Food Detection from Continuous Glucose Monitoring Sensors Using Pretrained Transformer-Based Models

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BACKGROUND AND AIMS

Healthy eating is a critical self-management behavior for a number of chronic health conditions such as diabetes and obesity. Manually logging meals can be burdensome, even with bar code scanning and automated photo food recognition capabilities, thus individuals with health conditions often do not track their meals consistently.

Sporadic meal entries in general will lead to sparse food logging data, which may hinder downstream data analysis, patient self-management coaching and clinical decision support.

In this study, we present a novel approach for automatedly detecting recent food intake solely based on continuous glucose monitoring (CGM) data.

METHODS

We created three transformer encoder-based food event detection models: CGMEncoder, CGMEncoder+Time, and CGMEncoder+Time+Pretraining. The model development workflow is described in Figure 1.

METHODS, continued

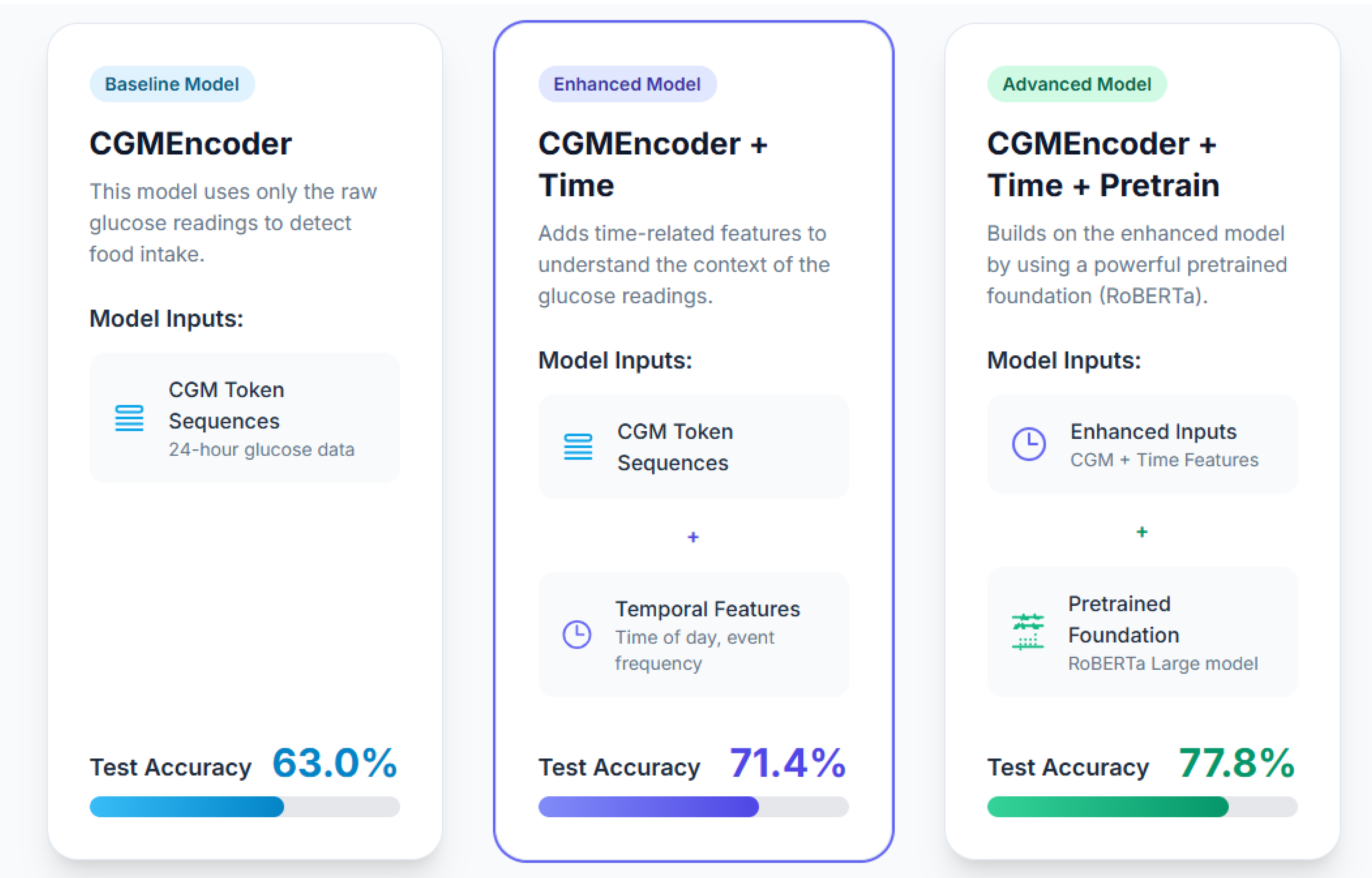
The differences in key attributes across the three models are summarized below in Figure 1. Adding a temporal component in CGM Encoder+Time allows the model to be trained on the CGM value series and associated time stamps, bringing increased knowledge of context to the model. The addition of pre-training in model 3 Pre-training adds the element of unsupervised learning and adds the ability to fine-tune how the model incorporates labeled data in training

The input to each of the models is a full, 24-hour CGM trace, and the output is a discrete label indicating the hour (within a specified range) when a food event occurs.

Our dataset consists of over 90,000 input-output pairs, partitioned into training, validation, and test sets. Each instance for the model includes CGM token sequences, hour-minute positional identifiers, and auxiliary time-related features capturing dietary event frequency and recency.

The CGM data were derived from a digital health platform for 129 individuals with type 1 (T1D) and 509 individuals with type 2 (T2D) diabetes.

Figure 1: Model Development Workflow



RESULTS

The study evaluated three distinct transformer encoder-based models to detect food events from 24-hour CGM traces. The models were tested for accuracy on a dedicated test set, which was partitioned from a dataset of over 90,000 input-output pairs.

The performance of the models showed significant improvement with the addition of temporal features and pretraining as illustrated in Table 1.

- The baseline CGMEncoder model achieved a test accuracy of 63.0%.
- By incorporating temporal information, such as hour-minute positional identifiers and features capturing dietary event frequency, the CGMEncoder+Time model's accuracy increased to 71.4%.
- The most advanced model, CGMEncoder+Time+Pretraining, which leveraged a pretraining strategy, achieved the highest test accuracy of 77.8%.

These results clearly demonstrate the importance of both temporal encoding and pretraining for building robust and generalizable food detection models from CGM data alone.

Table 1: Test Accuracy

Model	Test Accuracy
CGM Encoder	63.0%
CGM Encoder + Time	71.4%
CGM Encoder + Time + Pre-training	77.8%

CONCLUSIONS

This study addresses the challenge of inconsistent meal tracking, a common issue in the self-management of chronic health conditions like diabetes and obesity. Manual meal logging is burdensome, which can lead to sporadic entries and sparse data that hinder effective data analysis and clinical support.

The research successfully developed a novel approach to automatically detect food intake using only CGM data. The findings show that a pretrained transformer-based model that incorporates temporal features can identify food events with a test accuracy of 77.8%. This underscores the value of using temporal encoding and pretraining to create robust and generalizable models.

The practical application of this work is significant. These types of food event detection models can be embedded into digital health tools to automatically collect valuable food data. By automating this process, it is possible to generate more consistent and complete datasets, which can then be used for clinical applications such as enhancing clinical decision support and personalizing patient coaching.

REFERENCES

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