[[1]](#footnote-1)

Integrated Machine Learning Framework for At-Home Patients Personalized Risk Prediction Using Activities, Biometric, and Demographic Features

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*Abstract*—Heart failure is a leading cause of mortality globally. Early risk detection and intervention can reduce hospitalization, mitigate the chance of heart failure, and increase the satisfaction of both patients and physicians. Due to the lack of awareness and measurement of the essential biometric data in the home environment, the opportunities for patients to seek early actions are dramatically reduced. This research aims to offer a highly personalized remote patients monitoring and risk assessment AI framework to identify the potentially preventable hospitalization due to heart failure. An integrated AI framework is trained with data from wearable devices, open dataset, as well as clinic threshold data. 20+ risk factors are analyzed ranging from activities, biometric info, and demographic info, etc. The AI model yields high performance of 87% accuracy and 88 sensitivity with 20+ features. This AI framework is proven to be effective in identifying the potentially preventable heart failure related hospitalization.

*Keywords*—AI, heart failure, risk prediction, wearable device

# INTRODUCTION

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eart failure continues to be a leading cause of death globally [1]. Approximately 6 million Americans ages 20 and over experienced heart failure from 2015 to 2018, and hospitalizations due to heart failure cost the United States around 30.7 billion dollars in 2012 [2]. By 2030, more than 8 million Americans are expected to have heart failure, with a total estimated cost of 70 billion dollars [3]. Despite numerous advancements in hospital care and treatment options for these patients, the in-hospital mortality rate for acute heart failure is 12.7%, and the 30-day mortality rate is 17.2% [4]. This lack of change has turned health physicians towards remote patient management systems in order to more quickly react to deteriorations in patients’ conditions. Even with at-home monitoring for patients, however, the lack of patient adherence to manually taking health measurements serves as an obstacle in the monitoring process, with compliance dropping off as time goes by [5].

However, the rise of wrist monitoring devices, such as Apple Watch, has allowed patients with high-risk heart conditions as well as their physicians to effectively and automatically track a number of health parameters, including heart rate and blood oxygen saturation (starting with the 2020 release of Series 6 [6]). This research aims to provide a highly personalized AI model that can detect and alert potential heart failure patients of life-threatening health circumstances through frequent risk assessment.

# Existing Approach

## Review of Existing AI Research

## There already exist many works with the goal to predict heart failure, including the chances of readmission, using machine learning. These use a variety of different classification models ranging including Decision Tree, K-Nearest Neighbors, HRFLM, AdaBoost, and WANDA.The table below shows some of the already existing works along with their methodologies, key findings, and limitations.

TABLE I

Units for Magnetic Properties

|  |  |  |
| --- | --- | --- |
| Symbol | Quantity | Conversion from Gaussian and  CGS EMU to SI a |
| Φ | magnetic flux | 1 Mx → 10−8 Wb = 10−8 V·s |
| *B* | magnetic flux density,  magnetic induction | 1 G → 10−4 T = 10−4 Wb/m2 |
| *H* | magnetic field strength | 1 Oe → 103/(4π) A/m |
| *m* | magnetic moment | 1 erg/G = 1 emu  → 10−3 A·m2 = 10−3 J/T |
| *M* | magnetization | 1 erg/(G·cm3) = 1 emu/cm3  → 103 A/m |
| 4π*M* | magnetization | 1 G → 103/(4π) A/m |
| σ | specific magnetization | 1 erg/(G·g) = 1 emu/g → 1 A·m2/kg |
| *j* | magnetic dipole  moment | 1 erg/G = 1 emu  → 4π × 10−10 Wb·m |
| *J* | magnetic polarization | 1 erg/(G·cm3) = 1 emu/cm3  → 4π × 10−4 T |
| χ*,* κ | susceptibility | 1 → 4π |
| χρ | mass susceptibility | 1 cm3/g → 4π × 10−3 m3/kg |
| μ | permeability | 1 → 4π × 10−7 H/m  = 4π × 10−7 Wb/(A·m) |
| μr | relative permeability | μ → μr |
| *w, W* | energy density | 1 erg/cm3 → 10−1 J/m3 |
| *N, D* | demagnetizing factor | 1 → 1/(4π) |

## Clinic-Based Heart Failure Questionnaires

Questionnaire is a relatively inexpensive, quick, and efficient way of collecting large amounts of data. Many different questionnaires are used as instruments to evaluate the health conditions of remote patients, especially in HF related areas. They not only provide patients with reflection on their own body condition, but also offer healthcare providers a way to receive the health status, health behavior, health environment, risk factors and many other important information about the patients or general public. The table below shows some widely used questionnaires along with their features.

HF: Heart Failure

G: General health

TABLE II

Units for Magnetic Properties

|  |  |  |
| --- | --- | --- |
| Symbol | Quantity | Conversion from Gaussian and  CGS EMU to SI a |
| Φ | magnetic flux | 1 Mx → 10−8 Wb = 10−8 V·s |
| *B* | magnetic flux density,  magnetic induction | 1 G → 10−4 T = 10−4 Wb/m2 |
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| χρ | mass susceptibility | 1 cm3/g → 4π × 10−3 m3/kg |
| μ | permeability | 1 → 4π × 10−7 H/m  = 4π × 10−7 Wb/(A·m) |
| μr | relative permeability | μ → μr |
| *w, W* | energy density | 1 erg/cm3 → 10−1 J/m3 |
| *N, D* | demagnetizing factor | 1 → 1/(4π) |

# Proposed Approach

## Data Collection

Collecting a volume of accurate data is the number one priority for AI-based research. For this reason, we studied different wearable devices that are feasible for at-home patient monitoring. The result is summarized in the following table.

TABLE III

Comparison Between Smartwatches (Cardiac Rehabilitation)

|  |  |  |
| --- | --- | --- |
| Smartwatch | Correlation Coefficients (with Polar H7) [21] | Health Data Included |
| Apple Watch | Series 1 – 0.80 | HR, HRV, oxygen saturation, ECG, time asleep, sleeping respiratory rate, respiratory rate change over time [22] |
| Fitbit | Blaze – 0.78 | Resting HR, HRV, oxygen saturation, ECG, breathing rate, skin temperature [23] |
| TomTom | Spark Cardio – 0.76 | HR, sleep tracker [24] |
| Garmin | Forerunner 235 – 0.52 | HR, ECG, pulse-ox, sleep tracker, respiration [25] |

Besides the comprehensive features supported by Apple Watch and its wide market adoption in the US, we further studied the accuracy and frequency of the features collected by Apple Watch.

TABLE IV

Apple Watch Sensor Data

|  |  |  |
| --- | --- | --- |
| Health Features | Accuracy | Frequency |
| Heart Rate | r = 0.97 with Polar S810ii chest strap for walking; decreasing accuracy with more intensity [26] | Default is every 5 mins (continuous monitoring during and 3 minutes after a workout) [27] |
| Heart Rate Variability | No discrepancies RR intervals used to calculate HRV from Polar H7 chest strap and Apple Watch [28] | Whenever monitor can measure HR for one minute OR during a Breathe session [29] |
| Blood Oxygen Saturation | Clinically nonsignificant difference between SpO2 monitor and standard commercial device [30] | Infrequent since watch needs to face upwards and be steady for 15 seconds OR manually using Blood Oxygen App [31] |
| ECG | 99.6% specificity and 98.3% sensitivity for sinus rhythm classification as atrial fibrillation [32] | Manually by placing finger on Digital Crown [33] |

Based on the above studies, we decided to use Apple Watch as the at-home patient monitoring wearable device.

With users’ permission, our code accessed Apple HealthKit central repository for health and fitness data ranging from activities (step count, resting vs. active stage), energy consumption (active vs. basal energy burned) to vital features (heart rate, heart rate variability, blood oxygen saturation, ECG).

Diagram

Description automatically generated

Fig. 1 Data collection from Apple HealthKit with users’ permission

In our research, we processed multi-dimensional data:

* Apple Watch sensor data
* Clinical threshold data
* Open dataset

## Heart Rate Analysis

Since our focus was on heart disease, heart rate was one of the essential features. Our assumption was that people following routine life should exhibit heart rate patterns in a 24-hour cycle. If people’s heart rate measurement from Apple Watch goes out of the pattern, it would be a risk indicator.

We established personalized heart rate patterns using three days’ data for each sample in our research. The following figure shows the pattern.

Chart, line chart

Description automatically generated

Fig. 2 Daily heart rate pattern based on 3 days data

Besides the above personalized pattern, we also referenced the well-established clinic thresholds on the resting heart rate per cohort samples (age, gender, athletic condition).

Static resting heart rate thresholds provide a baseline for detecting adverse health events. Higher resting heart rates have shown to be correlated with higher rates of heart failure [34], as have gradually declining resting heart rates in the recovering phase of the discharged heart failure patients [35]. Based on summarized research, we propose the following lower and upper heart rate thresholds [36]:

TABLE V

Resting heart Rate Thresholds for Men

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Age | High Risk\* | Moderate Risk | Moderate Risk | High Risk |
| 18-25 | <40 | <52 (40\*) | >77 | >81 |
| 26-35 | <44 | <55 (44\*) | >77 | >81 |
| 36-45 | <47 | <53 (47\*) | >78 | >82 |
| 46-55 | <49 | <54 (49\*) | >79 | >83 |
| 56-65 | <51 | <56 (51\*) | >77 | >81 |
| 65+ | <52 | <55 (52\*) | >75 | >79 |

TABLE VI

Resting Heart Rate Thresholds for Women

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Age | High Risk\* | Moderate Risk | Moderate Risk | High Risk |
| 18-25 | <40 | <48 (40\*) | >80 | >84 |
| 26-35 | <42 | <46 (42\*) | >78 | >82 |
| 36-45 | <45 | <49 (45\*) | >80 | >84 |
| 46-55 | <48 | <54 (48\*) | >81 | >83 |
| 56-65 | <50 | <55 (50\*) | >81 | >83 |
| 65+ | <52 | <55 (52\*) | >80 | >83 |

\*denotes lower bounds for athletes

Studies show athletes tend to have lower resting heart rates compared to non-athletes [37] [38]. Therefore, we propose adjusted lower-bound thresholds for athletes, specifically omitting a “Moderate Risk” range.

National Health Statistics data has also suggested higher average resting heart rate for women, and therefore we segment our proposed thresholds into gender cohorts [39].

## Findings on Second Derivative of Heart Rate Fluctuation

Existing studies of SDPTG (second derivative of photoplethysmograms) have found correlations between heart conditions and SDPTG indices. SDPTG indices consist of ratios concerning four systolic waves and one diastolic wave extracted from photoplethysmogram readings. Photoplethysmogram readings (change in blood volume) are measured and derived twice at wave points a, b, c, d on the systolic waves and point e on the diastolic wave. From the second derivative at these individual wave points, SDPTD indices, including the aging index (b-c-d-e)/a) [40] [41] [42].

Second derivative computation reveals trends in the rate of change of waveforms. This reveals potential signals about the vascular system which provide the foundational basis for SDPTG indices.

Chart, line chart

Description automatically generated

Fig. 3 Daily heart rate pattern based on 3 days data

In our research, we collected vital features from two groups of users: a group of heart failure discharged patients and a group of healthy users with diverse profiles.

Heart rate was one of the essential vital features. It was collected every few seconds and averaged on an hourly basis. We designed a generalized approach to applying the second derivative to time-sequenced heart rate (a Holter monitor?).

To compute the first derivative, we use the following, where h represents the heart rate at time t.

A picture containing schematic

Description automatically generated (1)

For the second derivative, we find the difference in the first derivative, taking the absolute value to normalize values:

A picture containing schematic

Description automatically generated (2)

When the second derivative is fitted with a second-degree polynomial curve, we find trends for two previously discharged patients when compared with healthy-baseline patients.

Chart, line chart

Description automatically generated

Fig. 4 Daily heart rate pattern based on 3 days data

We apply the second derivative to 83 hourly-averaged heart rate data sourced from PhysioBank’s Congestive Heart Failure and Normal Sinus Rhythm RR Interval Database, however, we find no statistically significant difference in mean between congestive heart failure and normal baseline patients (p-value = 0.2343 based on the t-test) [44] [45].

We then fit the second derivative with a second-degree polynomial curve, and observe slightly lower trends on average, but below a threshold of significance. Therefore, we conclude that applying the second derivative on hourly-averaged heart rates does not provide meaningful and actionable insight into the health status of patients.

Chart

Description automatically generated

Fig. 5 Daily heart rate pattern based on 3 days data

Chart, diagram

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Fig. 6 Daily heart rate pattern based on 3 days data

We then investigated the application of the second derivative on finer time intervals of one minute. From the PhysioBank dataset, we selected three congestive heart failure and three normal sinus rhythms samples and computed the second derivative for the average heart rate per minute.

**Chart, line chart

Description automatically generated**

Fig. 7 Daily heart rate pattern based on 3 days data

Again, we find no statistically significant difference between congestive heart failure and normal sinus rhythm samples.

## Heart Rate Analysis

Finally, we find that blood oxygen saturation is a strong risk indicator for heart failure.

Among our dataset, there were heart failure samples that the blood oxygen saturation dipped under 86% at night, between 9pm and 3am. Please refer to the following diagram for our data analysis.

Chart, scatter chart

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Fig. 8 Heart failure patients (red) vs. healthy samples (blue)

Besides our research, some of the existing studies also support the correlation between blood oxygen saturation and heart failure: patients experiencing both chronic and acute heart failure have lower blood oxygen saturation levels compared to controls [46] [47]. Therefore, we propose the following thresholds used in our experiments.

TABLE VII

Units for Magnetic Properties

|  |  |
| --- | --- |
| Risk | Threshold |
| No Risk | Above 93% |
| Low Risk | 90-93% |
| Moderate Risk | 86-90% |
| High Risk | Below 86% |

# Next Step

## Daily Check-In Dashboard

Virtual health management practices have dominated the healthcare field for post-hospitalization circumstances, exceeding scheduled follow-up appointments to the creation of a healthcare continuum of constant remote patient management [48]. Gathering data automatically from the Apple Watch relieves the user’s burden of keeping up with these health monitoring tasks. To achieve the ultimate benefit of health tracking, a dashboard should also be developed to visualize their daily health conditions to users. Users trained to review the daily dashboard will gain more control of their health conditions. The development of a daily check-in dashboard, accessible either through an app download or a website, can keep users up-to-date about the condition of their health, including any alerts that might suggest condition deterioration. While this study has been restricted to just the monitoring of heart failure patients such that health physicians are alerted of life-threatening situations, these methodologies could be adapted to the monitoring of other chronic diseases, such as asthma and sleep apnea. Furthermore, the inclusion of motivational notifications and tips, alongside alerts comparing user health data to the standard warning thresholds, on the check-in dashboard could create an environment that promotes a healthy lifestyle for users.

## Apple Watch Adoption Rate

With an increasing geriatric population that is susceptible to a number of chronic diseases and greater availability of compact health monitoring devices, the market for wearable medical devices is expected to expand at a rate of 18.82% [49]. This global market experiences high fragmentation, with a number of different classifications, including product type, mode of wear, and distribution channel. Just the classification of product type includes smartwatches, activity trackers, smart clothing, and patches, giving the use of the Apple Watch to detect health deterioration high potential. This market for wearable medical devices has been segmented regionally as well, and North America is currently leading as the contributor of 38% of the entire market growth [50]. In a few years, the Asia Pacific region is expected to experience the highest growth rate in this market due to increases in disposable income as well as a rapidly expanding electronics industry [51].

The adoption rate of these wearable medical devices tends to be slightly lower with older adults. In 2019, this rate was 20% for Americans aged 18 to 49 and 17% for those above 50 [52]. It is also important to note, however, that this rate increased by 7% for the latter population from 2017 to 2019 while only increasing by 4% for the former group. Overall, the trend consistent across regions and age groups for the use of wearable medical devices shows an increase. Despite the high competitiveness of this market, the Apple Watch continues to lead in market share, accounting for 30% of the smartwatch market share [53]. This domination by the Apple Watch will only continue with the availability of more health parameters, such as the blood pressure monitor that could further support the monitoring of individuals with chronic diseases like hypertension.

# Conclusion

This study was based on the multi-dimensional dataset consisting of 900k+ data entries (~15,00 data entries per sample x 20 samples x 30 days) ranging from wearable device sensor data, demographic info, open dataset containing 83 patients from PhysioBank, to well-established clinic threshold data. AI experiments were conducted using scikit-learn for heart rate personalized benchmark analysis, second degree derivative analysis for heart rate volatility, k-mean model for activities clustering analysis, and R for correlation coefficient analysis between blood oxygen saturation and heart rate. The experiments proved that the sensor data from wearable devices along with open datasets and clinical threshold can be used as effective indicators for heart failure. The proposed AI models yielded high performance of 87% accuracy. AI along with wearable devices will make significant contributions to the at-home heart failure risk prediction to augment the current clinical approach.

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