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Development of early detection of pandemic outbreak using AI-augmented wearable datasets

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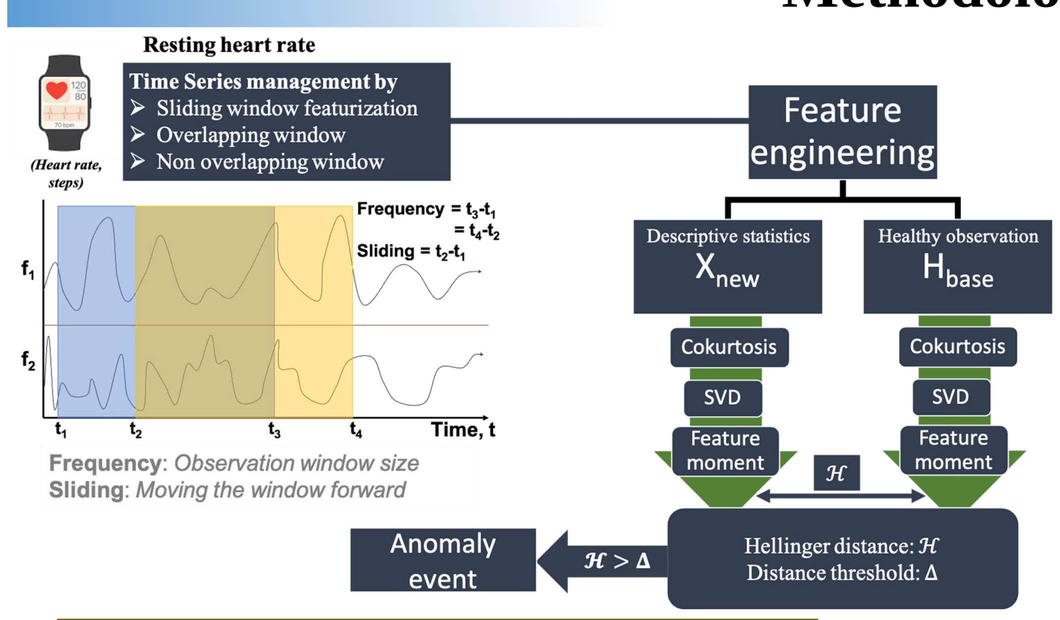
Abstract

Our primary objective is to bolster the far-reaching impact of false negative rate (FNR) in health monitoring (smartwatches) where subtle warning signs may go undetected, potentially leading to severe consequences. To address this critical issue, we've developed a lightweight and streamlined algorithm tailored to categorize irregularities in vital signs (Resting heart rate (RHR), a pivotal metric outlined by the CDC). Our methodology revolves around both real and synthetic datasets (Wasserstein Generative Adversarial Network (WGAN)), strategically navigating the uncertainty associated with anomaly detection thresholds and offering a nuanced and accurate understanding of potential health concerns while significantly reducing false negatives.

Dataset

- ❑ Smart wearable data for 119 users. Mean age (range): 44 (18-88)
- ❑ Data consists of steps and heart rate in at least 5-second intervals.

Methodology



Experimental setup

- ❑ Healthy RHR : ≤100 BPM
- ❑ RHR Ranges: 90-110 BPM (10% variability)
- ❑ Frequency or window size: 60 min, 120 min
- ❑ Overlapping windows:
  - Sliding 30 min for 60 min window
  - Sliding 60 min for 120 min window
- ❑ Non-overlapping windows:
  - Sliding 60 min for 60 min window
  - Sliding 120 min for 120 min window

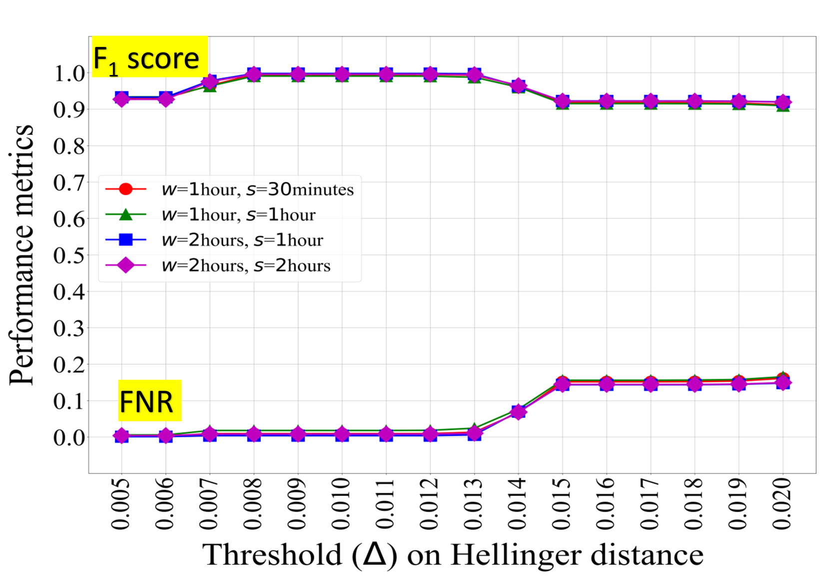
Sick: Given a patient $\mathcal{P}$ with the observation period from T_1 to T_2,
1. Resting heartrate (RHR) > 100.
2. Hellinger distance, $\mathcal{H}$ > threshold, Δ

$$Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN}$$

Population level	Sick ($\mathcal{H} > \Delta$)	Healthy ($\mathcal{H} \leq \Delta$)
Sick (RHR>100)	TP	FN
Healthy (RHR ≤100)	FP	TN

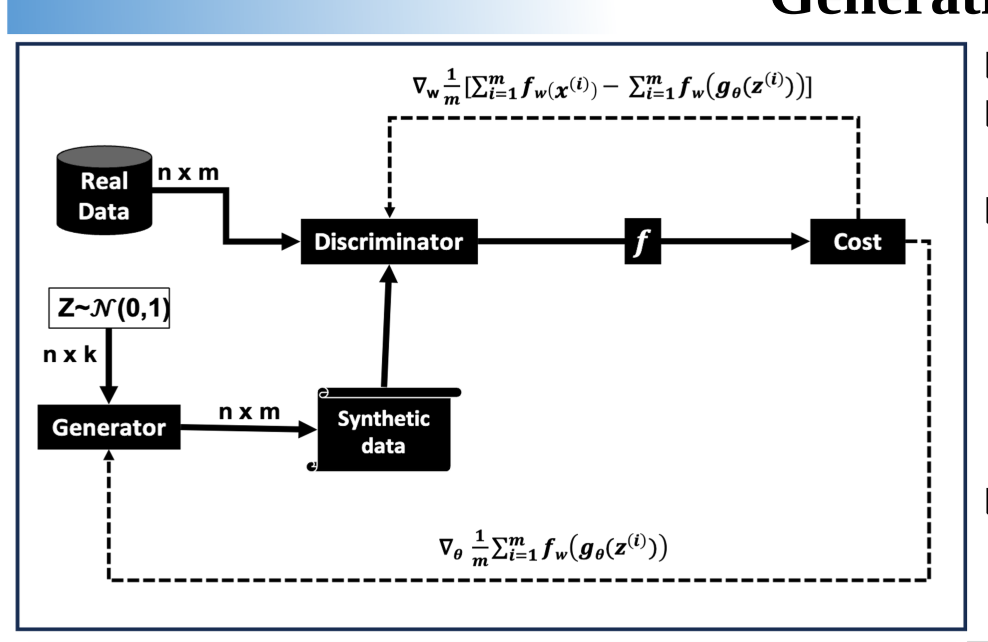
F_1 Score	FNR
$\frac{2 * Precision * Recall}{Precision + Recall}$	$\frac{FN}{TP+FN}$

Detecting proper window and sliding

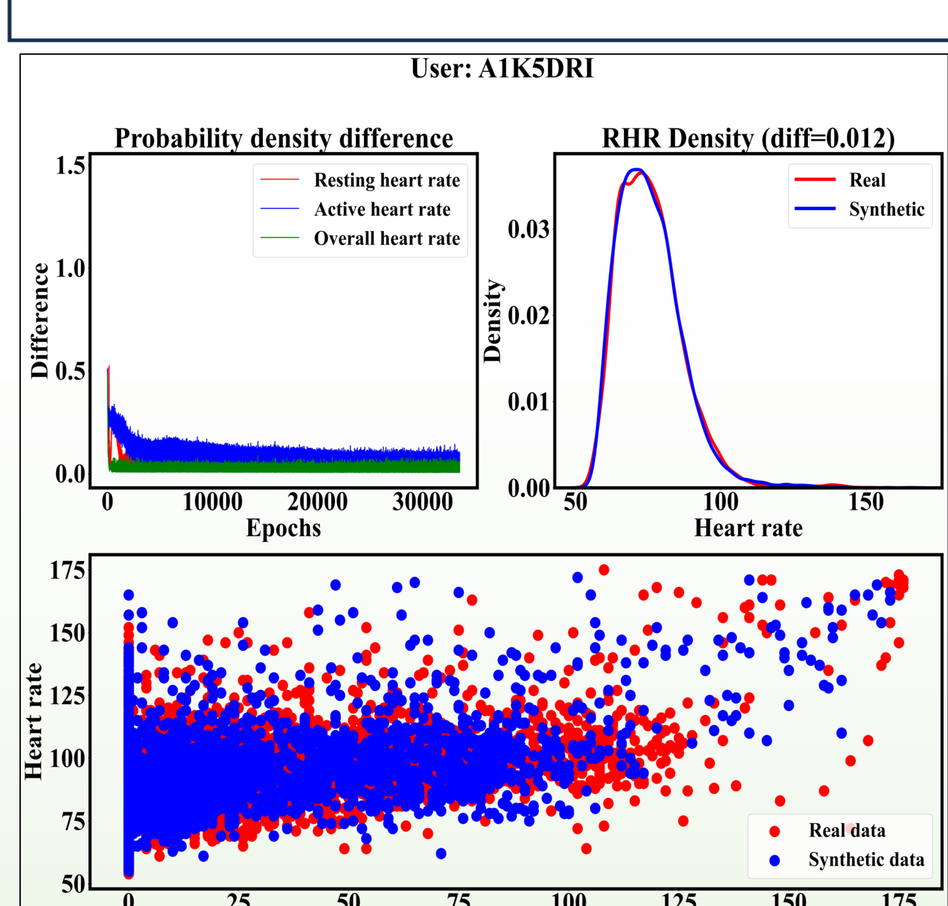


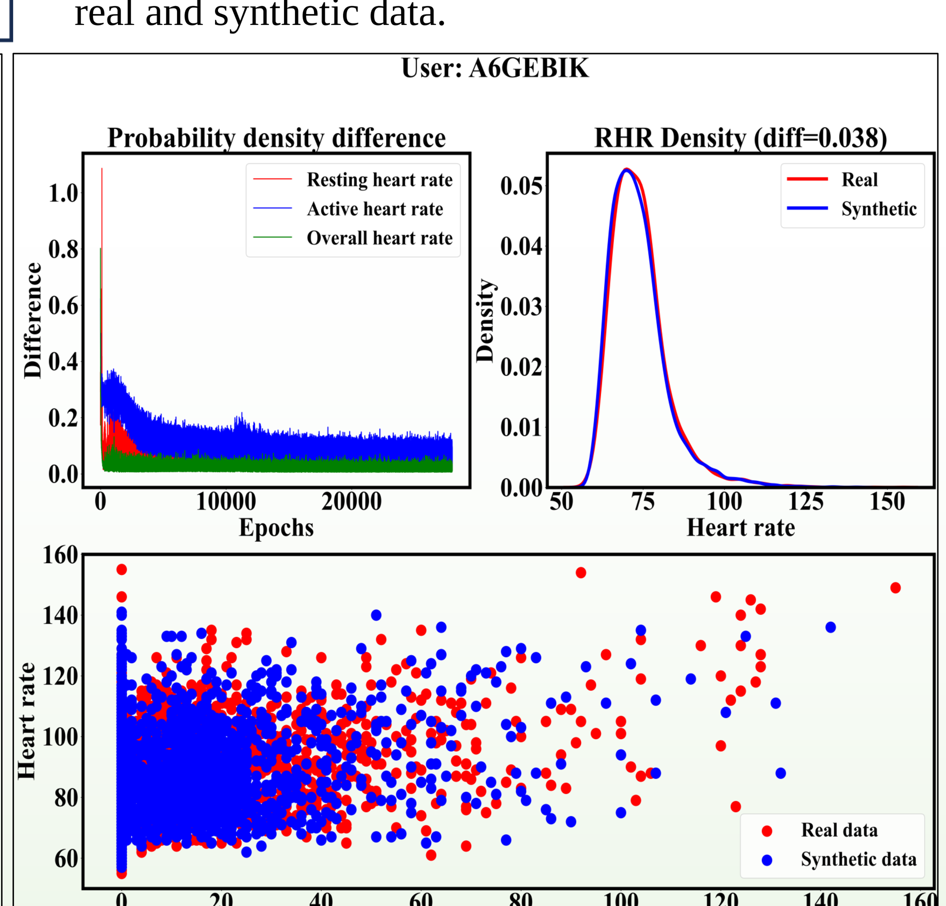
- ❑ Depicted both "F_1 score" and FNR for the RHR 100 BPM.
- ❑ Four different combinations of window and sliding are used.
- ❑ Higher "F_1 score" and lower FNR is better.
- ❑ Irrespective of the window and sliding you choose, the "F_1 score" remains high and FNR remains low for all threshold values.

Generative AI

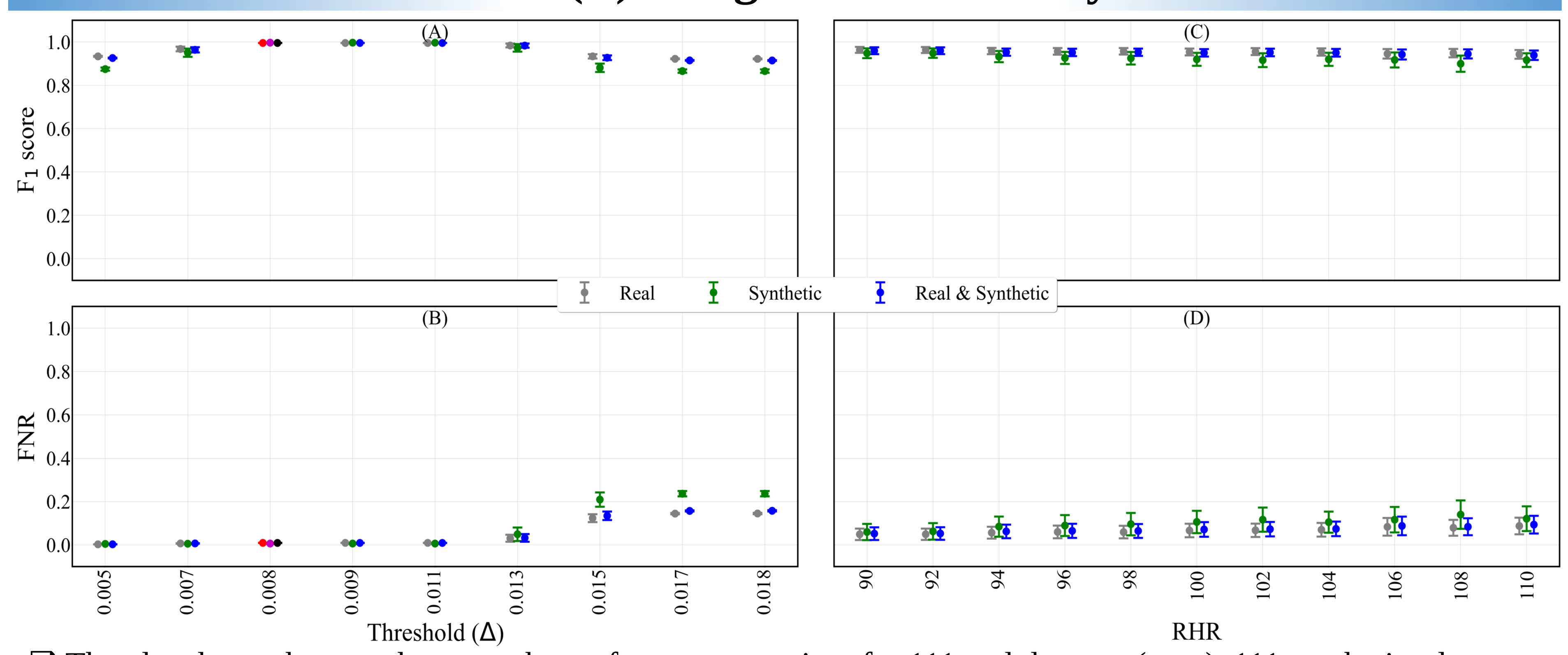


- ❑ Generator generates synthetic data from noise.
- ❑ Discriminator maximizes the Wasserstein distance between real and the synthetic data.
- ❑ The loss function helps to generate synthetic data such that:
  - The probability distribution of real features and generated features are very close.
  - The loss (Wasserstein distance) between real and synthetic data minimized.
- ❑ The process terminates based on the probability density similarity (Wasserstein distance) between real and synthetic data.



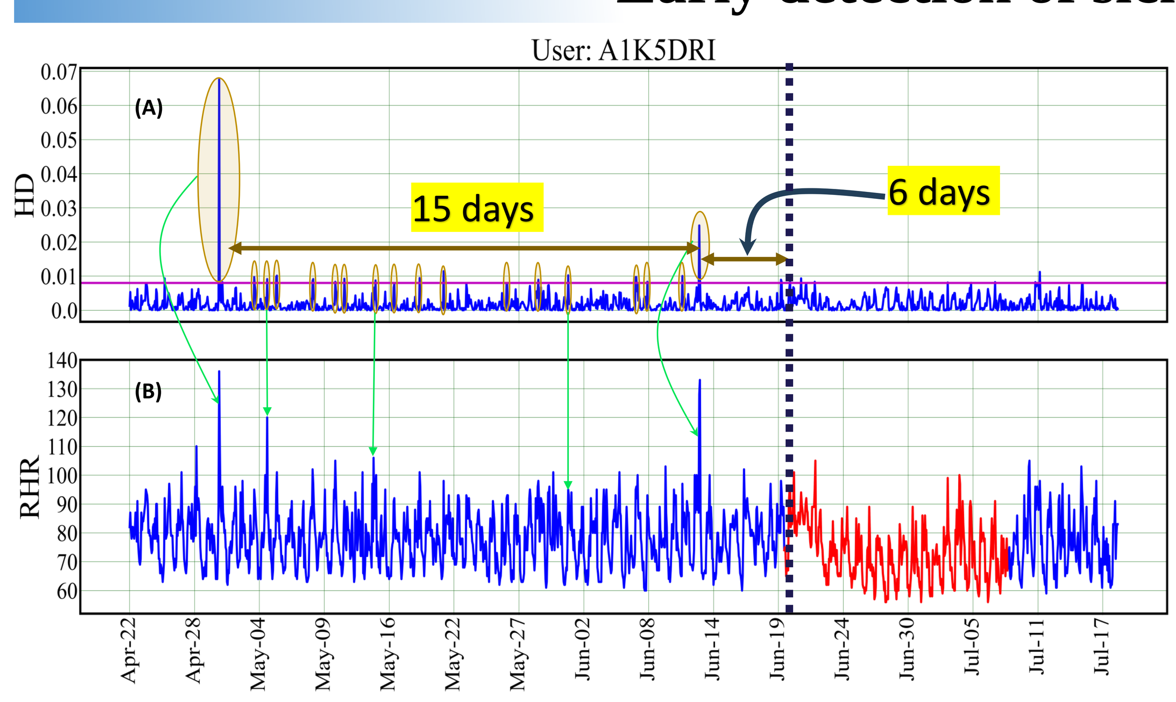


Detect threshold (Δ) using both real and synthetic data



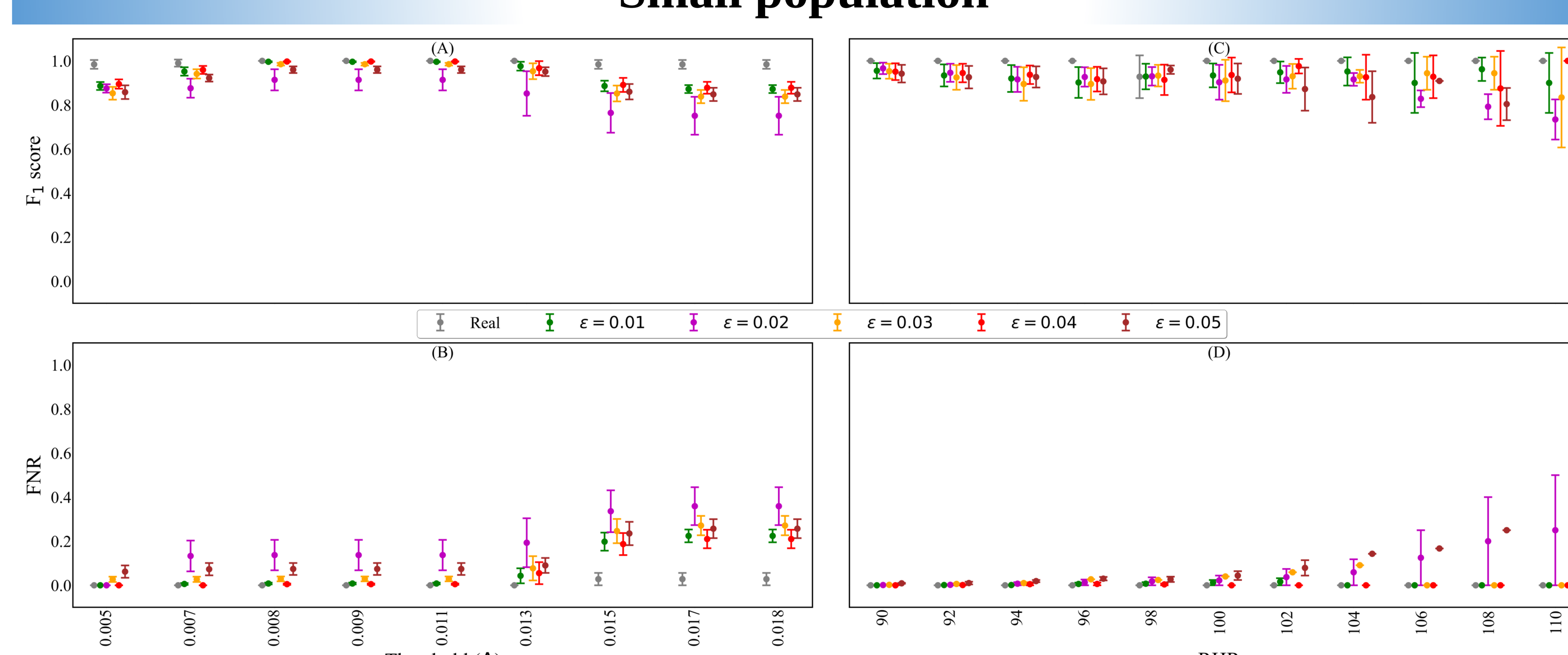
- ❑ The plot shows the error bar over the performance matrices for 111 real datasets (gray), 111 synthetics datasets (green) matching the real dataset, and 222 augmented dataset with a mix of real, and synthetic datasets (red).
- ❑ The small circle represents the mean, and the bar represents uncertainty over a 90% confidence interval.
- ❑ Plots (A) and (B) show the uncertainty in performance matrices over the range of threshold (Δ) on Hellinger distance.
- ❑ Plots (C) and (D) show the uncertainty in performance matrices over the range of RHR.
- ❑ We observed better performance for both "F_1 score" and FNR for all threshold values 0.008-0.011.
- ❑ Confirmed strong agreement in uncertainty analysis, boosting confidence in our generative algorithm for real-time anomaly detection in small populations.

Early detection of sickness



- ❑ Figure (A) shows the Hellinger distance and figure (B) shows the RHR.
- ❑ The red color segment indicates the sick period due to respiratory disease as per data.
- ❑ The magenta colored horizontal line in Figure (A) indicates threshold value 0.008.
- ❑ The number of spikes and duration between spikes could be used for early detection of sickness using inferential statistics.
- ❑ Our chosen threshold producing lot of warnings (alarms) before sickness.

Small population



- ❑ We created a small population using GenAI by perturbing (ε) only four user's real dataset with Latin Hypercube Sampling (LHS).
- ❑ Perturbations were applied ranging 1%-5% to maintain the characteristic signature of the real user (digital twin).
- ❑ We created digital twins from four users, approximately generating 2000-3000 synthetic datasets, representing a small village's population.
- ❑ To generate 500 digital twins, it costs 24 GPU Hours spread across 5 computing nodes.
- ❑ The performance metrics for the small population confirms the threshold chosen for anomaly detection and the robustness of our GenAI algorithm.

Conclusion & Future direction

- ❑ This versatile algorithm is applicable across a spectrum of datasets, from univariate to multivariate, and is compatible with various health data sources, including wearables.
- ❑ Its uniqueness lies in its ability to effectively reduce the FNR.
- ❑ Generate digital twins for multi-layer population (city, county, state) to leverage the early detection of any endemic.

References

1) Arjovsky, M., Chintala, S. & Bottou, L. Wasserstein generative adversarial networks. In International conference on machine learning, 214–223 (PMLR, 2017).
2) Mishra, T., Wang, M. & Metwally, A. e. a. Pre-symptomatic detection of covid-19 from smartwatch data. Nat. Biomed. Eng. 4, 1208–1220 (2020).

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