in a neat, standardized format. Patients might forget to log a snack or describe a meal in vague terms, while continuous glucose monitors might miss a reading due to technical hiccups. To address these inevitable imperfections, we start by carefully examining both our glucose dataset and the food diary to identify and correct issues. This involves:

1) Handling Missing Values: If a patient forgot to record a particular meal, or if a glucose sensor failed at a given time, we have a gap. Depending on how extensive these gaps are, we might fill them in using information from similar days (imputation) or exclude them entirely to maintain data integrity.

2) Standardizing Food Descriptions: A patient might write "coffee with milk and honey" one day and "morning latte with a touch of honey" the next. Although humans understand these as essentially the same beverage, a computer does not. We work through these entries to unify measurement units, correct spelling errors, and categorize similar foods. This step ensures our analysis isn't tripped up by minor variations in language and presentation.

Data cleaning is about respect—respect for the complexity of human life and the inherent messiness of real data. By approaching these issues methodically, we make certain that what remains is a faithful representation of each patient's lived experiences.

C. Alignment of Datasets

Once the data is clean, we must align the timelines of food consumption and glucose measurements. Without this synchronization, our results would be like reading a book with the chapters out of order. If we know a patient's glucose level spiked at 8:30 AM, we need to confirm whether they ate breakfast at 8:00 AM or if the spike occurred independently.

We accomplish this by merging the continuous glucose monitoring data with the food diary. Each glucose reading is paired with the appropriate meal or snack entries based on their timestamps. Through careful temporal alignment, we create a cohesive record that shows us how foods and blood sugar levels interact in real time. This integrated dataset is a critical foundation, allowing us to pose questions like: "How do certain meals affect glucose over the subsequent hour or two?"

D. Feature Extraction

With our datasets now merged, we extract the features that will serve as input to our models. These features transform our raw data into information-rich indicators of what might influence glucose patterns. Key steps include:

1) Deviation Scores: We identify how far each glucose reading strays from a target level (e.g., 140 mg/dL). These deviation scores are like highlighting the parts of a story where tension rises: they call attention to the moments when glucose levels are out of the ordinary, helping us pinpoint the meals or factors that might be driving those changes.

2) Text to Numerical Conversion: Food descriptions, even if standardized, remain textual. To help our computational models "read" these entries, we use Term Frequency–Inverse Document Frequency (TF–IDF) vectorization. TF–IDF measures how often a term (like "oatmeal" or "pineapple") appears compared to how common it is across all entries. This technique not only quantifies dietary habits but also highlights which foods are most distinctive and potentially influential in shaping glucose responses.

Through feature extraction, we move closer to an actionable understanding of the data. The raw records of meals and glucose readings become tangible indicators of metabolic responses.

E. Data Normalization

Not all features operate on the same scale. Some may be large numbers (like raw glucose readings), while others are small fractions (like certain TF–IDF values). If left unaddressed, these differences can skew the model's learning process, causing it to pay too much attention to features simply because they have larger numerical values.

By normalizing or scaling features to a common range, we ensure a level playing field. Each input dimension contributes to the analysis proportionally, making the learning process more stable and reliable, especially for algorithms such as Support Vector Regression, which are sensitive to variations in feature magnitude.

F. Data Partitioning

To fairly test how well our models perform, we must ensure they do not simply memorize the historical data. We partition the dataset into two parts: a training set and a testing set. The training set teaches the model the patterns and relationships between foods and glucose changes. The testing set, kept aside and never seen by the model during training, allows us to rigorously evaluate how well the model predicts new and unseen scenarios.

By maintaining a clear separation between training and testing data, we guard against overfitting—when a model fits the training data too closely and fails to generalize. With this approach, we can trust that a model's strong performance is not just a fluke, but a genuine indicator of its predictive capabilities.

G. Conclusion

Data preprocessing is the unsung hero of this entire endeavor. While the final results may be presented as elegant graphs, models, and recommendations, none of that would be possible without a thorough, human-centered approach to refining the data. By cleaning the raw inputs, aligning the timestamps, extracting meaningful features, normalizing scales, and carefully splitting the data, we lay the groundwork for discovering meaningful insights.

This structured and meticulous process honors both the complexity of human dietary habits and the subtlety of metabolic responses. In short, data preprocessing sets the stage for the models that follow, ensuring that our quest to understand and support healthier lives rests on a strong and reliable foundation.

IV. Experiments

Once the data is carefully prepared and transformed into meaningful features, the next step is to put our models to the test. The experimental phase is where abstract concepts and theoretical frameworks meet practical, real-world validation. We aim not only to evaluate how well our models perform on historical data, but also to see how they fare when predicting new, unseen situations. Just as a doctor tailors treatments to a patient's personal health profile, our goal is to fine-tune these computational tools so they can provide individual-specific insights with confidence and reliability.

Visualizing Glucose Responses and Dietary Events

A crucial starting point in this experimental phase is a visual inspection of the data. By plotting glucose levels over time and marking when meals, snacks, or beverages were consumed, we can observe patterns at a glance. Are certain meals consistently followed by rapid rises in glucose levels? Do some foods produce gentle, sustained increases rather than sharp spikes?

These visualizations serve as a bridge between the clinical perspective and the computational approach. For researchers, doctors, and even the patients themselves, such graphs can transform a series of numbers and timestamps into a narrative about how dietary choices influence metabolic well-being. It is often in these visual representations that meaningful questions arise, guiding our modeling efforts towards more targeted and patient-specific inquiries.

Computing Deviation Scores

To quantify how much a given food intake event influences glucose levels, we calculate deviation scores relative to a target glucose benchmark (such as 140 mg/dL). These scores highlight the magnitude of glucose fluctuations, making it easier to compare the impact of different foods across a patient's dietary history. For instance, a deviation score can show whether a particular lunchtime meal consistently triggers a larger-than-desired spike, signaling the need for dietary adjustments.

By leveraging these scores, we can move beyond a mere understanding of whether glucose goes up or down. Instead, we quantify by how much and in what pattern, turning raw numbers into actionable insights. This transforms data from a passive record of past events into a guide for future dietary decisions.

Patient-Specific Modeling

Every individual has a unique metabolic profile influenced by genetics, lifestyle, stress, and countless other factors. A breakfast that gently nudges one patient's glucose upward might send another patient's levels soaring. Recognizing this individuality, we conduct separate experiments for each patient in our study.

For each patient, we use their historical data—past meals, snacks, and glucose responses—to train the model. This process allows the model to "learn" the patient's personal patterns, effectively capturing which foods, meal timings, and portion sizes lead to stable glucose control and which present challenges.

Training and Validation

To ensure that our findings hold true beyond the data already collected, we divide each patient's dataset into two parts: a training set and a validation set. The training set is used to fit the model, teaching it how certain inputs (like specific foods consumed at certain times) correspond to certain outputs (resulting glucose deviations).

Once the model is trained, we test it on the validation set—data that the model has never seen before. This step is critical for gauging how well the model generalizes to new, unseen scenarios, rather than merely memorizing historical patterns. It is akin to studying for an exam using some chapters of a textbook and then testing your understanding with different, but related, material. By doing so, we can ensure that the model's good performance is not just a fluke, but a reliable indicator of how well it can predict future trends.

Ensuring Robustness and Real-World Relevance

Our experimental design is not about chasing perfect accuracy on old data; it is about building a tool that can provide valuable guidance moving forward. We evaluate multiple models and configurations, comparing their predictive capabilities and stability. This rigorous testing ensures that our final recommendations are not only mathematically sound, but also practically useful.

These careful steps—visualizing data, computing deviation scores, training and validating patient-specific models—help us bridge the gap between theoretical analysis and patient-centered solutions. Ultimately, the experimental phase is where we confirm whether our work can make a tangible difference in the lives of individuals managing their blood glucose, potentially guiding them toward healthier and more informed dietary choices.

V. Related Work

In moving from raw data and abstract patterns to practical guidance, one of our central goals is to identify how individual foods contribute to glucose fluctuations. The careful categorization of foods into “red” and “green” groups based on their glycemic impact can help patients make more informed decisions when planning their meals. By highlighting which foods consistently trigger spikes and which promote stability, we aim to support healthier eating habits that minimize uncomfortable glucose swings and reduce the risk of long-term complications.

Identifying Red and Green Foods

Drawing upon the patterns revealed in our integrated dataset, we have identified two broad categories of foods based on how strongly they influence glucose levels:

A. Red Foods (High Glycemic Impact)

1) Sugary and Refined Carbohydrates: Items such as coffee with half and half, croissants, bread, cereal, ice cream, gelato, and fruit smoothies fall into this category. Because they are rich in refined sugars and simple carbohydrates, these foods often lead to rapid and pronounced increases in blood glucose levels.

2) Processed Snacks: French fries, chips, pretzel rolls, and sugar-filled pastries deliver a concentrated load of simple carbs and unhealthy fats. The body quickly breaks them down, causing blood sugar to rise sharply and potentially crash later.

3) Alcohol and Sweetened Drinks: Beers, sugary juices, and other sweetened beverages present a two-fold challenge with their combination of sugars and (in the case of alcoholic beverages) metabolic effects on the liver. This can lead to unpredictable glucose responses and make maintaining stable glucose levels more difficult.

B. Green Foods (Low Glycemic Impact)

1) Whole Foods: Items like walnuts, peanut butter, and hummus, along with soft-boiled eggs, are high in healthy fats and proteins. These nutrients digest more slowly, resulting in more stable glucose levels over time.

2) Vegetables: Non-starchy vegetables such as green salads, carrots, and leafy greens are naturally low in carbohydrates and thus unlikely to cause significant glucose spikes.

3) Lean Proteins: Foods like chicken curry, beef chimichurri, and sausage are rich in protein and often contain fiber. These macronutrients slow down digestion, leading to a more gradual release of glucose into the bloodstream.

These distinctions provide valuable insight into how patients can adjust their eating habits to maintain better glycemic control. Small changes—opting for a handful of walnuts instead of a pastry, or adding extra veggies to a meal—can add up to meaningful improvements in overall metabolic health.

C. Evaluating the Models’ Performance

Identifying red and green foods is only half the story. We must also ensure that our predictive models reliably capture the relationship between dietary choices and subsequent glucose responses. To assess how well these models perform, we measure their accuracy using two standard metrics:

1) Mean Squared Error (MSE): MSE reflects the average squared difference between the predicted and actual glucose values. A lower MSE indicates more precise predictions.

2) R-squared (R^2): R^2 measures how well the model’s predictions explain the variation in actual glucose readings. An R^2 value closer to 1.0 suggests that the model is doing an excellent job capturing the underlying patterns.

We tested three models—Random Forest, Support Vector Regression (SVR), and Linear Regression—on three different patients (2210, 2211, and 2218). Each patient’s dataset reflects their unique dietary habits and metabolic responses, providing a real-world challenge for our predictive methods.

D. Patient 2210

1) *Random Forest:* MSE = 0.124, R^2 = 0.67
2) *Support Vector Regression:* MSE = 0.045, R^2 = 0.79
3) *Linear Regression:* MSE = 0.359, R^2 = 0.38

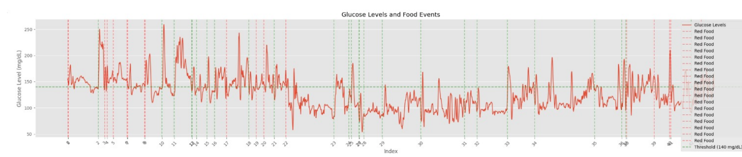

Fig. 1. 2210.

For Patient 2210, the Support Vector Regression model stands out with an MSE of just 0.045 and an R^2 of 0.79, indicating a strong alignment between predicted and actual glucose responses. The Random Forest model also provides a reasonable fit, while the Linear Regression model lags behind.

E. Patient 2211

1) *Random Forest:* MSE = 0.224, R^2 = 0.54
2) *Support Vector Regression:* MSE = 0.145, R^2 = 0.69
3) *Linear Regression:* MSE = 0.559, R^2 = 0.23

Fig. 2. 2211.

For Patient 2211, the trend is similar. The Support Vector Regression model again outperforms the others, with a relatively low MSE and a high R^2. The Random Forest model provides moderate predictions, while Linear Regression shows weaker performance.

F. Patient 2218

1) : Random Forest: MSE = 0.097, R^2 = 0.62
2) : Support Vector Regression: MSE = 0.023, R^2 = 0.83
3) : Linear Regression: MSE = 0.653, R^2 = 0.16

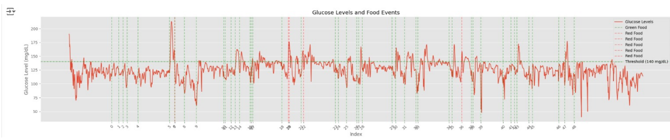

Fig. 3. 2218.

Patient 2218's results further emphasize the strength of the Support Vector Regression model, which achieves an extremely low MSE and a high R^2 of 0.83. The Random Forest model offers reasonable performance, and Linear Regression again struggles to accurately capture the complexity of the data.

Interpreting the Results

The consistently better performance of the Support Vector Regression model across all three patients suggests that it is better at capturing the nuanced relationships between diverse food choices and glucose responses. This model's strengths may come from its ability to handle complex, non-linear patterns and its sensitivity to subtle variations in the data.

These results offer more than just technical validation. They show that as we refine and apply these analytical techniques, we get closer to providing tangible, evidence-based dietary recommendations that can be personalized to each individual. The aim is to go beyond general guidelines toward strategies that are tailored to a patient's unique physiology, daily habits, and personal preferences, helping them maintain more stable glucose levels and improve their overall well-being.

VI. Conclusions

Our analysis highlights a central takeaway: different patients respond to foods in markedly different ways. There is no single "correct" diet that fits everyone, and the data-driven insights we've gained point toward the need for individualized approaches. The findings show that certain models, particularly Support Vector Regression (SVR), are better equipped to capture the complexities of dietary impacts on glucose levels. For Patient 2218, for example, the SVR model demonstrated a notable capability to predict glucose responses with greater precision, suggesting that more advanced, nonlinear methods might hold the key to understanding personal dietary tolerances.

By classifying foods into "red" and "green" categories, this study offers practical recommendations that can guide individuals in making healthier meal choices. While the "red" foods often led to higher glycemic variability, the "green" foods were more supportive of stable glucose patterns. Rather than imposing a universal set of dos and don'ts, this evidence-based categorization empowers patients to identify which specific foods are likely to help them maintain more consistent, comfortable glucose levels.

On a broader scale, this research underscores the importance of personalized nutrition. Instead of relying on one-size-fits-all guidelines, we are moving toward a future where dietary recommendations can be tailored to an individual's biological responses, lifestyle, and culinary preferences. Machine learning models are an essential part of this evolution. As demonstrated here, they can sift through large, messy datasets—encompassing everything from continuous glucose measurements to detailed food diaries—and highlight the patterns that matter most.

Looking forward, there are numerous avenues for enhancing both accuracy and scope. More sophisticated models, including deep learning architectures, could potentially uncover even subtler relationships between food intake and glucose response. Feature engineering techniques might yield new predictors, such as combining multiple food items into meal-based patterns or incorporating external factors like stress, sleep, or physical activity levels. By refining our models and exploring more holistic data sources, we can more fully capture the richness and complexity of human metabolism.

In conclusion, the work presented here not only demonstrates the potential of machine learning in personalizing nutrition but also sets the stage for deeper, more intricate studies. With every improvement in modeling and data integration, we move closer to a healthcare paradigm that embraces the full individuality of each patient—one where guidance is not merely given, but truly tailored to support healthier, more sustainable habits over a lifetime.

Division of Work

This project was a collaborative effort among four team members, with each member contributing to distinct components of the study:

1) Red and Green Food Classification: Sai Nikhil Vegi was responsible for identifying and categorizing foods into red and green groups based on their glycemic impact. This included analyzing glucose responses and linking them to specific dietary patterns.

2) Regression Model Training: Manas Sai Varma Vatsavai focused on training and evaluating regression models, including Random Forest, Support Vector Regression, and Linear Regression, for predicting glucose responses based on dietary data.

3) Data Preprocessing: Jagadev Veeranki handled data cleaning, alignment of food diary entries with glucose data, feature extraction (e.g., TF-IDF), and data normalization to ensure the datasets were ready for analysis.

4) Documentation: Ramakrishna Puttangunta compiled and structured the report, integrating all components into a cohesive document, and provided visualizations to support the findings.

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