SugarWave: A Non-destructive Estimation of Fruit Sugar Content Using Millimeter-Wave Sensing

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***Abstract*—Fruit's Soluble Sugar Content (SSC) indicates quality and ripeness, which is essential for fruit production. Quality control in fruit production optimizes shipping, storage, waste prevention, and consumer satisfaction. We investigate the feasibility of estimating SSC using a low-cost, non-destructive system based on 77-81 GHz mmWave sensing technology. *SugarWave* collects fruit reflection signals, trains machine learning models, and estimates SSC. Our study shows that *SugarWave* can correctly identify fruit quality with an accuracy as high as 83%. It can also measure the SSC, with a median error of 1.4 °Bx.**

***Index Terms*—Millimeter-wave; Wireless Sensing; Soluble Sugar Content; Fruit Quality.**

I. INTRODUCTION

Fruit products pass through a production chain involving farmers, distributors, retailers, and consumers. At each level, quality preservation methods, such as drying and cooling, require monitoring ripeness to prevent waste, optimize harvest, manage shipping and storage, and ensure high-quality groceries [2]. Ripeness assessment through smell, color, or texture can be unreliable [3], so measuring sugar content is preferred for determining ripeness and taste [4]. *Soluble Sugar Content (SSC) is one of the critical characteristics that directly determines fruit ripeness since a ripening fruit accumulates soluble sugars due to biochemical changes*.

Traditionally, SSC is determined by high-performance liquid chromatography [5], gas chromatography-mass spectrometry [6], or Brix measurement, where 1 °Brix (Bx) refers to 1 gram of sucrose in 100 grams of an aqueous solution [7]. These methods subject fruits to laborious and destructive processing, and professional analysts must do the assessment with sophisticated equipment. Recently proposed approaches, such as Near-infrared (NIR) [8] and Ultraviolet-visible spectroscopy [9], are non-destructive, but require specialized, expensive devices and a professional to calibrate and operate.

Towards developing a low-cost, non-destructive means for estimating the SSC in fruits, we propose SugarWave leveraging millimeter-wave (mmWave) wireless technology in 5G-and-beyond smart devices. *SugarWave* is based on the principle that the strength of signals reflected from objects depends on their material's inherent properties, and varying SSC levels alter these characteristics, influencing the reflected signals [10]. *SugarWave* employs a multi-antenna mmWave transceiver (Figure 1[a]) that touches the fruit (Figure 1[c]), transmits mmWave signals and receives the signal reflection off the fruit, processes the reflected signals received from all the antennas to extract features, and feeds those features into a machine learning model to estimate the SSC in fruits (Figure 1[d]).

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We design and prototype *SugarWave* using a Commercial-Off-The-Shelf (COTS) 77–81 GHz mmWave transceiver [11] for collecting the reflected signals and an ATAGO Digital Refractometer [12] to collect the ground truth Brix values. We collect reflected signals and ground truths from 450 sugar solutions of glucose, fructose, and sucrose, and 404 samples from fruits comprising of apples, oranges, kiwis, mandarins, red plums, and granny smiths. Our experimental results show that *SugarWave* can estimate SSC in sugar solutions and fruits with median errors of 0.52 °Bx and 1.4 °Bx, respectively, and classifies fruits as average, good, and excellent quality with an accuracy of up to 83%. As stated previously, a fruit's visual features might not be indicative of the quality of the fruit. Moreover, according to [13], there is more than $15 billion yearly waste of imperfect and ugly yet completely ripe fruits. This is because consumers attribute appearance to taste. Our system helps reduce waste and enables a more precise measurement of fruit ripeness, aiding consumers in purchasing high-quality produce.

II. BACKGROUND AND FUNDAMENTALS

A. Material Sensing with mmWave Signals

mmWave sensing approaches rely on transceivers that periodically transmit and receive Frequency Modulated Continuous Wave (FMCW) signals. Earlier studies have shown that the strength of received reflected signals from surrounding objects is strongly related to their material [14], [15]. This property has been explored in recent studies to distinguish different materials [10] and identify distinct liquids [16].

RSS can theoretically be related to a material's properties through the Friis Transmission Formula [10], [16]:

$$\frac{A_r}{A_t} \propto G_r G_t \frac{\lambda}{4\pi(2d)} \cdot r \tag{1}$$

where A_r and A_t denote the amplitude of the receiving and transmitting signals respectively, G_r and G_t are the antenna gains of the receiving and transmitting antennas, d is the propagation distance, r is the reflection coefficient of the target material, and λ is the wavelength. The reflection coefficient r

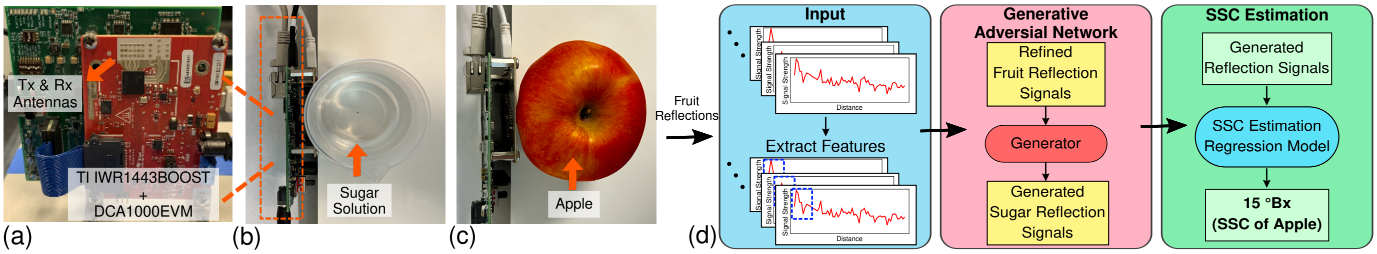

Figure 1: (a) *SugarWave* is implemented using a 77–81 GHz millimeter-wave (mmWave) transceiver with 3 transmit (Tx) and 4 receive (Rx) antennas to estimate the Soluble Sugar Content (SSC) of fruits; (b) Top-down view of ground truth data collection setup for estimating SSC of sugar solutions; (c–d) To estimate a fruit's SSC, we position it before an mmWave transceiver, capturing reflection signals from multiple antennas. These signals are processed to extract features and fed into a generator, mapping them to corresponding sugar solution reflections. The generated output is then passed through a sugar-solution-trained regression model, estimating the fruit's SSC on a °Brix (Bx) scale [1].

of a material is only related to the target materials relative permittivity [10]. Based on the above equations, we can conclude that if A_t, G_t, G_r, $2d$, and λ remain constant in Eq. (1), then the received power, A_r relies only on the reflection coefficient or permittivity of the target material.

B. Estimating SSC Using mmWave Signals

Previous studies have demonstrated that a change in the SSC of a sample affects its permittivity [17], [18]. The reason behind this phenomenon is that as the SSC increases, more water molecules attach to the sugar molecules, leading to a decline in the relative permittivity and impacting the reflected mmWave signal off the sample (Eq. (1)) [17].

To validate the above hypothesis, we conduct controlled experiments with water solutions containing glucose, fructose, and sucrose. Fruits contain these three sugars as well. For each of the three sugars, we create several solutions using 100 ml of distilled water with varying amounts of solid sugar, starting from 3g and going up to 24g in steps of 3g of solid sugar. For each sample, we employ a digital refractometer (Figure 2[a]) to measure the SSC. Then, we place the solution in front of the mmWave device, as shown in Figure 1(b), and capture the mmWave signal reflection.

The result of our experiments is demonstrated in Figures 2 (b-c) that show the relationship between the °Bx levels for different amount of sugars, and the RSS for one pair of transmit and receive antennas (Tx1, Rx4): This result conforms with the theoretical model (increasing SSC causes decreases in RSS). However, not all antenna pairs show consistent decrease in RSS: For the same Tx antenna, the relation between RSS from a different Rx antenna (Rx3) and °Bx level does not match the theoretical model (Figure 2[d]). Due to the spacing between the antennas and the curved shape of the objects, the reflected signals captured from different antennas, in this example Rx3 and Rx4, could be distinct and vary in strength. Therefore, we propose a multi-antenna design, capturing reflection signals from all pairs and allowing *SugarWave* to learn the accurate inverse relationship between RSS and SSC.

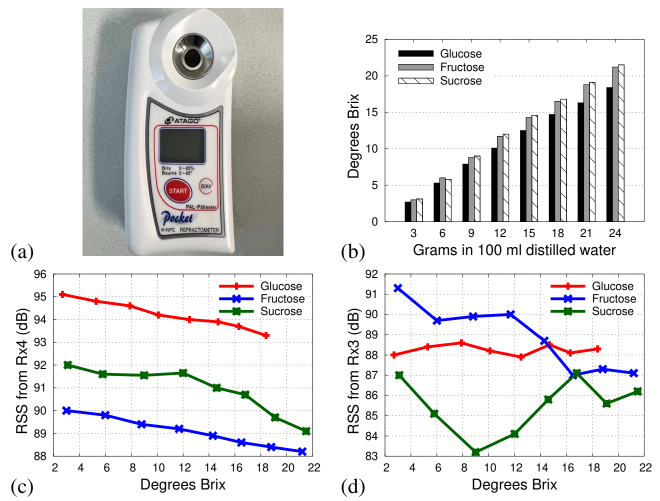

Figure 2: (a) ATAGO digital refractometer [12] is used to measure the Brix values; (b) Measured °Bx of glucose, fructose, and sucrose solutions; (c) Consistent with theory, the RSS from Rx4 decreases as SSC increases; (d) But such inverse relation is not observed between RSS from Rx3 and SSC.

III. SYSTEM DESIGN

A. Overview

SugarWave aims to enable hand-held and non-destructive estimation of SSC in fruits using COTS mmWave devices. It relies on the user positioning the fruit in front of the mmWave device and capturing the reflected signals from the fruit. After processing the signals, *SugarWave* will give users a Brix value indicating the fruit's SSC. The design of *SugarWave* is separated into two parts. First, we conduct controlled experiments by collecting reflection signals from sugar solutions containing glucose, fructose, and sucrose and then measure the SSC using a digital refractometer that measures the SSC on Brix scale. Following that, we build regression models using the reflected signals from sugar solutions and Brix values. Second, we proceed to use the sugar solution trained model for SSC estimation in fruits. We adopt this approach for several reasons: (1) Fruits come in a variety of shapes, sizes, and skin textures. These factors affect the signal reflection, hindering

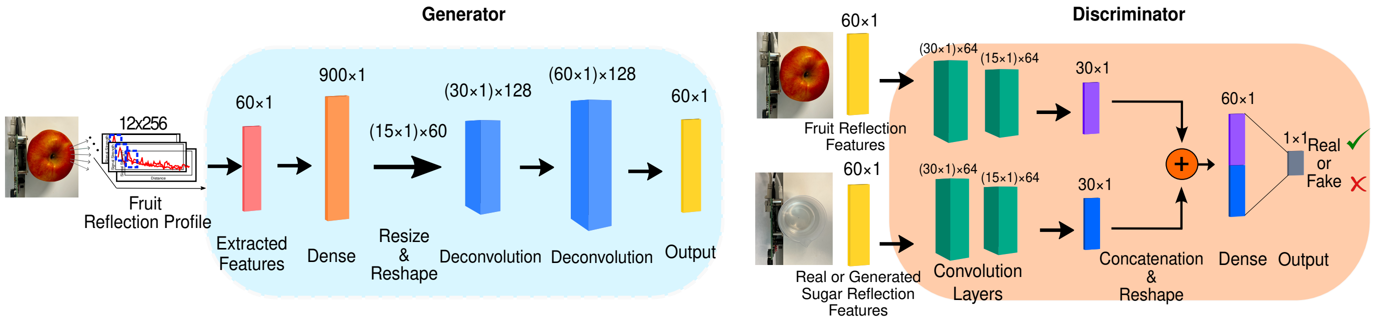

Figure 3: Generator and Discriminator networks of the *SugarWave* system.

the possibility of using reflected signals from different fruits to create a fruit-agnostic SSC estimation system. (2) Despite the dissimilarity in physical appearances, fruits are common in having high water content [19]. (3) Using sugar solutions for data collection is cheaper and more time-efficient.

There are two main challenges in the design of *SugarWave*. First, SSC is correctly measured by the Brix scale only when sucrose is present in the test sample. But other sugars, namely glucose and fructose, also affect the Brix value. To overcome this problem, we employ a Brix correction factor approach [20], in which we calibrate the Brix values of glucose and fructose solutions based on the Brix values of the sucrose solutions. Second, the RSS profiles for sugar solutions and fruits having the same SSC are different due to differences in the material that absorbs and scatters the mmWave signals. Therefore, it is not possible to directly apply a regression model trained on RSS values from sugar solutions to estimate SSC in fruits. To overcome this problem, we use a customized conditional Generative Adversarial Network (cGAN) that learns a mapping between sugar solution reflected signals and fruit reflected signals. Figure 1(d) shows an overview of the *SugarWave* system.

B. Multi-Antenna Signals Processing

As demonstrated by the theoretical model (Eq. (1)) and controlled experiments (Figures 2[b-c]), *SugarWave* aims to estimate SSC by learning the relationship between RSS and SSC. To this end, it uses a mmWave transceiver and a multi-antenna design since as we have shown before, a single antenna is not sufficient to learn the inverse relationship between the RSS and SSC (Figure 2[d]). The mmWave transceiver consists of 3 Tx and 4 Rx that can measure the reflections simultaneously from 12 (3×4) virtual channels. For all the 12 reflections, first, traditional FMCW processing is applied to the received signals to suppress environmental noise. Second, we calculate the average signal amplitude for the time-domain intermediate frequency (IF) signal. Third, we apply Fast Fourier Transform (FFT) on the received signal to create frequency spectrum. Peak zones in the frequency spectrum show IF signals with high RSS values and the location of each peak is proportional to the range of the object that reflected the signal [21]. Since we control the position of the target (sugar solution or fruit), and place it almost attached to the mmWave device (Figures 1[b-c]), by cropping the IF signal and focusing only on the peak zones, we ensure that reflections from background and clutters are discarded because they are far from the mmWave device. In the end, the set of cropped peak zones and average amplitudes in time-domain constitute the dataset used for building the SSC estimation model, giving us 12 features for the signal amplitudes and 48 (4 samples $\times$ 12 reflection profiles) features for all the peak zones.

C. Estimating SSC in Sugar Solutions

We use glucose, fructose, and sucrose solutions to collect reflection signals and measure their SSC in Brix using a refractometer. The refractometer is calibrated based on sucrose, so the Brix values that we get for glucose and fructose are not precise. To improve their accuracy, we find and apply a correction factor to the Brix values gotten from glucose and fructose. To this end, we consider a set of Brix measurements from glucose, fructose, and sucrose solutions where each of the solutions have 3 to 24 grams of solid sugar. Then, we divide the Brix measurements of sucrose by the Brix measurements of glucose and fructose for the same amount of solid sugar, which yields a correction factor respectively for Brix values in glucose and fructose solutions for each solid sugar amount. We apply this correction factor on Brix measurements of glucose and fructose and form a dataset of signal reflection features (from the multi-antenna signals processing) and corrected Brix values of all the sugar solutions.

In *SugarWave*, we consider three common regression algorithms: Linear Regression (LR), Support Vector Regression (SVR), and Random Forest Regression (RF) to develop an SSC estimation model from the 60 extracted features after multi-antenna signal processing and the collected ground truth Brix from sugar solutions. Eventually, *SugarWave* would employ only the best of these models. We develop the LR, SVR, and RF models to estimate SSC in sugar solutions first and then later adopt them for estimating SSC in fruits.

D. Estimating SSC in Fruits

Reflected mmWave signals from fruits and sugar solutions have different properties because of the difference in their physical material [16]. In experimenting with sugar solutions, reflections come from the container and the solution inside and the ground truth Brix is measured by extracting a few drops from the solutions. On the other hand, with fruits, reflections are from the skin and the high water content inside the fruit that has soluble sugars, and the ground truth is measured by using a juice extractor and measuring the Brix of juice. Therefore, using the SSC estimation model trained on sugar reflections to estimate SSC in fruits, first requires making fruit reflections similar to sugar solution reflections. To learn a mapping from fruit reflection signals to sugar reflection signals, we employ a conditional Generative Adversarial Network (cGAN). The cGAN involves a *Generator* **G** that learns the association between the fruit reflection signals and sugar reflection signals captured from targets with close Brix values (less than 0.5 °Bx difference), and a *Discriminator* **D** that helps to gradually improve the capabilities of **G** [22]. Once the cGAN is trained, given the fruit reflection features, it can generate the equivalent sugar solution reflection features, which are then fed to the SSC estimation model trained on sugar solution features for outputting the SSC in fruits.

***SugarWave*'s cGAN Model**: The cGAN architecture of *SugarWave* is shown in Figure 3. The core purpose of *Generator* is to convert the features extracted from fruit reflection to the features from sugar reflection that are used in training our model. To this end, the 60 extracted features from fruit reflections are converted to 1-D feature vectors, and given to a dense layer with 900 neurons where each of the features are mapped to 15 neurons ($15 \times 60 = 900$) to improve learning. Each set of 15 neurons are reshaped as smaller 1-D vectors and fed to two deconvolution layers for up sampling and spreading the information out over a larger feature space, since the output of the *Generator* also has to be signal reflection features with the same size as input. The purpose of *Discriminator* is to teach the *Generator* a better association between the fruit reflection features and sugar reflection features. This is accomplished by distinguishing between real and generated samples during the training process. It takes two inputs: fruit reflection features and sugar reflection features, which can either be real or generated. The system then produces an output, representing the probability that the input is real. The two input features are given to 2 convolution layers for encoding and extracting features. Then, the output of convolution layers are reshaped, concatenated, and fed into a fully-connected dense layer that finally reach a single neuron output layer. The final dense layer outputs the probability of being real or fake. Table I summarizes the *Generator* and *Discriminator* network parameters.

IV. Implementation

***SugarWave*'s Setup:** We implement and evaluate *SugarWave* using reflection data collected from a 77-81 GHz mmWave device, TI IWR1443BOOST [11], as shown in Figure 1(a). The mmWave transceiver has 3 transmit and 4 receive antennas that can measure the reflections simultaneously from 12 (3×4) virtual channels, and by operating on a 4 GHz of bandwidth, gives a depth resolution of 3.75 cm. The ground truth SSC is measured in Brix scale by a digital refractometer [12] (Figure

Table I: Generator and Discriminator network parameters for *SugarWave*'s cGAN. RSC: Reflected Signal Convolutional layer; RSDC: Reflected Signal Deconvolutional layer; FC: Fully Connected layer; Act. Fcn.: Activation Function; LReLU: Leaky ReLU.

	Layer	FC	RSDC1	RSDC2	RSC	Output
Generator	Filter #	900	128	128	1	
	Filter Size		4	4	4	
	Act. Fcn.	LReLU	LReLU	LReLU	LReLU	Linear

	Layer	RSC1	RSC2	FC	Output
Discriminator	Filter #	64	64	60	1
	Filter Size	4	4		
	Act. Fcn.	LReLU	LReLU	LReLU	Sigmoid

2[a]), with an accuracy of ±0.2 °Bx.

Data Collection: We gather two datasets in *SugarWave*:

(1) We collect data from sugar solutions to build our SSC estimation model. To this end, we use 100 ml distilled water inside a container and add sugar starting from 0g (no sugar and only distilled water) to 24g, with increments of 3g. At every step, we measure the SSC by extracting three drops from the solution and measuring the ground truth SSC in Brix scale. After that, we place the container in front of the mmWave transceiver, touching the antennas, and collect mmWave signal reflections (Figure 1[b]). This process is repeated separately for glucose, fructose, and sucrose (the three sugars found in fruits), and we gather 150 input-output pairs of mmWave reflections and Brix values for each sugar type. Then, we determine the Brix correction factors for glucose and fructose, with the method described in section III-C, which are found to be 1.16 and 1.03 respectively.

After applying the Brix correction factor, we combine the measurements and form a dataset with 450 input-output pairs of mmWave reflections and Brix values. (2) We collect reflection signals and measure SSC in real fruits. For each fruit, we collect four reflection signals from four different orientations, 90° apart, of the fruit placed in front of the mmWave transceiver while touching the antennas. Then, to measure the ground truth SSC in each orientation, we cut the fruit into 4 pieces, use a juicer to extract the juice, and measure the SSC from the juice in each cut using the refractometer. We have noticed that within a fruit, the SSC varies significantly with a maximum observed variation of 3.7 °Bx. This is because based on the orientation of the fruit on the tree or the condition that the fruit is stored, some parts will ripen faster, and, as a result, have a higher SSC. In total, we collect data from four different orientations in 101 fruits, giving us 404 (4×101) input-output pairs of mmWave reflections and Brix values. Our fruit dataset is summarized in Table II.

Data Generation: After collecting data from fruits, the re-

Table II: Fruit dataset information.

Fruit	Sample #	SSC Range (°Bx)
Apple	124	9.5 - 18
Orange	52	12.4 - 20.8
Mandarin	88	10.9 - 15.9
Green Kiwi	72	12.5 - 17.1
Golden Kiwi	28	14 - 18
Red Plum	20	13.7 - 16.4
Granny Smith	20	14 - 18

flection data has to be mapped to equivalent sugar solution reflection data. This is because we want to use a regression model that is trained only on data from sugar solutions, due to the reasons described at the end of section II, to estimate SSC in fruits. The *SugarWave*'s cGAN for this task uses the reflection features from sugar solutions and fruits as input-output pairs for learning and generating new data. The aim is such that for each fruit reflection data, an equivalent sugar solution reflection data is found, with both originating from samples having similar Brix values.

Network Training: *SugarWave* requires training of (1) SSC estimation regression model, and (2) cGAN. To train the LR, SVR, and RF models on reflection signals from sugar solutions, *SugarWave* searches for a set of hyperparameters that yield an optimal model which minimizes the loss function. A vanilla LR does not have any hyperparameters for tuning. For SVR we explore different kernels, such as, Linear, RBF, etc, different kernel coefficients (gamma), different penalty parameters (C), and observe that an SVR model with RBF kernel, gamma set to $\frac{1}{features\ \#}$, and C=1 performs best. For RF, we found that the best result is obtained when we use 100 decision trees. For training the cGAN, we observe that with *Adam* optimizer and a learning rate of 3×10^{-4} the model performs better. For the Leaky ReLU activation functions in the *Generator* and *Discriminator* model, the alpha (negative slope function) set to 0.2 gives us the best cGAN. We train the model with these specified parameters for 50 epochs, after which we see no further noticeable improvement.

V. Performance Evaluation

We perform experiments to assess *SugarWave*s performance in SSC estimation. Before providing the evaluation details, we summarize the key findings below.

- *SugarWave* estimates SSC in sugar solutions with a median error of 0.52 °Bx (Figure 4). This is a significant improvement due to our multi-antenna system compared to a previously proposed single-antenna design [1] that results in a median error of 2.63 °Bx (Figure 6[a]).
- *SugarWave* estimates SSC in real fruits with a median error of 1.4 °Bx (Figure 5[a]) and achieves an accuracy of 70% to 83% in classifying the quality of fruits as average, good, and excellent (Table III).

Effectiveness of Predicting °Bx: To evaluate *SugarWave*'s effectiveness in estimating SSC of sugar solutions, we train

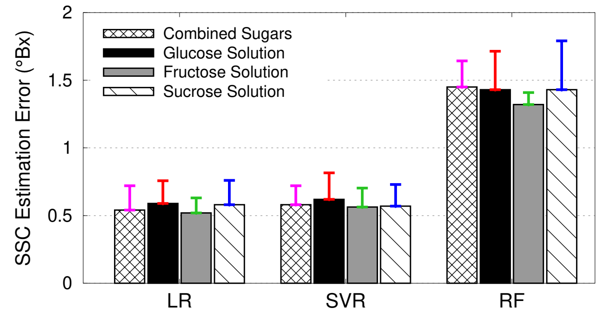

Figure 4: Prediction error of the regression models developed on the sugar solutions. Bars and errorbars represent the median and 90th percentile of the prediction error, respectively.

LR, SVR, and RF models on glucose, fructose, and sucrose sugar solution data and also the combined sugar solution data after applying the correction factor. Our evaluation results, presented in Figure 4, show that *SugarWave* is highly accurate at estimating SSC in sugar solutions using LR and SVR with median errors of 0.52 and 0.56, respectively. Using RF yields poor results in all the cases, therefore, we only focus on LR and SVR. Next, we evaluate SSC estimation in fruits by using the *SugarWave*'s cGAN to generate equivalent sugar solution reflection features from the fruit reflection features and feeding the generated features to the sugar-solution-trained regression models (Figure 1[d]). We observe that *SugarWave* achieves the best result using SVR model trained on the combined sugar solution data with the median and 90th percentile SSC estimation error of 1.4 °Bx and 3.1 °Bx, respectively. Figures 5(a-d) summarize the results of these evaluations.

Effectiveness of Multi-Antenna Signal Processing: To evaluate the effectiveness of our multi-antenna based approach, we compare its performance with that of single-antenna design. In each case, we consider the impact of selecting different extracted features from the reflection profiles, namely amplitudes from the time-domain signal and RSS values from the frequency-domain signal. As shown in Figure 6(a), using only time-domain features leads to a high prediction error of more than 3 °Bx for both single-antenna and multi-antenna based approaches. On the other hand, using both time-domain amplitudes and frequency-domain RSS profiles from multiple antennas as features brings down the SSC estimation error to 0.5 °Bx, whereas the corresponding error with a single antenna is still above 2.5 °Bx. This improvement is quite significant and it confirms that using a single-antenna design and time-domain features, as in a previous study [1], does not yield an accurate SSC estimation in a practical environment.

Multi-Antenna Feature Selection Based on Distance: To evaluate the effectiveness of choosing only a subset of components in the frequency-domain of reflection signals, i.e., removing the reflections from background objects, we conduct experiments by limiting the number of selected features in the frequency domain and monitoring the SSC estimation error. We start by limiting features to the signal amplitudes (named

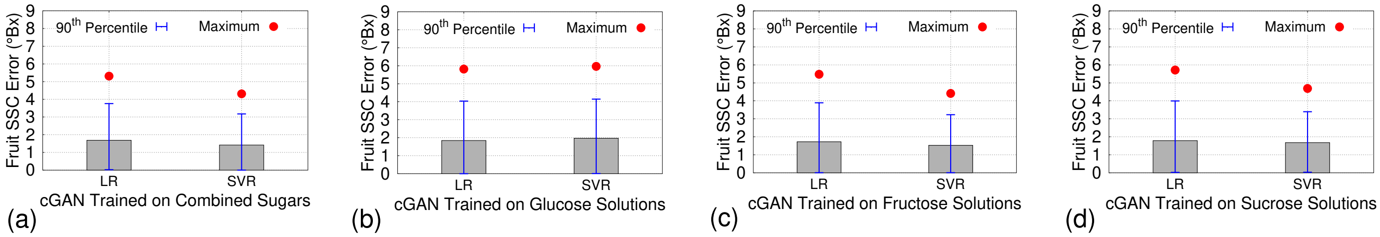

Figure 5: Evaluating the performance of *SugarWave* in estimating SSC of fruits with different cGANs and regression models.

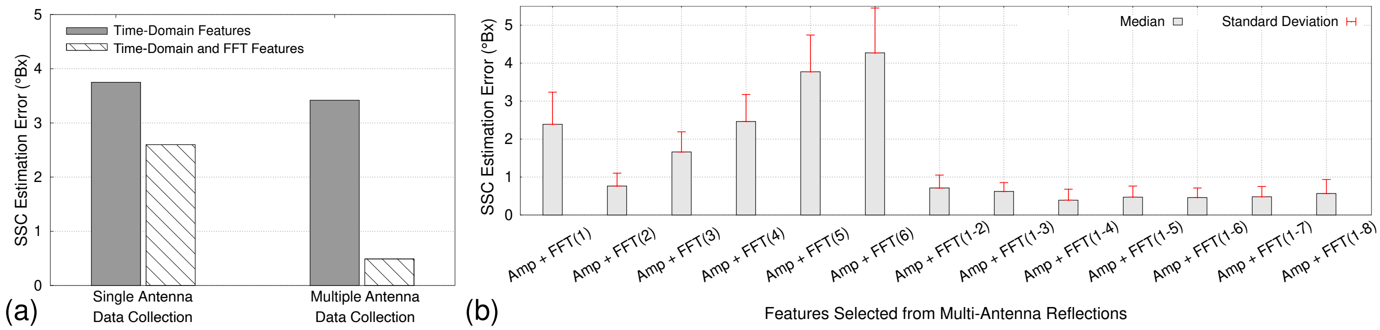

Figure 6: (a) Impact of multi-antenna data collection and frequency-domain features on estimation error. (b) *SugarWave*'s prediction error when different features are selected from the reflection signals.

Amp) in the time-domain and the first component in the frequency-domain (named FFT(1)), and build the regression model. We repeat this process for the second frequency component up to the sixth frequency component (FFT(2), ..., FFT(6)). Additionally, we consider selecting a set of consecutive frequency components (FFT(1-2), FFT(1-3), ..., FFT(1-6)) as features. The RSS values in each FFT point come from the objects at a specific distance. Since the depth resolution of our mmWave device is 3.75 cm, FFT(1) will have reflections from objects less than 3.75 cm from the mmWave device, and FFT(6) covers the distance of 18.75 to 22.5 cm from the mmWave device. We can observe from Figure 6(b) that using only a single point in the frequency-domain yields high errors in SSC estimation. Furthermore, selecting a range of FFT points results in a better performance up to FFT(4), and beyond that we see no improvements in the model. The features of FFT(1-4) cover a range of 0 to 15 cm and are suitable for evaluating the model on real fruits, since the height and width of our fruits are within this range.

***SugarWave*'s cGAN:** To evaluate the effectiveness of *SugarWave*'s cGAN, we compare the results of estimating SSC in fruits in two cases. First, we use LR and SVR models to directly build an SSC estimation model from fruit reflection features. Then, we evaluate these models on a test set containing 100 fruit samples. In the second case, we use a cGAN trained to generate equivalent sugar reflection features from fruit reflection features, and sugar-solution-trained LR and SVR models. We give the same 100 fruit samples as input to the cGAN's generator, and feed the generated features to the sugar-solution-trained LR and SVR models. Figure 7 shows the SSC estimation error of these 100 samples in both

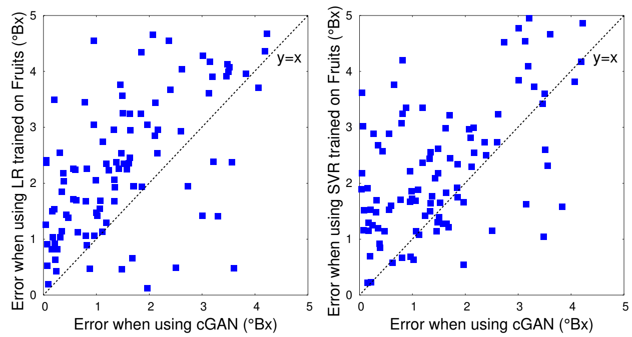

Figure 7: Performance of *SugarWave* with (x-axis) and without (y-axis) using a cGAN.

cases. Each point on the plot represents a test sample: x-value is the error when we use a cGAN, and y-value represents the error when the system is evaluated using fruit-trained model without a cGAN. For the same sample, the error using cGAN is typically lower than directly applying regression to fruit reflection data, demonstrating that incorporating a cGAN enhances *SugarWave*s SSC estimation accuracy in fruits.

Fruit Quality Assessment: Brix quality charts [23] are used for classifying the quality of fruit products as poor, average, good, and excellent. For example, an average quality apple has a Brix measurement between 8 and 12 °Bx. So, to evaluate *SugarWave*'s performance in terms of qualitative assessment of fruit, we use 100 fruit samples and measure the ground truth Brix values with a digital refractometer.

We then use these values and the Brix quality charts to categorize them as average, good, or excellent. In our dataset, no fruits were of poor quality. Next, we use *SugarWave*'s

Table III: Confusion Matrix for predicting fruit quality in *SugarWave*.

Actual/Predicted Quality	Average	Good	Excellent
Average	**73%**	27%	0%
Good	17%	**83%**	0%
Excellent	0%	30%	**70%**

SSC estimation model to calculate an estimated Brix for each sample, and use the Brix quality charts to classify the samples. Comparing actual and predicted fruit quality, we generate a confusion matrix, with rows and columns denoting actual and predicted quality classes respectively. This procedure, executed five times with varied fruit samples, computes an average prediction accuracy per class, displayed in Table III. *SugarWave* classifies fruits as average, good, and excellent quality with respective accuracies of 73%, 83%, and 70%.

VI. Related Work

Destructive Approaches: Industry-standard methods like gas chromatography-mass spectrometry and high-performance liquid chromatography are widely used for analyzing organic acids, amino acids, and sugars in fruits [7]. Both techniques demand professional training and expensive lab equipment, making them unsuitable for lay consumers. Evaporative light-scattering detection [7], another destructive approach, requires advanced processing and specialized equipment.

Non-Destructive Approaches: Spectroscopic techniques like nuclear magnetic resonance, high-resolution magic angle spinning, and near-infrared (NIR) spectroscopy enable nondestructive SSC measurement in fruits. Though non-destructive, it requires additional equipment like spectrophotometers. Recent low-cost, low-power mmWave devices for SSC estimation necessitate special equipment [1], [24] and single-antenna setups, our work refines these approaches, improving their real-world applicability.

VII. Conclusion

We introduce *SugarWave*, a promising solution for non-destructive SSC estimation in fruits. Unlike systems that destroy fruit, require expensive equipment, or use impractical antennas, *SugarWave* employs low-cost COTS mmWave devices. It utilizes learning models and customized generative adversarial networks for estimating SSC in fruits and sugar solutions. Future work includes testing with more fruit samples and reducing proximity requirements.

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