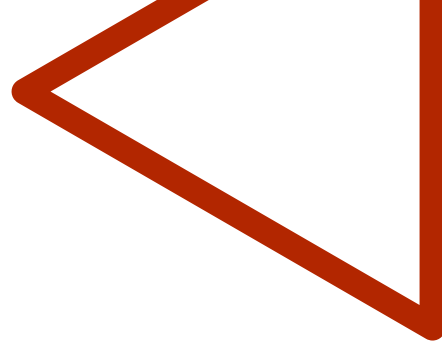




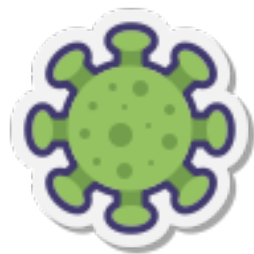
Wearable Health Condition Detection with Vector Database

Malinda Huang, Yucan Wu

COS597A



Why Wearable Health Condition Detection?



Why **Wearable** Health Condition Detection?

- **Limitations** of traditional health monitoring and disease detection:
 - Diagnosis is often delayed until symptoms become apparent
 - Subtle variations and early signs of conditions often go unnoticed
 - Require frequent visits to healthcare facilities
 - Limited personalization in one-size-fits-all approaches



What about Neural Network?

- **CovidDeep** framework [1] utilized deep neural networks with Wearable Medical Sensors and achieved great accuracy

Limitations

- **Model Adaptability**
- **Resource Intensity**



[1] S. Hassantabar, N. Stefano, V. Ghanakota, A. Ferrari, G. N. Nicola, R. Bruno, I. R. Marino, K. Hamidouche, and N. K. Jha, "CovidDeep: SARS-CoV-2/COVID-19 Test Based on Wearable Medical Sensors and Efficient Neural Networks," arXiv preprint arXiv:2007.10497, 2020.

Introducing Our Solution:

Vector-based Wearable Health Condition Detection

- A medical monitoring system that
 - **collects** physiological data from wearable devices
 - **monitors** health condition real-time through vector search using *Pinecone*
- Vector database advantages:
 - **Dynamic Learning:** New symptom patterns *without exhaustive retraining*
 - **Personalized Care:** Utilize user's history data
 - **Proactive Detection:** Early detection and continuous monitoring
 - **Edge Optimization:** Low cost and fast
 - **Explainable Results**
- **App Demo** at the end

Methodology

1. Data

- Publicly available electrocardiogram (ECG) datasets
- Pre-processing

2. **Vector Database** construction using training sets

3. **Evaluation** using testing sets

- Prediction accuracy: Top k similarity search majority vote ($k = 1, 5, 10$)

4. App

- Choose database(s) with satisfactory accuracy
- Build an app that takes in ECG data collected from Apple Watch for health condition detection

Experimented with three ECG datasets

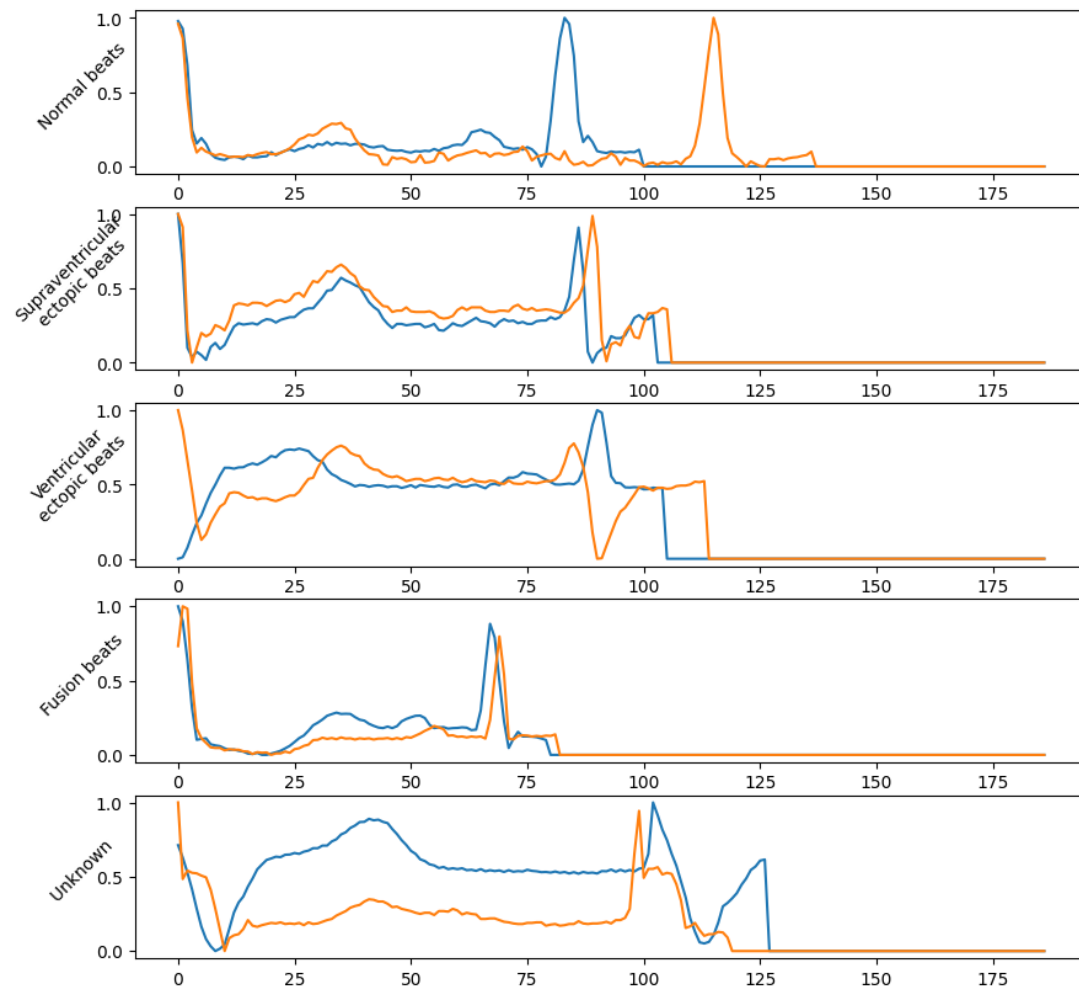
- MIT-BIH Arrhythmia Dataset [1]
- PTB Diagnostic Database [2]
- PhysioNet/CinC Challenge 2017 [3]

[1] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," in IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3, pp. 45-50, May-June 2001, doi: 10.1109/51.932724.

[2] R. Bousseljot, D. Kreiseler, and A. Schnabel, "Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet," Biomedical Engineering / Biomedizinische Technik, vol. 40, no. s1, pp. 317-318, 1995, doi:10.1515/bmte.1995.40.s1.317.

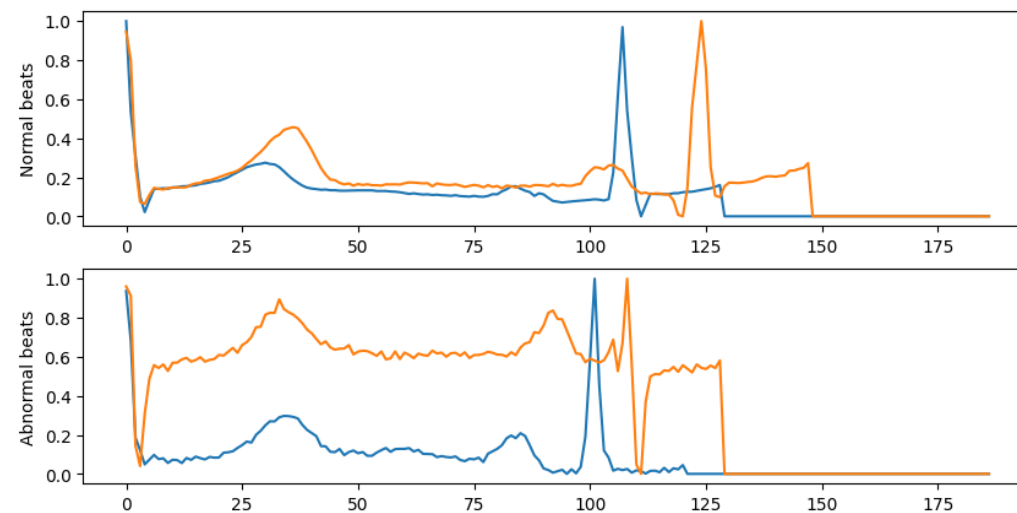
[3] G. Clifford et al., "AF Classification from a Short Single Lead ECG Recording: the Physionet Computing in Cardiology Challenge 2017," 2017 Computing in Cardiology Conference (CinC), Sep. 2017, doi: <https://doi.org/10.22489/cinc.2017.065-469>.

MIT-BIH & PTB Datasets: Beat type classification



MIT-BIH

- ECGs are **cropped** into single beats, **padded** to the same length, and **normalized**



PTB

MIT-BIH Dataset: Results

- Test accuracy:

Distance Metric	Top 1	Top 10
Cosine	97.69%	97.30%
Dot product	71.66%	77.85%
Euclidean	97.62%	97.17%

- Compare with EfficientNet accuracy: 96.62%



PTB Dataset: Results

- Test accuracy:

Distance Metric	Top 1	Top 10
Cosine	95.81%	93.34%
Dot product	71.56%	71.56%
Euclidean	99.21%	95.26%

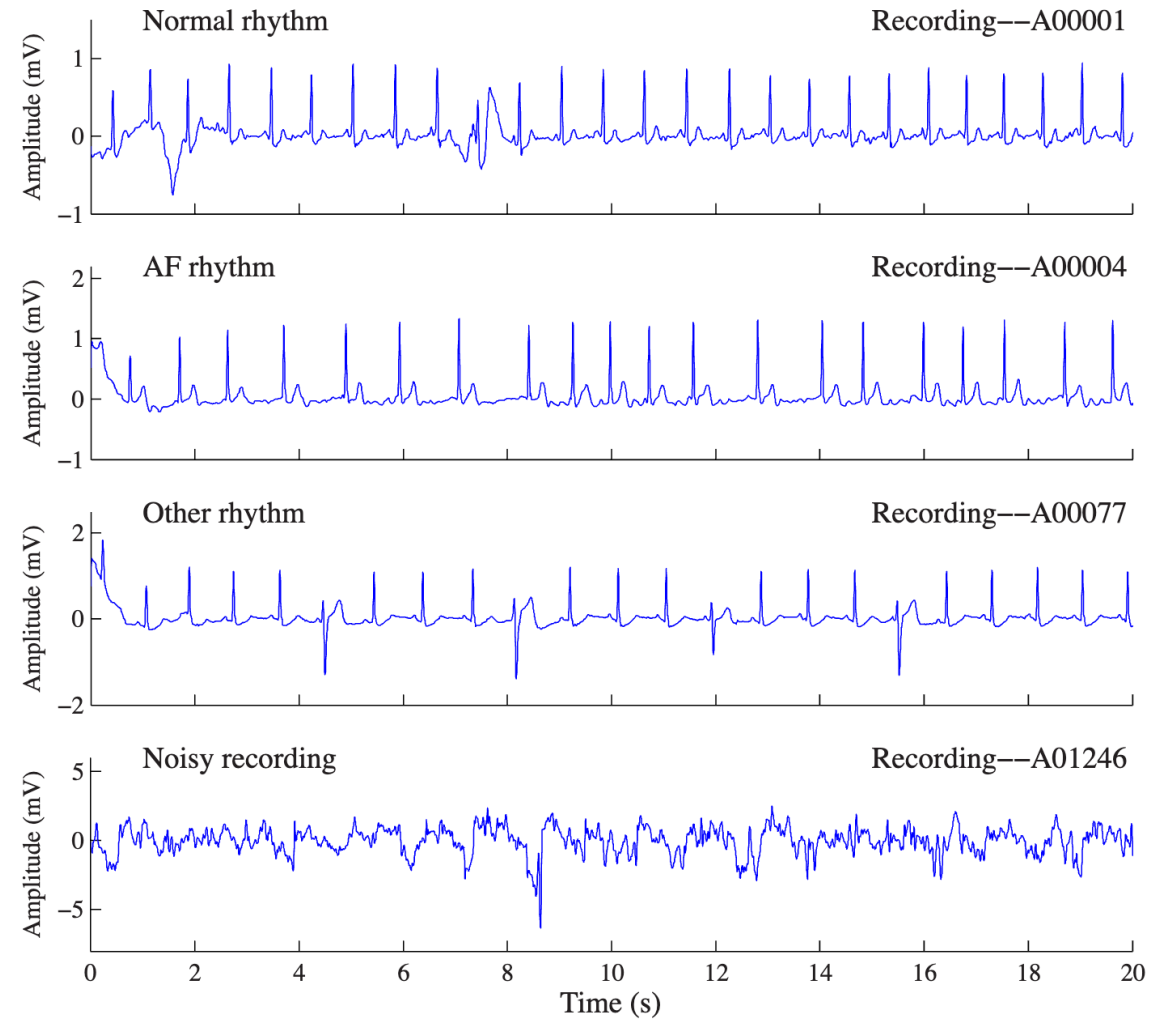
- Compare with CNN Autoencoder accuracy: 99.9%

Insights from MIT-BIH & PTB datasets

-  • Vector search methods can achieve **comparable or higher accuracy** than neural network models without the need of training
-  • Different datasets have different optimal **distance metrics**

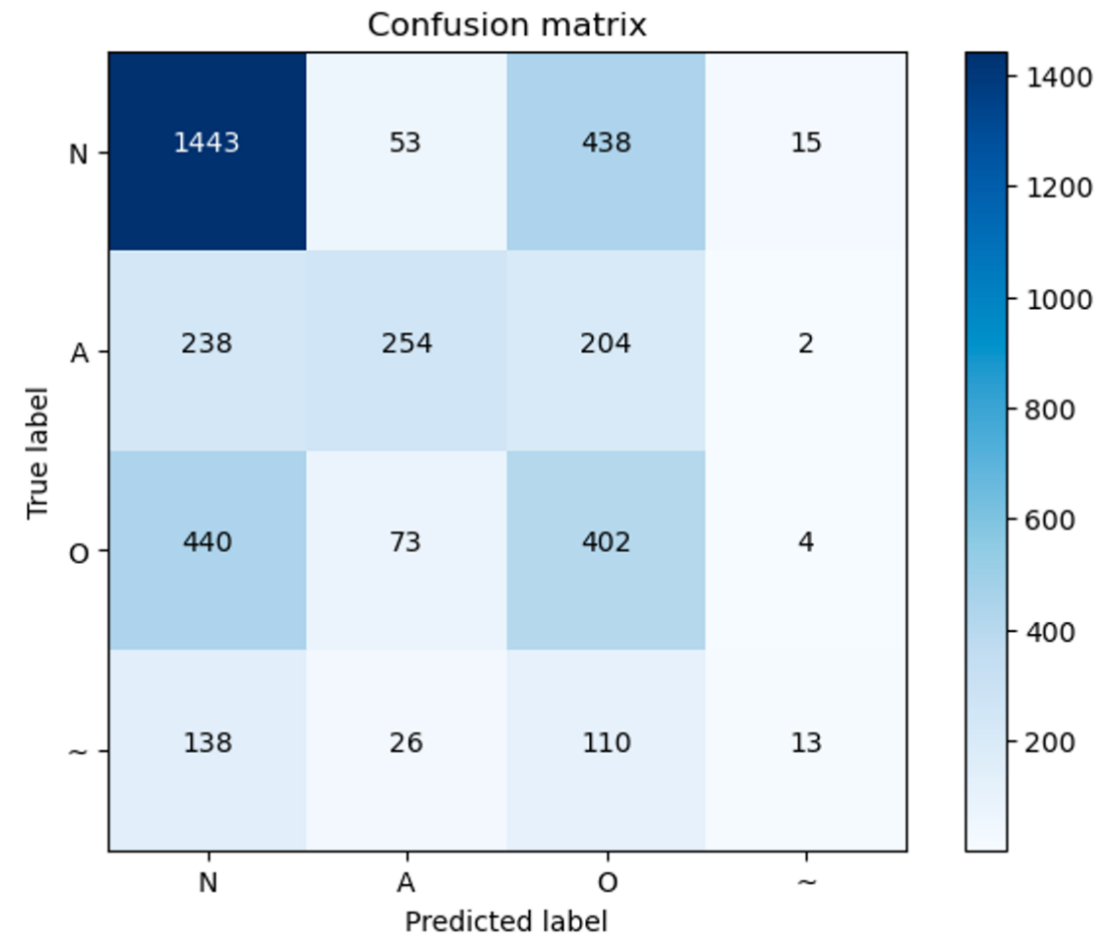
Atrial Fibrillation Detection

PhysioNet/CinC Challenge 2017 Dataset



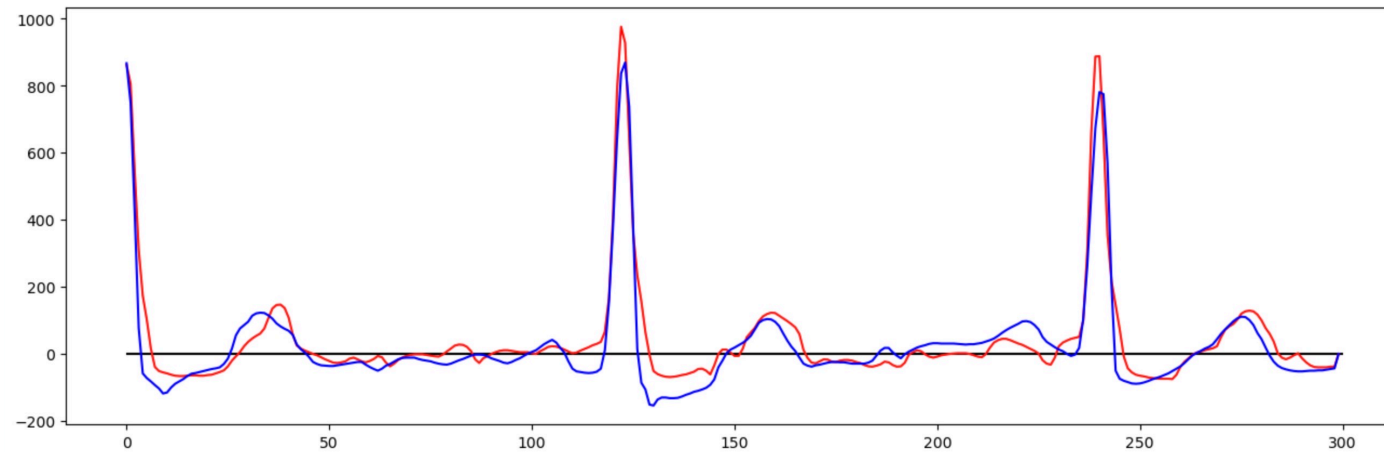
PhysioNet/CinC Challenge 2017 Dataset: Results

- Top 1 Accuracy: 54.81%
- Top 10 Accuracy: 58.29%
- Confusion among classes 1,2,3



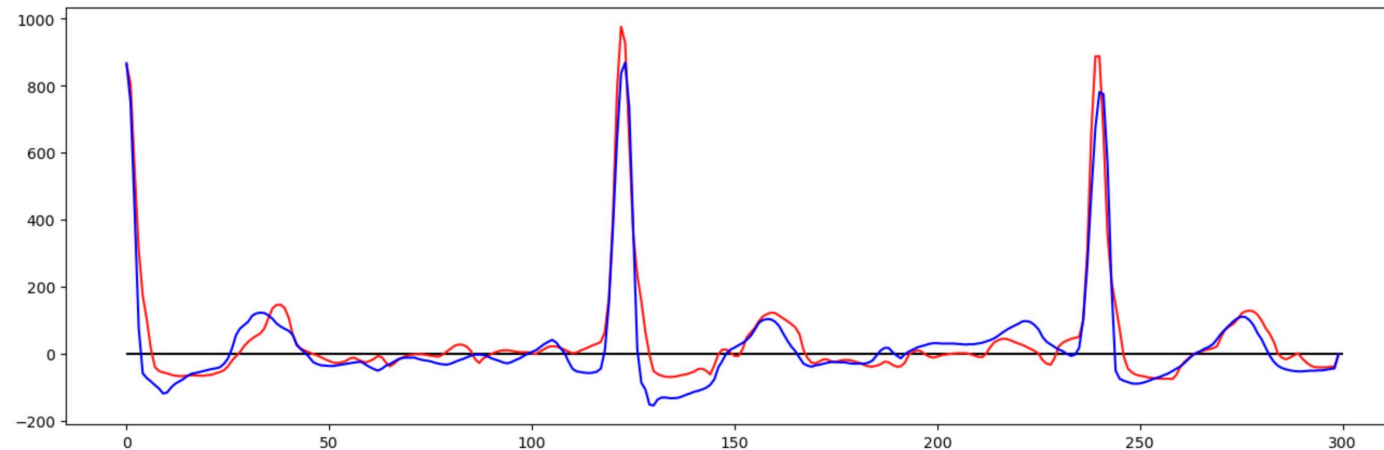
PhysioNet/CinC Challenge 2017 Dataset: Results

- Unable to achieve high accuracy due to the **difficulty level of the data & task**



PhysioNet/CinC Challenge 2017 Dataset: Results

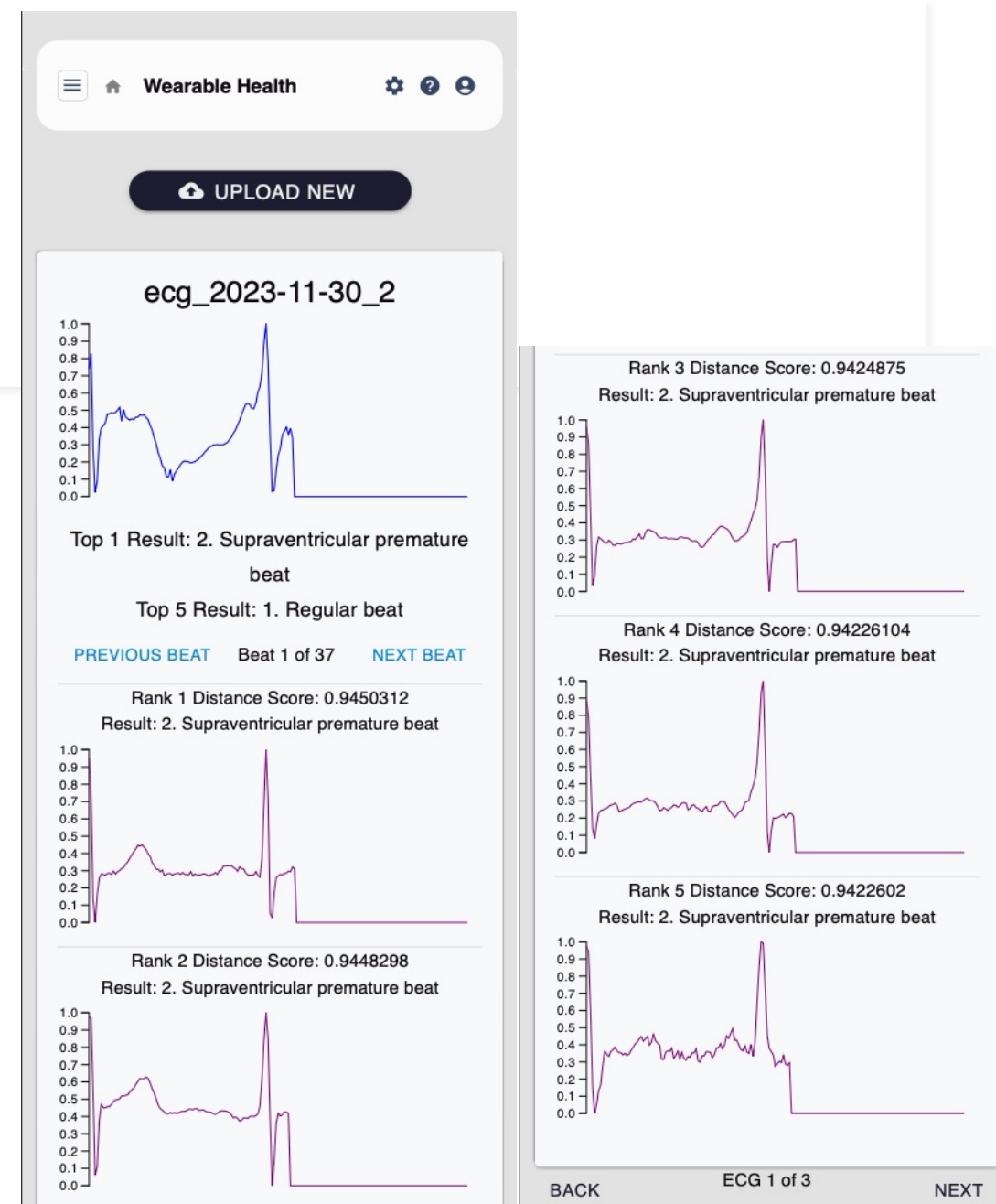
- Unable to achieve high accuracy due to the **difficulty level of the data & task**



- Blue = normal, red = other rhythm!

App demo

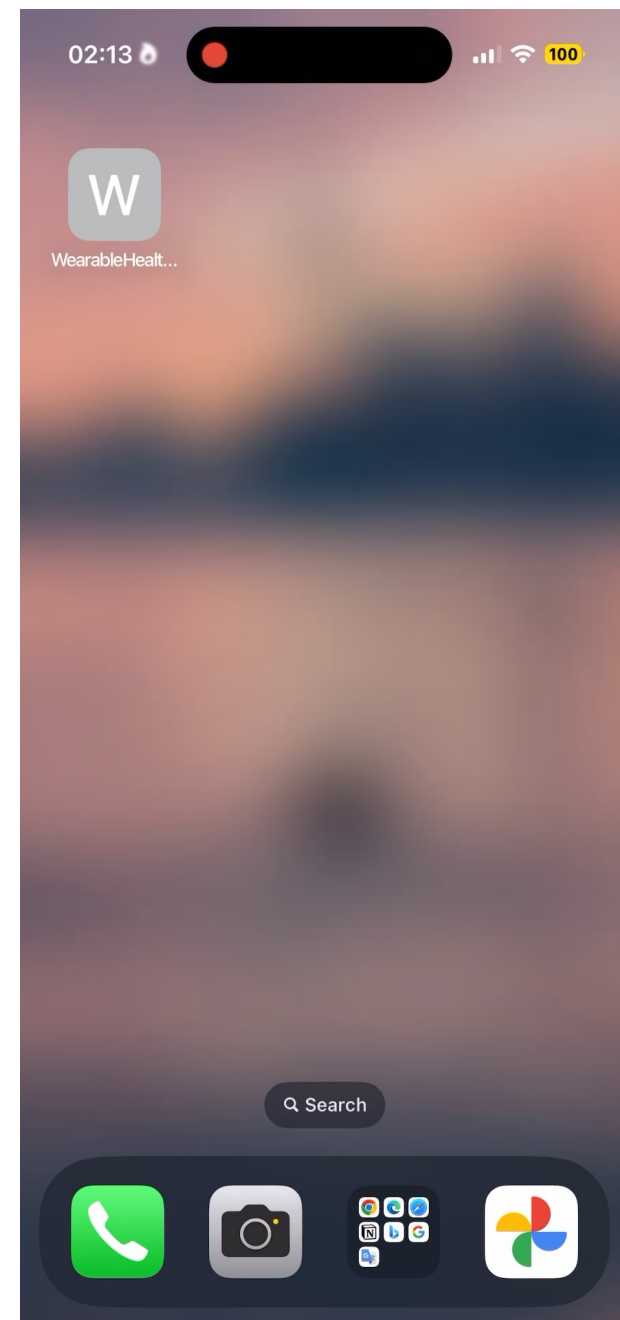
- Use ECG data collected from Apple Watch
 - In Apple Health app, click profile icon and scroll down to the end
 - Click "Export All Health Data" button, save the export.zip, and upload it to app
- Pinecone with MIT-BIH dataset



Video Demo

<http://cos597a.yucanwu.com/>
(available until Dec 9, 2023)

<http://cos597a.yucanwu.com/demo>
(available until Dec 31, 2023)



Video Link: https://drive.google.com/file/d/1_WHb4aabwujUbzh40ARQyKZ5RU7dtKKe/view?usp=sharing

Findings:

Pros and Cons of Vector-Search-Based Approach



- On certain tasks, vector database can perform comparably **well** or **better** than other machine learning models **without the need of training**
- Can add newly collected data, thereby "**fine-tune**" without re-training (and **personalization**)



- Direct vector database is only suitable for **certain easy datasets** & classification tasks due to the inability of **feature selection/extraction**
- Need to **tune hyperparameters** (distance metric, top k nearest neighbors, padding, etc.)
- Doesn't work well on class-imbalanced datasets

Conclusion & Future Work

- We showed that **real-time ECG health condition detection** is possible with high accuracy through vector database & similarity search

Future work:



- Incorporate **multiple** vector databases in the app => detect **multiple** health conditions
- Incorporate **multi-modal data** collected from smart watches
 - WESAD Dataset [1]: ECG, temperature, acceleration, electrodermal activity, etc.



Challenges:

- **Feature extraction** to make more complicated tasks possible

[4] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing WESAD, a Multimodal Dataset for Wearable Stress and Affect Detection," Proceedings of the 20th ACM International Conference on Multimodal Interaction, Oct. 2018, doi: <https://doi.org/10.1145/3242969.3242985>.