



FruitPhone: Detecting Sugar Content in Fruits Using Unmodified Smartphones with Spectral Imaging

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Motivation

- Consumers should detect sugar content in fruits to manage health conditions like diabetes or weight control effectively.
- Current solutions asking for **intrusive analysis** or **special equipment** hinders the acceptability for average users.



Consumers have concerns whether the sugar content fit the requirements.







Spectrometer





Wireless Signal

Special Equipment

Motivation

- Consumers should detect sugar content in fruits to manage health conditions like diabetes or weight control effectively.
- Current solutions asking for **intrusive analysis** or **special equipment** hinders the acceptability for average users.

Can we achieve fruit sugar content detection using only the ubiquitous devices (like an unmodified smartphone)?

Consumers have concerns whether the sugar content fit the requirements.

Refractometer

Invasive

Spectrometer

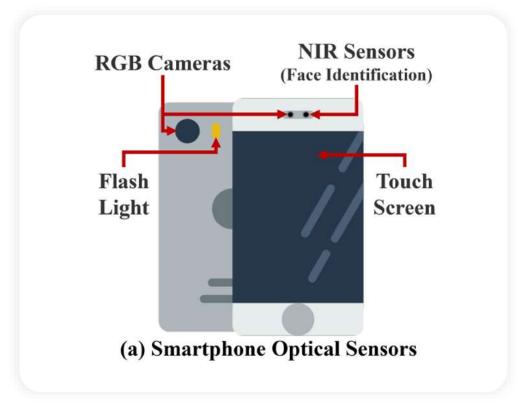
Expensive

Wireless Signal

SpecialEquipment

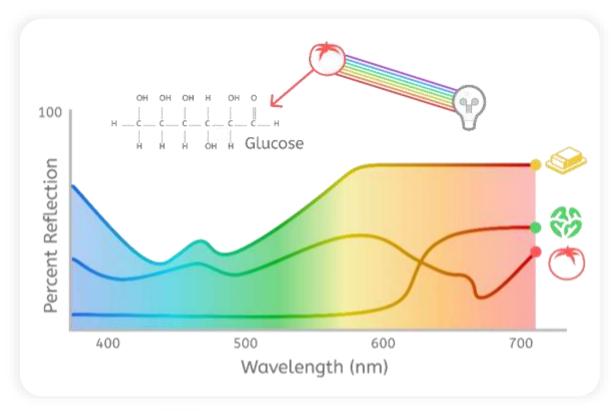
Background

• Smartphone has many optical sources and sensors that have the potential to be reused as a spectral system.





Smartphone Optical Sensors





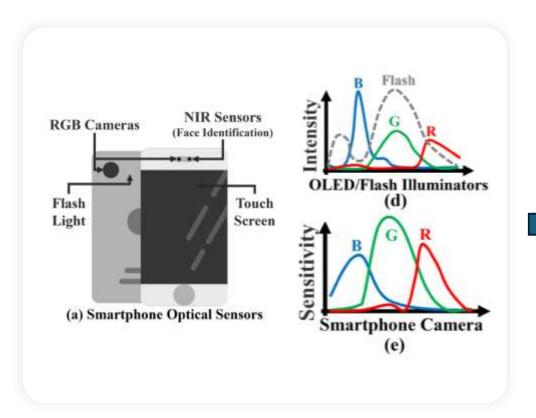
Rationale of Spectroscopy

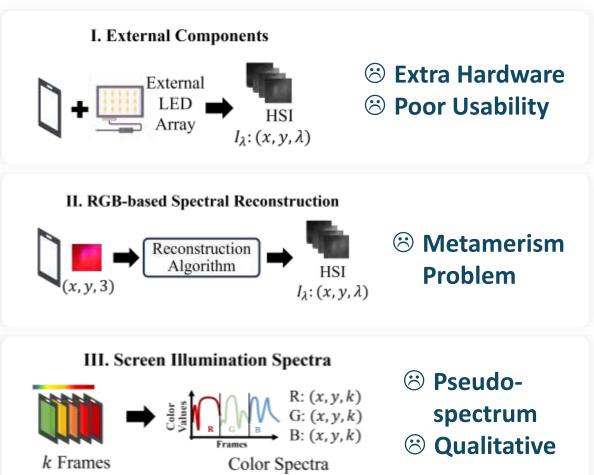
Background

• The smartphone has only three wavelengths of light (RGB), which significantly reduce the performance of spectral analysis.

Extend

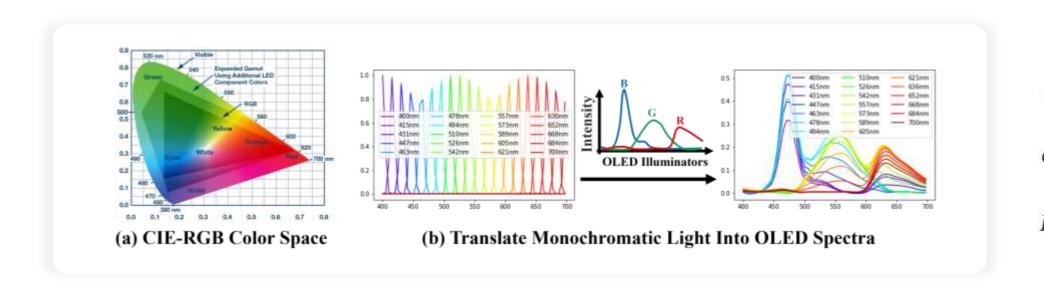
RGB





Observation

 The screen-simulated monochromatic light can be viewed as a mapping from a real monochromatic wavelength to RGB colors.



$$R = Y \cdot \frac{x}{y},$$

$$G = Y \cdot \frac{1 - x - y}{y},$$

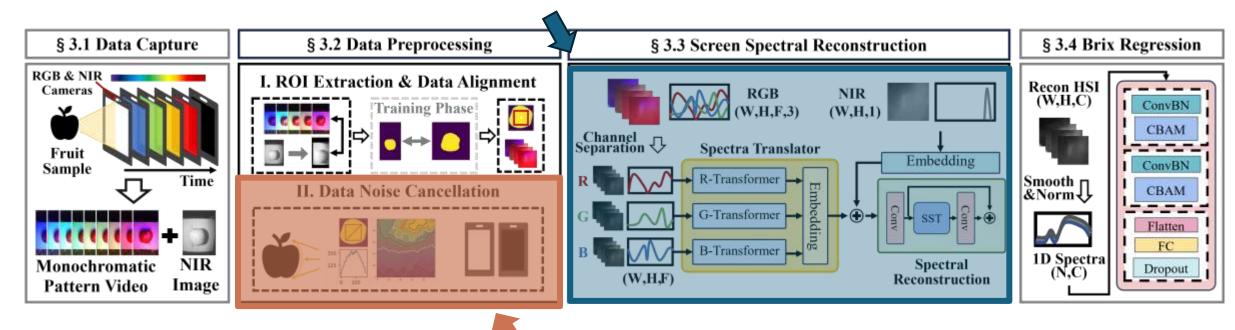
$$B = Y \cdot \frac{(1 - y)}{y}.$$

We have the opportunity to reconstruct the real hyperspectral image from screen-simulated color spectra!

Our System: FruitPhone

• We propose Fruitphone, which reconstructs the color spectra illuminated by smartphone screen light sources into a real hyperspectral image for fruit sugar content prediction.

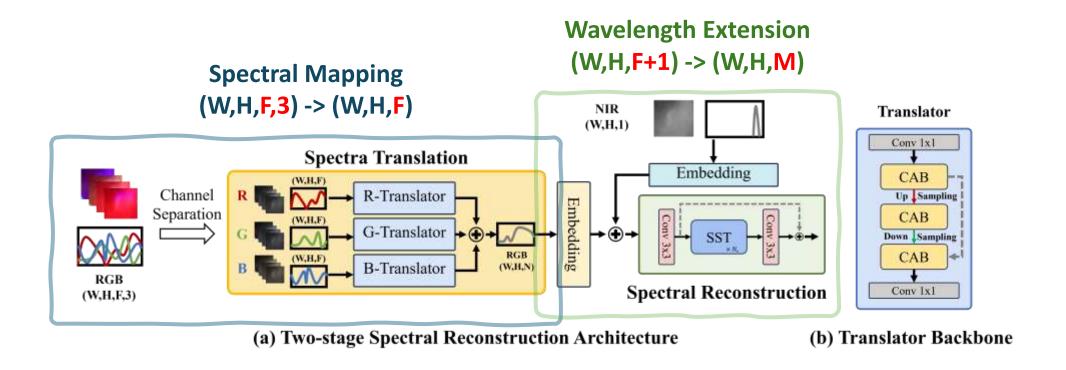
Challenge #1: Reconstruct Screen Spectra



Challenge #2: Calibrate Environment Noises

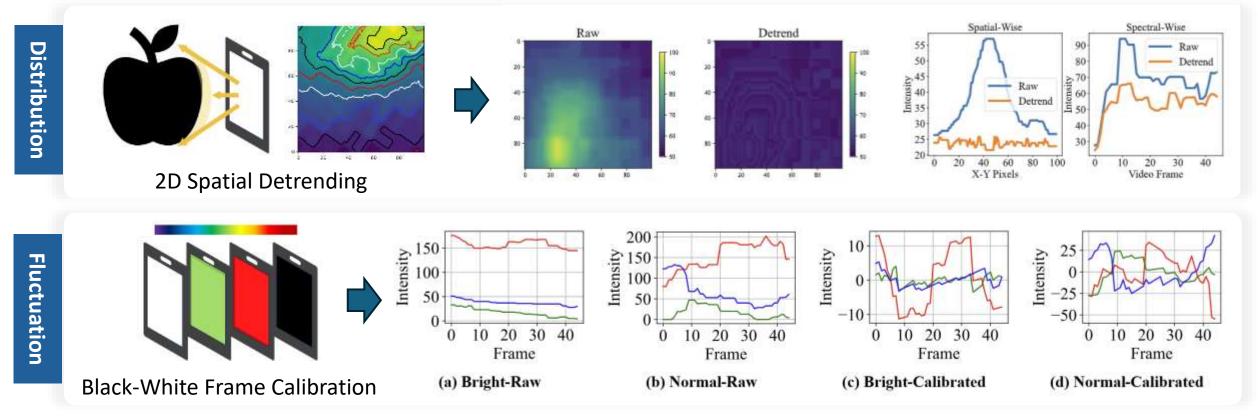
Challenge #1: Reconstruct Screen Spectra

- We introduce a two-stage spectral reconstruction algorithm:
 - Stage 1: translates the collected pseudo-spectral images into real multi-spectral images
 - Stage 2: derives full spectra from the translated features



Challenge #2: Calibrate Environment Noises

- Distribution: Spatial unevenness due to sample shape and screen light distribution
- Fluctuation: Surrounding interferences such as ambient light or user jitter may introduce inconsistence of the sample



Evaluation: Setup

• We evaluate the performance of FruitPhone on **37** types of fruit with **335** fruit samples in total.

Category	Fruit Type (Number of Varieties)	Sample	Brix Range (° <i>Bx</i>) 3.1-23.1	
Berry	Grapes (6), Tomato (2), Strawberry (1), Blueberry (1), Mulberry (1), Guvav (1), Kiwi (1), Passion Fruit (1), Pepino (1)	180		
Drupe and Kernel	and Kernel Apples (4), Pear (2), Peach (1), Jujube (1), Loquat (1), Mango (1), Cheery (1), Persimmon (1)		8.9-20	
Citrus	Mandarin (3), Orange (2), Lemon (2), Kumquat (1), Grapefruit (1)	75	4.6-21.5	
Cucurbits	Longan (1)	5	11.4-16.3	









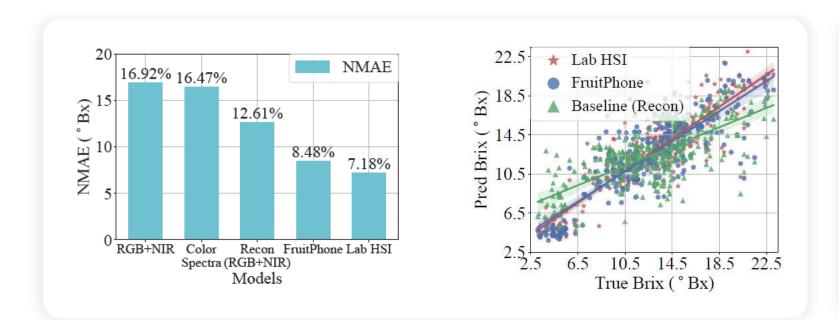
(a) Partial Fruit Samples in Training Dataset

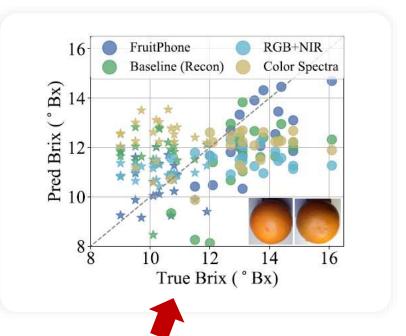
(b) FruitPhone Setups

(c) Brix Ground Truth

Evaluation: Results

FruitPhone achieves a normalized mean-absolute error (NMAE) of 8.48%, which is only
 1.3% higher than that of an expensive laboratory hyperspectral spectrometer (priced over \$10,000).

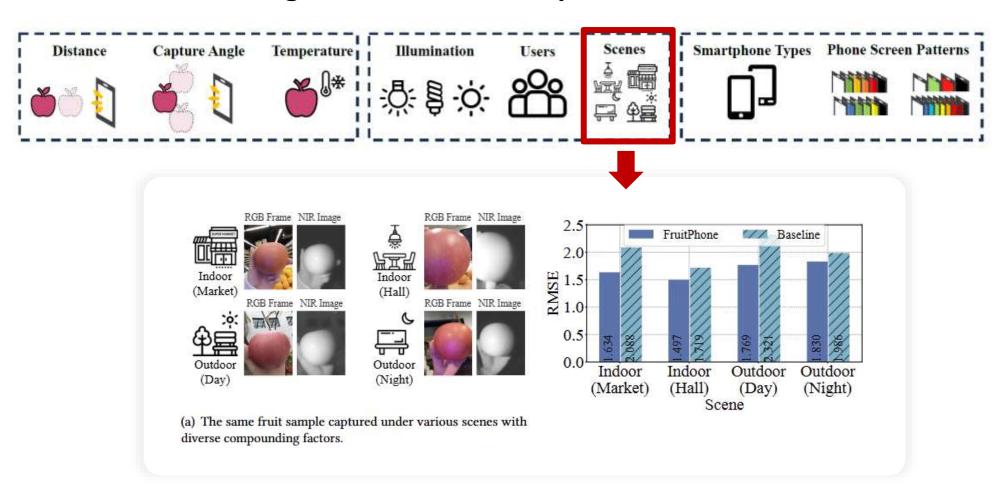




FruitPhone shows great improvement than baselines on metameric samples.

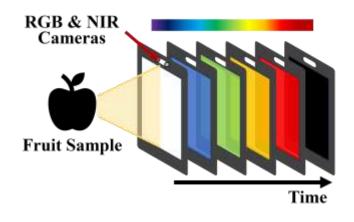
Evaluation: Robustness

 FruitPhone demonstrates remarkable robustness across various setups, including diverse fruit placements, user configurations, and smartphone models.



Conclusion

- Enabling quantitative fruit sugar measurement using only a smartphone.
- Overcoming hardware limitations via screen-based illumination and a two-stage spectral algorithm.
- Opening our dataset (with 335 hyperspectral images, RGB color spectra, near-infrared reference, and ground true brix values) to involve more investigations in this area.





Scan QR Code to access our dataset





Thank you!

Homepage: https://hyanhu.github.io/

October 15, 2025

Espoo, Finland



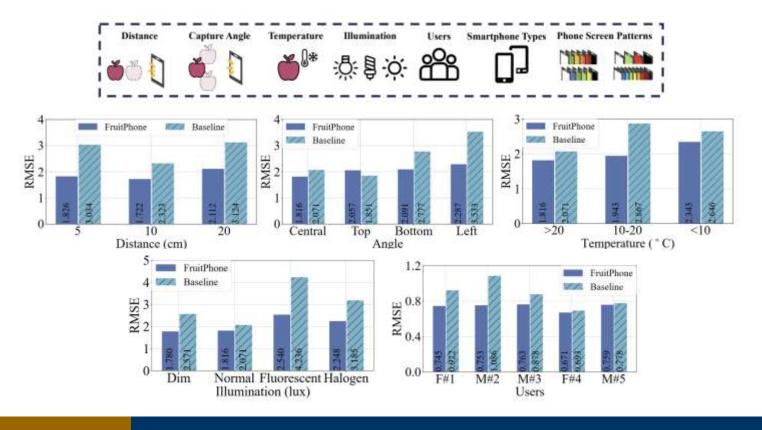




Evaluation: robustness

- Compared to the state-of-the-art smartphone-based spectral system baseline, our solution reduces reconstruction errors by 19.98%.
- A single run of the app on Google Pixel 4 XL consumes 2.945 mAh (0.079% of the battery capacity).

	FruitPhone	Baseline		
MRAE	0.1803	0.2643		
RMSE	0.0981	0.1226		
PSNR	23.81	20.19		
Flops (G)	230.6	221.7		
Params (M)	31.44	31.26		



Evaluation: Robustness

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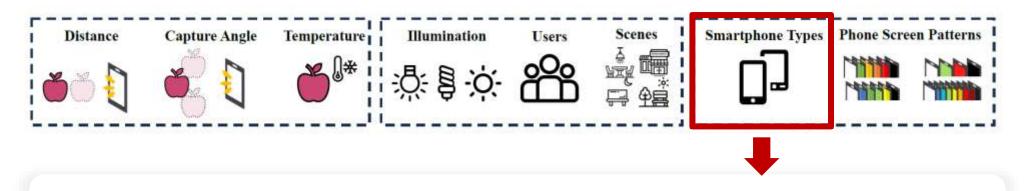


Table 5. Comparing the parameters across three smartphones and FruitPhone's performance on them after fine-tune.

	Screen Type	Screen Resolution	Refresh Rate	Camera Resolution	HDR Support	MRAE	RMSE	R2	NMAE
Google Pixel 4XL	OLED	3040×1440	90Hz	8MP	HDR10	0.1954	0.1032	23.15	8.90%
OnePlus 8 Pro	Fluid AMOLED	3168×1440	120HZ	16MP	HDR10+	0.2120	0.1476	20.26	9.97%
IQOO Z9X	LCD	2400×1080	120HZ	16MP	HDR10	0.2068	0.1353	20.79	9.25%