A Hybrid LLM based Model for Calorie Tracker and Dietary Control

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***Abstract*—The importance of attainable and efficient dietary management options is clearly visible through the increasing occurrences of obesity and associated health conditions. While traditional techniques of calorie tracking are useful, they can be labor-intensive and highly prone to errors, highlighting the requirement for novel technology alternatives. This work presents the use of advanced natural language processing to intensify user experience and accuracy in dietary control for a Large Language Model (LLM)-based calorie tracker. To get a more natural approach for measuring calorie intake, creating customized dietary goals, and receiving real-time feedback we use AI and machine learning algorithms in the program (GPT-3 and GPT-4). To control intermittent fasting habits, measure hydration, and monitor weight variations, various tools are provided by the device. Deep learning techniques such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) are implemented to give support and personalized recommendations to help users overcome hindrances and achieve their health goals, thus contributing to overall health and well-being.**

Keywords*—Calorie Tracking, Large Language Model (LLM), Natural Language Processing (NLP), Obesity Management, AI-Powered Health Solutions, Intermittent Fasting, Machine Learning.

I. INTRODUCTION

To maintain a healthy lifestyle, dietary balance and rigorous calorie tracking is a must. Calories, or the quantity of energy that meals provide, are essential to reach a proper weight and assure nutritional sufficiency. This can be a grinding task if appropriate tools are not present to track calories. Conventional calorie-tracking systems are helpful, but they have a drawback of being labor-intensive and are prone to human error. Technical developments in the present provide new solutions to these difficulties, such as some software to streamline the process of nutritional control. Calorie counter applications, particularly those which are built on heavy frameworks, provide users with straight-forward and fascinating ways to register meals, manage calorie consumption, and discover different dietary patterns. For the present world that strives towards a health-conscious environment, these applications are very crucial. They provide a reliable tool for maintaining a balanced diet and meeting nutritional targets. The backend architecture of such applications provide scalability, security, and effective data administration, and combined with the present web technologies, they enhance user engagement with reactive interfaces and dynamic visualizations. Healthcare has gained a lot of attention and popularity nowadays owing to the rising global prevalence of health related issues. According to the World Health Organization, the critical need for easily available nutritional solutions is highlighted by the fact that worldwide obesity incidence has topped 1 billion individuals. Obesity, a grave health concern with possibly fatal implications, emphasizes the need of the hour which is proper dietary control. Traditional approaches, though simple and useful, have many drawbacks like high fees, dependency on personal trainers, and restricted customization, to name a few. Solutions that are powered by AI are giving way to many creative methods to improve individual lifestyle management. Even without the need of extra equipment, these systems can determine Basal Metabolic Rate (BMR), offer suitable recipes based on the ingredients available and suggest and track good exercises in real-time to help in burning fats and prevent or overcome injuries. Intermittent fasting has also gained much popularity for losing weight, improving metabolic health, and giving way to longer longevity. But the main issue faced by majority individuals is that they fail to adhere to fasting rules and successfully monitor health indicators.

With the use of natural language processing the work strives to design a Language Model (LLM)-based Calorie Tracker to improve user experience and accuracy in diet management. Similar to OpenAI's GPT-3 and GPT-4 that have already been trained on large datasets. They incorporate transformer architectures to analyze and synthesize human-like writing, which facilitates enhanced production of content, answering questions, and providing personalized suggestions. The Calorie Tracker that we propose employs AI and machine learning technologies to allow consumers to get a more intuitive and effective way to measure calorie consumption, create personalized dietary goals, and receive real-time feedback on eating and workout patterns. Thus calorie tracking is simplified and users are enabled to make educated decisions, benefiting overall health and wellness. The software also promises to make intermittent fasting easier by providing tools for managing fasting regimens, tracking water, and monitoring weight swings.

II. LITERATURE REVIEW

In paper [1], the impact of using the MyFitnessPal calorie-tracking app among individuals with eating disorders was explored by the researchers. Upon which they found out that despite providing users with a sense of control over their diet,

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it posed some risks by amplifying unhealthy behaviors, highlighting the need for careful consideration in clinical settings when implementing these tools.Thus it stresses on the importance of thoughtful and careful implementation of these tools in clinical contexts. Researchers investigated the role of LLMs in improving smart automation processes in paper [2] by emphasizing how LLMs improve natural language processing(NLP) and decision-making which in turn leads to a more adaptive system. The authors in paper [3] demonstrated a practical guide to develop such applications by outlining tools and techniques for efficient LLM application development using LangChain. According to paper [4], the researchers demonstrated the potential of LLMs in enhancing food entity recognition from recipes provided. They showed that LLMs outperformed traditional methods by identifying the ingredients and preparation methods, which enhances the recipe analyzing and indexing. Yang et al. (2024) [5] introduced the ChatDiet framework, that uses LLMs to provide customized nutrition advice based on user preferences and dietary goals. It also integrates advanced natural language understanding with nutrition databases for practical applications. The effectiveness of integrating LLMs with IoT devices in healthcare settings was found by De Vito [6]. The highlights of this study acted as an improvement in healthcare delivery and patient monitoring. Simpson and Mazzeo (2017) [7] examined the correlation between fitness tracking technology and eating disorder symptoms and found that while technology could aid in calorie counting and fitness tracking, it might also be associated with increased eating disorder symptoms, suggesting a need for balanced application. Researchers in paper [8] studied the use of LLMs for health predictions based on the data from wearable sensors, showcasing the model's ability in personal health management by offering insights into various health markers. Paper [9] explored the application of graph-augmented LLMs to be able to suggest personalized health insights.It was evident that there was improvement in sleep analysis as we benefited from the wearable data and graph-based insights, which also contributed to more effective personal health management. According to researchers in paper [10], it came into light that these apps significantly improved nutritional awareness and promoted lifestyle changes among young adults in India, emphasizing the role of technology in dietary management.

III. Proposed Methodology

Figure 1 shows the information regarding the working and framework of the model proposed i.e. LLM based calorie application. Using machine learning principles and wearable device's integration goal is to give personal dietary guidance to the end user.

➢ *User Interface*

The user interface is fundamental to the user experience as it offers a smooth functioning by including user details, regular upgradation of food intake and getting feedback [11].

User Profile Setup: In order to get the right amount of calorie intake for an individual to consume on a daily basis according to their needs is done by entering the personal details like age, height, weight and region.

User Input Methods:

Describing via Texts: The consumed food item's details are entered manually.

Scanning Bar-code: Scanning the bar-code to get the calorie details automatically.

Pictures: Images of the meals consumed are uploaded for the model to process its details.

Scanning Labels: Nutritional values are scanned to estimate the calorie details.

User Engagement and Social Features: By providing features like daily challenges, awards and social connections, the user's involvement is increased so that the user can complete challenges of eating healthy and gain inducement.

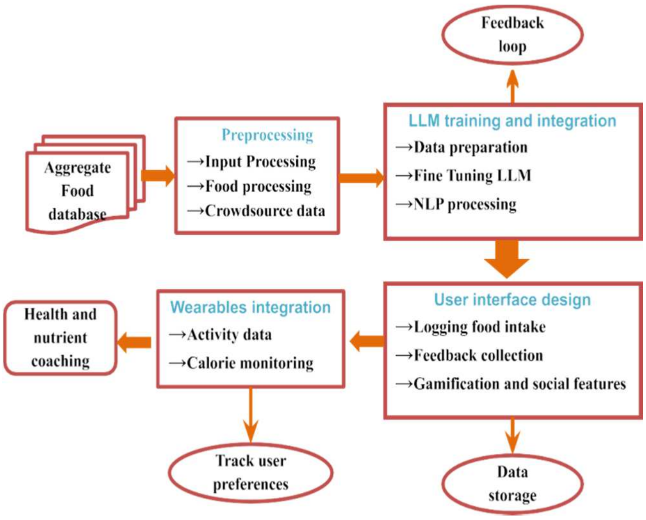

Figure 1. Proposed LLM based model for calorie monitoring

➢ *Data Collection*

In order to get accurate nutritional details and app performance, an effective set of data needs to be collected.

Food Database: Region based detailed database is created to get comprehensive information regarding the regional dishes.

Pre-processing: To get the calories and other nutritional details certain algorithms are used that pre-process the data provided by the user be it text, image or label [12].

Crowd-sourced Data: To make the database more diverse, users can provide the application with new recipes and food items.

➢ *LLM Integration*

In order to estimate calories and provide recommendations, the LLM model relies heavily on processing user inputs.

NLP Processing: The food items consumed including user-specific and particular regional based are interpreted by the LLM [13].

Estimating calories: Analyzing the food database and added ingredients provides the approximate calorie content.

Recommendations: Based on remaining calories, recommend the user with healthier options and alternatives.

AI-Powered Insights: Help users in making dietary decisions based on having an insight into the user's eating habits [14].

➢ *Feedback Loop*

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To make sure that the app remains correct and relevant, a continuous feedback loop is used.

Feedback by users: Feedback on estimation of calories and subsequent recommendations is important for model improvement [15].

Model Updates: Accuracy and customization is enhanced by continuous updates to the LLM based on user feedback.

- ***Wearable Integration***

For thorough monitoring of physical activity and calorie expenditure, integration with wearables has been done [16].

Activity Data: Information is gathered based on physical activities.

Calorie Tracking: The daily calorie allocation is utilized and adjusted based on wearable data to provide a more realistic balance between intake and expenditure.

- ***Health and Nutrition Coaching***

Personalized nutritional suggestions and educational content is provided by the app.

An AI-powered virtual dietitian provides nutritional suggestions based on user activity and objectives [17].

Educational Content: A well organized group of articles, videos, and wellness-related suggestions are available for the users.

- ***Data Privacy and Security***

One major concern is to ensure data privacy and security.

Data Encryption: Encryption is done in a robust manner to protect personal and dietary data [18].

Privacy Controls: The sharing of data and its visibility settings is managed by the users by making use of a clear, interactive privacy dashboard [19].

Implementation Steps

Setting-Up User Profile: Develop an interface for the user to enter all his/her details.

Data Collection and Pre-processing: To understand inputs, algorithms are implemented for processing. To enhance input ways allow the user to contribute to the food database.

LLM Training: Fine-tuning the LLM and developing algorithms for estimation, recommendation and insights to user's calories.

Development of User Interface: From food logging, feedback to gamification, all should be a part of the design .

Feedback Loop Implementation: For continuous model improvement, collect and use feedback.

Wearable Integration: APIs that integrate with wearable devices are developed.

Health and Nutrition Coaching: Providing educational content regarding nutrition by creating a virtual assistant.

Data Privacy and Security: Privacy is managed by implementing encryption.

A critical feature that improves the app's ability to form an entire scenario of the user's health is by the integration of wearable devices. To help the user in meeting their health goals, the data from wearable is synchronized so that the tracker provides precise estimations and recommendations. Having end to end encryption of data transmitted between the wearables and tracker ensures the program will have advanced privacy and security measures. The user will have total control over their data as they will be having the permissions to share data, being visible and changing permissions. Data protection regulations, such as GDPR and CCPA ensures user's privacy. Standardized protocols, modular frameworks, and strict security measures will allow the LLM-based Calorie Tracker application to provide a seamless user experience. By ensuring all these problems get solved while building the application, more efficient lifestyle control will be provided to the users.

IV. RESULT ANALYSIS

In order to maintain deftness processing, Kalinga Institute of Industrial Technology (KIIT) has provided support which was extremely beneficial as they provided computing systems that had powerful GPUs. These systems helped us to use frameworks like TensorFlow, PyTorch and Hugging Face's Transformers in an efficient manner for our model deployment. The GitHub repository was also updated from time to time so that people involved in the model's development can track each other's progress.

An accurate recognition of the food and the amount of calories in it was facilitated by the collection of a huge amount of data that included both text and images. The data was also region based so that the model can be more user-friendly. Using a wearable device that was compatible with the model proved out to be an enhancing factor to our model, as it was able to closely monitor and synchronize (with the model) the user's calorie expenditure by tracking their physical activity. The main goal i.e. that is to improve user experience, protect data and give accurate estimations was ensured by a detailed and specific approach during the development and design of the LLM-based Calorie Tracker.

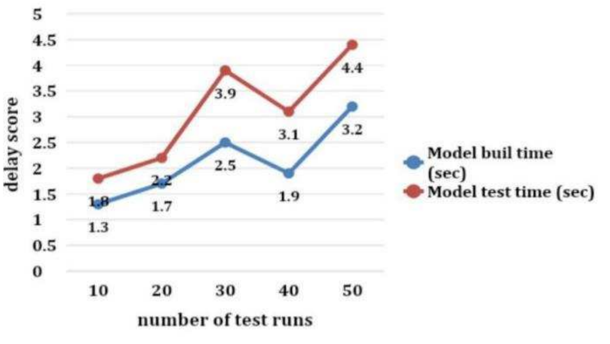

Figure 2. Model development and testing delay related to test runs

Depiction of delay scores are shown in the graph in figure 2 for the build time and test time of the model by carrying out a number of test runs(10-30). In the case of build time a practicable and steady growth was observed, as the score started from 1.3 seconds and went on to 3.2 seconds by the end of test series. Similarly, in the case of test time the potential of the model to take care of complicated tasks was observed as the number of test cases were increased. Here the test time starts at 1.8 seconds and goes on to increase up until

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4.4 seconds. The system was efficient in managing the intensified complexity and went on to show good performance in extreme testing environments, despite the increased delay scores as the build and test times of the model remained low.

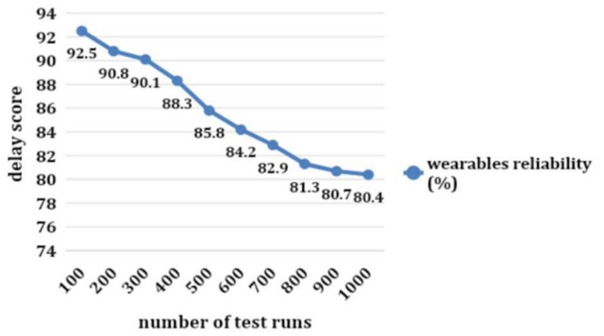

Figure 3. Model reliability and testing delay related to test runs

The relation between the delay score and the number of test runs for the model, measuring its performance is demonstrated in the graph in figure 3. The delay score was observed to be gradually decreasing from 92.5 to 80.4 as the series of test runs were increased from 100 to 1000. Despite this decline, after 1000 tests it got stable at around 80% which concludes that the wearable functioning was still relatively dependable and robust. Even after using the wearable over and over again, it showed satisfactory performance as it was able to maintain the 80% delay score after extreme testing.

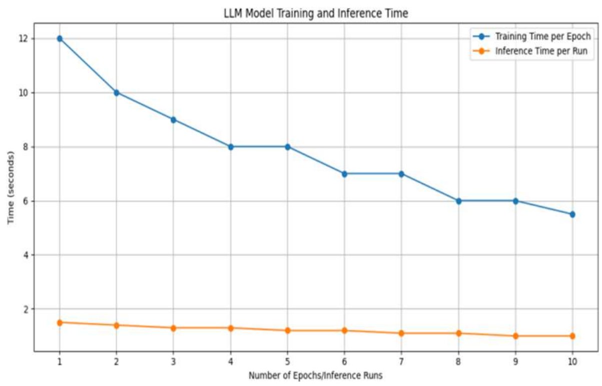

Figure 4. LLM train and inference delay with respect to epochs

The inference and training for the LLM model is shown in the graph in figure 4 for 10 epochs. A significant decrease is observed in the training time per epoch, starting from 12 seconds in the first epoch to 6 seconds by the last epoch. As more and more epochs pass, the inference time shows that it is massively unaffected. This happens because the inference time remains relatively stable at around 1.5 seconds.

V. CONCLUSION

The Calorie Tracker proposed in this paper makes use of LLM, and takes a huge leap forward in personalizing dietary controls. It is able to do so as it combines the capabilities of Large Language Models (LLMs) with cutting-edge AI approaches. With the use of powerful NLP capabilities, meal tracking has been simplified, and it also gives personalized suggestions based on individual nutritional requirements, and strives to increase user engagement through gamification and social features. To sum up, while the effectiveness of the LLM-based Calorie Tracker as a dietary control tool is undeniable, there are opportunities for expanding its capabilities and effectiveness through future development and research. If those areas are addressed properly, it will provide customers with a more comprehensive way of answering their health related queries.

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