ERIC: Estimating Rainfall with Commodity Doorbell Camera for Precision Residential Irrigation

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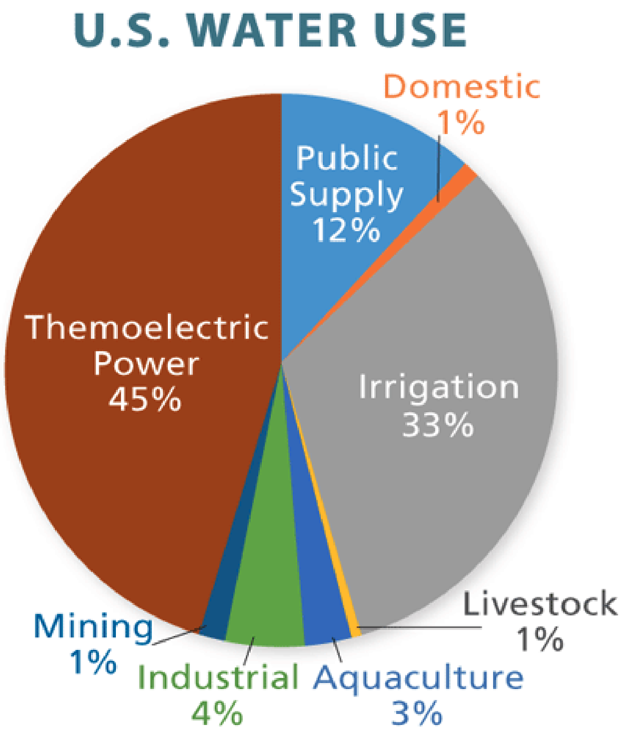
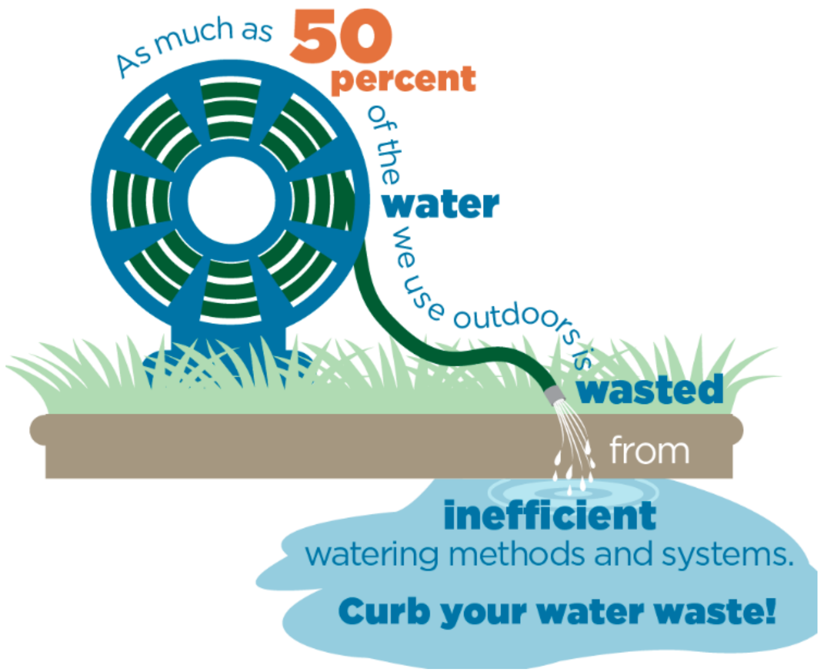
Motivation: substantial waste of irrigation water

Environmental Protection Agency reports that landscape irrigation accounts for 1/3 of U.S. water use, **over 9 billion gallons per day**.





(photos from USGS and EPA)

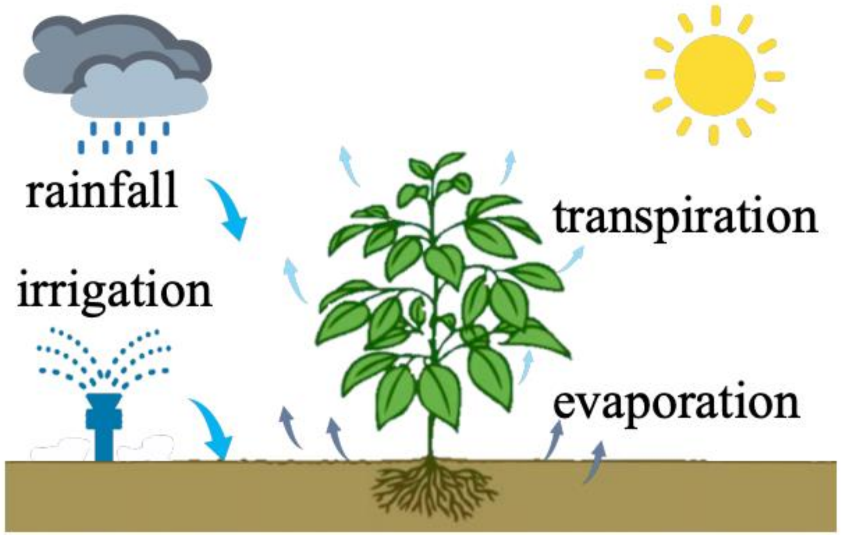
Traditional irrigation methods are inefficient, high-cost

- Traditional “set it and forget it”
  - Fixed schedule regardless of rainfall, solar radiation, plant and soil types, etc.
  - Significant waste of water
- Soil moisture sensor
  - Limited measurement range (12 in)
  - Frequent calibration and high maintenance cost

(photos collected from google search)

U.S. states widely adopt weather-based scheduling

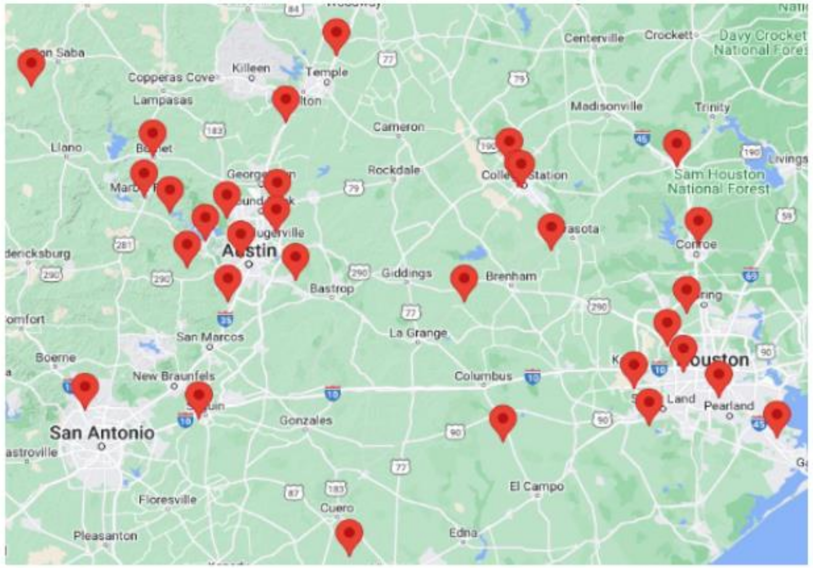
- Weather-based method considers the water balance between incoming water and outgoing water to calculate irrigation amount
- Relies on accurate rainfall measurement from nearby weather station
- Homeowners receive weekly irrigation guidance from government agency and adjust irrigation valves manually



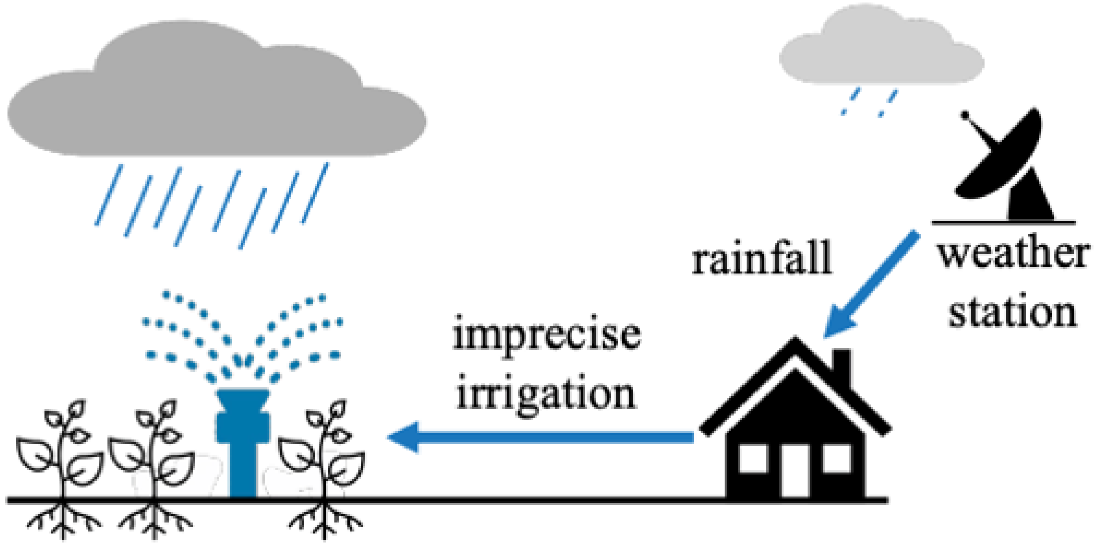
Irrigation = Evapotranspiration - Rainfall

Weather-based method is limited by inaccurate rainfall

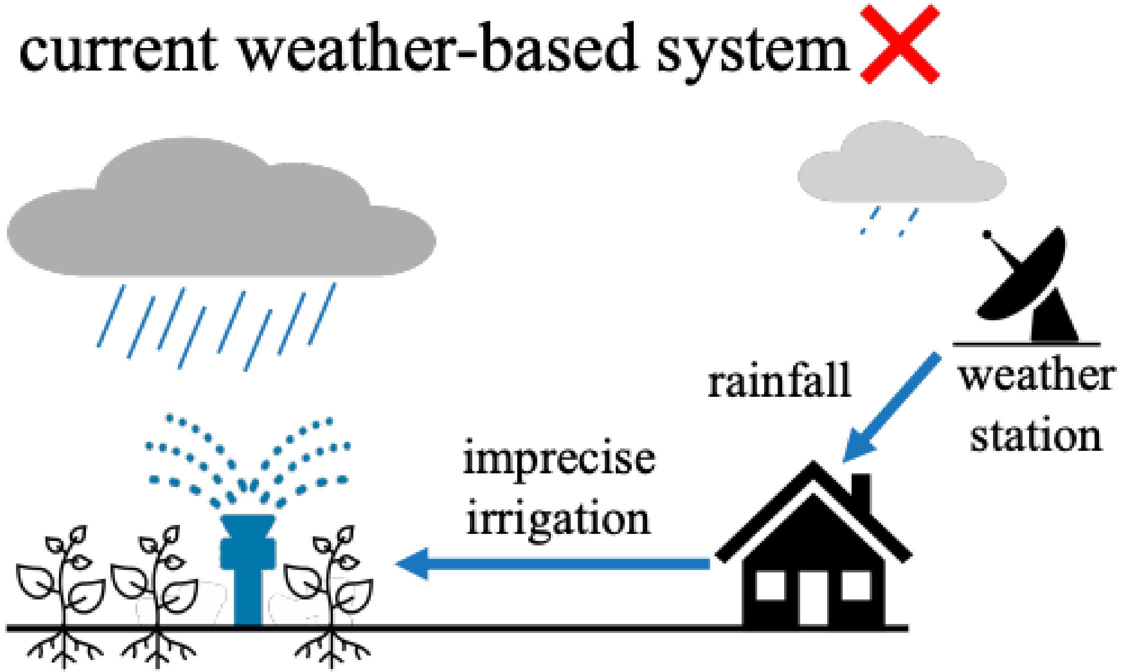
- WaterMyYard (TX), CIMIS (CA) programs built 50-70 weather stations to obtain accurate rainfall measurement
- However, our field experiments show that rainfall measured from nearby weather station (only 1.7 miles away) differ as much as **54%** from the actual hyperlocal rainfall



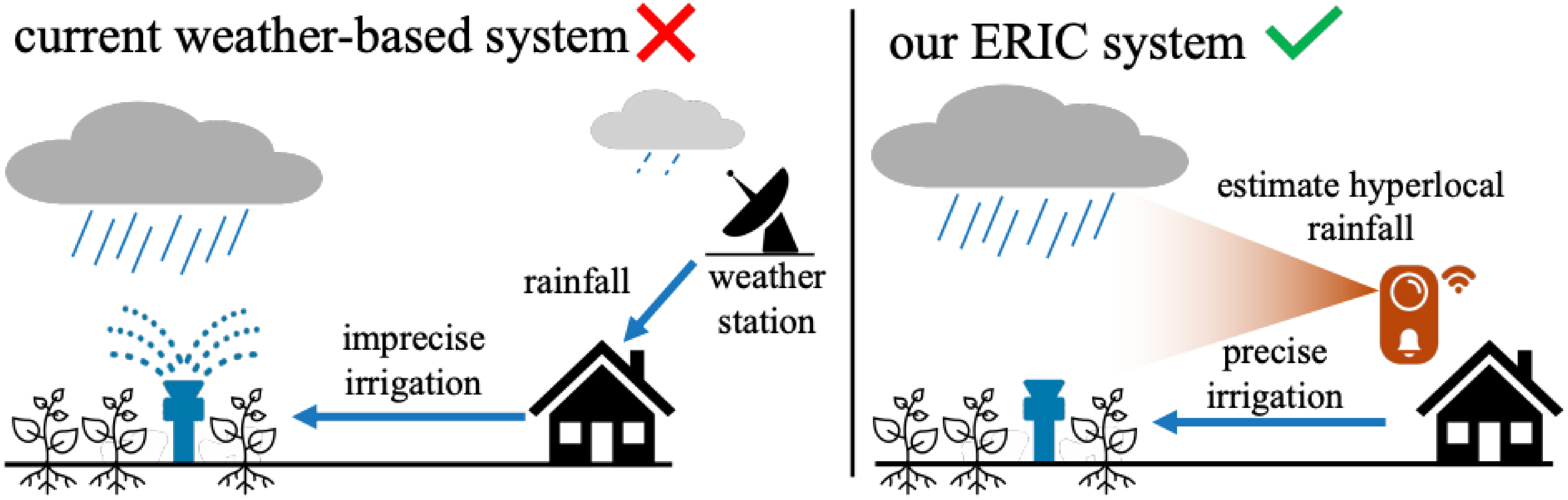
(Part of WaterMyYard weather stations)



Question: how to obtain more accurate hyperlocal rainfall measurement?

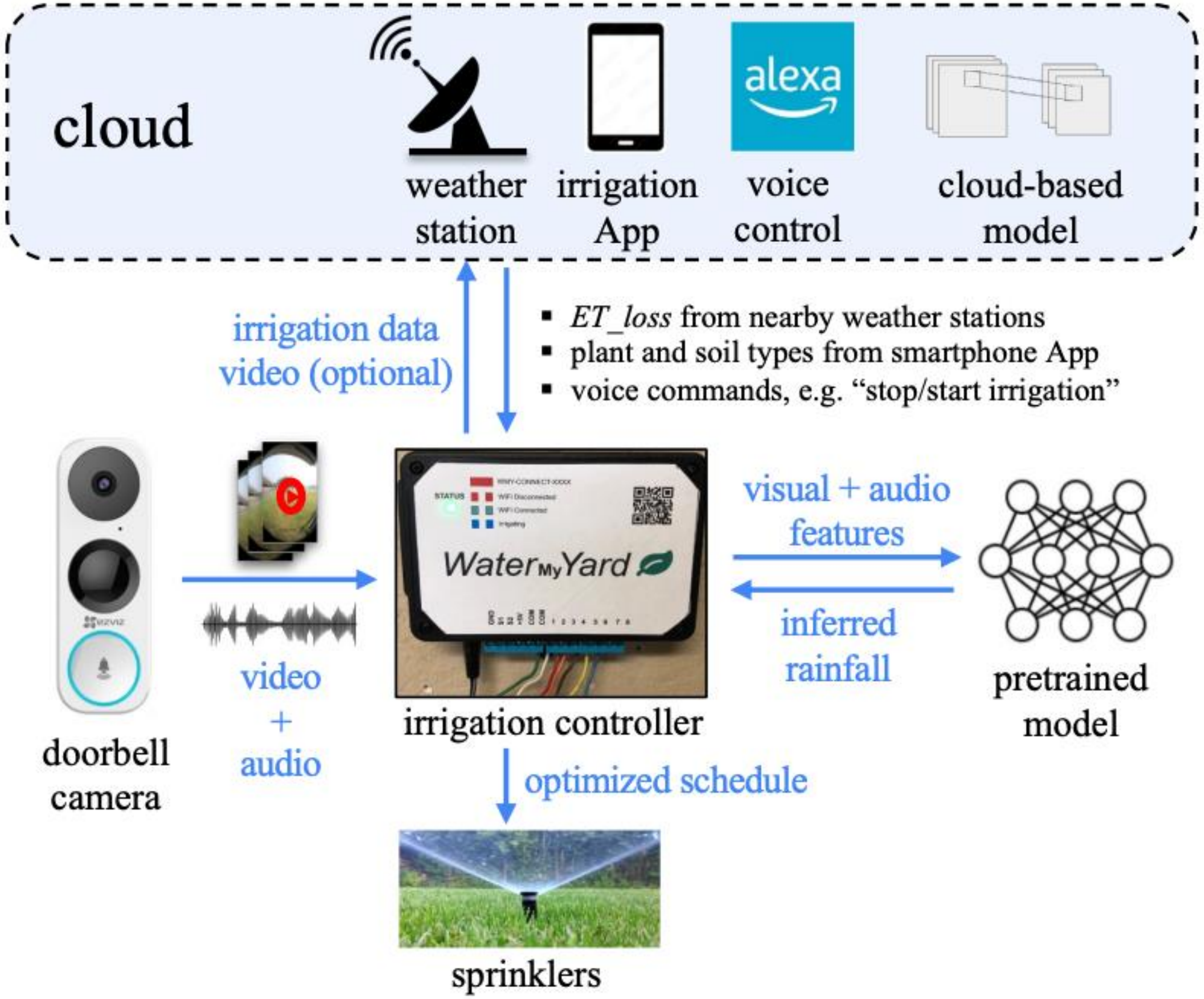


Our solution: estimating hyperlocal rainfall using doorbell camera

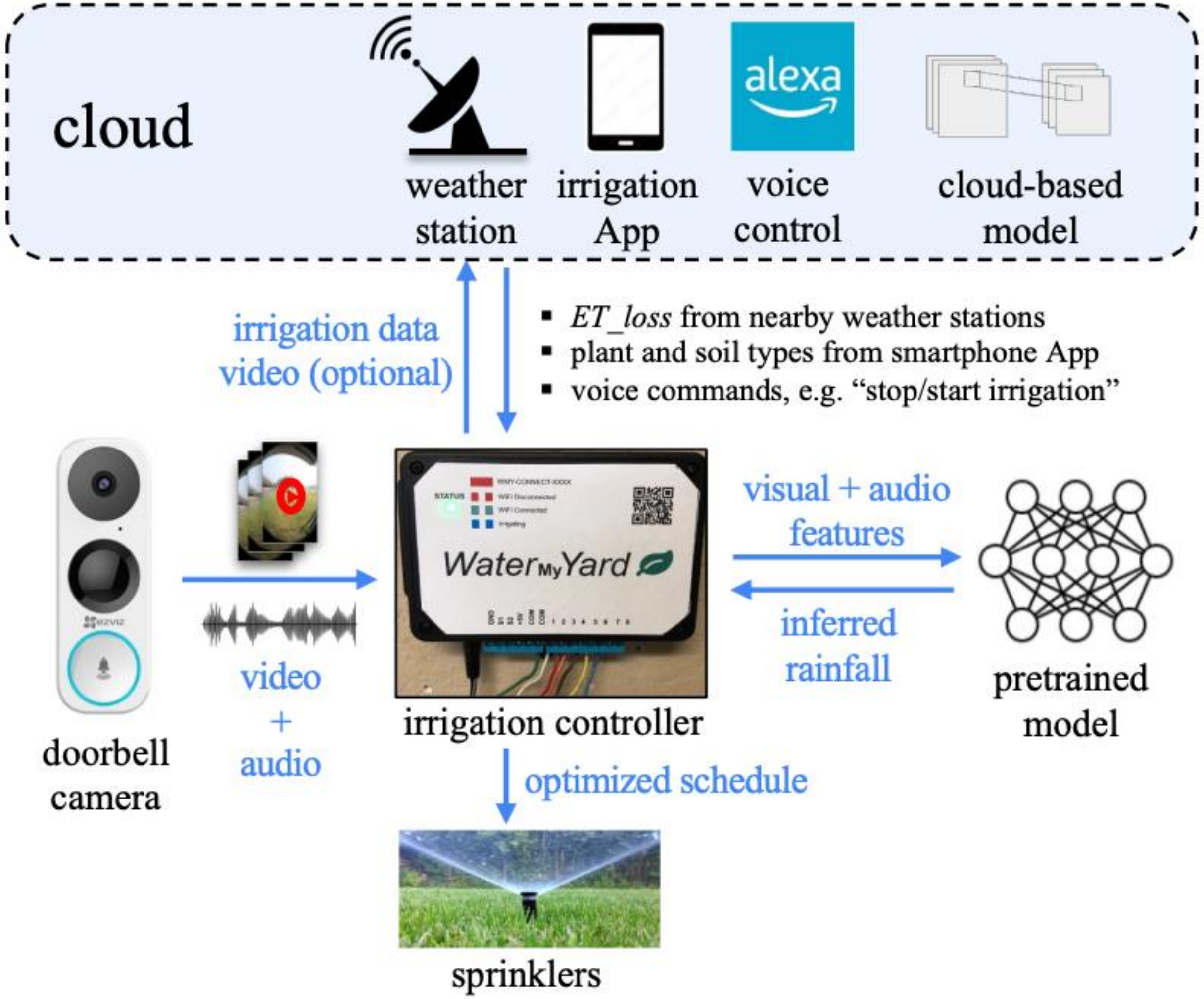


Our idea: exploit the multi-modal (visual, audio) information captured by video recordings to estimate hyperlocal rainfall

ERIC System: accurate, efficient, privacy-preserving



ERIC System: accurate, efficient, privacy-preserving



- **Accurate** rainfall estimation using ML models
- **High system efficiency** for real-time inference
- **Preserve user privacy** by training and inference at the edge
- **Low-hardware cost**: $75 for Raspberry Pi 4 device
- **Fully automated** scheduling without manual intervention

How to estimate rainfall with commodity camera?

- Existing methods
  - **Extraction-based**: extracting rain streaks via geometric and photometric models
    - Need to tune camera settings for optimal visibility
    - Faces significant challenges in practice: rain fog effects, residual water, wind, shape distortion, poor lights
  - **Deep learning-based**: CNN model
    - Requires large training cost, expensive GPUs that are not commonly available to homeowners
    - Lacks rigorous evaluation on continuous streaming videos, likely due to insufficient opensource video data

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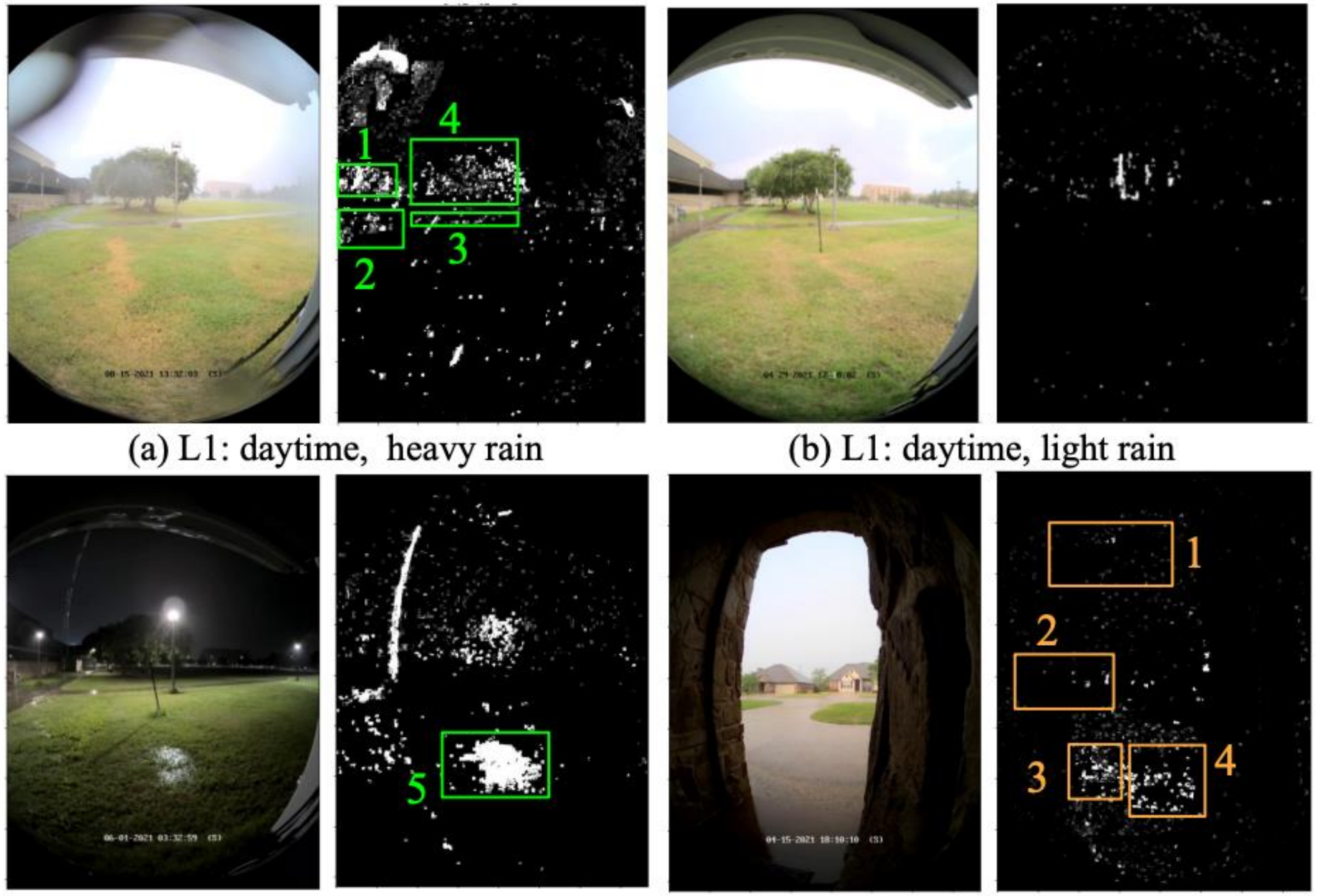
Challenge 1: how to develop model that is accurate, generalize (no tuning on camera), and robust?
Challenge 2: how to achieve high efficiency and low compute cost for processing video streams?

Our key intuition: estimate rainfall from reflections!

- $\Delta I = |I_{n+1} - I_n|$
- Reflections capture the fast-moving raindrops and splashes from the ground in adjacent video frames
- Intensity and density of reflections correlate to rainfall intensity
- Reflections is robust to different light conditions, background, camera placement, etc.
- Commodity doorbell camera ($30) works!

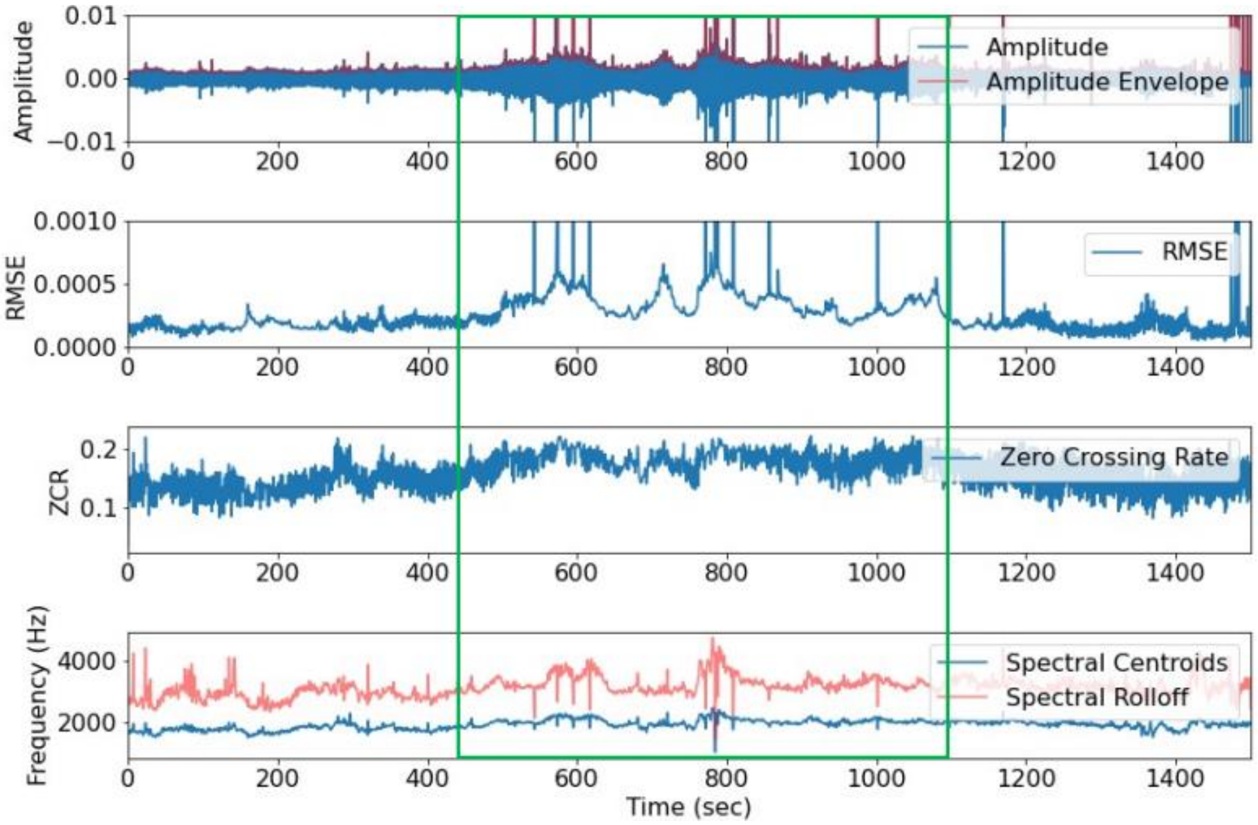


(a) L1: daytime, heavy rain (b) L1: daytime, light rain
(c) L1: nighttime, heavy rain (d) L2: daytime, heavy rain

Challenge 1: how to develop model that is accurate, generalize (no tuning on camera), and robust?

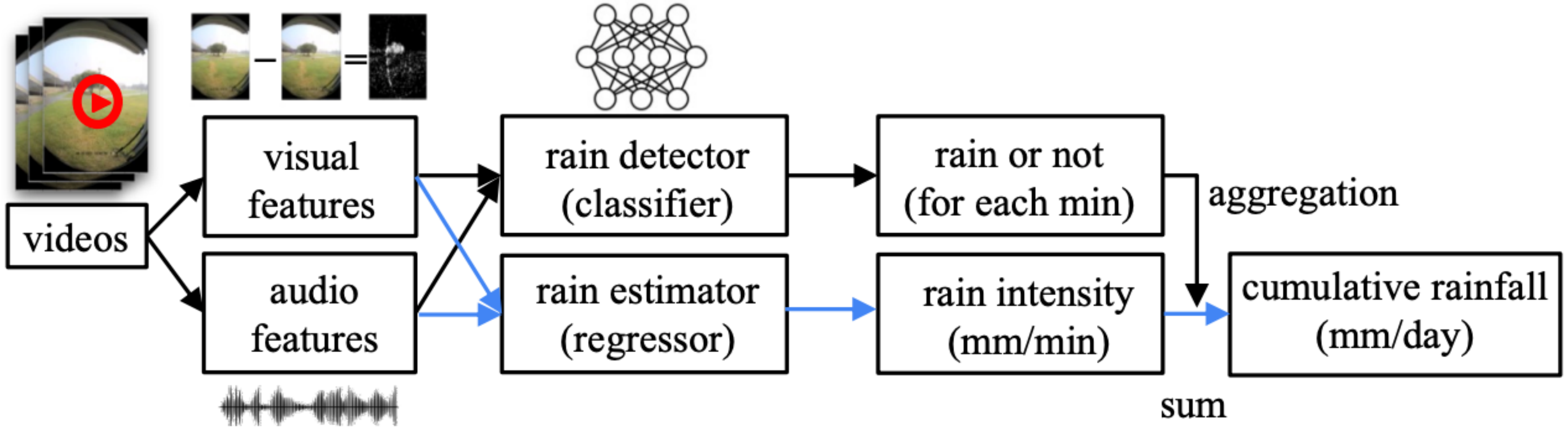
Our key intuition: audio features also help!

- Rainfall introduces repetitive “drum-hitting” sound
- Heavier rains lead to increased amplitude and frequency-based audio features



Our multi-modal rainfall estimation pipeline at the edge

- Lightweight neural network models (MLP with only 2 hidden layers)
- Cloud version uses CNN model for automatic feature extraction



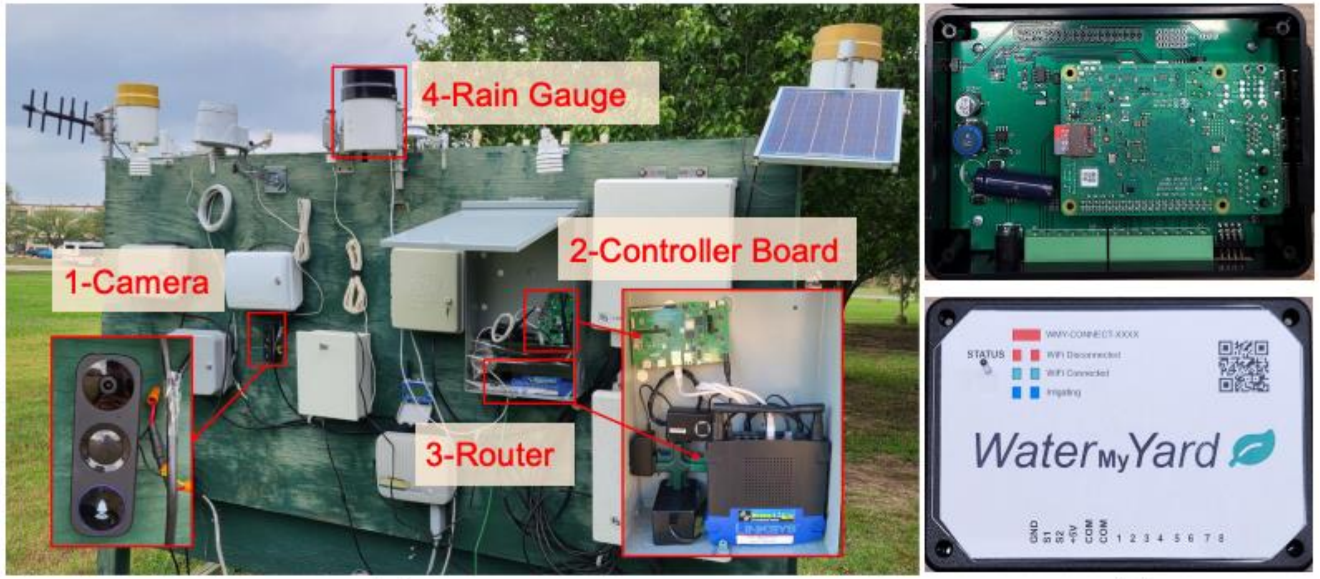
Challenge 2: how to achieve high efficiency and low compute cost for processing video streams?

Our rainfall estimation method vs. existing methods

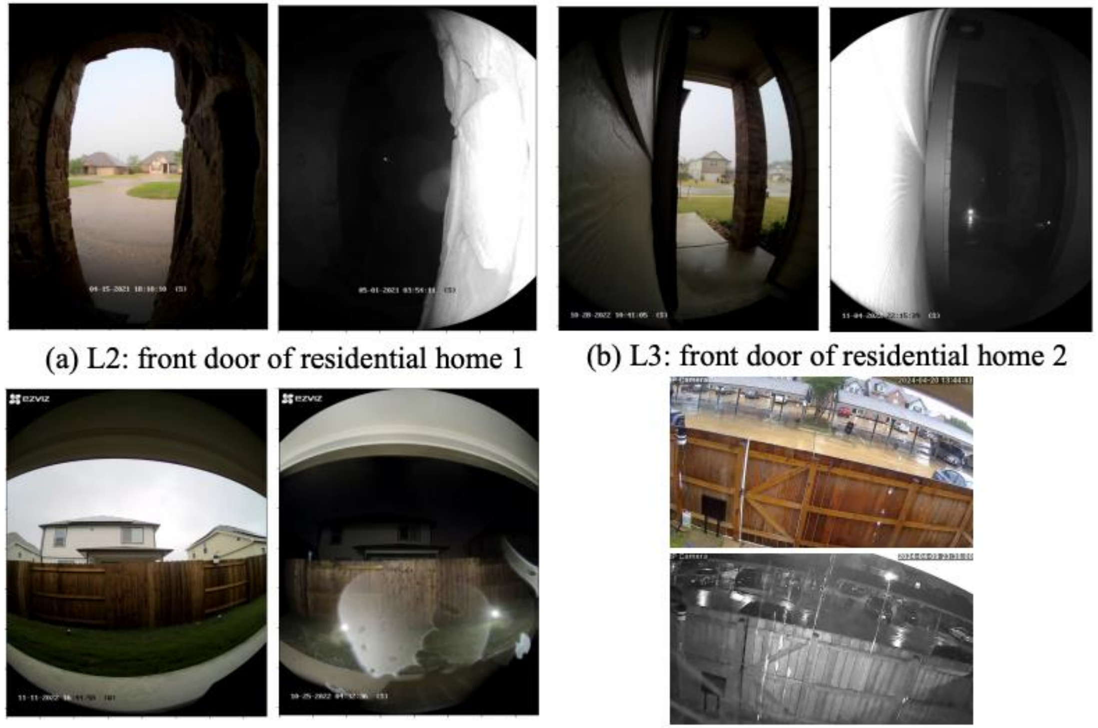
Methods	Model	Tune camera	Accuracy	Efficiency	Works at night	Preserve privacy
Extraction-based	Photometric	Yes	Low	Low	No	No
Deep learning-based	CNN	No	Low	Low	Maybe	No
Reflection-based	MLP	No	High	High	Yes	Yes

System deployment and evaluation

- Deployed at five locations with diverse background, light conditions, camera types, camera placement, collecting over 750 hours of video data.



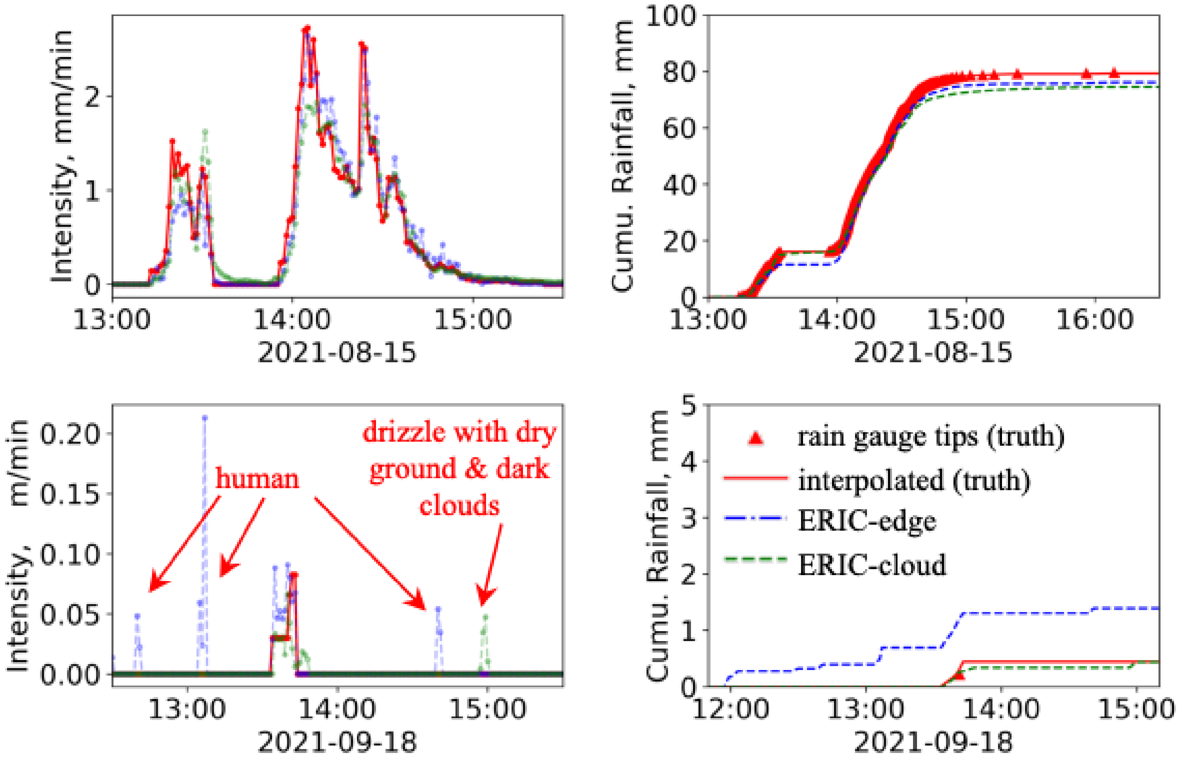
(a) (b)



(a) L2: front door of residential home 1
(b) L3: front door of residential home 2
(c) L4: backyard of residential home 2
(d) L5: backyard of residential home 3

ERIC achieves SOTA rainfall estimation performance

	Jiang et al. [25]	3DCNN [27]	ERIC-edge (ours)	ERIC-cloud (ours)
Camera model	EZVIZ C5Si	AXIS M/Q-E	NSC-DB2 / Topodome	
Camera cost	$100	$300	$30	
Background	Cropped roads	Cropped crossing	Diverse residential	
Video size	7 hrs	215 hrs	750 hrs	
Rain condition	Rain only	Rain + no rain	Rain + no rain	
Lightning	daytime only	daytime only	daytime + nighttime	
Model	Decomposition	3DCNN	ANN	ResNet18
# of params	10	0.45M	205	11.7M
MAPE	21.8%	19.7%	12.3%	10.6%



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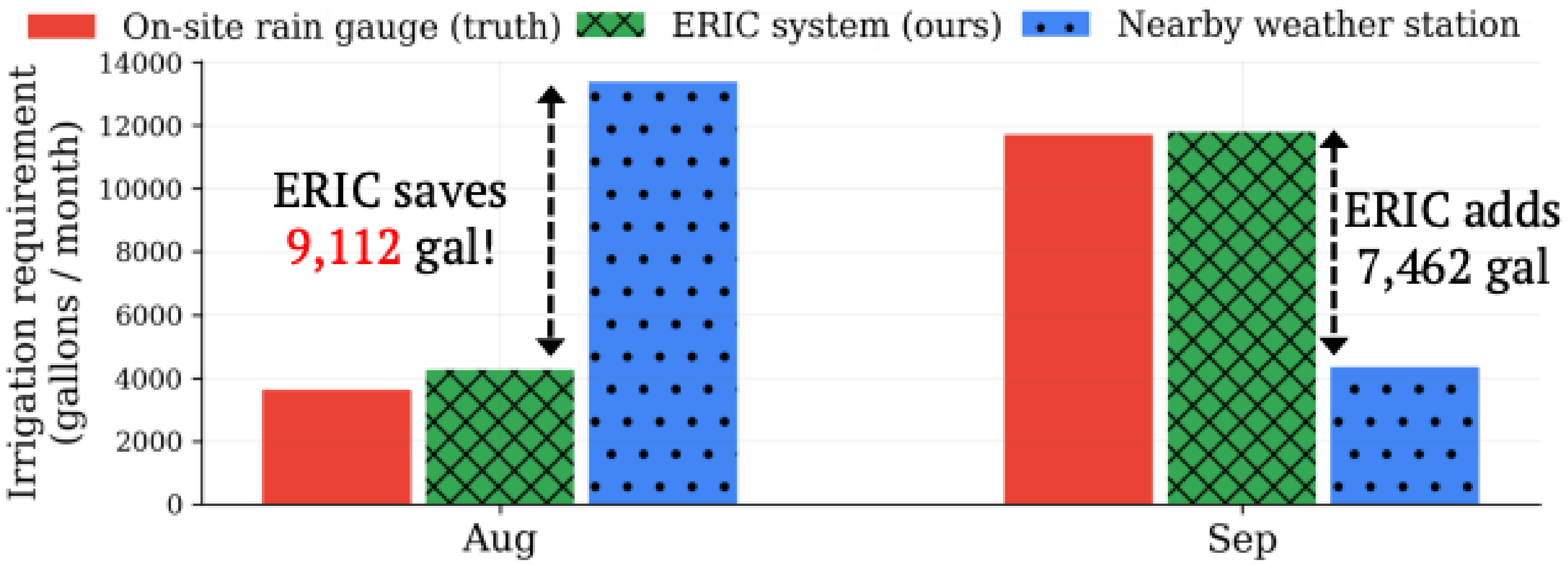
ERIC can run real-time inference!

	Jiang et al. [25]	3DCNN [27]	ERIC-edge (ours)	ERIC-cloud (ours)
Platform	Workstation	Cloud	Raspberry Pi 4	Cloud
RAM	32 GB	10 GB	0.5 GB	3 GB
GPU	12 GB	12 GB	0 GB	5 GB
Storage	0.5 GB	4 GB	0.5 GB	1.5 GB
Time	3.3 hrs	5 mins	12 mins	1.5 mins
real-time	×	✓	✓	✓

ERIC saves over 9,000 gallons of water!



Conclusions

- Developed an end-to-end irrigation system, ERIC, which estimates rainfall from commodity doorbell camera for precision residential irrigation
- Comparing with prior rainfall estimation methods, ERIC is:
  - ✓ Accurate and robust: no tuning on camera, works in challenging conditions
  - ✓ Efficient: real-time inference
  - ✓ Low-cost: $75 Raspberry Pi 4
  - ✓ Privacy-preserving: training and inference at the edge
- Field evaluation shows ERIC:
  - achieves SOTA rainfall estimation performance
  - saves over 9,000 gallons of water per month, translating to $29/month in utility savings

Thank you!

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