MetaGlucose: Low-cost and Practical Cold Liquid Glucose Level Measurement for Health

Yilin Song[1,ξ], Xinmin Fang[2,ξ], Zheshuo Li[2], Zhengxiong Li[2,*]
[1] Cherry Creek High School, Denver, Colorado, USA
[2] University of Colorado Denver, Denver, Colorado, USA

ABSTRACT

Measuring the glucose concentration in liquids is crucial for ensuring the safety of products for individuals with diabetes. This process not only aids in diabetes management but also highlights the importance of taking additional precautions after a diabetes diagnosis. Currently, glucose test strips are widely used to measure the glucose concentration of liquids. It's safe, effective, easy to use, and a cheap alternative to other complex technology with the same use. However, it has sevral setbacks, such as its inability to accurately measure the glucose concentration of cold liquids (0°C - 10°C). This lack of variability can lead to more inconvenience for individuals than benefits. Therefore, in this paper, we propose the usage of millimeter-wave (mmWave) sensing as a contactless, versatile, and easy method to measure glucose levels in cold liquids accurately.

CCS CONCEPTS

• **Computer systems organization → Embedded and cyber-physical systems**; • **Applied computing → Health care information systems**.

KEYWORDS

mmWave Sensing, Non-Invasive Sensing, Glucose Monitoring

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ξ Y.S. and X.F. contribute equally.
* Corresponding E-mail: zhengxiong.li@ucdenver.edu (Z.L.).

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1 INTRODUCTION

As recently recorded by the U.S. Centers for Disease Control and Prevention (CDC), a staggering 29.7 million Americans have been diagnosed with diabetes as of 2021—in other words, around 9% of the population [5]. This alarming rise in diabetes cases underscores the critical need for effective monitoring methods to manage its impact on health. Diabetes is a metabolic disorder affecting the body's ability to metabolize and is characterized by high blood glucose levels. This disease has many complications as it requires constant monitoring of blood glucose levels and its rate of change. If these tasks are neglected, it can lead to fatal damage to the body, such as seizures and loss of consciousness [6]. Accurate measurement of glucose levels in a low-cost and practical way is essential for effective monitoring and treatment of diabetes and ensuring the nutritional quality of beverages. In addition to its applications for regular diabetes management, this technology can also significantly benefit other prevalent health conditions, including aging rehabilitation, gestational diabetes, and cardiovascular diseases [7, 13, 16].

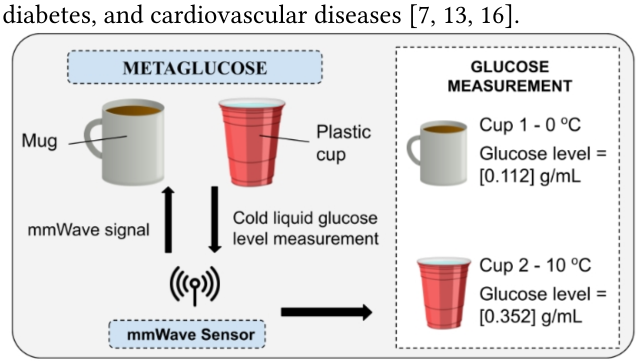

Figure 1: The overview of MetaGlucose, a low-cost and practical cold liquid glucose level measurement for health.

Measuring glucose levels in cold liquids is essential for ensuring accurate and reliable monitoring in various real-world scenarios where temperature fluctuations can impact measurement accuracy [14]. For instance, in medical diagnostics, beverages, or stored samples, liquids are often subject to varying temperatures. Ensuring that glucose sensors can perform accurately in cold conditions enhances their reliability and applicability across diverse environments. This capability is particularly important for diabetic patients who need to monitor their glucose levels consistently, regardless of ambient temperature, and for quality control in the food and beverage industry where cold storage is common.

Traditional methods, such as low-cost glucose test strips, are commonly used due to their affordability and ease of use. However, these methods often fail to accurately measure glucose levels at low temperatures, particularly in cold beverages. Cold temperatures can affect the chemical composition of the strips, leading to inaccurate glucose level readings [1]. Another popular tool is glucose monitors, which are invasive, harmful, costly, and extremely uncomfortable for patients [29]. Besides, there has been some exploration using mmWave sensing to measure glucose in liquids, demonstrating the technology's potential. However, these experiments were predominantly conducted at room temperature (around 20°C) [17]. The efficacy of mmWave sensing in cold environments remains unexplored, leaving a gap in the research.

Therefore, we propose an innovative method that uses mmWave sensing as a low-cost, non-invasive, and efficient tool to measure glucose levels in cold liquids, called MetaGlucose, as shown in Figure 1. This work culminates in several salient advantages, such as (1) **low-cost**: utilizing affordable components to create an accessible solution (low-cost sensors), (2) **practical**: maintaining accuracy and reliability across a wide range of temperatures, especially in cold conditions, and (3) **efficient**: accentuating efficiency in ensuring ease of use in everyday settings, including various liquid types, cup types, and sensing distance.

However, it is important to note that mmWave sensing toward liquid glucose levels still faces several technical challenges. (i) **Temperature Variations**: The dielectric properties of liquids change with temperature, affecting the accuracy of glucose measurements. To ensure consistent sensor accuracy across a wide range of temperatures, particularly in cold liquids, thorough noise reduction filters are essential. The system integrates real-time temperature monitoring and employs advanced mmWave Signal to spectrogram transformation techniques to account for these variations. (ii) **Complex Liquid Matrices**: The presence of solutes and particles in beverages can affect mmWave signal propagation. Differentiating the glucose signal from other components in complex liquid matrices necessitates sophisticated deep learning-based analytical models. The system uses cross-validation techniques to isolate the glucose concentration accurately, even in the presence of interfering substances.

Our main contributions are summarized as follows:

- We propose MetaGlucose to use mmWave sensing for glucose measurement in cold liquids, addressing a significant gap in current research. To our best knowledge, it is the first work to advance the field of glucose monitoring, offering a low-cost, practical, and robust solution for measuring sugar levels in cold liquids.
- We develop and implement a practical and robust system that leverages mmWave technology to provide accurate glucose readings with physical AI technology. The system utilizes advanced temperature compensation techniques, ensemble learning methods, and feature extraction techniques to identify the glucose concentration accurately, even in the presence of interfering substances.
- We conduct comprehensive evaluations to validate the system's performance in various conditions, especially at low temperatures. Results show that MetaGlucose achieves an accuracy of 99% for liquid glucose level measurement in the range of 0°C to 40°C.

2 BACKGROUND

Diabetes poses severe risks to individuals, including damage to blood vessels and kidneys, and increased risk of heart attacks and strokes, etc [2]. Consuming high-sugar beverages can can cause dangerous blood glucose spikes in diabetics. Healthier choices include tea and coffee, whereas soda and fruit juice are least advisable [3]. Our experimentation involves testing glucose levels in drinks across the spectrum.

mmWave sensing, primarily used in communication and imaging, exceeds all mentioned criteria. It has gained traction due to its potential in biomedical applications. Operating in the 30-300 GHz frequency spectrum, mmWave sensors offer high resolution and material penetration capabilities [21]. By placing the mmWave sensor near or in the proximity of a certain object, it transmits signals and measures the returned signal's strength and amplitude, providing a non-invasive method to gauge liquid glucose concentrations.

Preliminary Results: To further validate the shortcomings of glucose test strips, we measured the glucose levels of the same liquid at different temperatures. We added identical amounts of sugar to two cups and adjusted the temperatures from 0°C to 10°C. This resulted in varying outcomes from the glucose test strips, suggesting different glucose levels. Such discrepancies can mislead patients about the safety of beverages and present a significant challenge for individuals and healthcare providers requiring reliable glucose readings under varying conditions.

3 SYSTEM DESIGN

The proposed system utilizes mmWave sensors to measure glucose levels in cold liquids. The system consists of three main components: the mmWave sensor, a signal processing unit, and an analytical model module, shown in Fig 2.

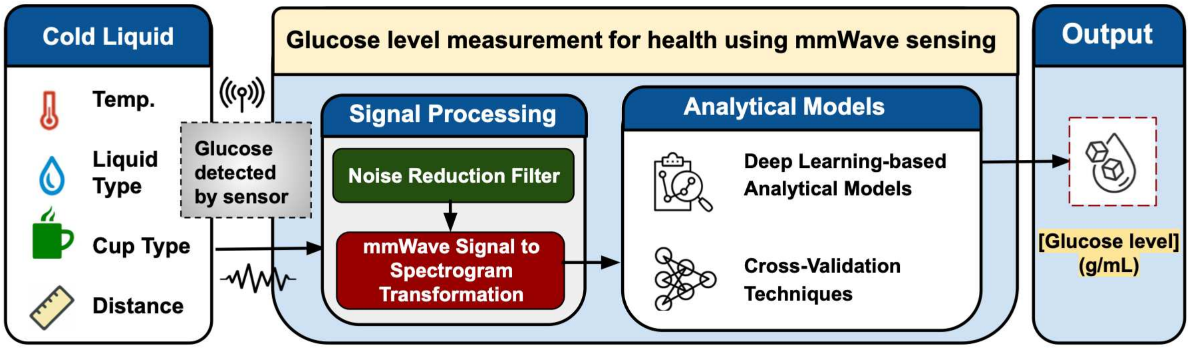

Figure 2: The system design of the mmWave sensing model for glucose level measurement.

mmWave Sensor: The mmWave sensor is at the core of the system, utilizing its high-frequency capabilities to penetrate cold liquids and measure glucose levels. The choice of a 24 GHz frequency range is crucial as it ensures adequate penetration depth while maintaining high-resolution measurements [15]. The sensor is designed to operate efficiently across a broad temperature spectrum, ensuring consistent performance even in cold conditions.

Signal Processing Unit: This module plays a crucial role in filtering and preprocessing the raw signals from the mmWave sensor. It includes:

(i) *Noise Reduction Filters*: These filters are carefully designed to minimize signal attenuation and scattering, particularly at low temperatures, which can affect glucose measurement accuracy. By using advanced techniques like wavelet denoising [26], the filters effectively isolate the glucose signal from background noise, This ensures that only relevant signal information is retained, improving the signal-to-noise ratio and the overall reliability of the measurement process.

(ii) *mmWave Signal to Spectrogram Transformation*: To better compensate for temperature variations and achieve accurate glucose level measurement, it is essential to transform the mmWave response signal from a one-dimensional spectral-temporal function into a two-dimensional spectral-image function. Given the advantage that continuous-time short-time Fourier Transform (STFT) offers in terms of real-time processing efficiency compared to the computationally intensive two-dimensional wavelet transform, we adopt STFT [9] for this transformation. The formula of STFT is:

$$\text{STFT}\{x(t)\}(f,\tau) = \int x(t)w(t-\tau)e^{-j2\pi ft}\,dt, \quad (1)$$

where $x(t)$ is the signal, $w(t)$ is the window function, f is the frequency, and τ is the time shift of the window. The resulting spectrogram offers a detailed two-dimensional representation of the signal's frequency over time, enabling more precise glucose level analysis and measurement.

Analytical Models: To handle the complexity of liquid matrices, this module employs sophisticated analytical models and cross-validation techniques. Key features include:

(i) *Deep Learning-based Analytical Models*: To solve the problem of mapping spectrogram images to glucose level values, we implement a neural network-based approach. EfficientNetV2 [23] is employed due to its superior performance in computational efficiency and accuracy. EfficientNetV2 employs compound scaling, significantly enhancing the model's performance in processing mmWave data. The formula for compound scaling is as follows: depth: $d = \alpha^{\phi}$, width: $w = \beta^{\phi}$, resolution: $r = \gamma^{\phi}$, where α, β, and γ are constants that determine the degree to which each dimension is scaled by a compound coefficient ϕ. This method ensures a balanced scaling across all dimensions, ensuring accurate and robust glucose level estimation. EfficientNetV2's ability to balance speed and precision enhances the reliability of glucose level measurement, making it highly suitable for real-time and low-power applications.

(ii) *Cross-Validation Techniques*: To ensure the accuracy and reliability of the glucose level measurements, the system employs rigorous cross-validation techniques. These techniques involve comparing the sensor's readings with known glucose concentrations under similar conditions, verifying the consistency and reliability of the results. Methods such as 5-fold cross-validation [8] and leave-one-out cross-validation [25] are used to validate the models. These methods help in assessing the generalizability and robustness of the predictive models, ensuring that the system performs well across different datasets and conditions, thereby instilling confidence in the measurement outcomes.

4 EVALUATION SETUP

4.1 Experimental Preparation

The evaluation setup involves measuring glucose levels in various cold liquid samples, as shown in Figure 3. The samples are prepared by dissolving sugar in water and cooling them to temperatures ranging from 0°C to 10°C. A digital thermometer [4] was placed to record the temperature of the liquid. The ground truth of the glucose concentrations is pre-designed through recording and calculating the sugar-to-water ratio/concentration.

Application Protocol: We begin by confirming the accuracy of the mmWave sensor by recording the sugar-to-water ratio/concentration of 5 trials: In trial 1, we combined one cup of water (250 mL) with one packet of sugar (22 grams), resulting in a known glucose concentration of 0.0880 g/mL (Level 1). In trial 2, we combined one cup of water with two packets of sugar (44 grams) to get a glucose concentration of 0.176 g/mL (Level 2). For trial 3, we mixed one cup of water with 3 packets (66 grams) of sugar to get a concentration of 0.264 g/mL (Level 3). Trial 4 includes one cup of water with 4 packets (88 grams) of sugar to get a concentration of 0.352 g/mL (Level 4). Finally, trial 5 consisted of one cup of water to act as our control group, no sugar (Level 0). We then measure the glucose concentration using the mmWave sensor and compare the results to determine its accuracy. These five glucose levels are close to real-world conditions, reflecting different liquids in health applications.

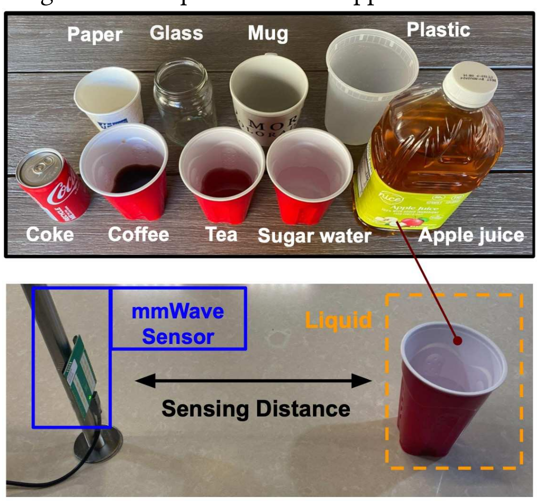

Figure 3: The experimental setup of the mmWave sensor and the various conditions that are tested.

Data Collection and Preparation: As a result of high-speed continuous data collection from MetaGlucose, 150,000 lines of feature array are collected and a 80%-20% split is utilized to separate the training and testing data. To effectively assess the performance of the model, we collect a single group of data for training and test it against different scenarios that were not trained.

4.2 Performance Metrics

The performance of MetaGlucose for measuring glucose levels in cold liquids was evaluated based on several factors to ensure effectiveness across a multitude of variations:

Percentage accuracy: Measured as the percentage of correctly identified glucose concentrations within a specified range and conditions (data range between 0-100%). A value close to 100% signifies higher accuracy, reflecting the precision of the mmWave sensing system.

Standard deviation (STD): The data from each condition and trial showed a low standard deviation, close to zero (range 0-1), demonstrating the consistent reliability of the glucose measurements. This low variability indicates the results are both reliable and accurate.

5 METAGLUCOSE EVALUATION

5.1 Overall Performance

The results show the accuracy is consistently close to 100% between the sensor readings and the actual glucose concentrations, indicating its high reliability. Furthermore, the standard deviation remains around 0.2%, across all trials, it exemplifies the system's high precision and accuracy. These results indicate a highly reliable relationship between the mmWave sensing outputs and the actual glucose concentrations, highlighting the potential of this technology for non-invasive glucose monitoring and its expansiveness to provide real-time data to users and healthcare providers under various conditions.

5.2 Impact of Temperature

In order to investigate the impact of temperature variations of the liquid on the glucose readings by the mmWave sensor, we take many measures into consideration. For each liquid, we adjust the temperature by microwaving the liquid first for 30 seconds to reach a temperature of 40°C, and we measure its concentration using the mmWave sensor. We let it cool down to 30°C then 20°C and measure its concentration at each temperature. For the trials with cold temperatures, we leave it in the fridge for 30 minutes and measure its concentration at 10°C using the mmWave sensor. We put the solutions in the freezer for another 30 minutes until they reach approximately 0°C and measure the glucose concentration using the mmWave sensor. Finally, we compare our results, which show a consistent 99% accuracy between the measured glucose level and the actual glucose level, as shown in Figure 4.

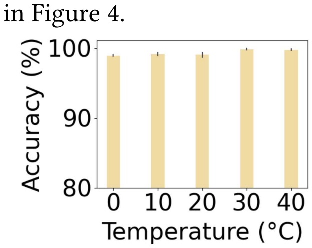

Figure 4: Performance under different temperatures.

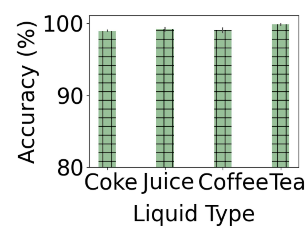

Figure 5: Performance among various liquid types.

5.3 Impact of Liquid Type

To evaluate the performance of the mmWave sensor across different types of liquids, we use popular drinks with known glucose concentrations: Coca-Cola (0.110 g/mL), apple juice (0.116 g/mL), coffee, and tea. For the coffee and tea trials, we aim to determine whether the mmWave sensor could differentiate the sugar molecules from the other liquid components. We add 2 packets of sugar to the coffee and tea, detect the concentration using the mmWave sensor, then add another packet (for a total of 3 packets of sugar) and measure the concentration using the sensor in the same fashion. For Coca-Cola and apple juice, we pour the liquid into plastic cups. Finally, we analyze the sensor's performance variability concerning liquid type and its account for the varying matrices of each liquid. The result shows high accuracy as the percent accuracy stayed constant throughout (all values are around 99%), as shown in Figure 5. The standard deviation is also maintained at values close to zero (0.2, 0.3, 0.4, 0.2). These results prove the mmWave sensor to be highly sensitive, accurate, and precise, further validating it as a promising and reliable tool for glucose monitoring.

5.4 Impact of Sensing Distance

We account for an assessment of whether changing the distance between the mmWave sensor and the liquid surface affects glucose readings. We place the liquid medium at varying distances using a standard 12-inch ruler for precision, including 15 centimeters, 30 cm, 45 cm, and 60 cm, all conduct at cold temperatures (10°C). We use the mmWave sensor to detect the glucose concentrations at each distance. The results show the performance stays relatively constant (around 99% each trial) with a standard deviation close to zero, as shown in Fig 6. This proves that, even as the distance between the mmWave sensor and the liquid medium changes, there is no significant impact on its ability to accurately read glucose levels in cold liquids.

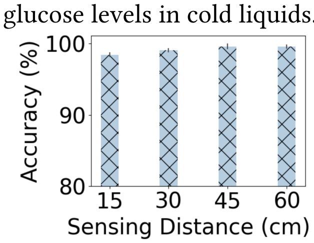

Figure 6: Performance under different sensing distances.

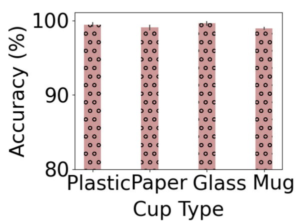

Figure 7: Performance among various cup types.

5.5 Impact of Cup

Another critical factor in determining the accuracy and reliability of the mmWave sensing system is its ability to penetrate various materials, such as cup type. Thus, we choose four commonly used materials: paper cups, plastic cups, glass cups, and mugs. We measure the glucose concentration using the mmWave sensor in each cup. The results indicate high accuracy of around 99% and low standard deviations of around 1%, as shown in Figure 7.

6 RELATED WORK

Glucose Level Measurement: Several studies have explored practical methods for glucose measurement in liquids, particularly focusing on overcoming the limitations of traditional test strips. For example, infrared (IR) spectroscopy has been investigated as a non-invasive method for glucose monitoring, but its accuracy is affected by temperature variations and requires complex calibration procedures [12, 27, 30]. Another technique is Raman spectroscopy, which offers high sensitivity but is cost-prohibitive [11, 18, 22]. Additionally, research by Zhu et al. demonstrated the potential of multiple sensors for non-invasive glucose measurement in human tissues, which requires precise calibration and is easily affected by ambient environment factors such as temperature and hydration levels [31]. Conversely, this paper proposes a low-cost and practical method for measuring glucose levels using mmWave sensing.

mmWave Sensing for Glucose: Advancements in mmWave sensing offer promise in various biomedical applications, including glucose monitoring. Researchers developed a prototype mmWave sensing system for detecting glucose levels, showing promising results at room temperature [24, 28]. Similarly, research conducted by SA Qureshi further implements the use of a mmWave-inspired sensor to detect glucose levels in blood samples[19]. Besides, AE Omer used an FMCQ mmWave radar to measure glucose concentrations in blood samples and aqueous solutions[17]. Helena CG used mmWave sensing for glucose concentration changes in pigs, which can be applied in a broader, real-world context and extent to individuals with diabetes[10]. Research by Saha S used a glucose sensing system based on mmWaves using microstrip patch antennas[20]. However, the use of mmWave sensing for glucose measurement in cold liquids hasn't been well studied. This paper addresses this gap by evaluating mmWave sensor performance under cold conditions in liquids (especially 0-10°C), providing a practical solution for accurate glucose monitoring.

7 CONCLUSION

In this paper, we introduce a novel mmWave sensing-based method for measuring glucose levels in cold liquids. Our mmWave sensing system overcomes the challenges at low temperatures using its high sensitivity and penetration capabilities. The system includes a 24 GHz mmWave sensor, a signal processing unit, and a data analysis module equipped with advanced machine learning algorithms. In our evaluation, the system consistently achieved near 100% accuracy, correlating closely with actual glucose concentrations. These findings demonstrate mmWave sensing's potential as a cost-effective, practical solution for glucose monitoring in medical and health applications, especially for cold beverages.

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